The Power and Pitfalls of Techno-Industrial Policy: Evidence from China*

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Abstract

How effective is industrial policy at fostering innovation? I study this question through China's Strategic and Emerging Industries (SEI) initiative from 2010 to 2018, a large-scale fiscal intervention targeting frontier technologies. Employing a staggered difference-in-differences (DiD) design with city-sectoral level patent data, I find that the policy substantially increased innovation quantity: patenting in targeted sectors rose by 184 percent. These gains reflect a reallocation of innovative effort rather than a pure expansion: patenting in non-targeted sectors fell by 14 percent. Importantly, cities that targeted industries aligned with pre-existing technological strengths experienced more than twice the patent growth of other cities, highlighting the importance of local capabilities. By contrast, average patent quality remained broadly unchanged, suggesting that quality upgrading is more difficult to steer than quantity expansion. The results highlight both the power and the limits of state-led techno-industrial policy.

Keywords: industrial policy, innovation, strategic emerging industries, comparative advantage, quantity-quality tradeoff.
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1. Introduction

Industrial policy is far from a new idea. It has been pivotal in the economic success stories of many nations. Japan's emergence as a global automotive powerhouse (Porter, 1990), South Korea's transformation through its heavy and chemical sectors (Lane, 2025), and Singapore's ascent through manufacturing (van Elkan, 1995) all stand as key pillars of the East Asian miracle. China, often seen as the latecomer among the "Asian Tigers", has placed firm belief in the power of industrial policy (Aghion et al., 2015).

China is striving for a change. For decades, its rapid growth was fueled by low-cost manufacturing and trade liberalization (Brandt et al., 2017). However, rising labor costs, mounting environmental pressures, and an aging population have pushed this growth model to its limits (Ebenstein et al., 2015). At the same time, intensifying global technological competition and Western decoupling have exposed China to risks of technological blockades (Bown, 2020). In response, the national government launched the innovation-centric Strategic and Emerging Industries (SEI) initiative in 2010. The policy aimed to foster innovation autonomy in selected frontier sectors through subsidies, tax incentives, and land support, among many instruments.[1] By 2011, the SEI had become a top priority across the national, provincial, and city-level 12th Five-Year Plans. Its strategic importance extended beyond a single five-year period, with SEI reaffirmed as a central element in the 13th Five-Year Plan (2016-2020).

This paper deciphers China's landmark Strategic and Emerging Industries (SEI) initiative, a decade-long industrial policy experiment targeting high-tech sectors. The SEI drive has two key features. First, although it was launched nationally in 2011 with seven broad priority sectors, the specific sectors prioritized varied across Chinese cities, as the central government encouraged local diversification. Second, the policy had a staggered rollout at the city level between 2010 and 2018, resulting in variation not only in sectoral focus but also in timing and geographic coverage. To capture these dynamics, I construct a novel panel that tracks SEI implementation at the four-digit industry level across 123 Chinese cities, drawing on nearly 1,500 city-level policy documents.

To measure SEI's innovation impacts, I merge this hand-collected treatment data with detailed patent metrics from IncoPat. The integrated dataset captures: (1) innovation quantity (counts of granted invention patents and patenting firms); (2) innovation quality (forward citations, patent lifespan, and count of internationally vetted PCT patents);

[1] China's *innovation autonomy* refers to its ability to independently develop cutting-edge technologies without reliance on foreign expertise or intellectual property. This concept has gained prominence in key events and policy discussions, including during the U.S.-China trade war and through initiatives like the Belt and Road Initiative.

and (3) collaboration networks (co-patenting relationships among firms, universities, and government entities). These measures are augmented with firm entry and exit records to assess market dynamism. The final panel spans 2009-2021 across cities and four-digit industries (harmonized with China's 2017 National Economic Industry Classification), allowing assessment of treatment effects before and after SEI's 2010-2018 rollout period.

I evaluate the SEI policy impact by employing a staggered differences-in-differences design. Considering the spatial, temporal, and sectoral variations of SEI, I estimate the policy's impact by comparing changes in outcomes between targeted and non-targeted city-industry pairs for each year, before and after the policy's launch. To address potential biases from staggered treatment in canonical two-way fixed effects (TWFE) models (Goodman-Bacon, 2021), I adopt methods from Callaway and Sant'Anna (2021) that account for treatment heterogeneity. Additionally, I demonstrate that my baseline results remain robust when using doubly robust estimators, combining outcome regression and propensity score models to adjust the counterfactual (Sant'Anna and Zhao, 2020). Furthermore, my estimates hold up under a variety of robustness checks and placebo experiments.

I highlight three key findings. First, the SEI initiative successfully boosted innovation quantity, with patent counts in targeted city-industry units expanded by more than 180% over non-targeted units, yet struggled to spur meaningful quality improvement. While aggregate quality metrics rose significantly (e.g., 29% for citations), scale-adjusted measures showed stagnation (e.g., 0.1% increase in average citation). This quantity-quality divergence extends to patent collaboration outcomes: while collaborative patent volumes surged, their share of total patents remained insignificant, indicating limited structural change in the innovation ecosystem. The policy also induced classic industrial policy churn, with comparable increases in both firm entry and exit rates, consistent with subsidy-driven market selection where entrants are drawn by government incentives while less competitive firms exit.

Second, the SEI-led patent boom masks a more complex reality of sectoral redistribution. While treated sectors achieved unprecedented growth, non-treated sectors within the same cities experienced a 14% decline in patent count, suggesting crowding-out effects. Though this redistribution modestly attenuates the net gains, it does not negate the overall positive impact. This asymmetry exposes industrial policy's inherent tension, where selective interventions create distributional winners and losers. The contrast with South Korea's heavy-chemicals drive (Lane, 2025), where crowd-out effects were absent, reveals industrial policy's context-dependent nature. Importantly, SEI avoided within-sector displacement of non-priority entities – innovation in private firms, for instance,

was not crowded out by state-owned enterprises within the targeted sectors.

Third, despite central government directives promoting local diversification, three-quarters of cities closely adhered to national priorities, resulting in striking convergence: fewer than 10% of industries (e.g., AI, biomedicine) accounted for 40% of all city-level targeting. This clustering reflects intense intercity competition for high-profile sectors rather than strategic specialization, heightening risks of resource misallocation. This raises a critical question: Did cities that leveraged local comparative advantages achieve better innovation? I test this by analyzing heterogeneous treatment effects using pre-policy innovation capacity, drawing on Aghion et al. (2019) and Lin (2011). The results demonstrate strong path dependence, with sectors possessing pre-existing innovation advantages experiencing patent growth rates more than double those of other industries under the SEI initiative. Yet, this "smart targeting" failed to break the quality trap as citation rates flatlined, pointing to unresolved barriers in innovation quality.

Taken together, this study uncovers three critical blind spots in industrial policy design: First, the patent quantity-quality paradox reveals that rigid output targets may distort research priorities, requiring incentives that reward genuine technological impact rather than numerical quotas. Second, crowding-out effects demonstrate industrial policy's inherent trade-off: absent compensatory measures (e.g., workforce transition programs, SME innovation vouchers), sectoral targeting may erode existing productive capacities in traditional sectors. Third, and most fundamentally, while latent comparative advantage effectively scales innovation volume, it cannot independently succeed in quality upgrading.

While this paper focuses on industrial policy in China, and much of the literature has extensively centered on East Asia, the relevance of industrial policy extends far beyond this region. In the U.S., initiative like the CHIPS Act underscores its continued importance (Goldberg et al., 2024), while in Europe, Germany's Industry 4.0 and the European Green Deal signal similar strategic priorities (Bongardt and Torres, 2022). The resurgence of industrial policy worldwide has not only reignited debates about its effectiveness, but also prompted policymakers to reassess what makes for successful policies (Juhász et al., 2023; Evenett et al., 2024; Garcia-Macia, 2024).

My analysis reveals China's unmatched success in accelerating patent production and market entry, yet exposes quality deficiencies that may threaten long-term competitiveness. These findings necessitate policies that transcend conventional sectoral targeting, balancing scale with ecosystem building. The precise mechanisms for quality upgrading remain unresolved – a critical avenue I leave for future research.

Related Literature. This study makes three key contributions. Building on the technocratic foundation of industrial policy (Juhász and Lane, 2024; Beraja et al., 2023), I first demonstrate how state-led interventions shape technological trajectories through China's SEI initiative, with quantity growth mirroring East Asia's most successful transformations: South Korea's heavy industry (Lane, 2025), Taiwan's semiconductors (Chu, 2019), and Japan's postwar catch-up (Beason and Weinstein, 1996; Rodrik et al., 1995). The observed firm dynamics also align with Lu et al. (2019)'s findings on Chinese market entry. Additionally, employing the multi-sector SEI initiative, I extend research of industrial policies affecting individual sectors in China, complementing work by Barwick et al. (2025) on shipbuilding, Pizer and Zhang (2018) on carbon emissions and Banares-Sanchez et al. (2023) on solar energy, all of which fall under the SEI framework.

Moreover, this study reveals two fundamental tensions in industrial policy implementation. First, the crowding-out of non-targeted sectors replicates the spatial displacement effects observed in U.S. place-based policies (Kline and Moretti, 2014), yet contrasts sharply with both South Korea's positive productivity spillovers (Lane, 2025) and China's own crowd-in effects in AI sectors (Beraja et al., 2024). Second, while local governments' rigid synchronization with national strategies often ignores regional heterogeneity, my findings confirm that adherence to local advantages significantly boosts patent growth, consistent with Aghion et al. (2019) and Thrane et al. (2010) on innovation path dependence, and with Lin (2011) and Ramondo (2015) on the productivity benefits of comparative advantage. Yet these quantitative gains remain qualitatively insufficient, validating Cherif and Hasanov (2019)'s critique of static advantage models and highlighting the imperative of complementary institutional reforms.

Finally, this study provides new empirical evidence of China's innovation quantity-quality divide through the SEI initiative, complementing existing research on its patent surge and quality limitations (Ang et al., 2024; Li, 2012; Hu and Jefferson, 2009; Cai et al., 2023). Notably, while innovation quantity outperformed, I find no evidence of quality erosion, marking a departure from earlier findings that linked China's patent surges to declining quality during the early 2000s (Boeing and Mueller, 2016).

The documented quality paradox also substantiates concerns raised in prior studies on challenges in China's industrial development, particularly: institutional distortions that favor imitation over genuine innovation (König et al., 2022), wasteful entry subsidies that misallocate resources (Barwick et al., 2025), Western decoupling efforts targeting critical semiconductor technologies (Goldberg et al., 2024), and target-driven governance under political promotion tournaments (Zhou, 2007).

The remainder of this paper is structured as follows: Section 2 provides an overview of the SEI initiative. Section 3 describes the data and Section 4 discusses the differences-in-differences method. In Section 5, I estimate the SEI policy impacts across various dimensions and show that they survive a broad range of robustness checks. Section 6 concludes.

2. Background on the Strategic and Emerging Industries

Technological leadership has been a central pillar of China's strategy since the Reform and Open-up period, with the 2006 Medium-Long Term Plan for the Development of Science and Technology (MLP) establishing "indigenous innovation" as a national priority. While the MLP set broad R&D goals, its successor – the 2010 Strategic Emerging Industries (SEI) initiative – adopted a more targeted approach, designating seven priority sectors with a hybrid governance model balancing central coordination with localized adaptation.

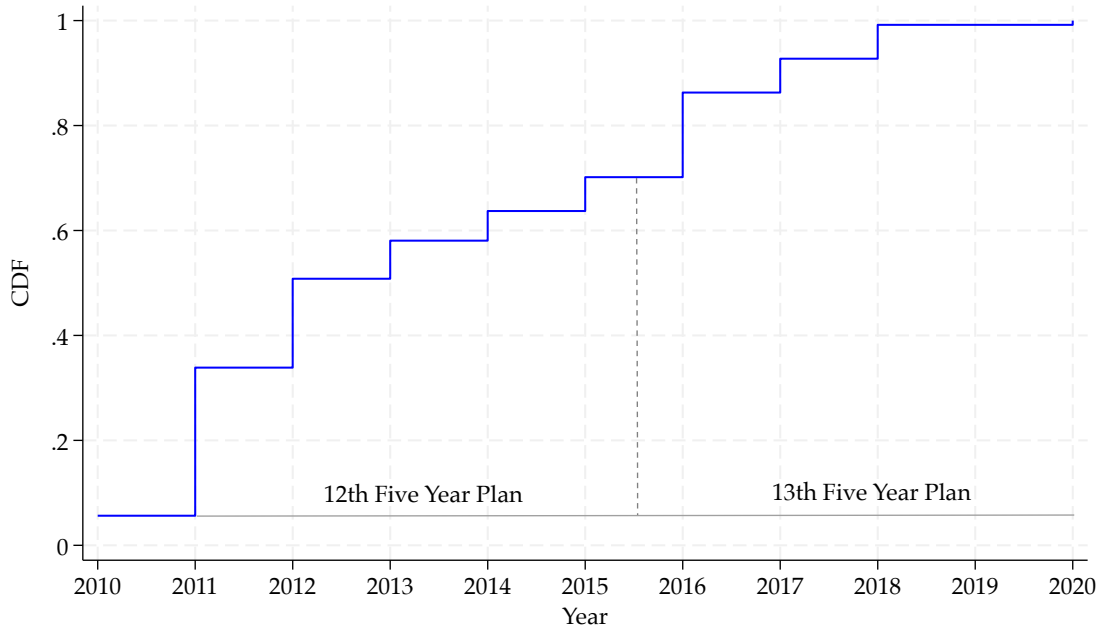
This policy evolution reflected dual pressures. Domestically, rising labor costs and environmental constraints demanded economic upgrading. Internationally, escalating risks of technological containment compelled a shift toward reducing reliance on foreign technology (Bown, 2020). Rather than abandoning previous approaches, SEI intensified them, maintaining the MLP's techno-nationalist vision while introducing greater operational flexibility that surpassed earlier drives like the 863 Program. This section describes SEI's defining characteristics in detail.

Timeline. The SEI initiative was formally launched in 2010 through the State Council's *Decision on Accelerating the Cultivation and Development of Strategic Emerging Industries*, strategically timed ahead of its incorporation as a centerpiece of the 12th National Five-Year Plan (2011-2015). Implementation unfolded through three phases: initial local adoption (2010-2012), when pilot cities began integrating SEI priorities into their local Five-Year Plans; systematic expansion (2013-2015), following the State Council's dedicated SEI Five-Year Plan that prompted widespread municipal replication; and consolidation (2016-2018), as the initiative continued under the 13th Five-Year Plan while approaching saturation in city-level adoption. While the SEI remains active under the 14th National Five-Year Plan (2021-2025), city-level adoption plateaued after 2018. This paper consequently focuses on the core implementation period (2010-2018), excluding marginal late adopters (post-2020) with inadequate time for policy effects to materialize.[2]

[2]While the latest SEI document in the PKU Law Database was issued in 2023, fewer than 10 local documents related to SEI have been published since 2019, and they rarely reveal concrete policy targets. This could be attributed to poor data quality in recent years, delays in obtaining permission to publish government-authorized documents in the database, or a shifting focus away from SEI over time. The intro-

City-level Rollout. China's governance, often described as "centralized decentralization," involves the Communist Party and State Council setting broad directives, while local authorities manage the detailed policy implementation based on regional needs. Although the SEI impact has been studied (e.g., Wang et al. (2022) and Zhang et al. (2025)), it was perceived as a nationwide policy uniformly applied to all cities with a sharp execution in 2010. However, by tracking city-level Five-Year Plans, I highlight the staggered nature of the SEI rollout. This pattern is similar to other national initiatives in China and often attributed to differences in administrative processes, development levels, and political priorities across cities (Alder et al., 2016). Figure 1 shows the distribution of SEI implementation across Chinese cities, starting with 7 cities in 2010 and concluding in 2018 with the last observed SEI-related policy documents.[3] Significant bursts in adoption occurred in 2011 and 2016, aligning with the launch of the 12th and 13th National Five-Year Plans.

Figure 1. Staggered SEI Rollout Across 123 Chinese Cities



Note: This figure shows the cumulative distribution of 123 Chinese cities that implemented SEI policies, categorized by policy year, alongside the periods of the 12th (2011–2015) and 13th (2016–2020) National Five-Year Plans.

duction of *Made in China 2025* in 2020 may have overshadowed SEI, despite the latter also being mentioned in the 14th National Five-Year Plan. This underscores the importance of examining policy rollout at the city level, rather than the national level, to fully understand the policy landscape (Banares-Sanchez et al., 2023).

[3]More precisely, the treatment varies across Chinese prefectures, including prefecture-level cities (the most common), autonomous prefectures, and special administrative regions. They are similar to cities in the international sense, such as the EU NUTS-3 classification. I refer to these prefectures as cities throughout.

Sectoral Focus. The SEI sectoral selection is hardly random. Internationally, China's SEI sectors closely mirrored global technological priorities. In biotechnology, for example, the U.S. launched the National Biotechnology and Biomanufacturing Initiative in 2022. In next-gen IT, the U.S. leads with the CHIPS and Science Act, focusing on semiconductors and AI, while the Korean New Deal prioritizes 5G. In high-end manufacturing, Japan's SIP program targets advanced materials in semiconductors and aerospace, paralleling China's interest in new materials. In green energy, the European Green Deal and Germany's Industry 4.0 focus on renewable energy, echoing China's emphasis on energy conservation. Beyond global competitiveness, SEI sectors were also chosen for their relevance to China's national security, comparative advantages, and their potential to address internal challenges such as environmental sustainability (State Council, 2012).

Initiated in 2010 with seven broad strategic sectors and expanded in 2016 to incorporate digital creation, the SEI program maintained eight core industries over its decade-long implementation.[4] While these broad categories established the national focus, local execution was more decentralized, permitting more granular targeting with regional adaptation. This model yields a paradox: although cities collectively pursued 264 distinct 4-digit sectors (19% of all 1,382 classifications), demonstrating targeting breadth, 95% of these selections remained firmly within national priorities, particularly concentrated in semiconductor, AI, and electric vehicle. The minimal divergence from national targets indicates that while local governments exercise some flexibility in sector selection, substantive local innovation remains constrained by the overarching national agenda.[5]

The SEI's sectoral focus reveals two interrelated patterns. First, while foundational industries like solar and wind energy maintained stable prioritization across both Five-Year Plans, local governments demonstrated adaptive capacity by gradually incorporating emerging technologies. Figure 2 captures this evolution: where Software Development dominated 12th Plan targeting, Robotics and 5G infrastructure emerged as 13th Plan priorities, aligning closely with global technological frontiers.

Second, this adaptability coexisted with pronounced intercity competition, as Figure

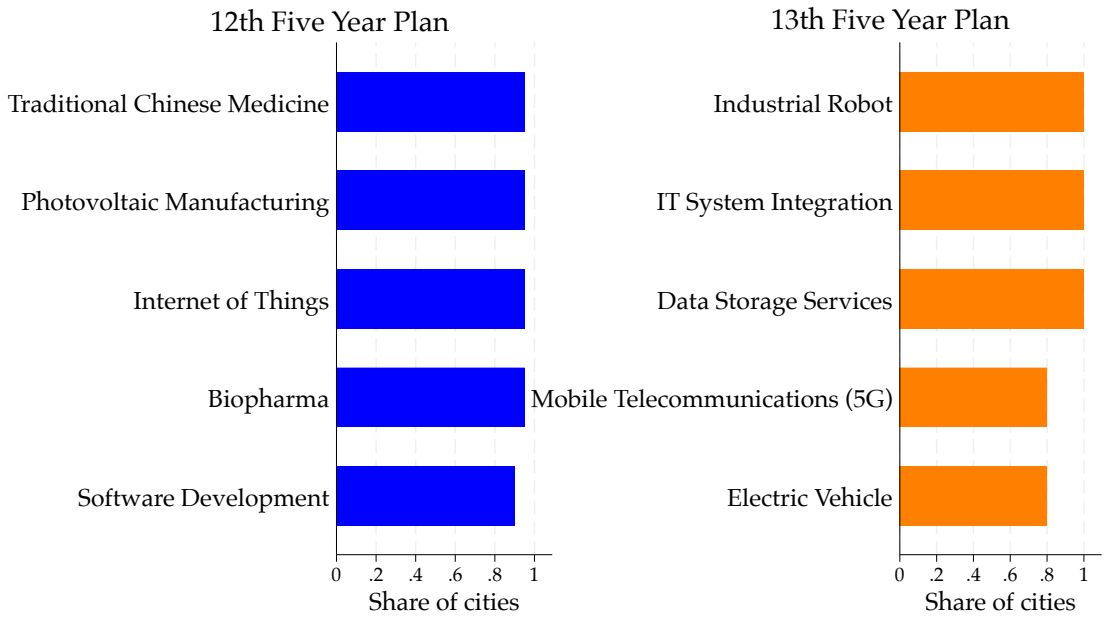
[4]The national prioritized industries are: biotechnology, next-generation information technology, high-end equipment manufacturing, new energy, energy conservation and environmental protection, new materials, new energy vehicles, and (after 2016) digital creation. Source: *The 12th Five-Year Plan for the Development of National Strategic Emerging Industries (General Office of the State Council)*.

[5]This reflects a top-down approach that prioritizes national cohesion over local diversification, extending beyond the SEI initiative, evident in major policies like the Belt and Road Initiative, Social Credit System, and Targeted Poverty Alleviation.

Even when regional diversification is encouraged, as with the SEI, China's political system offers limited incentives for local autonomy. Local officials, appointed and promoted based on adherence to central targets, have career incentives to align with national priorities, dissuading independent policy decisions that might invite scrutiny or political risk (Zhou, 2007). These dynamics underscore a political economy that shapes place-based policies across China and invite future empirical research.

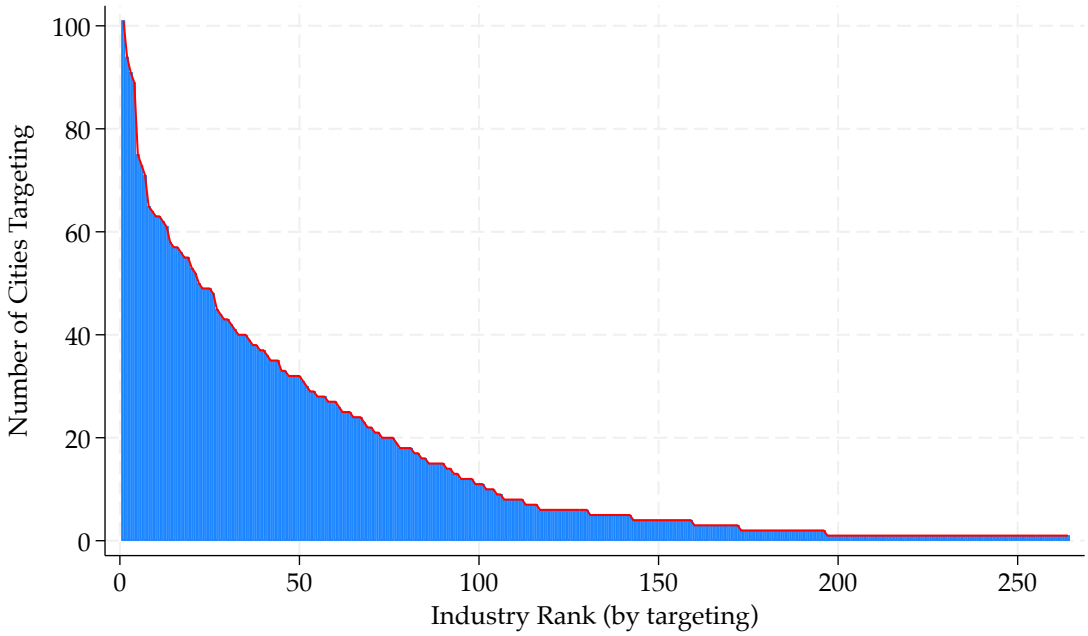
2 shows nearly all cities converged on identical frontier sectors, irrespective of local capabilities. The right-skewed distribution in Figure 3 quantifies this imbalance: the top 25 sectors (representing less than 10% of all targeted sectors) absorbed 40% of city-level prioritization. This skewness suggests potential inefficiencies in a top-down approach, where the strong pull of national technological priorities may marginalize regional comparative advantages in traditional sectors while spurring redundant investment in designated priority sectors. These targeting patterns highlight the need to examine the role of local comparative advantages in improving policy outcomes, which I explore in Section 5.4.

Figure 2. Top 5 Targeted Strategic and Emerging Industries



Note: This figure compares the top five SEI-targeted subsectors by city adoption rates between the 12th (2011–2015) and 13th (2016–2020) Five-Year Plans, revealing shifts in sectoral priorities.

Figure 3. Concentration of Municipal SEI Targeting Across 4-Digit Industries



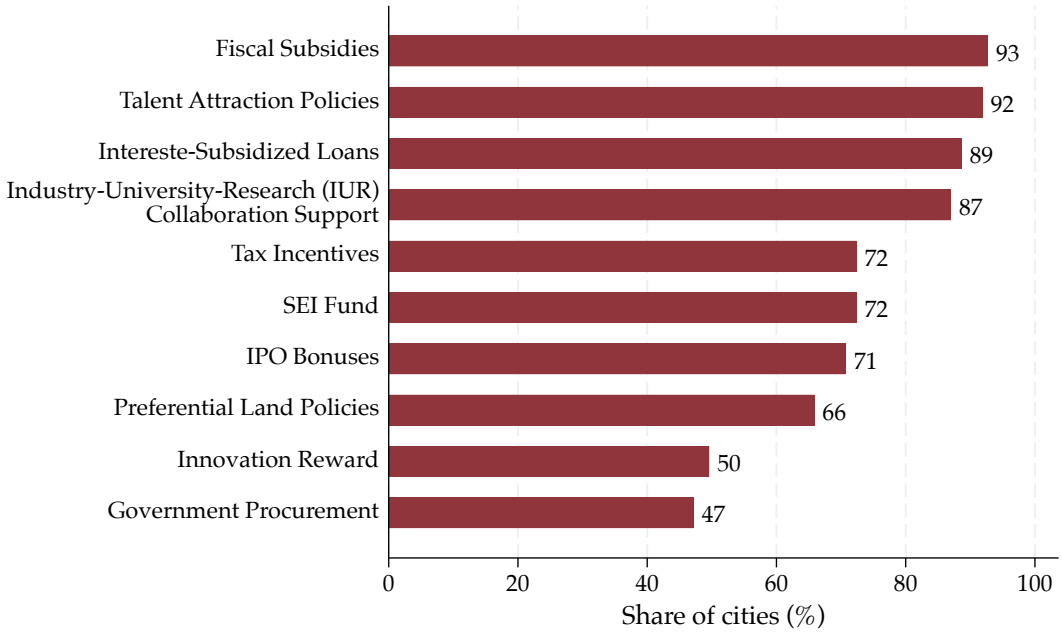
Note: This figure presents the distribution of SEI sectoral targeting across Chinese cities. The x-axis ranks 264 targeted 4-digit industries by the number of cities that targeted them (descending). The y-axis shows the count of adopting cities. The figure reveals strong concentration, with the top-ranked industries attracting disproportionate attention relative to lower-ranked sectors.

Policy Instruments. Identifying the precise industrial policy tools and associated costs across time and regions remains challenging due to the opacity of government documents, though recent literature has shed light on this issue. Juhász et al. (2023) show that industrial policies often combine multiple instruments, such as tax rebates, interest-free loans, and subsidies. China's SEI is no different, with Figure 4 revealing direct subsidies as the dominant tool, frequently combined with dedicated SEI investment funds.

Notably, while cities exhibit some variation in policy mixes, over 90% converge on three core instruments: (1) fiscal subsidies, (2) talent incentives, and (3) low-interest loans. Even the least common measures – government procurement and innovation rewards – were adopted by nearly 50% of municipalities. These instruments are predominantly funded by the local government's fiscal budget, with additional funding granted by the central and provincial governments for outstanding projects.[6]

[6]While some SEI documents disclose partial expenditure data, this study refrains from comprehensive cost estimation due to inconsistent fiscal reporting across government sources – an enduring data challenge in China's industrial policy research, also noted by Goldberg et al. (2024).

Figure 4. Key SEI Policy Instruments Across Chinese Cities



Note: This figure shows city adoption rates of industrial policy instruments. "Talent Attraction Policies" typically are financial incentives (e.g., housing subsidies, research grants) for high-skilled workers; "Innovation Subsidies" target patent creation; "SEI Funds" are local government investment vehicles that occasionally substitute for direct subsidies. Policies are counted as adopted if referenced at least once in city-level SEI documents.

SEI Today. Over the past decade, China has made significant strides in frontier industries such as automotive and renewable energy. In 2023, China accounted for approximately 50% of global electric vehicle (EV) sales (World Economic Forum, 2024), with companies like BYD and NIO emerging as global competitors – a stark contrast to a decade ago when China's presence in the EV market was negligible. By 2024, renewable energy comprises over 53% of China's total installed power capacity, a substantial increase from 19.9% in 2009 before the SEI launch, when solar and wind were still in their early development stages (Chambers and Partners, 2024). The success of these sectors has been widely promoted as evidence of effective industrial policy.

On the flip side, sectors like aircraft (Luo et al., 2024) and semiconductors (Bown and Wang, 2024) continue to encounter technological bottlenecks. As discussed previously, the Strategic Emerging Industries (SEI) initiative has led to a substantial reallocation of government resources, with central and local authorities actively directing funds away from traditional sectors, an effort specifically encouraged in various policy documents. However, this shift has raised concerns about budget distortions and misallocations, as resources are often redirected without considering local comparative advantages. Addi-

tionally, issues like the *New Energy Subsidy Fraud* demonstrate how these resource shifts can be exploited,[7] with unrelated companies fraudulently claiming subsidies meant for clean energy, exposing inefficiencies and misuse of public funds.

These patterns raise three critical questions, which I empirically test next:

1. **Technological Advancement**: How effectively has the SEI initiative fostered technological advancement in targeted sectors?
2. **Structural Trade-offs**: Did resource allocation to SEI sectors come at the expense of traditional industries?
3. **Regional Fit**: To what extent does policy alignment with local comparative advantages determine outcomes?

3. Data

This section details the data collection and cleaning process. First, I identify treated industries by analyzing city-level SEI documents. Next, I construct innovation outcomes using city- and sector-level patent data. Finally, I discuss the covariates used in the propensity score model. A full summary of variables is provided in Appendix (Table 6).

3.1 SEI Treatment

China's comprehensive Five-Year Plan documentation at all government levels provides unique tracking of local SEI implementation. I identify SEI treatment using policy documents from the PKU Law Database (also known as ChinaLawInfo), a highly regarded source archiving policy texts from national to city-level governments (Banares-Sanchez et al., 2023; Ji et al., 2022). The policy panel draws on 1,456 municipal SEI documents (2009-2024), including both specialized SEI Five-Year Plans and SEI-specific sections within comprehensive local FYPs.[8]

Document Processing. Recent advances, such as Fang et al. (2025)'s large-scale machine learning framework for identifying Chinese industrial policies nationwide, demonstrate the feasibility of high-throughput text processing for broad policy mapping. However, the

[7] China's new energy subsidy fraud saw companies exploiting government incentives for clean energy. In 2016, an investigation revealed that Jinhua Youth Automobile fraudulently promoted a "water-powered" car to access funds. The government responded with stricter regulations, uncovering 118 million yuan in misused subsidies by 2017. Source: China Daily.

[8] Among the 123 sampled cities, 99 (80.5%) adopted standalone SEI Five-Year Plans, underscoring local governments' strong commitment to the initiative.

SEI corpus examined in this paper is substantially smaller and requires fine-grained identification of city-specific targeted sectors and policy instruments. Given this need for precision, and the nuanced language typical of SEI planning documents, I manually review each document to identify SEI-targeted industries by city, minimizing misinterpretation from automated text analysis.

I identify SEI treatment initiation as the first year a city publishes formal SEI planning documents containing both clearly specified target sectors and at least one concrete policy instrument (e.g., subsidies, preferential loans), while excluding vague or non-specific policy statements. To my knowledge, this is the first study to systematically link city-level SEI policy texts to disaggregated sectoral targeting. The Appendix (Section B) features a cropped excerpt from Changsha's SEI plan, exemplifying the parsing of policy attributes. Below, I discuss important caveats regarding city, year, and sector identification.

City Coverage. Although China has nearly 300 prefecture-level administrative units, not all have publicly accessible SEI records due to varying transparency and accountability standards.[9] While some undocumented cities may have adopted SEI policies through informal channels or lack public records, this analysis conservatively focuses on the observed 123 cities with definitive written plans, categorizing the remaining cities as having missing policy data. By establishing this rigorous lower bound, the study prioritizes verifiable evidence over potential undercoverage, though the findings should be interpreted as representing minimum implementation levels rather than the full national scope. The observed SEI cities are fully listed in Appendix Table 8 and mapped in Figure 12.

Temporal Scope. Consistent with my conservative approach for city identification, I focus on the core 2010-2018 period of peak SEI implementation. Although the PKU Law Database contains sporadic SEI documents through 2023, fewer than ten additional cities adopted concrete SEI targets post-2019. This pattern suggests either lags in authoritative document release, or diminished policy focus following the 2020 launch of *Made in China 2025*, despite SEI's nominal retention in the 14th Five-Year Plan. This delimitation captures the initiative's active phase while ensuring sufficient post-treatment observation for impact analysis, albeit potentially excluding late-stage adopters.

Sectoral Classification. City-level SEI policies employ more granular sectoral targeting

[9]For cities absent from the PKU Law Database, I verify that they also do not reveal related documents elsewhere, including on their official government websites. This cross-validation further attests to the database's reliability as a sourcing benchmark. While the identified SEI cities do not represent exhaustive policy implementation, they exhibit nationally representative diversity: geographically distributed across 28 provinces and spanning all city tiers (1 to 4, as classified by Yicai Global based on economic scale, commercial resources, and urban centrality).

than national guidelines, necessitating alignment with standardized industry classifications. This creates a trade-off between aggregation levels: while 2-digit sector classification maximizes city coverage (by including cities with vaguer targeting), 4-digit classification enhances sectoral precision at the cost of reduced sample size.[10] To ensure conservative but robust impact evaluation, I prioritize granularity by mapping the SEI sectors to the 4-digit National Economic Industry Classification (2017).[11] Alternative 2-digit and 3-digit classifications are available upon request, supplemented by insights from Wei (2025).

Resulting Policy Panel. Combining these dimensions yields a novel policy panel, including the publication date of the SEI initiative and the targeted SEI sectors for each city. The dataset encompasses 4,086 unique city-industry level treatments, across 123 targeted cities and 264 targeted 4-digit sectors from 2010 to 2018.

3.2 Innovation Measures

Given SEI's innovation-centric mandate, this paper examines its impact on innovation performance using multi-dimensional patent-based measures. By leveraging various patent metrics, this approach aligns with established innovation literature in China and globally, where patents serve as a well-validated proxy for technological advancement and knowledge creation (Aghion et al., 2013; Kogan et al., 2017; Hall et al., 2005; Bloom et al., 2015). While alternative measures of innovation output – such as product-based indicators derived from customs and firm-level data (Beraja et al., 2023; Antràs et al., 2017) or technology-driven employment shifts (Bastos et al., 2026) – have gained traction, patent data stands out due to its unique city- and sector-level granularity, which precisely matches SEI's city-industry policy framework.[12]

Patent Data from IncoPat. Prior studies of China's innovation predominantly rely on the CSMAR database, which is limited to listed firms (Cui et al., 2018; Wang et al., 2022). However, the SEI policy's city-industry implementation requires data covering all entities, not just publicly traded companies. To address this, I use patent data from the IncoPat Database, which builds on CNIPA (China National Intellectual Property Administration) records to provide comprehensive coverage of Chinese patent filings. Though relatively

[10]The sample includes 138 cities when using 2-digit sector classification (accommodating broader targeting) but narrows to 123 cities at 4-digit precision, which excludes cities with vague sectoral designations.

[11]Covering 1,382 unique sectors, the 4-digit national economic industry classification remains the most detailed official industrial taxonomy in China, and is more detailed than the 4-digit ISIC codes.

[12]China's customs data provide detailed sector-level trade values through the HS product code, but their lack of city-level granularity – a limitation shared by most alternative datasets – renders them inadequate for evaluating the city-industry specific SEI policies.

new, IncoPat has gained increasing recognition in the literature (Wu et al., 2022; Li et al., 2025) and offers three key advantages over raw CNIPA data: real-time legal status tracking for patent lifespan measurement, complete citation linkages, and standardized assignee names for accurate city-level geolocation.

Additionally, a critical challenge in working with raw patent data is the absence of standardized sectoral classification, which requires manual mapping between IPC codes and industry classification systems. IncoPat addresses this limitation by providing pre-mapped alignment of IPC codes with China's 4-digit National Industry Classification system, thereby eliminating manual matching errors. Leveraging this enhanced dataset, I extract the applicant's address, sector code, and application year, enabling precise city-sector-year identification for each patent.

Following established practice, I focus exclusively on the granted invention patents, which represent the most reliable indicator of meaningful innovation in China (Hu and Jefferson, 2009; Zhang et al., 2014).[13] I focus on patents applied since 2009, when China's Third Patent Law Amendment (2008) already took effect, raising grant standards (reducing inflated pre-reform patent counts) and aligning examination with international norms. This cutoff also avoids contamination from earlier policies like the 2006 Medium-Long Term Plan (MLP), ensuring cleaner identification of SEI effects.[14] From an initial pool of approximately 464 million raw invention patent records (that have been granted by the end of 2024), I construct a final dataset encompassing 821 four-digit sectors across all 123 SEI-targeted cities during the 2009–2021 period. Merged with SEI treatment indicators in Section 3.1 and the covariates described below in Section 3.3, this city-industry panel yields nearly one million observations that form the core dataset for the difference-in-differences analysis. Below, I detail the specific variables measuring three dimensions of innovation: (1) patent quantity, capturing the scale of innovative activity; (2) patent quality, reflecting the technological, commercial and global value of each invention; and (3) patent collaboration patterns, revealing knowledge network dynamics.

Innovation Quantity Measures. On the quantity front, I consider both the count of granted patents and the number of patenting firms. These metrics reflect intensive margin innovation (innovation output per firm) and extensive margin activity (participation breadth), respectively, providing a comprehensive view of innovation scale.

[13]Chinese patents are classified into three categories: invention, utility, and design patents, listed with descending order of patent quality. All invention patents included in the analysis are those ultimately granted (Kogan et al., 2017), excluding unapproved patent applications that typically hold lower value.

[14]The staggered difference-in-differences design in Section 4 inherently accounts for early-treated cohorts with limited pre-treatment observations, making the patent sample period starting in 2009 analytically appropriate for capturing SEI treatments (2010–2018).

Innovation Quantity Measures: Scientific Value and Commercial Worth. Following Hall et al. (2005), I use forward citation counts as a proxy for scientific value, with cohort adjustments to control for application-year biases in citation patterns.[15] For a patent's commercial worth, patent lifespan serves as a natural proxy, since annual maintenance fees are costly to inventors, who would only maintain patents whose expected returns justify these cumulative renewal costs. The lifespan analysis is limited to patents applied by 2017 to avoid right-censoring, as later applications would have incomplete lifespan observation periods.[16]

Additionally, China's patent system creates another quality threshold at three-year lifespan through its fee structure: subsidization of maintenance fees for the initial three-year period when base fees are already lowest, followed by progressively higher annual fees beginning in year four.[17] Continued protection beyond this subsidized phase reveals owners' true commercial valuation, as they must bear the higher market cost of renewal. I therefore focus on the number of 'durable patents' – those remaining active past three years – as another quality measure, identifying innovations whose demonstrated value justifies maintenance without subsidy support or artificial pricing incentives.

Innovation Quantity Measures: Global Impact. For a patent's global recognition, I analyze both Patent Cooperation Treaty (PCT) filings and foreign citations (Boeing and Mueller, 2016). PCT patents are costly international applications enabling patent protection across multiple countries. They represent particularly meaningful quality signals in China's context, as their substantial costs indicate genuine global commercial potential beyond domestic subsidy incentives. The foreign citation metric (i.e., the number of patents cited by foreign sources) provides complementary evidence of global scientific influence.

Addressing Measurement Trade-offs in Patent Data. While my primary analysis utilizes absolute counts of patent outcomes, I also employ quantity-adjusted measures, such as average citation and the share of PCT patents, to isolate quality effects independent of scale. These adjusted metrics introduce an important methodological constraint: they are mathematically undefined when the denominator (patent counts) equals zero, which

[15] I also consider forward citations with self-citation removed as a robustness check.

[16] The 2017 application-year cutoff ensures measurement reliability, corresponding to the 7-year average lifespan of Chinese invention patents in my sample. This window guarantees that the majority of patents would have reached their expiration date by the observation cutoff (December 2024).

[17] For example, multiple provincial governments, including Shanghai, Xinjiang, and Guangxi, provide subsidies for annual patent maintenance fees during the first one to three years (source: Newhope Law, PC). Additionally, as of 2021, China's invention patent maintenance fees follow a standardized rate of 900 RMB annually for years 1-3, rising to 1,200 RMB from year 4 onward.

occurs for nearly 46% of city-industry-year observations. This limitation presents a consequential analytical choice between maintaining the full sample for count variables while accepting varying sample sizes for adjusted measures, or restricting analysis only to observations with non-missing values across all metrics.[18]

I prioritize the former approach for two substantive reasons. First, systematically excluding non-patenting units would introduce selection bias by removing policy-relevant cases where innovation outcomes may be zero precisely due to industrial characteristics that the SEI policy aims to transform. Second, restricting to balanced panels would discard nearly half of all observations, severely threatening estimation precision. Robustness checks using a balanced panel, where all measures have the same non-missing observations, confirm that the core findings are not driven by sample size differences (Section 5.5). This approach preserves the policy evaluation's external validity while addressing measurement concerns.

To mitigate the right-skewness of patent data and retain zeros, I log-transform all count variables (log(x+1)) throughout my specifications. As a robustness check, I relax this functional form assumption by employing Poisson pseudo-maximum likelihood (PPML) estimation, which directly models count data without requiring log transformation. Both approaches yield qualitatively similar results, supporting the robustness of my findings to alternative distributional assumptions.

Together, these metrics provide a multidimensional assessment where patent counts and participating firms measure scale, while citation patterns, maintenance duration, and international activity gauge quality across scientific, commercial, and global dimensions.

Complementary Innovation Collaboration Measures. Beyond patent quantity and quality measures, I analyze innovation collaboration patterns using IncoPat's detailed applicant classifications (e.g., firm-only, firm-university). Specifically, I examine three main patent collaboration types: (1) firm-firm partnerships, (2) firm-university collaborations, and (3) firm-government alliances. These metrics provide additional insights into how SEI reshapes collaborative innovation networks.

3.3 Supplementary Data and Propensity Score Covariates

While innovation metrics constitute my primary outcome variable, I supplement the SEI analysis with two additional measures of industrial dynamics: firm entry and exit rates

[18] Empirical results remain consistent when imputing missing values as zero, available upon request.

from the China Industrial and Commercial Registered Enterprises Database (sourced from CNOpenData). This comprehensive database offers a complete spectrum of Chinese firms across all ownership types and sizes. The entry and exit data are aggregated at the city and 3-digit sector level (the finest available sectoral disaggregation) for the 2009–2021 period, providing complementary insights into SEI's broader economic impacts.

To address selection bias in SEI implementation, I construct a propensity score model (detailed in Section 4) using pre-treatment covariates influencing both policy adoption and outcomes. The city-level covariates include fiscal capacity (fiscal and science expenditures) and economic structure (GDP per capita and tertiary sector share of GDP), all drawn from the City Statistical Yearbooks. For industry-specific factors, I incorporate sectoral trade exposure (real exports and imports, sourced from the General Administration of Customs) to control for globalization pressures and sectoral shocks, particularly important given SEI's disproportionate targeting of strategic sectors like high-tech and export-oriented industries.[19] The customs data are initially classified using the Harmonized System (HS) coding system. To ensure consistency, I first harmonize all product codes to the HS2012 classification, then map these to the 2017 4-digit national economic industry classification, leveraging established open-source crosswalks.

This integrated approach, combining fiscal, geographic, and industrial dimensions, mitigates the most salient sources of selection bias. The subsequent section formalizes the empirical framework building on these matched samples.

4. Dynamic Differences-in-Differences

4.1 Baseline

Group-Time Average Treatment Effect. The estimation bias in the canonical two-way fixed effect (TWFE) differences-in-differences design with staggered treatment adoption has been a focal point in recent literature. Notably, Baker et al. (2022), Goodman-Bacon (2021), de Chaisemartin and D'Haultfœuille (2020), and Borusyak et al. (2024) emphasize that in TWFE settings, later-treated units are often used as controls for earlier-treated ones, despite being partially treated themselves. This introduces negative weights in the TWFE estimation, which can result in a negative average treatment effect (ATT), even when the true treatment effect is positive – commonly referred to as the "negative weight problem".

[19] Alternative industry-level measures from input-output tables were unsuitable due to large year gaps and inconsistent sectoral coverage across years.

Callaway and Sant'Anna (2021) effectively address staggered treatment adoption by estimating treatment effects separately for each cohort, using only units that have not yet been treated or will never be treated as controls. I adopt their methods in my empirical specifications and estimate the average treatment effect for each treated group g using the following equation:

$$\hat{ATT}_{g,t} = \mathbb{E}[Y_t - Y_{g-1} \mid D_g = 1] - \mathbb{E}[Y_t - Y_{g-1} \mid D_g = 0] \tag{1}$$

, where group g refers to the city-industry units that receive treatment (i.e., became an SEI target) in the same year, and D_g is a dummy variable indicating SEI designation. $\mathbb{E}[Y_t - Y_{g-1} \mid D_g = 1]$ denotes the average difference in the outcome between time t (post-treatment) and time $g-1$ (one period before treatment) for treated units. $\mathbb{E}[Y_t - Y_{g-1} \mid D_g = 0]$ represents the same difference for control units, i.e., those that did not receive treatment at time t. The difference between these two terms, $\hat{ATT}_{g,t}$, captures the causal impact of the SEI treatment for each group and time period, controlling for time trends and individual time-invariant characteristics. This is also known as the "group-time average treatment effect."

Binary Treatment Specification. As discussed in Section 2, the SEI's decentralized design produced heterogeneity in policy tools across cities, despite convergence toward core instruments such as subsidies and subsidized loans. While this experimental governance style characterizes China's local policy innovation, it complicates causal estimation. A further challenge, as Goldberg et al. (2024) documents, is the systematic unavailability of granular Chinese subsidy data in public sources.

Given these constraints, I employ a binary treatment specification, where D_g in equation (1) is coded 1 when industry j in city i is officially designated as an SEI-supported sector, and 0 otherwise. Though this approach necessarily masks nuanced implementation differences, the binary treatment circumvents measurement error from incomplete financial disclosures, and provides a robust lower-bound estimate of SEI's average impact – a trade-off that aligns with similar challenges in evaluating large-scale industrial policies (Athey and Imbens, 2022).

Aggregation of the Group-Time ATT. Equation (1) estimates the ATT for each group and time period, generating numerous estimates. For easier interpretation, I follow the approach of Callaway and Sant'Anna (2021) to aggregate the group-time average treatment effects into event-study estimators, using the following equation:

$$\text{ATT} = \frac{\sum(w_{g,t} * ATT(g,t))}{\sum(w_{g,t})} \tag{2}$$

Here, $ATT(g,t)$ represents the estimated ATT for group g at time t, and $w_{g,t}$ are the weights, determined by the proportion of units in cohort g (the cohort treated at time g) relative to the total number of treated units across all cohorts. These weights ensure that the overall treatment effect accurately reflects the relative sizes of different groups (cohorts) and time periods in the data.

The weighting scheme also favors the use of all available data rather than binning event periods to specific time intervals. Specifically, it assigns greater weight to larger cohorts and more precise estimates, while downweighting those derived from smaller or less reliable samples. As a result, I estimate the ATT using data from all periods and plot the coefficients for the 5 periods before and 9 periods after treatment, offering a clear view of pre- and post-treatment dynamics without including periods too distant to be of policy relevance. The final estimated ATT, representing the weighted average of treatment effects across groups and time, is presented in Section 5 as the baseline SEI impact.

4.2 Propensity Score Model and the Doubly Robust Estimator

As previously discussed, the SEI initiative is not a random experiment that is completely isolated from selection issues. As a result, I also consider the doubly-robust estimator (Sant'Anna and Zhao, 2020) which combines inverse probability weighting (IPW) with outcome regression through Equation (3):

$$ATT(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1})\right] - f_{0,Y_t-Y_{g-1}}(X) \tag{3}$$

, where G_g is a binary variable that equals one if a unit is first treated in period g, and C is a binary variable that equals one for units that do not participate in the treatment in any time period. $p_g(X) \equiv \mathbb{E}[\text{treated} \mid X]$ is the propensity score – the probability that a unit is treated in group g given covariates X. The last term, $f_{0,Y_t-Y_{g-1}}(X) \equiv \mathbb{E}[Y_t - Y_{g-1} \mid C = 1, X]$, estimates the expected outcome change between period t and the pre-treatment baseline (t = –1) for never-treated units (C = 1), conditional on covariates X. The propensity score $p_g(X)$ is estimated via logistic regression, implementing IPW to balance covariates between treated and control groups. The outcome model $f_{0,Y_t-Y_{g-1}}(X)$, estimated by OLS, adjusts for residual imbalances.

The core advantage of the doubly robust estimator, as shown in Equation (3), is that it

yields consistent estimates even if only one of the two models – the outcome model or the propensity score model – is correctly specified. This dual protection against misspecification of one model, while the other remains accurate, is what makes the estimator "doubly robust."

For the propensity score model accounting for potential differences between treated and untreated units, I incorporate the aforementioned city- and industry-level covariates. These include: real fiscal and science expenditures, GDP per capita, the share of GDP contributed by the tertiary sectors (all at the city level); and the real imports and exports (all at the 4-digit sectoral level). The inverse probability weighting is performed using only the pre-treatment covariates and excludes post-treatment covariates as they can potentially be affected by the treatment (Wooldridge, 2005; Callaway and Sant'Anna, 2021).

5. The SEI Impacts: Innovation and Market Dynamics

5.1 Core Empirical Results

This section presents estimates of the SEI initiative's effects across four key dimensions: innovation quantity, innovation quality, innovation collaboration, and market churn (firm entry and exit). Both static ATT and event-study estimates are provided to assess the average policy impact and its dynamics over time.

Sustained Quantity Increase. The SEI policy generated substantial scaling effects on innovation output. As shown in Figure 5, the event-study plots reveal immediate treatment effects on innovation quantity, measured through patent counts and patenting firms, that stand in sharp contrast to the near-zero pre-treatment trends.[20] Baseline outcome regression estimates indicate SEI-targeted city-industry pairs experienced an average 187% increase in patent production (Table 1, Column 1), accompanied by a 17.4% expansion in the number of patenting firms.[21] The doubly robust estimator (Table 1, Column 2) corroborates these findings, though with marginally attenuated magnitudes: 184% for patents

[20]The event study estimates reveal a disproportionately large increase in innovation in the first year following SEI adoption. Several mechanisms may account for this pattern. First, SEI subsidies are partly front loaded, giving firms immediate incentives to accelerate the submission of patent applications or to assign ongoing R&D outcomes to SEI priority sectors. Second, firms operating across multiple cities or with flexible internal reporting structures may quickly redirect patent filings to SEI designated locations to qualify for targeted support, consistent with the discussion in Section 5.3. In addition, local governments may face strong performance pressures after SEI designation and actively encourage early patent submissions. Together, these factors suggest that the large first-year effect reflects a combination of genuine inventive activity and rapid strategic or administrative responses to SEI incentives.

[21]Percentage changes calculated using $100 \times \left(\exp\left(\hat{\beta} - 0.5 \times (\text{SE})^2\right) - 1\right)$.

and 14.2% for firms, reflecting conservative bounding under rigorous selection controls. These effects exhibit remarkable persistence, remaining statistically and economically significant throughout the nine-year post-treatment period, indicating the policy's success in both intensifying innovation output among existing firms and expanding the pool of innovating enterprises.

Stagnant Quality Improvement. The SEI's effects on innovation quality reveal a striking contrast with its quantity impacts. While total citations rose by 29.6% (and 28.9% under doubly robust estimation) on average, this growth primarily reflects expanded patent volume rather than enhanced per-patent impact. Average citations per patent show negligible gains (an average 0.23% increase for outcome regression; and just 0.13% for doubly robust estimation), with the latter estimate statistically insignificant. Event-study plots in Figure 6 visually reinforce this divergence: Panel A.1 demonstrates rising aggregate citations, while Panel B.1 reveals flatlined per-patent quality. These patterns persist when excluding self-citations (Panels A.2 and B.2), ruling out artificial inflation through self-referencing. The evidence collectively suggests the policy boosted citation counts mechanically through increased output, without improving the underlying scientific influence of individual patents.

This quantity-quality gap extends beyond citations to other dimensions of patent quality. While total counts of durable patents and cumulative lifespan durations more than doubled (increasing by over 100%), their quantity-adjusted metrics showed modest declines: a 0.4 percentage-point reduction in the share of durable patents and a 2% decrease in average lifespan (doubly robust estimates). Quality metrics reflecting global recognition exhibit a similar dichotomy: foreign citations and PCT filings increased on average by 4% and 8% (doubly robust estimates), yet their shares of total patents declined by approximately 0.6 and 0.5 percentage points, respectively. The stagnant or declining shares of high-value patents require careful interpretation. On one hand, their absolute growth confirms the SEI succeeded in expanding the stock of quality innovations, with more durable patents, more PCT filings, more globally cited work. On the other hand, their proportional decline (or non-growth) relative to ordinary patents suggests this expansion occurred along the pre-existing quality gradient, without altering the ecosystem's underlying composition.

This fundamental divergence between aggregate and per-patent outcomes is visually confirmed in Figure 7, which demonstrates persistent positive effects for total quality measures alongside statistically insignificant results for nearly all scale-adjusted indicators throughout the post-treatment window. These quality metrics paint a consistent picture:

while the SEI policy successfully expanded innovation quantity, it generated minimal improvements in the quality of individual patents, whether measured through scientific influence (citations), commercial durability (lifespan), or international recognition (foreign citations and PCT filings).

Taken together, the policy's impacts appear to have operated almost exclusively through scaling effects rather than through meaningful quality enhancements. Yet two interpretations temper this conclusion: First, quality improvements may require a longer timeframe to become observable than what my current data can capture, as scientific influence and commercial value often mature years after filing. Second, while critiques of China's subsidy-driven 'junk patents' might predict severe quality erosion, the near-zero and only marginally negative per-patent effects imply neither meaningful degradation nor enhancement. Thus, the SEI's legacy appears to be one of expansion without dilution: it dramatically increased patent volumes without substantially elevating their average quality, for better or worse.

Expanding Innovation Collaboration without Structural Change. Innovation collaboration sits at the core of China's industrial policy ambitions. Firm-firm partnerships represent private-sector knowledge flows, while university-firm and government-firm collaborations embody the state's priority to bridge public research with commercial applications. The SEI explicitly targeted these linkages to transform China's innovation ecosystem from quantity-driven to collaboration-driven growth. My analysis thus tests whether these policy ambitions materialized in practice – both in the scale and structure of patent collaborations.

As shown in Table 2, the SEI initiative unequivocally increased collaborative patenting across all types, but this expansion followed the existing structure of China's innovation ecosystem rather than reshaping it. For the preferred doubly robust estimates, firm-firm collaborations saw the strongest absolute growth (38.7%), followed by university-firm (22.5%) and government-firm partnerships (2.2%). These gains were both statistically and economically significant - the policy clearly worked in boosting collaborative output.

Yet the persistent stagnation in collaboration shares (Figure 8) reveals a critical limitation. While collaborative patent counts rose across all types, their proportion of total innovation remained static, insignificant, and marginal. This reveals the SEI's failure to trigger structural transformation, as firm-firm, university-firm, and government-firm collaborations simply grew in parallel with solo patents, leaving China's innovation ecosystem compositionally unchanged. By subsidizing more of the same collaborations rather than rewarding cross-sector integration, the SEI acted as a scaling mechanism rather than

a transformative one. For a policy explicitly designed to reshape innovation networks, the SEI initiative clearly achieved breadth but not depth of collaboration. These patterns also mirror the quantity-quality divergence seen previously.

Policy-Induced Market Churn. China's industrial policies often reshape markets through directed firm turnover (Lu et al., 2019) – a dynamic the SEI exemplifies. Firm entry and exit rates both rose substantially (15.6% and 13.9%, under doubly robust estimation), with Figure 9 showing sustained increases throughout the event window. This symmetrical churn suggests the policy created active turnover, consistent with subsidy-driven market selection where entrants respond to incentives while less competitive firms exit.

Supplementary Analysis on Patenting Activity by Firm Type. China's industrial policies have long exhibited a preference for domestic firms, state-owned enterprises (SOEs), and large listed companies – typically viewed as vehicles for national strategic objectives. Although not explicitly stated in the national SEI Plan, some city-level Plans followed this preference. This supplementary analysis examines whether the SEI succeeded in reshaping China's innovation landscape along these ownership dimensions.

Using detailed patent-firm ownership linkages, I track the number of granted patents applied by firms across three critical divides: listed versus unlisted firms, SOEs versus private firms, and domestic versus foreign firms. The results, shown in Appendix Section E, present a striking departure from conventional expectations. While all ownership groups showed substantial absolute increases in patenting activity, their relative shares of total patent output remained statistically unchanged. In other words, while state-owned enterprises experienced more patents, their share of total patents (combining patents filed by SOEs and private firms) remained unchanged.

The stability of patent shares by firm type, despite absolute growth across all ownership types, suggests the SEI avoided within-sector crowding out of disfavored entities. This contrasts with industrial policy's typical winner-picking distortions, implying the SEI's incentives were broadly accessible rather than narrowly targeted. Yet this neutrality came with a catch: as I show next, displacement instead occurred across sectors, with untargeted industries bearing the cost.

SEI Amid Broader Industrial Policy Activism. SEI was introduced during a period of broader industrial policy activism in China, raising the possibility that other national or provincial initiatives, such as high tech zone upgrades, talent attraction programs, or the early stages of reforms later formalized under Made in China 2025, may also have in-

fluenced innovation outcomes. These initiatives, however, were not systematically synchronized with SEI designation and were generally implemented nationwide, in different sectors, or according to criteria unrelated to the SEI city-industry structure. While such policies may contribute to overall increases in patenting, they are less likely to generate the sharp, discontinuous, city-industry specific shifts that the difference in differences design identifies.

Consistent with this, the placebo exercise in Section 5.5, which assigns false treatment years to control cities, reveals no systematic post treatment patterns, indicating that the estimated dynamic effects are not simply capturing generic upward trends driven by contemporaneous policy reforms. Nonetheless, given the unprecedented scope and scale of Chinese industrial policies over the past two decades, as documented by Fang et al. (2025), some degree of overlap cannot be fully ruled out. The SEI estimates should therefore be interpreted as measuring the relative reconfiguration of innovation activity within SEI targeted city-industry cells, over and above any broader policy environment, rather than as isolating the exclusive causal effect of SEI in a setting where multiple industrial instruments possibly have operated in parallel.

Table 1. Average Impact of SEI on Innovation Quantity and Quality

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
I. Innovation Quantity		
Number of Granted Patent (log)	1.0556***	1.0434***
	(0.0181)	(0.0184)
Number of Patenting Firm (log)	0.1603***	0.1324***
	(0.0070)	(0.0070)
II. Innovation Quality: Patent Citation		
Total Citation (log)	0.2595***	0.2540***
	(0.0075)	(0.0091)
Total Citation (log, excl. self-citation)	0.2294***	0.2371***
	(0.0068)	(0.0079)
Average Citation (log)	0.0023*	0.0013
	(0.0014)	(0.0017)
Avg. Citation (log, excl. self-citation)	0.0020*	0.0015
	(0.0011)	(0.0015)
Number of Patent Cited by Foreign Source (log)	0.0433***	0.0368***
	(0.0026)	(0.0023)
Share of Patent Cited by Foreign Source (%)	-0.6409***	-0.6043**
	(0.2147)	(0.2568)
III. Innovation Quality: Patent Lifespan and Global Reach		
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	1.0565***	1.0432***
	(0.0171)	(0.0187)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	-0.2442	-0.4088***
	(0.1422)	(0.1576)
Total Patent Lifespan (log, capped at 2017)	1.2869***	1.2511***
	(0.0297)	(0.0341)
Avg. Patent Lifespan (log, capped at 2017)	-0.0205***	-0.0232***
	(0.0059)	(0.066)
Number of International (PCT) Filing (log)	0.0822***	0.0700***
	(0.0066)	(0.0063)
Share of International (PCT) Filing (%)	0.0014	-0.0464
	(0.0847)	(0.0985)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

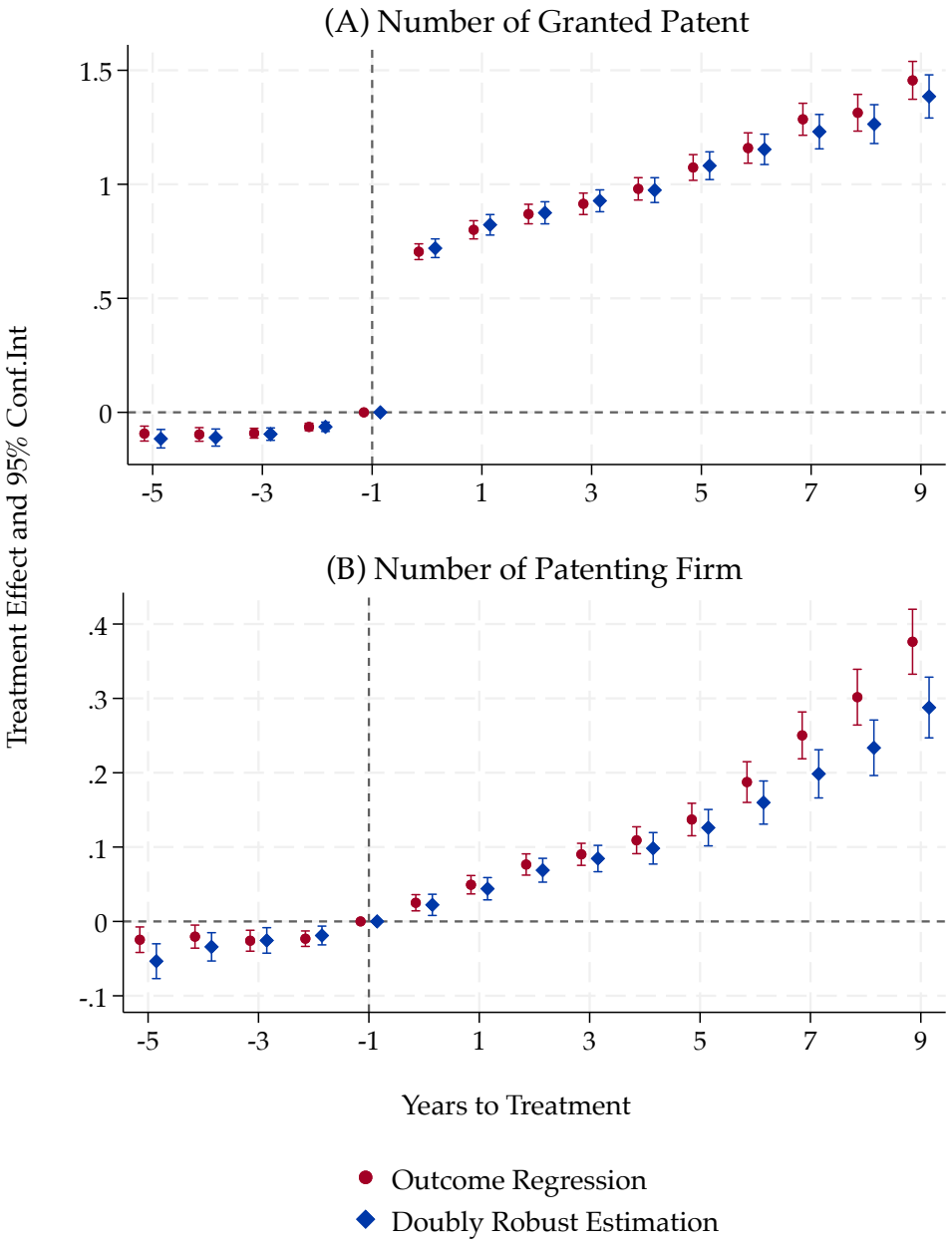
Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation quantity and quality, estimated using difference-in-differences models in Equations (1) and (3), corresponding to columns (1) and (2), respectively. Citation measures use forward citations, while patent lifespan is right-censored in 2017 to ensure complete observation periods. All regressions include year and city-industry fixed effects. All outcome variables are constructed from granted patents filed in China from 2009 to 2021. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Average Impact of SEI on Innovation Collaboration and Firm Dynamics

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
I. Innovation Collaboration Type		
Total Collaborative Patent (log)	0.4904***	0.4325***
	(0.0136)	(0.0139)
Total Collaborative Patent (% share)	0.4430	0.1636
	(0.3461)	(0.4328)
Firm-Firm Patent (log)	0.3731***	0.3273***
	(0.0126)	(0.0131)
Firm–Firm Patent (% share)	0.4378*	0.4209
	(0.2496)	(0.2851)
University-Firm Patent (log)	0.2412***	0.2025***
	(0.0087)	(0.0091)
University-Firm Patent (% share)	0.0173	-0.0206
	(0.1730)	(0.2140)
Gov-Firm Patent (log)	0.0312***	0.0222***
	(0.0030)	(0.0030)
Gov-Firm Patent (% share)	-0.0037	0.0152
	(0.0595)	(0.0359)
II. Firm Participation		
Firm entry (log)	0.1054***	0.1454***
	(0.0180)	(0.0168)
Firm exit (log)	0.1140***	0.1304***
	(0.0144)	(0.0139)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

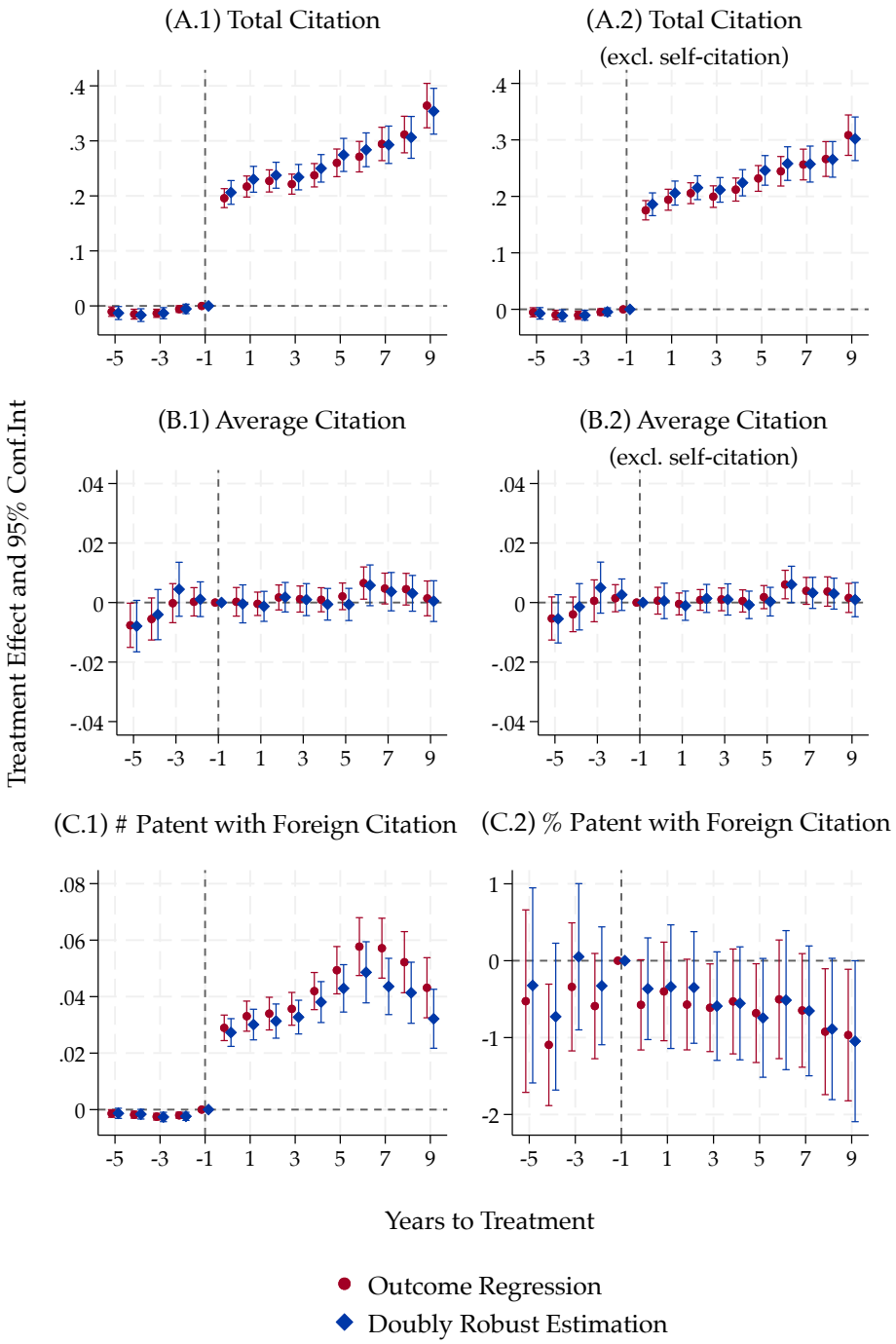
Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation collaboration structure and firm participation, estimated using difference-in-differences models in Equations (1) and (3), corresponding to columns (1) and (2), respectively. All regressions include year and city-industry fixed effects. All outcome variables are constructed from granted patents filed in China from 2009 to 2021. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 5. Impact of SEI on Patent Number and Firm Participation



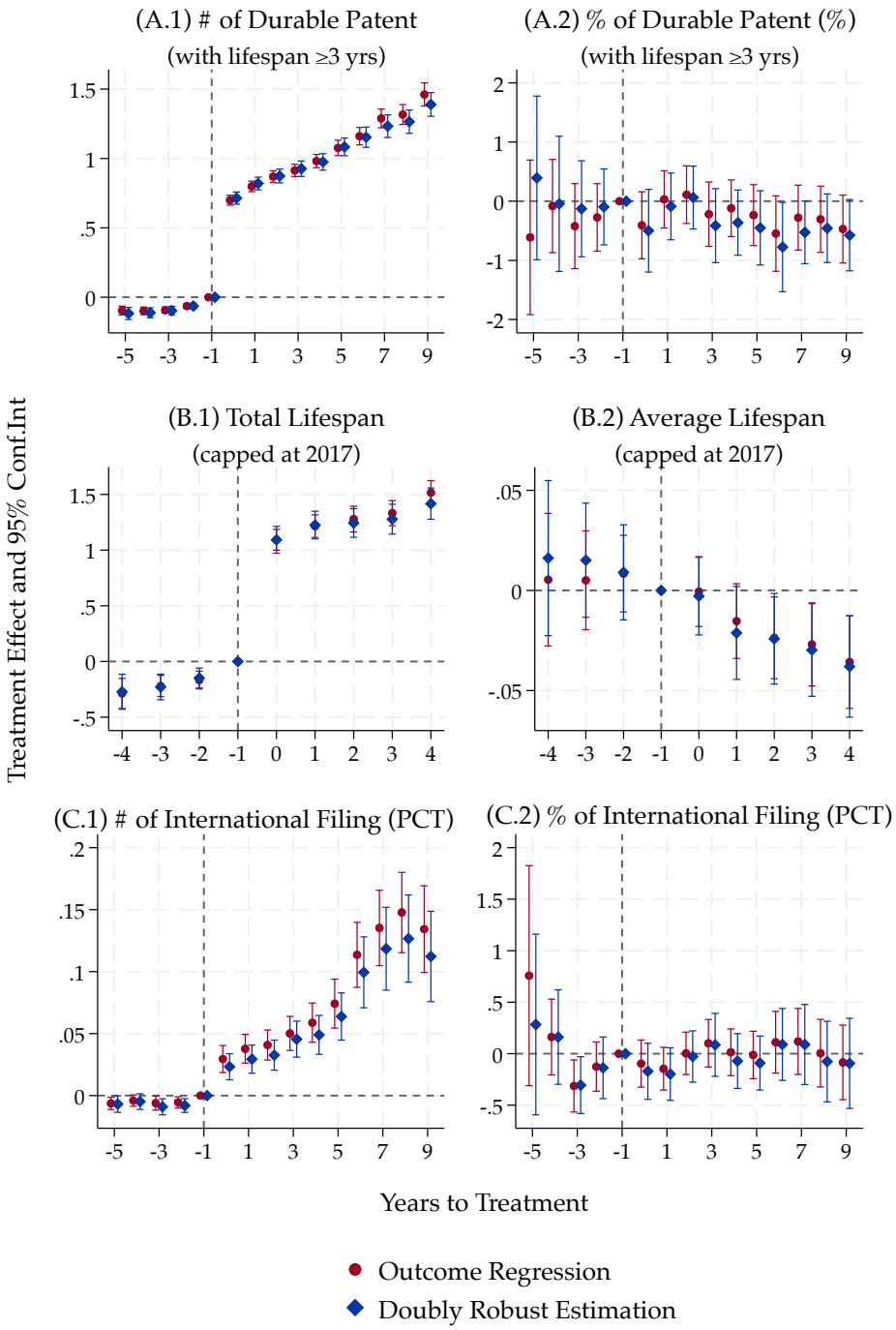
Notes: This figure presents dynamic difference-in-differences estimates of the SEI policy's effects on innovation quantity, measured by the (log) counts of granted patents (Panel A) and patenting firms (Panel B). Red and blue markers indicate outcome regression and doubly robust estimates, respectively. All specifications include city-industry and year fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 6. Impact of SEI on Patent Quality: I. Citation



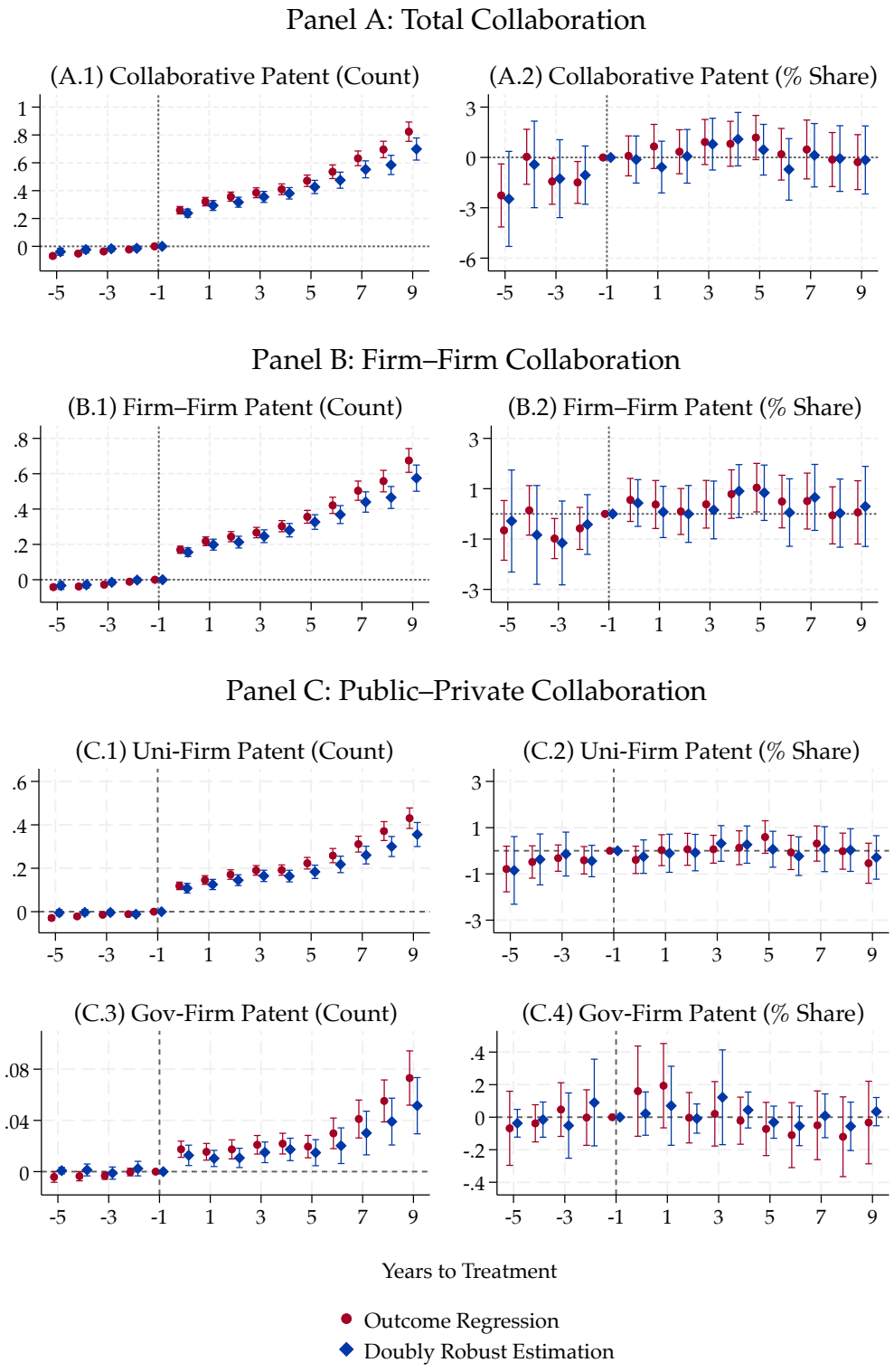
Notes: This figure presents dynamic difference-in-differences estimates of the SEI policy's effects on innovation quality, measured by total citation (Panel A.1) and average citation (Panel B.1). Parallel measures excluding self-citation are displayed by Panel A.2 and B.2. The number and share of patents cited by foreign patents are shown in Panel C.1 and C.2, respectively. Red (outcome regression) and blue (doubly robust) markers represent estimates with city-industry and year fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 7. Impact of SEI on Patent Quality: II. Lifespan and Global Reach



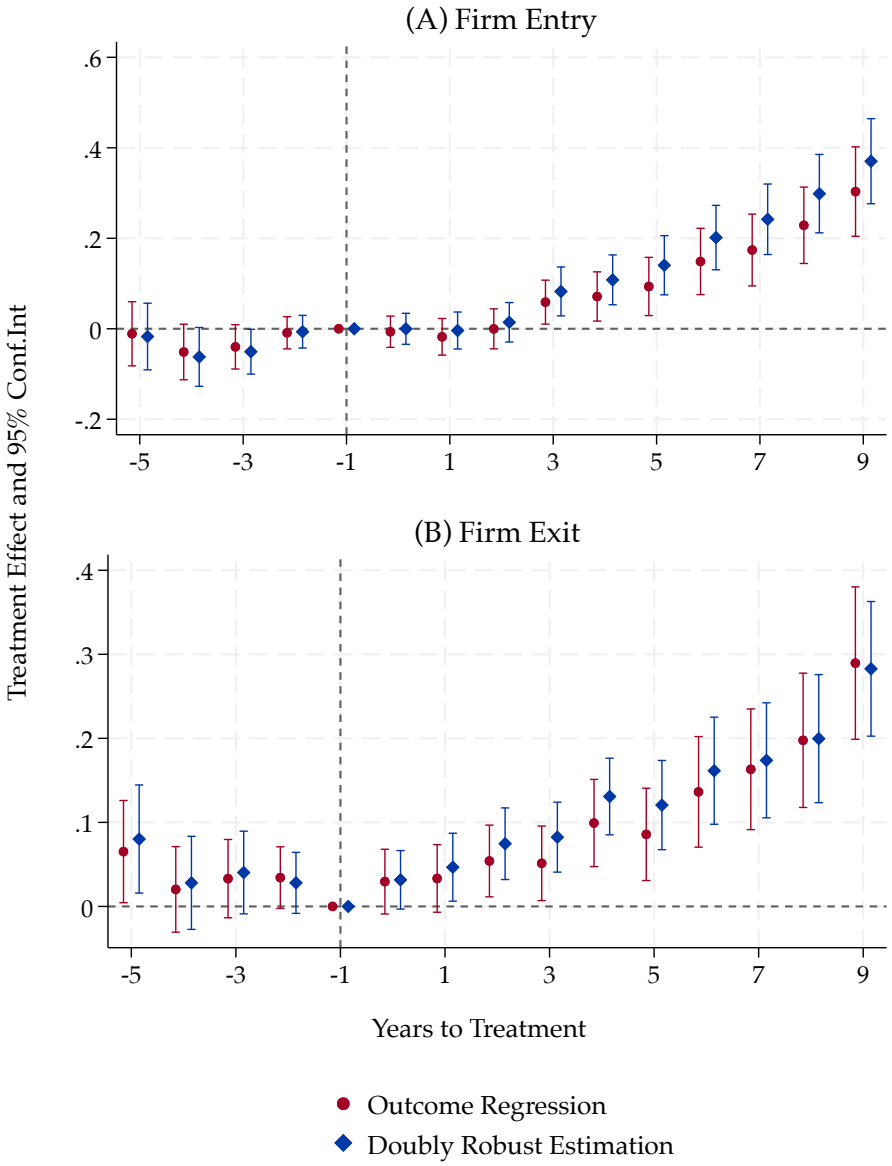
Notes: This figure presents dynamic differences-in-differences estimates of the impact of the SEI policy on innovation durability and global impact. Red (outcome regression) and blue (doubly robust) markers represent estimates with city-industry and year fixed effects. Panel (A) reports the number and share of durable patents (those active for three or more years). Panel (B) shows the total and average patent lifespan, with the dataset truncated at 2017 to allow for full observation of lifespan outcomes. Panel (C) shows the number and share of internationally vetted PCT patents. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 8. Impact of SEI on Collaborative Innovation



Notes: This figure presents dynamic differences-in-differences estimates of SEI's impact on patent collaboration types: sum of all types (Panel A), firm-to-firm (Panel B), and public-private partnership (Panel C). Red (outcome regression) and blue (doubly robust) markers represent estimates with city-industry and year fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 9. Impact of SEI on Firm Dynamics



Notes: This figure displays dynamic differences-in-differences estimates of SEI's impact on firm churn, measured by firm entry (Panel A) and firm exit (Panel B). Red (outcome regression) and blue (doubly robust) markers represent estimates with city-industry and year fixed effects. The firm churn analysis employs 3-digit sectoral classification, which is the most disaggregated level available. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

5.2 Sectoral Displacement Effects: Innovation Crowding-Out in Non-Targeted Industries

Recent research has made significant strides in mapping industrial policy spillover through production networks and input-output linkages (Lane, 2025; Liu, 2019), yet these channels represent only part of the transmission mechanism. I complement this literature by examining sectoral displacement that could stem from local fiscal reallocation – an overlooked but critical pathway in China's regional governance context. The SEI initiative reveals this dimension with particular clarity, with local policy documents revealing explicit redistribution strategies. For instance, Hefei (2011) and Heilongjiang (2010) both outlined in their SEI plans the intention to redirect preferential land supply towards SEI-targeted sectors. Similarly, Beijing (2011) advocated for reallocating funds from traditional sectors to support SEI industries, particularly in the Zhongguancun Innovation District. This deliberate fiscal diversion creates a zero-sum environment where non-SEI sectors within the same city face disproportionate budget cuts, talent drains, and reduced administrative support.

In this section, I empirically assess whether untreated sectors in SEI-treated cities experienced sectoral displacement, mirroring spatial displacement tests in U.S. enterprise zone studies (Neumark and Kolko, 2010). To isolate the SEI's spillover on non-targeted sectors, I restrict the sample to never-treated sectors and employ a difference-in-differences design. This design compares untreated industries in two distinct groups: (1) those in cities that have already implemented the SEI (the treatment group) and (2) those in cities not yet implementing the SEI (the control group).[22] Leveraging the staggered SEI rollout which prevents contamination of the control units, this approach effectively measures whether the introduction of SEI in a city disadvantages non-priority sectors within the same city, relative to comparable industries in cities not yet implementing the SEI.[23]

Table 3 presents evidence of innovation crowd-out in non-targeted sectors. These estimates, obtained using the preferred doubly robust approach, compare outcomes relative to untreated sectors in cities that had not yet implemented the SEI policy. The results reveal a striking pattern: nearly all aggregate quantity and quality metrics exhibit consistent declines. The most pronounced effect is an average 14.1% drop in patent numbers, accompanied by a 0.7% reduction in the number of patenting firms among the untreated sectors

[22]The analysis window is truncated to $t \in [-4, +6]$ for the crowd-out analysis due to smaller sample sizes of never-treated units at extreme leads and lags.

[23]For the crowd-out analysis, I employ doubly robust (DR) estimation (Callaway and Sant'Anna, 2021), which combines outcome and propensity score models while requiring only one to be correctly specified. This proves crucial given the never-treated sample and staggered SEI timing. DR estimates demonstrate greater stability than outcome regression (OR) alternatives, which produce implausibly sensitive results. Due to these robustness concerns and DR's theoretical advantages, only DR estimates are reported here (full OR results available upon request).

in already-treated SEI cities.

On the quality side, cumulative patent lifespan and durable patent count show substantial declines of 46.9% and 14.1%, respectively, though these effects are likely driven by the sharp decrease in patent volume. Other quality metrics show more modest reductions: total citations decline by 2.3% and average citations by just 0.24% (both statistically significant). In contrast, indicators of global impact (i.e., PCT filings and foreign-cited patents) remain stable, with statistically insignificant, near-zero estimates.

Figure 10 provides compelling visual evidence of the crowd-out effects, showing parallel pre-treatment trends followed by clear post-SEI declines in both innovation quantity and aggregate quality measures. The last four panels reveal particularly muted responses for scale-adjusted quality metrics and global impact measures.[24] Critically, while economically meaningful, these spillover costs are dwarfed by the program's direct benefits: the 14% reduction in patent counts represents less than one-tenth of the 184% innovation gains in treated sectors. The initiative's innovation benefits to treated sectors thus dominate any secondary crowd-out costs.

Innovation collaboration patterns exhibit similar crowding out with smaller magnitudes. Total collaborative patents decline by 1.75%, driven primarily by a 1.33% drop in firm-firm partnerships. In contrast, university-firm and government-firm collaborations remain nearly unchanged (declines less than 1%), suggesting that institutional partnerships, anchored by long-term commitments and non-market incentives, might be more resilient to fiscal reallocations than market-driven alliances. This divergence underscores how public-private ties can act as stabilizing buffers during innovation-oriented policy shocks.

Interestingly, rather than suppressing economic activity, both firm entry and exit rates increased in non-targeted sectors, rising on average by 5.4% and 7.0% respectively.[25] This simultaneous growth suggests that resource reallocation toward SEI sectors created competitive pressures in untreated industries, accelerating the exit of less productive firms that release underutilized assets while generating opportunities for new entrants (Aghion et al., 2005). However, when considered alongside the observed innovation crowd-out effects, this heightened turnover appears to reflect scarcity-driven competition rather than productive market dynamics. Surviving firms in non-targeted sectors consequently face

[24]Caution is warranted when interpreting the average lfespan results due to significant pre-treatment trends. These patterns likely stem from the 2017 sample truncation, which reduces observation counts, and the restriction to never-treated units, which may introduce selection bias. The estimates should thus be treated as suggestive correlational evidence rather than definitive causal effects.

[25]The firm churn patterns should be interpreted as descriptive rather than causal evidence. I omit event study visualizations due to significant pre-treatment trends that violate the parallel trends assumption required for causal inference.

intensified rivalry with diminishing returns, all while experiencing reduced innovation capacity.

The findings in this section expose industrial policy's inherent tension: while the SEI program delivered spectacular 184% innovation growth in prioritized sectors, it systematically drained 14% of innovative capacity from non-targeted industries. This crowding-out effect emerges inevitably from resource constraints: when the state channels scientists, funding, and institutional support toward strategic priorities, other sectors necessarily lose out. The critical question for policymakers thus becomes not whether such displacement occurs, but whether the trade-off between cultivating advanced technologies and diminishing legacy sector innovation represents a desirable reallocation for regional development goals.

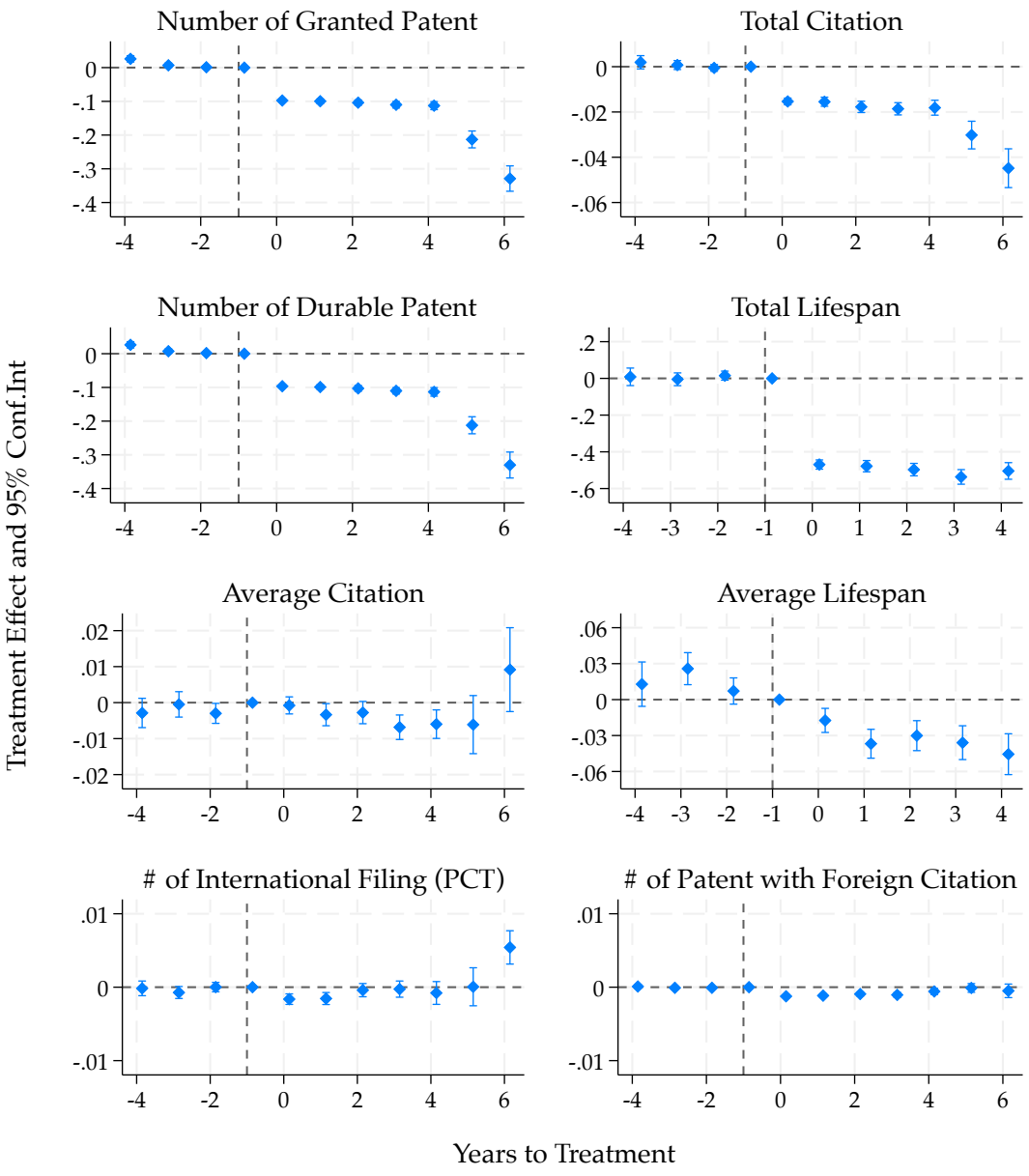
Crucially, the crowd-out patterns reveal strategic selectivity. The preservation of global impact metrics (PCT filings, foreign citations) demonstrates that internationally competitive inventions weather the storm, while domestically focused innovation bears the brunt of displacement. Meanwhile, the 46.9% collapse in cumulative patent lifespan reflects the deliberate phase-out of obsolete technological pathways. These findings thus establish a critical foundation for future industrial policy studies: successful industrial transformation requires not only cultivating advanced sectors, but also actively mitigating displacement effects in declining industries. The ultimate economic impact depends on whether displaced resources are successfully redeployed to more productive uses in targeted industries.

Table 3. Average Crowd-Out Impacts in Untreated Sectors

Dependent Variable	Doubly Robust Average Treatment Effect
I. Innovation Quantity	
Number of Granted Patent (log)	-0.1522***
	(0.0045)
Number of Patenting Firm (log)	-0.0065**
	(0.0027)
II. Innovation Quality	
Total Citation (log)	-0.0229***
	(0.0011)
Average Citation (log)	-0.0024**
	(0.0012)
Total Lifespan (log, capped at 2017)	-0.6326***
	(0.0140)
Average Lifespan (log, capped at 2017)	-0.0501***
	(0.0079)
Number of Durable Patent (log)	-0.1520***
	(0.0046)
Number of PCT Filing (log)	0.0001
	(0.0004)
Number of Patent with Foreign Citation (log)	-0.0008***
	(0.0001)
III. Innovation Collaboration Type	
Total Collaborative Patent (log)	-0.0177***
	(0.0017)
Firm–Firm Patent (log)	-0.0134***
	(0.0014)
University–Firm Patent (log)	-0.0060***
	(0.0007)
Government–Firm Patent (log)	-0.0004**
	(0.0002)
IV. Firm Participation	
Firm Entry (log)	0.0522***
	(0.0105)
Firm Exit (log)	0.0672***
	(0.0103)
City–Industry Fixed Effect	✓
Year Fixed Effect	✓

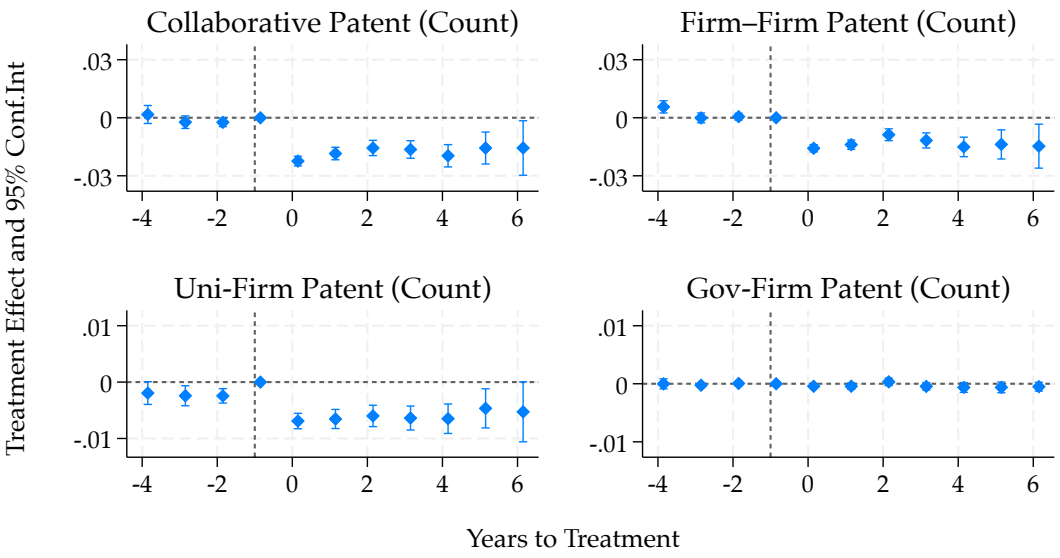
Notes: This table presents the average treatment effect on the treated (ATT) of SEI-induced crowd-out effects, estimated using the doubly robust difference-in-differences specification in Equation (3). The treatment group consists of untreated sectors in SEI-implementing cities, while the control group comprises untreated sectors in cities not yet implementing SEI. All specifications include year and city-industry fixed effects. Standard errors are clustered at the city-industry level and calculated via bootstrapping (999 iterations). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 10. SEI-Induced Crowd-Out Effects on Innovation Quantity and Quality (Doubly Robust Event-Study Estimates)



Notes: This figure presents dynamic difference-in-differences estimates of SEI-induced crowd-out effects on selected innovation outcomes, using doubly robust estimation. The treatment group consists of untreated sectors in SEI-implementing cities, while the control group comprises untreated sectors in cities not yet implementing SEI. All specifications include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 11. SEI-Induced Crowd-Out Effects on Innovation Collaboration
(Doubly Robust Event-Study Estimates)



Notes: This figure presents dynamic difference-in-differences estimates of SEI-induced spillover effects on innovation collaboration outcomes, using doubly robust estimation with year and city-industry fixed effects. The treatment group consists of untreated sectors in SEI-implementing cities; control group comprises untreated sectors in cities not yet implementing SEI. Bootstrapped standard errors (999 iterations) clustered at the city-industry level. The error bars represent 95% confidence intervals.

5.3 Interpreting SEI Estimates: Distinguishing Growth from Reallocation

An important interpretive nuance concerns the Stable Unit Treatment Value Assumption (SUTVA), which in difference in differences designs requires that the treatment status of one unit does not affect the potential outcomes of another. In the SEI context, this assumption is unlikely to hold perfectly, as the policy is explicitly spatial and sector specific. Designating a city as SEI targeted can reshape incentives, resource allocation, and patenting behavior in neighboring non targeted cities or sectors.

Section 5.2 documents one such mechanism: the reallocation of innovative activity from untreated sectors toward SEI priority sectors within treated cities. These sector level displacement effects imply that part of the observed gains in treated sectors reflect internal reallocation rather than entirely new inventive activity. This highlights the broader point that the DID coefficients capture relative increases in patenting within treated city-industry units, not aggregate innovation growth.

A similar caution applies to potential spatial reallocation across cities. Although the empirical design identifies the relative rise in innovation in treated cities compared to

untreated ones, it does not fully separate genuine technological advances from strategic shifts in where patents are filed. This concern is particularly salient in China's institutional environment, where SEI offers targeted incentives for patenting in designated sectors and cities. Firms – especially those operating across multiple locations or able to assign R&D outcomes to different subsidiaries – may redirect patent filings toward SEI cities to access benefits. In such cases, increases in patent counts would reflect relocation of innovation, not a proportional expansion in inventive activity. The estimates therefore speak to where innovation is registered, not to net economy wide growth.

Other forces may operate simultaneously, including cross city competition for skilled labor and R&D resources, or positive spillovers to untreated upstream or downstream sectors. These mechanisms imply that SEI can generate both spillovers and reallocation pressures, further limiting the extent to which the estimates can capture pure, unit level treatment effects. Fully identifying these channels lies beyond the scope of this study, but they motivate a cautious interpretation.

Taken together, the DID estimates capture changes in recorded innovation activity within treated city-industry units relative to comparable untreated units. The nearly 200% increase in patenting in targeted sectors at baseline should therefore not be read as an equivalent aggregate gain, as it may partly reflect shifts in where innovation is filed – across cities, across industries, or both. More broadly, the results indicate that SEI reconfigured the geography and composition of innovation in China by boosting activity in prioritized city-industry cells while potentially drawing innovation away from other locations or sectors. The estimates thus reflect local, relative increases in recorded innovation arising from a mix of genuine inventive expansion and reallocation.

5.4 Innovation Path Dependence and the Role of Comparative Advantages

Path Dependence and Comparative Advantage in the SEI Context. While sectoral displacement from the SEI initiative is evident, a deeper question emerges: Do industrial policies yield uniform outcomes across all treated units? And if not, what explains the heterogeneity in their success? As discussed in Section 2, the close alignment between city-level and national sectoral choices may, to some extent, compromise local comparative advantage, raising the question of whether tailoring policies to local strengths would lead to more efficient outcomes. Alternatively, alignment with central government priorities may prove more advantageous, as a cohesive national strategy may more effectively mobilize financial and infrastructural resources. Understanding these dynamics

has broader implications for the coordination between central and regional policies, particularly in balancing national strategies with regional autonomy.

In this section, I examine whether city-industry units with a pre-existing comparative advantage in innovation experience stronger post-treatment effects. This inquiry builds on the idea that innovation is path-dependent, where sectors with established innovation capabilities are more likely to continue advancing, as accumulated knowledge and deep-rooted networks reinforce future growth, making it harder for less-innovative sectors to catch up (Aghion et al., 2019).

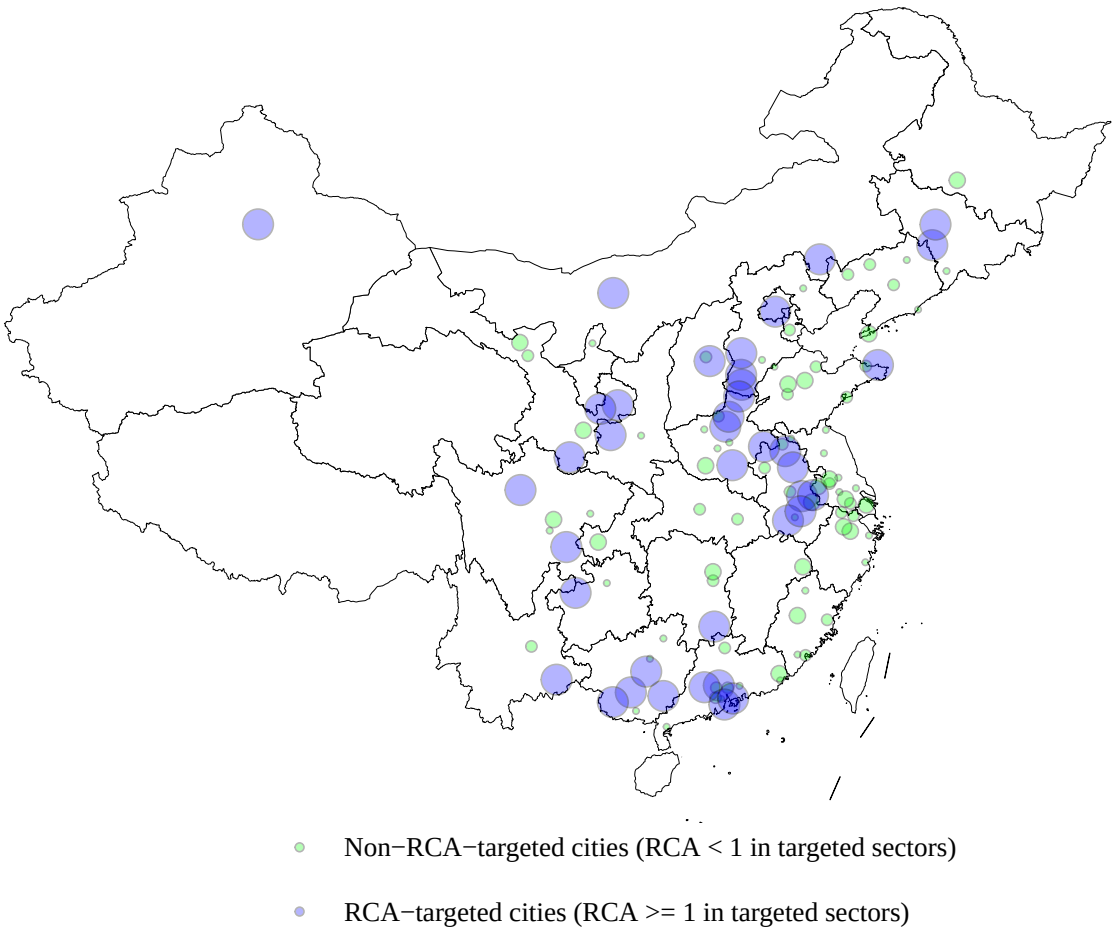
Building on Balassa (1965)'s foundational work on the revealed comparative advantage (RCA) in exports at the national level, I evaluate comparative advantage in innovation among Chinese cities. For each city i and industry j, I compute the patent-based RCA as follows:

$$RCA_{i,j} = \left(\frac{X_{i,j}}{X_i}\right) \Big/ \left(\frac{X_{country,j}}{X_{country}}\right) \tag{4}$$

, where X represents the number of granted invention patents. The numerator reflects the share of patents in industry j within city i relative to the total patents in that city, while the denominator represents the share of patents in industry j relative to the national total. This ratio indicates the relative innovation position of each city-industry unit compared to the national level. An RCA value greater than 1 suggests that the city is relatively more specialized in that sector compared to the average level of specialization across the country, while an RCA less than 1 indicates a relative disadvantage.

Local Alignment with Comparative Advantage. At the city level, local governments might be expected to prioritize industries where they hold a pre-existing comparative advantage in innovation, particularly since national security and global competitiveness are typically less immediate concerns than local economic development. This approach would align with the central government's strategic guidance outlined in the 12th SEI Five-Year Plan. However, among the 123 cities that implemented SEI policies, only 41 (33%) targeted industries where they demonstrated a prior comparative innovation advantage, defined as an overall RCA index > 1 for the combined targeted sectors within each city. Notably, nearly two-thirds of cities selected sectors without a strong pre-existing technological foundation. Figure 12 visually distinguishes these two groups: cities adhering to the comparative advantage principle are marked in blue (RCA > 1), while those with RCA < 1 are shown in green.

Figure 12. Treated cities and pre-treatment revealed comparative advantage (RCA)



Notes: This map illustrates the 123 Chinese cities where the SEI initiative has been identified for rollout, with each city represented by a circle. The size of the circles corresponds to the proportional magnitude of the average pre-treatment innovation advantage across the treated sectors in each city. The innovation advantage is calculated using the concept of revealed comparative advantage (RCA) in Equation (4). Cities with RCA > 1 are highlighted in larger blue circles, while those with RCA < 1 are shown in smaller green dots.

To test whether alignment with pre-existing innovation capacity improves innovation outcomes further, I divide the full sample based on the average pre-treatment revealed comparative advantage (RCA) for each city-industry pair. I then estimate the difference-in-differences model separately for these two groups, using the preferred doubly robust estimation.

Methodological Constraints. An important identification challenge arises from fundamental differences between RCA < 1 and RCA > 1 groups that extend beyond innova-

tive capacity (e.g., market size, institutional support). These concerns are compounded by non-parallel pre-trends in some outcomes, which further limit causal interpretation. While the stratified analysis cannot fully isolate RCA's independent effect from these factors, it nonetheless provides correlated evidence of policy-relevant heterogeneity.

In principle, a triple difference (DDD) design comparing high- versus low-RCA sectors could better address these confounds by controlling for time-varying sectoral characteristics. However, as Strezhnev (2023) demonstrates, current methodological limitations render DDD estimates with staggered adoption unreliable, often yielding misleading coefficients. This constraint is particularly salient given that my primary estimator does not support triple difference specifications (Callaway and Sant'Anna, 2021). Consequently, this section avoids causal claims regarding RCA itself, and instead interprets these results as characterizing differential policy impacts across distinct sector types, rather than as causal effects of RCA per se.

Quantity Gains from RCA-Aligned Targeting. Table 4 reports the differential impacts of SEI policies on innovation quantity and quality, stratified by pre-policy comparative advantage. Treated sectors with established innovation capabilities (RCA > 1, Column 1) show a robust response to SEI, with granted patents increasing by 233% on average, which is nearly double the 122% gain observed in sectors lacking prior specialization (RCA < 1, Column 2). This stark divergence, visually emphasized in Figure 13, persists throughout the decade-long study period, highlighting that while industrial policy elevates innovation across all targeted sectors, its effectiveness is amplified by pre-existing advantages, a pattern consistent with innovation's path-dependent nature. A similar but attenuated pattern emerges for the number of patenting firms: RCA > 1 sectors show an 18.3% increase, compared to 8.0% for RCA < 1 sectors. These results suggest that SEI policies generate broad-based innovation participation but yield disproportionately larger patent gains in sectors with prior specialization.

Quality Stagnation Under RCA-Aligned Targeting. Innovation quality reveals distinct patterns. Aggregate quality metrics, including total citations, foreign-cited patents, PCT filings, and durable patents, show significant divergence between treatment groups, with RCA > 1 units achieving consistently stronger performance than RCA < 1 units (Figure 15). For instance, total citations increased by 39.9% for RCA > 1 sectors versus 15.3% for RCA < 1 sectors. Yet this observed quality advantage dissipates when evaluating scale-adjusted metrics, including average citations and shares of foreign-cited, PCT, and durable patents, as policy effects diminish to marginal and often statistically insignificant levels

for both groups. The absence of meaningful divergence in per-patent quality between treatment groups further underscores that RCA-driven policies excel at replicating proven capabilities rather than transforming the innovation ecosystem.

Collaboration and Market Dynamics. The benefits of RCA-targeting for innovation collaboration appear to operate primarily through quantity rather than composition. Treated units with RCA > 1 exhibit consistently stronger effects across all collaboration types: total collaborative patents increase by 68.9% (compared to 27.2% for RCA < 1 units), while firm-firm collaborations rise by 50.3% (versus 17.5%). Yet, when examining the shares of these collaborative patents, all coefficients become negligibly small and statistically insignificant, with Figure 16 revealing persistent stagnation over time. This pattern indicates that RCA-driven policies expand the volume of collaborative patents without altering their underlying composition, reinforcing existing collaboration patterns rather than transforming them.

While patent quantity diverged between strong (RCA > 1) and weak (RCA < 1) innovators, market churn followed a more uniform pattern. If anything, firm churn for weak innovators was even higher than for strong innovators. Figure 14 reveals nearly parallel trends in firm entry and exit across both groups, with Table 5 quantifies this: firm entry rose by 14.4% in RCA > 1 sectors compared to 18.2% in RCA < 1 sectors, while exits increased by 13.5% and 14.8%, respectively.

The similarity in churn dynamics suggests that competitive forces rather than innovation capacity drive firm turnover. Weak innovators face lower barriers to entry, attracting transient firms that experiment but struggle to survive, amplifying their churn rates. In contrast, RCA > 1 sectors are likely dominated by entrenched incumbents, where higher innovation efficiency stabilizes participation. The modestly larger entry response among RCA < 1 firms aligns with Schumpeterian Mark I markets, where turbulence and experimentation coexist, while RCA > 1 sectors resemble Mark II environments, characterized by cumulative advantage and stability (Malerba and Orsenigo, 1995).

Policy Implications: Scaling vs. Transformation. Together, my analysis reveals that industrial policy's effectiveness in innovation, at least on the quantity front, is strongly mediated by pre-existing comparative advantage in innovation. Sectors with prior innovation strengths exhibit significantly larger gains in patent quantity and collaboration volume, compared to RCA < 1 sectors, consistent with path-dependent theories of innovation (Aghion et al., 2019; Thrane et al., 2010). However, the absence of meaningful divergence in per-patent quality or collaboration composition underscores a critical lim-

itation: while RCA-aligned policies efficiently scale existing capabilities, they do little to disrupt incremental trajectories or foster frontier breakthroughs.

This scaling effect is further reflected in market dynamics where high RCA sectors show lower firm entry and exit than their RCA < 1 counterparts. These empirical patterns directly mirror the theoretical tension highlighted by Arthur (1989) and Martin (2010), who argue that path dependence reinforces local competencies but risks locking economies into suboptimal equilibria, where cumulative advantage perpetuates incremental (rather than transformative) innovation.

These findings thus present policymakers with a paradox. On one hand, targeting comparative advantage maximizes short-term returns, as seen in the outsized quantity gains for RCA > 1 sectors. On the other hand, overreliance on path-dependent strategies may stifle the very leaps needed for long-term competitiveness, echoing Martin (2010)'s caution that "history-friendly" policies can entrench technological lock-in. This trade-off suggests that effective industrial policy must balance path-dependent scaling with deliberate interventions to counteract inertia. For example, coupling RCA targeting with supply-chain-linked spillover incentives (as evidenced by Liu (2019)) could help diffuse policy gains across sectors. While the correlational nature of my results demands caution, the persistent heterogeneity underscores that achieving high-quality innovation requires more than passive alignment with existing strengths. The precise 'policy dosage' between path dependence and quality transformation remains a critical blind spot for future research.

Table 4. Average Impact of SEI on Innovation Quantity and Quality by Comparative Advantage (RCA)

Dependent Variable	(1) RCA ≥ 1	(2) RCA < 1
I. Innovation Quantity		
Number of Granted Patent (log)	1.2022***	0.7962***
	(0.0211)	(0.0228)
Number of Patenting Firm (log)	0.1682***	0.0774***
	(0.0086)	(0.0097)
II. Innovation Quality		
Total Citation (log)	0.3359***	0.1428***
	(0.0114)	(0.0099)
Average Citation (log)	0.0012	0.0044*
	(0.0014)	(0.0025)
Number of Patent Cited by Foreign Source (log)	0.0574***	0.0213***
	(0.0034)	(0.0028)
Share of Patent Cited by Foreign Source (%)	-0.6344**	-0.6568
	(0.2591)	(0.4092)
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	1.2043***	0.7941***
	(0.0212)	(0.0256)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	-0.0121	-0.5571**
	(0.1671)	(0.2322)
Total Patent Lifespan (log, capped at 2017)	1.4389***	1.0663***
	(0.0380)	(0.0465)
Avg. Patent Lifespan (log, capped at 2017)	-0.0145**	-0.0155
	(0.0073)	(0.0111)
Number of International (PCT) Filing (log)	0.1039***	0.0454***
	(0.0093)	(0.0083)
Share of International (PCT) Filing (%)	0.0076	0.0255
	(0.1078)	(0.1116)
City-industry FE	✓	✓
Year FE	✓	✓

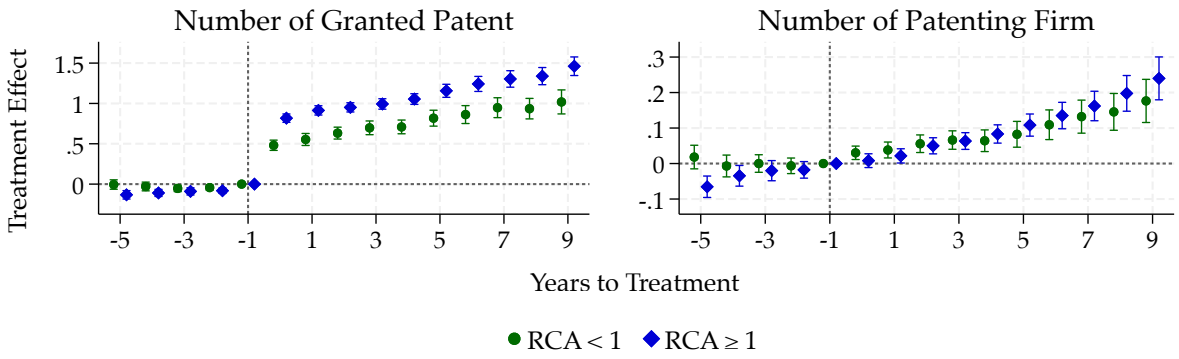
Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation quantity and quality, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with column (1) showing effects for RCA > 1 (comparative advantage) and column (2) for RCA < 1 (no advantage). All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Average Impact of SEI on Innovation Collaboration and Firm Participation by Comparative Advantage (RCA)

Dependent Variable	(1) RCA ≥ 1	(2) RCA < 1
I. Innovation Collaboration Type		
Total Collaborative Patent (Count)	0.5243***	0.2406***
	(0.0183)	(0.0182)
Total Collaborative Patent (% Share)	0.0874	0.0795
	(0.4409)	(1.1283)
Firm-Firm Patent (Count)	0.4072***	0.1612***
	(0.0175)	(0.0153)
Firm–Firm Patent (% Share)	0.3567	0.3086
	(0.3146)	(0.7043)
University-Firm Patent (Count)	0.2474***	0.1068***
	(0.0125)	(0.0105)
University-Firm Patent (% Share)	-0.0399	-0.1395
	(0.2143)	(0.7119)
Gov-Firm Patent (Count)	0.0258***	0.0145**
	(0.0039)	(0.0055)
Gov-Firm Patent (% Share)	0.0008	0.0409
	(0.0372)	(0.1264)
II. Firm Participation		
Firm entry (log)	0.1343***	0.1670***
	(0.0207)	(0.0277)
Firm exit (log)	0.1270***	0.1383***
	(0.0171)	(0.0258)
City-industry FE	✓	✓
Year FE	✓	✓

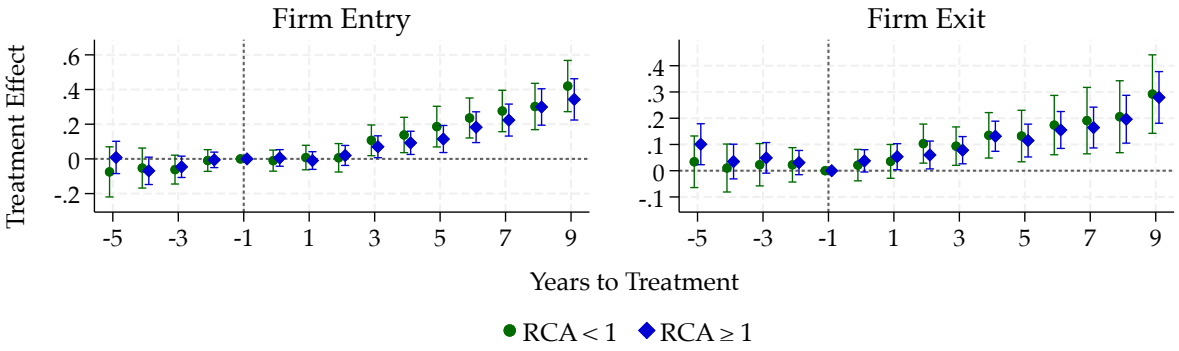
Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation collaboration and firm participation, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with column (1) showing effects for RCA ≥ 1 (comparative advantage) and column (2) for RCA < 1 (no advantage). All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 13. Impact of SEI on Innovation Quantity by Comparative Advantage (RCA)



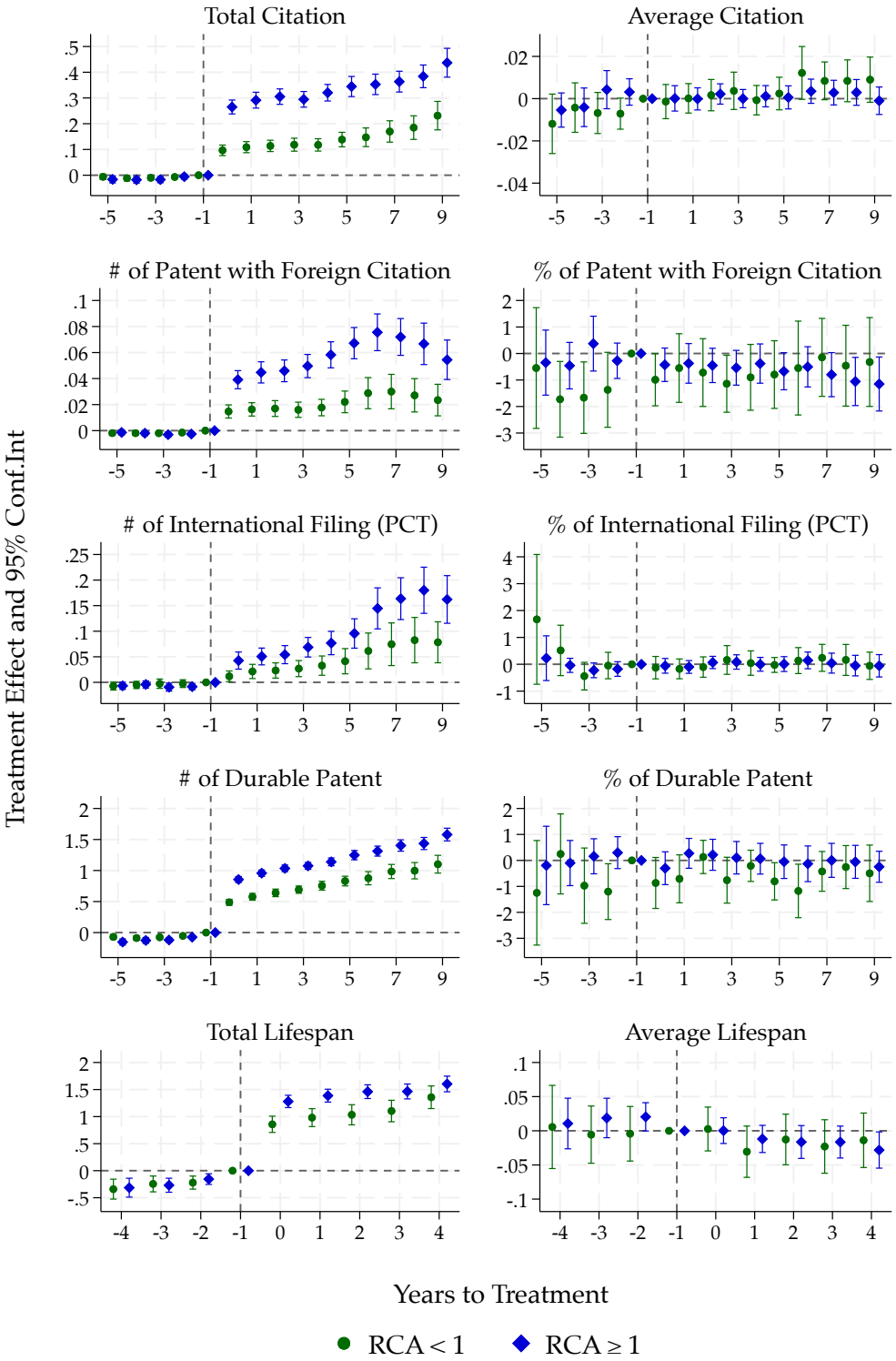
Notes: This figure presents dynamic differences-in-differences estimates of the SEI's impact on innovation quantity, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with RCA > 1 (comparative advantage) in blue and RCA < 1 (no advantage) in green. All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

Figure 14. Impact of SEI on Firm Participation by Comparative Advantage (RCA)



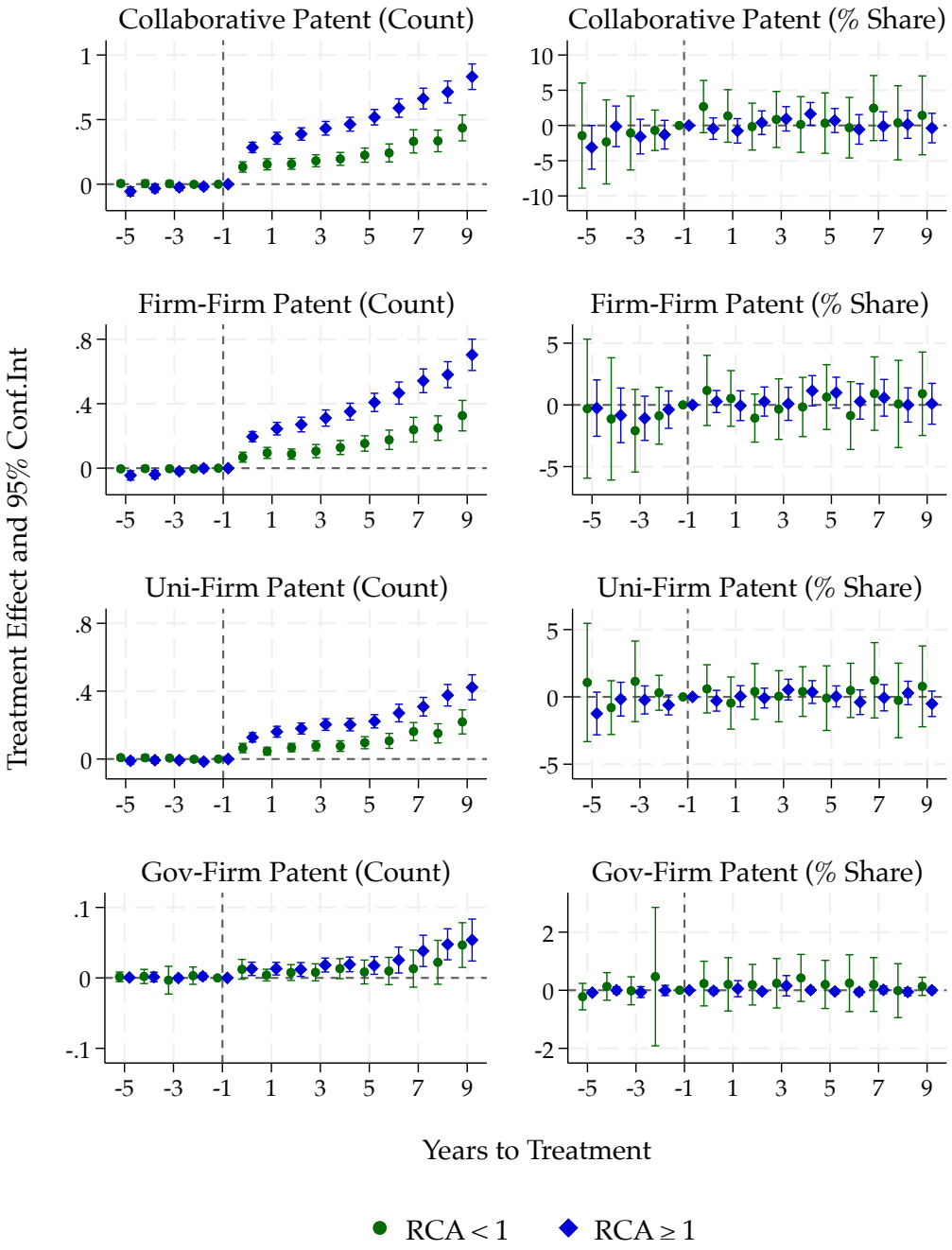
Notes: This figure presents dynamic differences-in-differences estimates of the SEI's impact on firm entry and exit, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with RCA > 1 (comparative advantage) in blue and RCA < 1 (no advantage) in green. All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

Figure 15. Impact of SEI on Innovation Quality by Comparative Advantage (RCA)



Notes: This figure presents dynamic differences-in-differences estimates of the SEI's impact on innovation quality, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with RCA > 1 (comparative advantage) in blue and RCA < 1 (no advantage) in green. All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

Figure 16. Impact of SEI on Innovation Collaboration by Comparative Advantage (RCA)



Notes: This figure presents dynamic differences-in-differences estimates of the SEI's impact on patent collaboration, estimated via doubly robust difference-in-differences (Equation 3). Results are stratified by pre-treatment revealed comparative advantage (RCA), with RCA > 1 (comparative advantage) in blue and RCA < 1 (no advantage) in green. All specifications control for year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

5.5 Robustness Check

This section addresses five critical concerns in evaluating the SEI's impacts. First, I employ placebo tests to verify that the estimated effects reflect true policy impacts rather than coincidental trends. Second, I handle zero-inflated outcome variables through alternative estimation strategies. Third, I account for treatment variation where local governments discontinued the policy for certain sectors (likely due to perceived ineffectiveness) or added new sectors later on – these rare cases have been excluded to ensure clean identification. Next, I use a balanced panel, addressing potential bias from undefined averages or shares (e.g., the PCT share of total patents) in units with zero patents. Lastly, I include both the RCA index and a green sector dummy in the propensity score model to account for pre-existing innovation advantages and the SEI's strong environmental targeting. Across all specifications, the core treatment effects from Section 5 remain robust.

Placebo Validation of SEI Impacts. The treatment effects documented in Section 5 withstand rigorous falsification testing. A central identification challenge in policy evaluation lies in distinguishing true causal effects from spurious correlations arising from coincidental timing or unobserved shocks. While the difference-in-differences design accounts for aggregate time trends and time-invariant heterogeneity, I further validate the findings by implementing a stringent placebo test that randomly assigns artificial treatment years (2010-2018) exclusively to control units. This approach creates a counterfactual scenario where the "policy" occurs at arbitrary times unrelated to the actual SEI rollout.

The results of this exercise provide clear validation of the main findings. As Figures 17-19 demonstrate, the placebo estimates show precisely estimated null effects across all outcome variables, with coefficients tightly clustered around zero and showing no systematic patterns over time. This clean null result stands in sharp contrast to the strong, statistically significant effects observed for the actual SEI implementation in Section 5. The complete absence of any meaningful placebo effects thus provides compelling evidence that the SEI's effects on innovation and firm churn are genuine policy-driven phenomena, unlikely to have occurred by chance, rather than statistical artifacts.

PPML Estimation for Outcome Variables in Counts. All count-based outcome variables in this study, including patent counts, citations, durable patents, PCT patents, foreign-cited patents, firm churn, lifespan, and collaborative patents, are log-transformed (log(x+1)) to accommodate zero counts. To address potential biases associated with this transformation, I implement a robustness check using Poisson pseudo-maximum likelihood (PPML) estimation via the extended two-way fixed effects (ETWFE) framework (Wooldridge, 2023,

2021). This approach simultaneously accounts for treatment heterogeneity under staggered adoption and permits nonlinear models such as the PPML, which has been favored by recent empirical studies (Nagengast and Yotov, 2025).

The results, presented in Figure 20, largely corroborate the baseline findings. The counts of granted patents, citations, durable patents, foreign-cited patents, lifespan, and collaborative patents exhibit persistent and statistically significant increases, consistent with the Callaway and Sant'Anna (2021) estimates. Additionally, mirroring the baseline, average citations continue to fluctuate near zero.[26] The remarkable consistency between PPML and linear estimates across nearly all outcomes reinforces the robustness of the SEI's impacts.

Policy Adjustments: Accounting for Treatment Status Changes. A critical assumption in difference-in-differences analysis is the stability of treatment status over time (**?**). In the context of China's SEI policy, I document and address two types of policy adjustments made by local governments when transitioning from the 12th to the 13th Five-Year Plan period: (1) withdrawn sectors (those prioritized in the 12th Plan but later discontinued) and (2) newly added sectors not present in the 12th Plan but later emerged.[27]

Notably, the SEI initiative reveals striking policy continuity, consistent with China's distinctive approach to long-term industrial targeting: only 5% of city-industry pairs (218 out of over 4,000) experienced status changes, comprising just 5 cities that withdrew a few sectoral supports and 28 that added new sectors. To assess the robustness of my findings, I conduct complementary analyses that alternately exclude withdrawn sectors and incorporate newly added ones. As Figure 21 demonstrates, the estimated treatment effects remain virtually unchanged across both standard outcome regression and doubly robust estimation.[28] This consistency across outcome variables provides strong evidence that the core results are not sensitive to these marginal policy adjustments.

Addressing Sample Selection via Balanced Panel. As discussed in Section 3, outcome variables expressed as averages or shares (e.g., citations per patent, PCT filing shares) have reduced sample sizes because they are undefined for city-industry units with zero

[26]The sole exception is the count of patenting firms, which exhibits a relatively delayed effect, with an initial decline before rebounding significantly in later periods.

[27]I can only identify withdrawn units that were targeted during the 12th Five-Year Plan but were no longer prioritized in subsequent plans. For some cities that did not participate in the SEI drive during earlier plans and only began targeting sectors after 2016 (under the 13th Five-Year Plan), it remains unclear whether their sectors were withdrawn, as policy documents from the PKU Law Database were only well-updated through 2020 (prior to the 14th Five-Year Plan).

[28]For conciseness, Figure 21 presents a subset of representative outcome variables; complete results for all outcomes are available upon request.

patents. While my baseline analysis retains the full sample for other outcomes to properly account for non-patenting units, the particularly stagnant patterns observed for share and average variables raise concerns about potential sample selection bias.

To mitigate this concern, I construct a balanced panel restricted to observations with non-missing values across all variables. This ensures a consistent sample for count-based, average, and share-based measures. Reassuringly, the results (plotted in Figure 22) closely align with the baseline findings in Section 5, demonstrating that neither the exclusion of zero-patent units nor sample composition variations materially affect the estimated effects.[29]

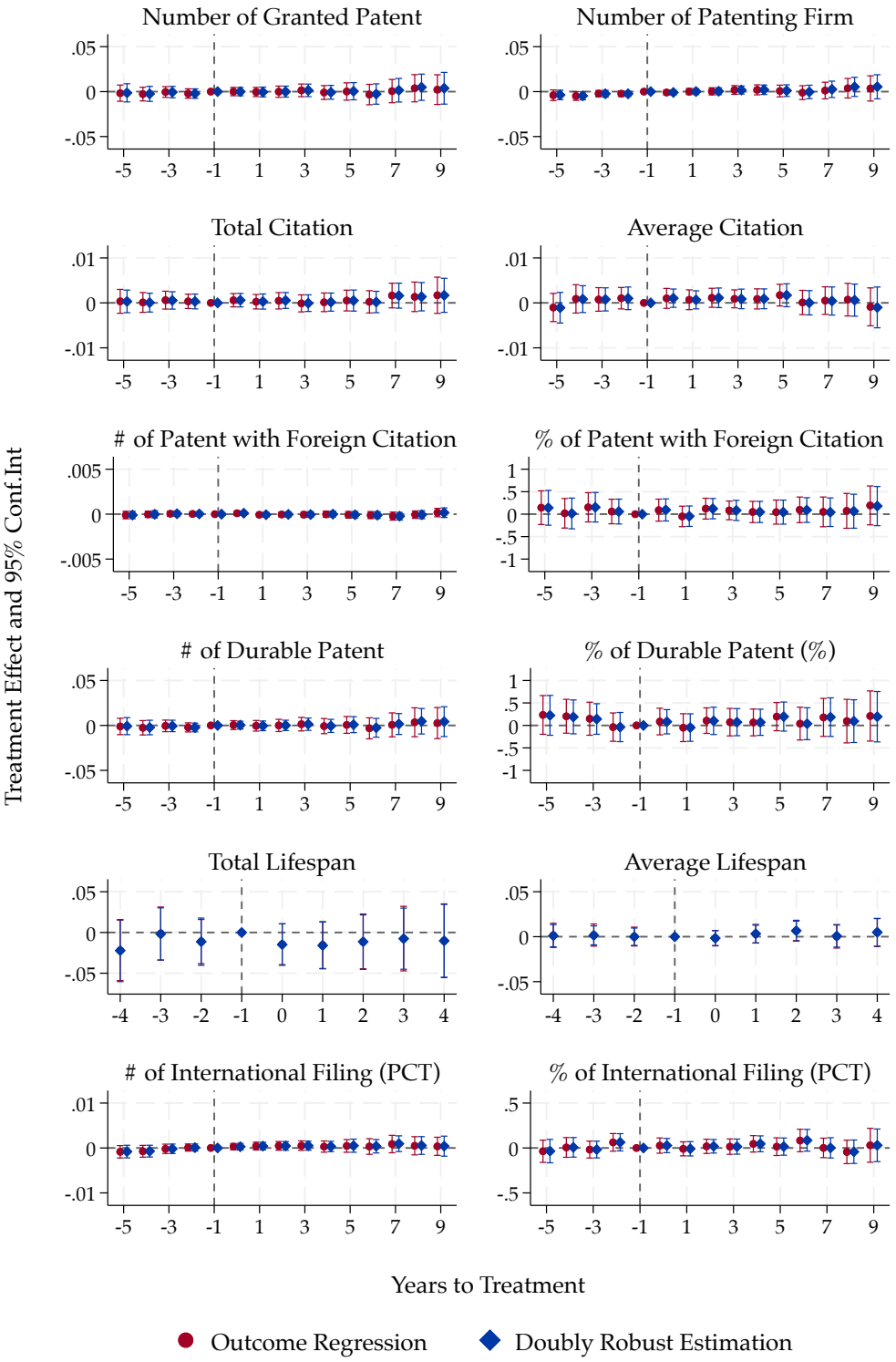
As a further robustness check, I test an alternative approach where missing values for average and share variables (due to zero patents) are imputed as zeros rather than treated as missing. The results, available upon request, remain qualitatively unchanged, reinforcing the baseline conclusions.

Accounting for Sectoral Heterogeneity. Building on the heterogeneous treatment effects documented in Section 5.4, where sectors with prior innovation strengths responded differentially to SEI, I address potential confounding from sectoral characteristics. If unaccounted for, pre-existing differences in green sector status or RCA-based comparative advantage could mechanically drive the estimated policy effects, conflating sectoral selection with SEI's true impact. To isolate the policy's role, I augment the propensity score model with two covariates: (1) pre-treatment RCA values and (2) a green sector dummy (manually coded using China's *Green Industry Catalogue*), the latter motivated by Wei (2025)'s findings that SEI not only prioritized environmental objectives but also achieved particularly strong outcomes in its targeted green sectors. As Figure 23 shows, the core results remain stable, with nearly identical effect sizes and significance levels. This consistency suggests that baseline estimates reflect true policy effects rather than latent sectoral disparities.

The full results for all robustness checks, including average treatment effects across specifications, and dynamic difference-in-differences plots using the balanced panel, are reported in Appendix (Tables 9–14).

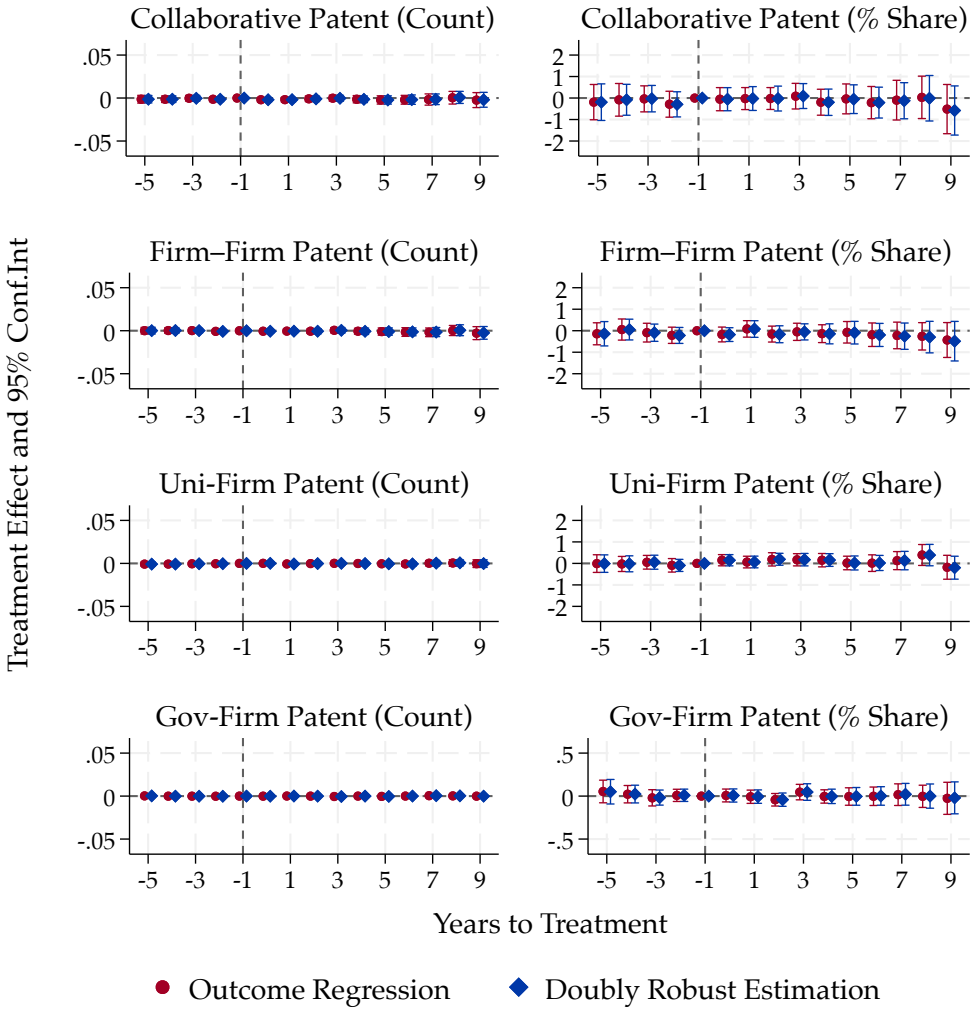
[29]Figure 21 presents only estimated effects on innovation quantity and quality for conciseness. Supplementary results on patent collaboration, available upon request, are also highly consistent with the baseline.

Figure 17. Placebo Test I: Event Study Estimates on Innovation Quantity and Quality



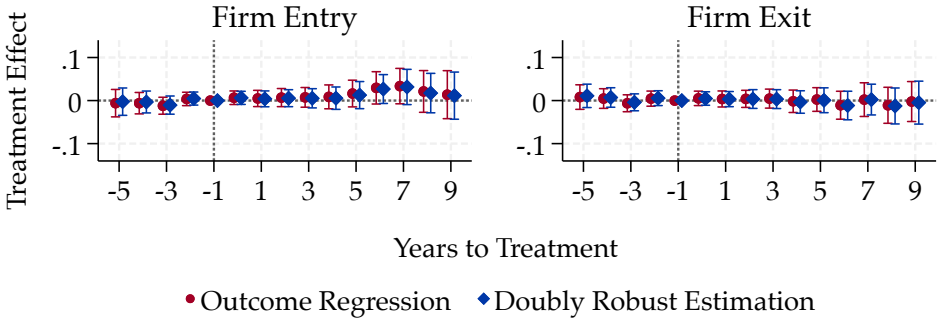
Notes: This figure presents event study estimates of the SEI impact on patent quantity and quality, from a placebo test randomly assigning treatment years to control units, simulating a pseudo-SEI rollout. All specifications are the same as those in baseline (Section 5). Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

Figure 18. Placebo Test II: Event Study Estimates on Innovation Collaboration



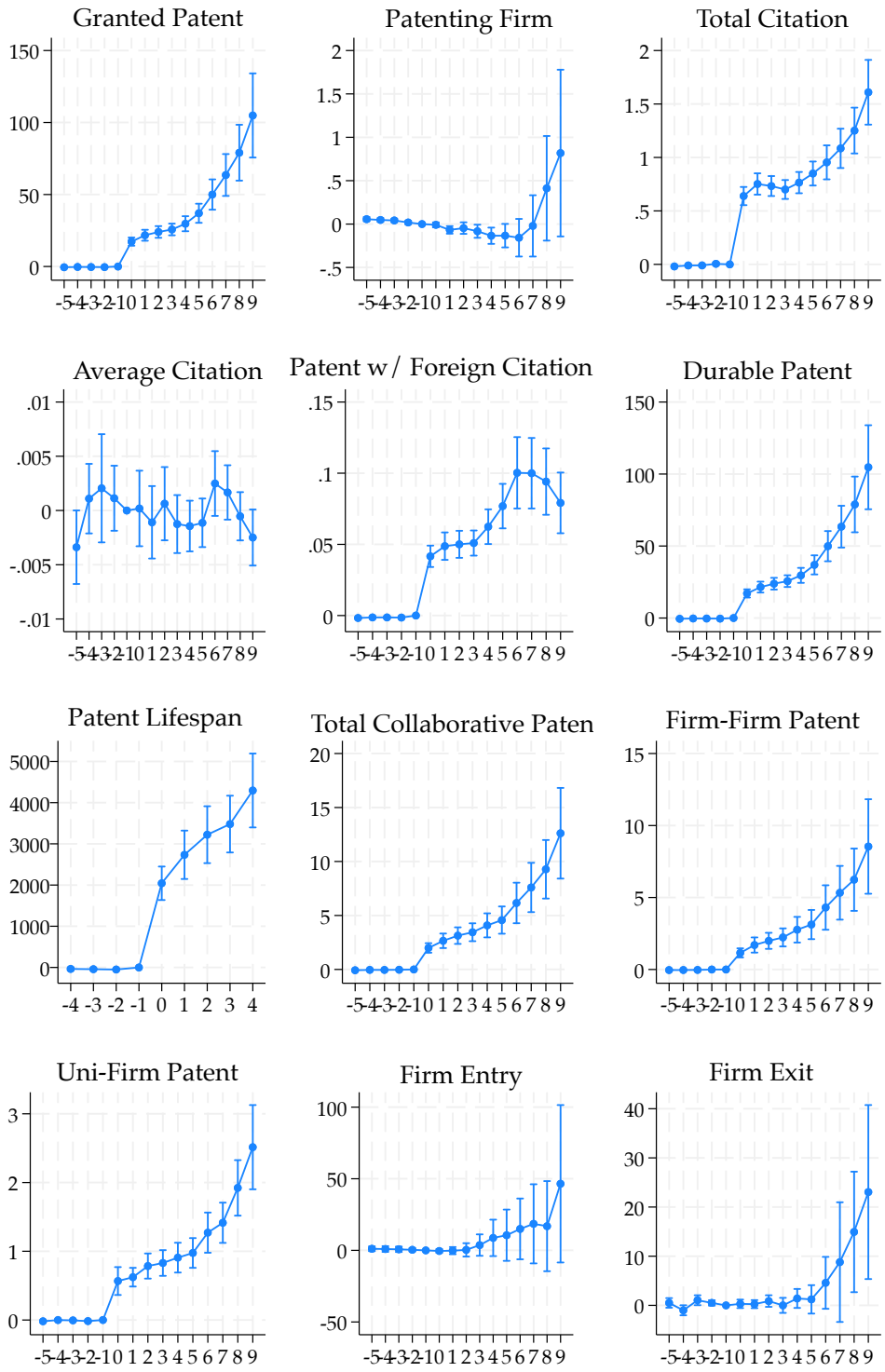
Notes: This figure presents event study estimates of the SEI impact on patent collaboration, from a pseudo-SEI rollout. Same specification design as Figure 17.

Figure 19. Placebo Test III: Event Study Estimates on Firm Participation



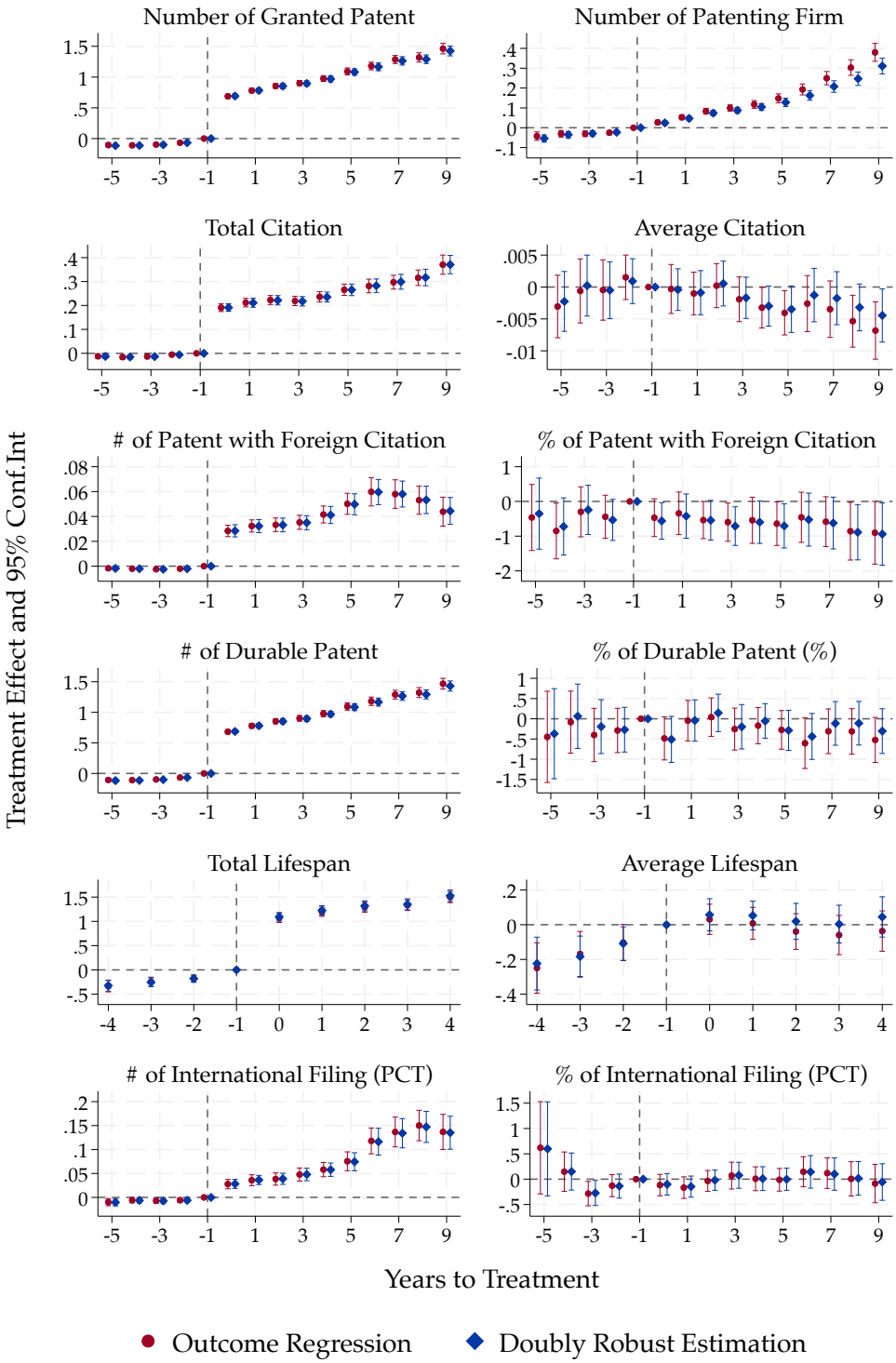
Notes: This figure presents event study estimates of the SEI impact on firm entry and exit, from a pseudo-SEI rollout. Same specification design as Figure 17.

Figure 20. Robustness Check: PPML Estimation for Count-Based Innovation Outcomes



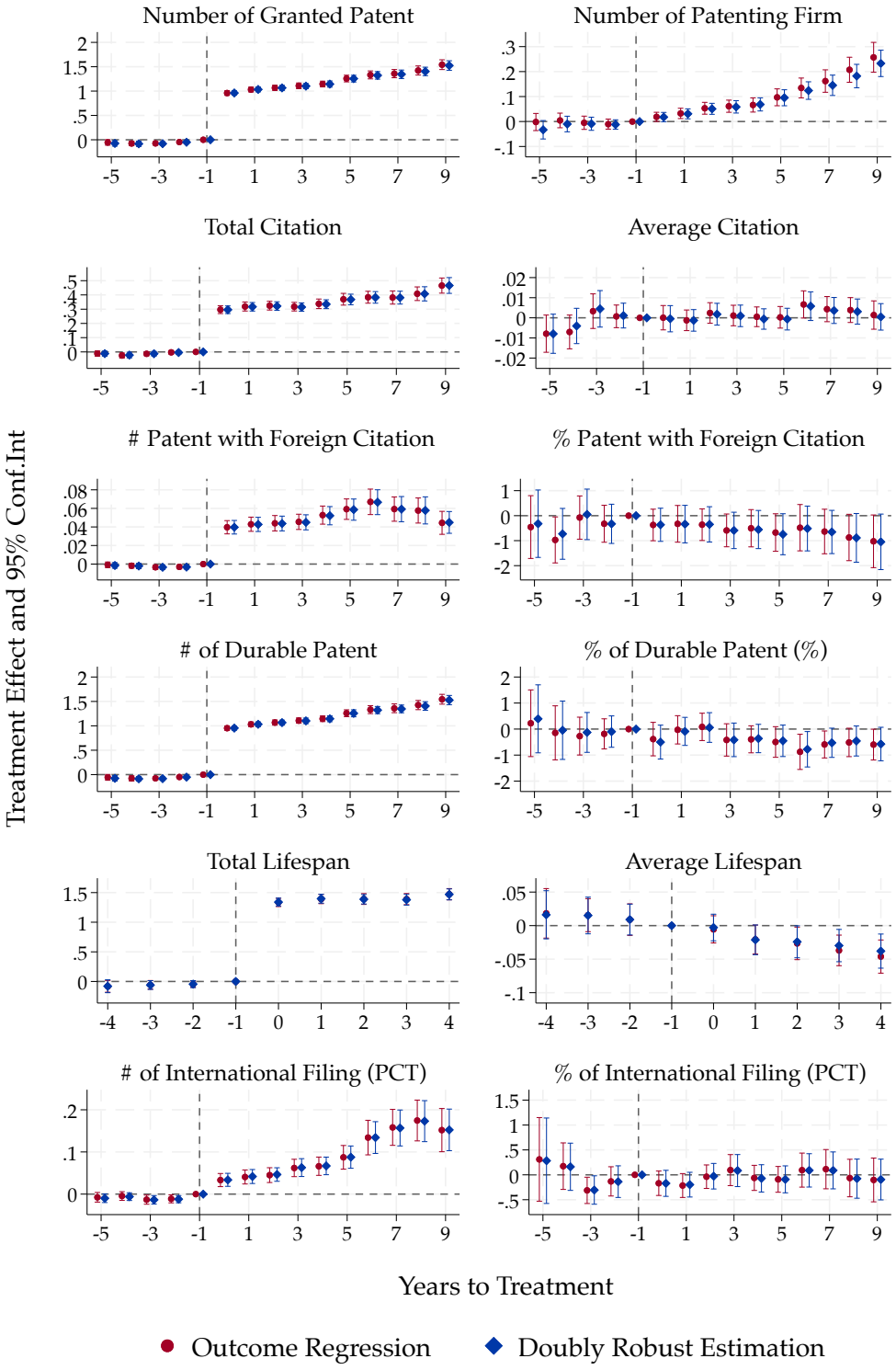
Notes: This figure shows the dynamic differences-in-differences estimates of SEI's impact on all count outcome variables, estimated via Poisson pseudo-maximum likelihood (PPML) within the extended two-way fixed effects (ETWFE) framework (Wooldridge, 2021). Standard errors are clustered at the city-industry level, with 95% confidence intervals shown by the error bars.

Figure 21. Robustness Check: Impacts of SEI on Innovation Quantity and Quality (Accounting for SEI Additions and Withdrawals)



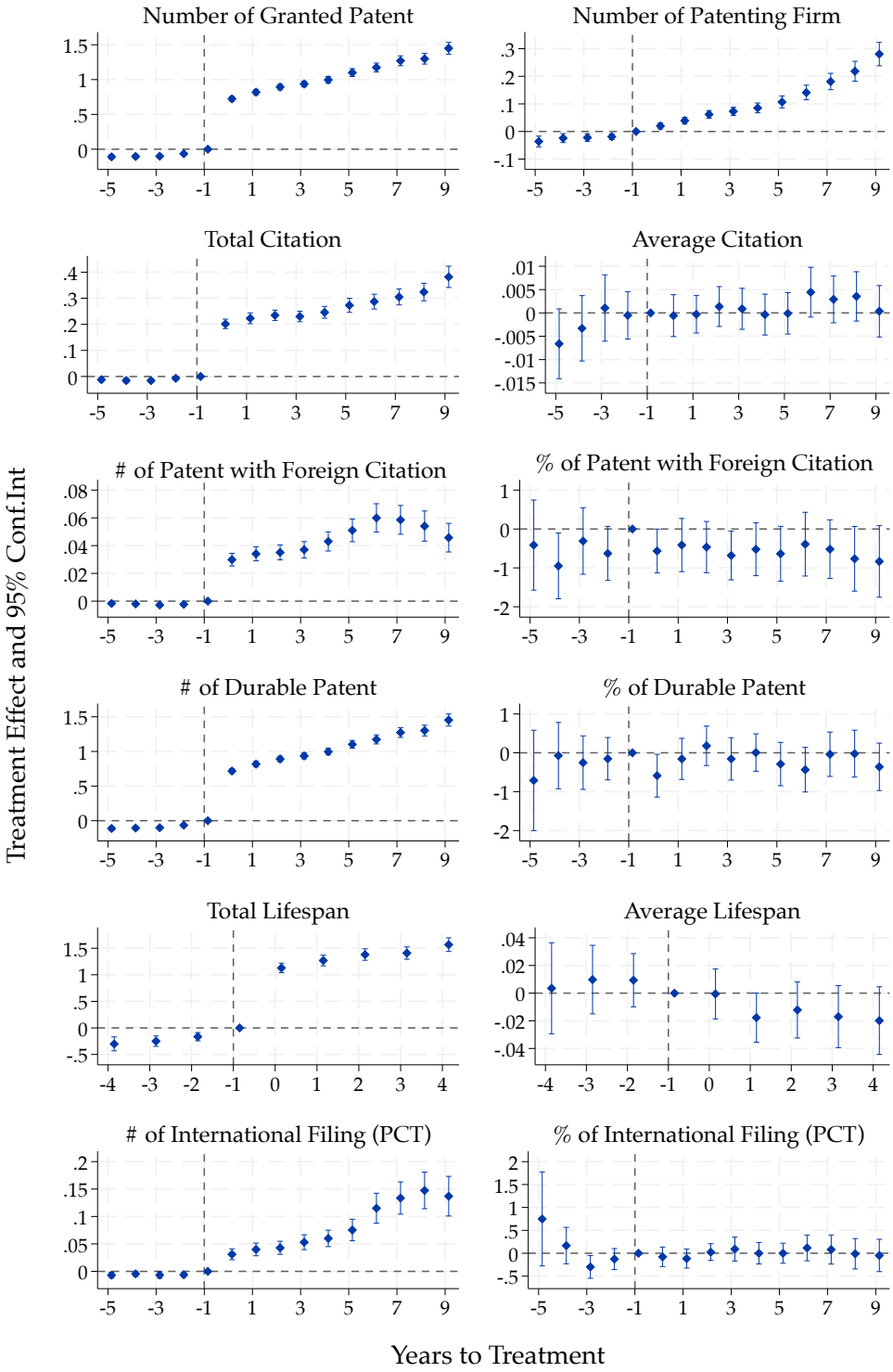
Notes: This figure shows the dynamic differences-in-differences estimates of SEI's impact on innovation quantity and quality, excluding the previously targeted city-industry pairs (under the 12th Five-Year Plan) that were no longer treated during the 13th while adding the newly targeted sectors. All specifications are the same as those in baseline (Section 5). Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. Error bars indicate 95% confidence intervals.

Figure 22. Robustness Check: Impacts of SEI on Innovation Quantity and Quality (Balanced Panel Only)



Notes: This figure displays dynamic differences-in-differences estimates of SEI's impact on innovation quantity and quality, using a balanced panel where all outcome variables have the same non-missing observations. All specifications are the same as those in baseline (Section 5). Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

Figure 23. Robustness Check: Impacts of SEI on Innovation Quantity and Quality (Accounting for Sectoral Heterogeneity)



Notes: This figure displays dynamic differences-in-differences estimates of SEI's impact on innovation quantity and quality, estimated via the doubly robust estimator (Equation 3). The propensity score model augments baseline covariates with: (1) a green sector dummy and (2) the RCA index, accounting for heightened policy effects in environmentally targeted sectors and those with pre-existing innovation advantages. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.

6. Conclusion

Amid the global resurgence of protectionism and technological rivalry among major powers, understanding the impacts of techno-industrial policies has become more critical than ever. This paper examines China's landmark Strategic Emerging Industries initiative over the past decade and reveals complex outcomes. While the policy has fostered remarkable growth in patent numbers, it has yielded limited gains in innovation quality across targeted city-industry pairs.

This mixed picture reflects China's broader challenge in structural innovation transformation: while achieving numerical growth is feasible, advancing widespread, quality-driven upgrading remains elusive. Yet two caveats bound this conclusion: First, while critiques of China's subsidy-driven 'junk patents' predict severe quality erosion through patent inflation, the near-zero quality effects estimated in this paper imply neither meaningful degradation nor enhancement. Second, quality improvements may require a longer timeframe – potentially decades – to mature than my current data can capture. Consequently, a complete evaluation of the SEI initiative may only be possible once it has become a historical episode. However, I contribute to the prudential making of industrial policy today in two areas.

First, I quantitatively demonstrate how industrial policies generate sectoral displacement when fiscally constrained governments prioritize strategic sectors. While the SEI initiative's direct innovation benefits in treated sectors outweigh crowd-out costs, policymakers must carefully evaluate whether sacrificing legacy sector innovation constitutes desirable regional restructuring. Successful industrial transformation thus requires a dual approach: nurturing advanced sectors while actively mitigating displacement in declining industries.

Second, I reveal inefficiencies in China's top-down governance model, where rigid adherence to central targets often suppresses local comparative advantages. My analysis shows that local governments achieve superior outcomes when targeting sectors with pre-existing innovation strengths. However, even this "smart" targeting proves insufficient, as it boosts patent volume without comparable quality gains. These findings reveal the limitations of comparative advantage as a standalone strategy. While path-dependent approaches successfully scale existing capabilities, they risk trapping economies in incremental innovation rather than fostering transformative breakthroughs. Determining the optimal policy mix to harness path-dependent strengths while deploying disruptive interventions to break incrementalism traps remains a critical avenue for future research.

Nearly fifteen years have passed since the initial launch of the Strategic Emerging In-

dustries in 2010. Once prominent in policy documents, the SEI has gradually waned from public view. In recent years, the Chinese government has broadened its policy scope, not only concentrating on large firms and state-owned enterprises, as seen in *Made in China 2025*, but also shifting focus toward small and medium-sized enterprises through initiatives like the *Little Giants*. Analyzing the policy tools, implementation patterns, and impacts of these recent initiatives holds important implications for China's ambition to overcome the middle-income trap. While this paper illuminates both the strengths and limitations of China's industrial policy, data constraints prevent a full examination of its associated costs. Future empirical research with more comprehensive data could quantify these costs, along with a closer examination of more recent policies.

Contrary to common Western perceptions, China has exhibited significant policy responsiveness in its innovation governance. Critiques regarding quantity-quality divergence and subsidy overuse have not only been acknowledged but have spurred concrete reforms in recent years, including the Special Action for Patent Commercialization (State Council, 2023) which supports small firms through intellectual property backed financing; the Circular on Further Strictly Regulating Patent Applications (CNIPA, 2021) with official directives criticizing low-quality patents; and various efforts to phase out patent subsidies (State Council, 2021). While China's innovation quality still lags its quantitative expansion, this ongoing transition provides valuable lessons for developing nations pursuing innovation-led growth.

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Appendix

A. Data Summary

Table 6. Summary Statistics of Main Variables:
Innovation Quantity, Quality and Propensity Score Covariates

	Obs	Mean	Std. dev.	Min	Max	Data Source
I. Outcome Variables: city-industry (4-digit) level						
Innovation Quantity						
Count of granted patent	1062726	3.73	57.51	0	19826	IncoPat
Number of patenting firm	1062726	0.93	6.97	0	1181	IncoPat
Innovation Quality I: Scientific Value						
Total forward citation	1062726	0.97	9.36	0	1850	IncoPat
Total forward citation (Excl. self-citation)	1062726	0.77	7.13	0	920	IncoPat
Average forward citation	574984	0.39	1.59	0	246	IncoPat
Average forward citation (Excl. self-citation)	574984	0.33	1.49	0	246	IncoPat
Innovation Quality II: Commercial Worth						
Total lifespan (in month)	1,062,726	306.56	4168.11	0	1043740	IncoPat
Average lifespan (in month)	574,984	88.72	34.81	4	193	IncoPat
Number of durable patent	1,062,726	3.70	57.40	0	19812	IncoPat
Share of durable patent	574,984	98.28	9.44	0	100	IncoPat
Innovation Quality III: Global Reach						
Number of PCT patent	1,062,726	0.04	2.64	0	827	IncoPat
Share of PCT patent	574,984	0.20	2.77	0	100	IncoPat
Number of patent cited by foreign source	1,062,726	0.05	0.70	0	141	IncoPat
Share of patent cited by foreign source	574,984	1.32	7.36	0	100	IncoPat
II. Propensity Score Covariates						
City level						
Real science spending (2010 RMB, in 10,000s)	1,062,726	210895.2	487321.3	1253.87	4563994	City Statistics Yearbook
Real GDP per capita (in 2010 RMB)	1,062,726	55605.12	31160.34	5601.65	162661.1	City Statistics Yearbook
Tertiary industry's share of GDP (%)	1,062,726	44.40	10.41	14.8	83.87	City Statistics Yearbook
Fiscal share of GDP (%)	1,062,726	5651808	8231050	220714.1	68680400	City Statistics Yearbook
4-digit Industry level						
Real Exports (2010 USD, in million)	1,062,726	2330.78	8872.05	0	133608	Customs Statistics
Real Imports (2010 USD, million)	1,062,726	1979.36	11045.84	0	267450.5	Customs Statistics

Notes: This table presents summary statistics for innovation quantity/quality metrics and propensity score covariates, sourced from 2009 to 2021. All statistics are based on raw variables, though the empirical analysis employs log-transformed variables (except for variables in percentage). Nominal monetary covariates (e.g., spending, trade value) are deflated to 2010 real values. For variables expressed as averages or shares (e.g., citations per patent), observations with zero patents are treated as missing because these measures are undefined when the denominator (patent count) is zero. As a result, these variables have fewer observations than count-based measures in the dataset.

Table 7. Summary Statistics of Main Variables:
Innovation Collaboration and Firm Churn

	Obs	Mean	Std. dev.	Min	Max	Data Source
Outcome Variables: city-industry (4-digit) level						
Innovation Collaboration						
Total number of collaborated patent	1062726	0.44	9.21	0	3053	IncoPat
Share of collaborated patent (%)	574984	8.54	19.81	0	100	IncoPat
Number of firm-firm-collaborated patent	1062726	0.29	7.23	0	2412	IncoPat
Share of firm-uni-collaborated patent (%)	574984	4.14	13.95	0	100	IncoPat
Number of firm-uni-collaborated patent	1062726	0.09	1.63	0	409	IncoPat
Share of firm-uni-collaborated patent (%)	574984	2.08	9.69	0	100	IncoPat
Number of firm-gov-collaborated patent	1062726	0.01	0.18	0	58	IncoPat
Share of firm-gov-collaborated patent (%)	574984	0.13	2.65	0	100	IncoPat
Firm Churn: city-industry (3-digit) level						
Number of firm entry	370015	21.66	191.44	0	27192	SAIC (CNOpenData)
Number of firm exit	370015	8.14	62.61	0	9988	SAIC (CNOpenData)

Notes: This table presents summary statistics for innovation collaboration and firm churn measures, sourced from 2009 to 2021. All statistics are based on raw variables, though the empirical analysis employs log-transformed variables (except for variables in percentage). For variables expressed as shares, observations with zero patents are treated as missing because these measures are undefined when the denominator (patent count) is zero. As a result, these variables have fewer observations than count-based measures in the dataset. Firm churn, while offering supplementary insights beyond the paper's core focus on innovation, is analyzed as a distinct panel at the most disaggregated available sectoral level (3-digit classification).

B. Policy Excerpt Example

The figure below illustrates how SEI-related documents are parsed to extract key information, including the issuing city, policy year, and SEI-focused sectors with the four-digit national economic industry classification. It shows a subsection from an SEI plan issued by the Changsha municipal government, which prioritized sectors such as renewable energy and environmental protection. Source: PKULaw.

C. SEI cities

Table 8. List of SEI Pilot Cities

Province	City	Province	City	Province	City
Anhui	Anqing	Guangxi	Laibin	Jilin	Changchun
Anhui	Bengbu	Guangxi	Liuzhou	Jilin	Liaoyuan
Anhui	Bozhou	Guangxi	Nanning	Jilin	Tonghua
Anhui	Chaohu	Guangxi	Qinzhou	Liaoning	Anshan
Anhui	Chizhou	Guangxi	Yulin	Liaoning	Chaoyang
Anhui	Fuyang	Guizhou	Bijie	Liaoning	Dalian
Anhui	Hefei	Guizhou	Zunyi	Liaoning	Dandong
Anhui	Huaibei	Hebei	Chengde	Liaoning	Fuxin
Anhui	Ma'anshan	Hebei	Handan	Liaoning	Shenyang
Anhui	Suzhou	Hebei	Hengshui	Liaoning	Tieling
Anhui	Tongling	Hebei	Shijiazhuang	Ningxia	Yinchuan
Anhui	Wuhu	Hebei	Xingtai	Shaanxi	Baoji
Beijing	Beijing	Heilongjiang	Harbin	Shaanxi	Xi'an
Chongqing	Chongqing	Henan	Anyang	Shandong	Dezhou
Fujian	Fuzhou	Henan	Jiaozuo	Shandong	Dongying
Fujian	Nanping	Henan	Luoyang	Shandong	Heze
Fujian	Sanming	Henan	Nanyang	Shandong	Jinan
Fujian	Xiamen	Henan	Pingdingshan	Shandong	Qingdao
Fujian	Zhangzhou	Henan	Xinxiang	Shandong	Tai'an
Gansu	Jinchang	Henan	Xuchang	Shandong	Weihai
Gansu	Longnan	Henan	Zhengzhou	Shandong	Yantai
Gansu	Pingliang	Henan	Zhumadian	Shandong	Zibo
Gansu	Qingyang	Hubei	Jingmen	Shanghai	Shanghai
Gansu	Wuwei	Hubei	Wuhan	Shanxi	Jinzhong
Gansu	Tianshui	Hunan	Changsha	Shanxi	Taiyuan
Guangdong	Chaozhou	Hunan	Chenzhou	Sichuan	Aba
Guangdong	Dongguan	Hunan	Xiangtan	Sichuan	Chengdu
Guangdong	Foshan	Inner Mongolia	Bayannur	Sichuan	Meishan
Guangdong	Guangzhou	Inner Mongolia	Chifeng	Sichuan	Nanchong
Guangdong	Huizhou	Jiangsu	Changzhou	Sichuan	Zigong
Guangdong	Jiangmen	Jiangsu	Huai'an	Tianjin	Tianjin
Guangdong	Shantou	Jiangsu	Lianyungang	Xinjiang	Urumqi
Guangdong	Shanwei	Jiangsu	Nanjing	Yunnan	Kunming
Guangdong	Shaoguan	Jiangsu	Nantong	Yunnan	Wenshan
Guangdong	Shenzhen	Jiangsu	Suzhou	Zhejiang	Hangzhou
Guangdong	Zhanjiang	Jiangsu	Taizhou	Zhejiang	Huzhou
Guangdong	Zhaoqing	Jiangsu	Wuxi	Zhejiang	Jiaxing
Guangdong	Zhongshan	Jiangsu	Xuzhou	Zhejiang	Ningbo
Guangdong	Zhuhai	Jiangsu	Yangzhou	Zhejiang	Shaoxing
Guangxi	Chongzuo	Jiangsu	Zhenjiang	Zhejiang	Taizhou
Guangxi	Guilin	Jiangxi	Shangrao	Zhejiang	Wenzhou

Notes: This table documents the 123 cities confirmed as SEI adopters through a comprehensive review of municipal policy documents. The conservative inclusion criteria demand verifiable written documentation with sectoral targets precisely mappable to 4-digit national industry codes. While some undocumented implementations may exist through informal channels, and other cities were excluded for vague targeting, this approach establishes a rigorous lower bound. These 123 cities thus represent confirmed implementation levels, not exhaustive national coverage.

D. Robustness Check Tables

Table 9. Placebo Test I: Average SEI Impact on Innovation Quantity and Quality

Dependent Variable	**(1) Outcome Regression**	**(2) Doubly Robust**
Innovation Quantity and Quality Measures		
Number of Granted Patent (log)	0.0003	0.0008
	(0.0029)	(0.0028)
Number of Patenting Firm (log)	0.0011	0.0017
	(0.0020)	(0.0020)
Total Citation (log)	0.0007	0.0007
	(0.0006)	(0.0007)
Average Citation (log)	0.0007	0.0006
	(0.0006)	(0.0006)
Number of Patent Cited by Foreign Source (log)	0.0000	0.0000
	(0.0001)	(0.0001)
Share of Patent Cited by Foreign Source (%)	0.0752	0.0726
	(0.0755)	(0.0842)
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	0.0005	0.0009
	(0.0028)	(0.0027)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	0.1000	0.0986
	(0.0903)	(0.0925)
Total Patent Lifespan (log, capped at 2017)	-0.0118	-0.0120
	(0.0010)	(0.0010)
Avg. Patent Lifespan (log, capped at 2017)	0.0026	0.0028
	(0.0032)	(0.0033)
Number of International (PCT) Filing (log)	0.0005	0.0005
	(0.0004)	(0.0004)
Share of International (PCT) Filing (%)	0.0180	0.0189
	(0.0247)	(0.0268)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI impact on patent quantity and quality, from a placebo test randomly assigning treatment years to control units, simulating a pseudo-SEI rollout. Column (1) reports estimates from the outcome regression model in Eq. (1); column (2) shows doubly robust estimates using Eq. (3). All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Placebo Test II: Average SEI Impact on Innovation Collaboration and Firm Churn

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
Innovation Collaboration Type		
Total Collaborative Patent (log)	-0.0014	0.0013
	(0.0012)	(0.0013)
Total Collaborative Patent (% share)	-0.1046	-0.1189
	(0.1778)	(0.1795)
Firm-Firm Patent (log)	-0.0009	0.0008
	(0.0012)	(0.0012)
Firm–Firm Patent (% share)	0.1607	-0.1791
	(0.1224)	(0.1176)
University-Firm Patent (log)	-0.0001	-0.0001
	(0.0006)	(0.0006)
University-Firm Patent (% share)	0.1091	0.1095
	(0.0804)	(0.0781)
Gov-Firm Patent (log)	0.0000	0.0000
	(0.0002)	(0.0002)
Gov-Firm Patent (% share)	-0.0021	0.0002**
	(0.0288)	(0.0291)
Firm Participation		
Firm entry (log)	0.0149	0.0127
	(0.0095)	(0.0086)
Firm exit (log)	-0.0004	-0.0014
	(0.0078)	(0.0078)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI impact on innovation networks and firm churn, from a placebo test randomly assigning treatment years to control units, simulating a pseudo-SEI rollout. Column (1) reports estimates from the outcome regression model in Eq. (1); column (2) shows doubly robust estimates using Eq. (3). All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Robustness Check: PPML Estimation for Count-Based Innovation Outcomes

Dependent Variable (for all count-based variables)	**Extended Two-Way Fixed Effect (PPML)**
Number of Granted Patent	41.8767***
	(4.5822)
Number of Patenting Firm	0.0447
	(0.1016)
Total Citation	0.9073***
	(0.0640)
Average Citation	-0.0003
	(0.0009)
Patent Lifespan (capped at 2017)	3439.616***
	(372.2701)
Average Patent Lifespan (capped at 2017)	-5.5763***
	(0.9084)
Number of Durable Patent	41.7379***
	(4.5735)
Number of Patent with Foreign Citation	0.0660***
	(0.0069)
Total Collaborative Patent	5.1138***
	(0.7320)
Firm–Firm Patent	3.4094***
	(0.5701)
University–Firm Patent	1.1105***
	(0.1207)
Firm Entry	9.2615
	(6.8056)
Firm Exit	4.7115**
	(1.9291)
City–Industry Fixed Effect	✓
Year Fixed Effect	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI impact on all count-based outcome variables, estimated via Poisson pseudo-maximum likelihood (PPML) using the extended two-way fixed effects (ETWFE) framework (Wooldridge, 2021). Standard errors are clustered at the city-industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12. Robustness Check: Average SEI Impact on Innovation Quantity and Quality (Accounting for SEI Additions and Withdrawals)

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
I. Innovation Quantity		
Number of Granted Patent (log)	1.0537***	1.0416***
	(0.0167)	(0.0166)
Number of Patenting Firm (log)	0.1653***	0.1394
	(0.0070)	(0.0067)
II. Innovation Quality: Patent Citation		
Total Citation (log)	0.2613***	0.2612***
	(0.0077)	(0.0075)
Average Citation (log)	-0.0029***	-0.0020*
	(0.0010)	(0.0010)
Number of Patent Cited by Foreign Source (log)	0.0436***	0.0435***
	(0.0026)	(0.0024)
Share of Patent Cited by Foreign Source (%)	-0.5932***	-0.6514***
	(0.2169)	(0.1998)
III. Innovation Quality: Patent Lifespan and Global Reach		
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	1.0544***	1.0422***
	(0.0182)	(0.0166)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	-0.2938**	-0.1911
	(0.1461)	(0.1362)
Total Patent Lifespan (log, capped at 2017)	1.2779***	1.3032***
	(0.0301)	(0.0308)
Avg. Patent Lifespan (log, capped at 2017)	-0.0192	0.0356
	(0.0278)	(0.0301)
Number of International (PCT) Filing (log)	0.0825***	0.0817***
	(0.0067)	(0.0064)
Share of International (PCT) Filing (%)	-0.0070	-0.0017
	(0.0863)	(0.0860)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI impact on selected innovation quantity and quality measures, estimated using difference-in-differences models in Equations (1) and (3), corresponding to outcome regression estimates in columns (1) and doubly robust estimates in (2), respectively. The sample excludes the previously targeted city-industry pairs (under the 12th Five-Year Plan) that were no longer treated during the 13th, and adds the newly targeted sectors. All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13. Robustness Check: Average Impact of SEI on Innovation Quantity and Quality (Balanced Panel Only)

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
I. Innovation Quantity		
Number of Granted Patent (log)	1.2223***	1.2185***
	(0.0202)	(0.0213)
Number of Patenting Firm (log)	0.1090***	0.1010***
	(0.0092)	(0.0089)
II. Innovation Quality: Patent Citation		
Total Citation (log)	0.3604***	0.3596***
	(0.0114)	(0.0107)
Average Citation (log)	0.0019	0.0012
	(0.0016)	(0.0015)
Number of Patent Cited by Foreign Source (log)	0.0512***	0.0512***
	(0.0031)	(0.0031)
Share of Patent Cited by Foreign Source (%)	-0.5843**	-0.5986*
	(0.2790)	(0.2624)
III. Innovation Quality: Patent Lifespan and Global Reach		
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	1.2222***	1.2185***
	(0.0200)	(0.0207)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	-0.4210**	-0.3883**
	(0.1642)	(0.1624)
Total Patent Lifespan (log, capped at 2017)	1.3963***	1.4031***
	(0.0266)	(0.0269)
Avg. Patent Lifespan (log, capped at 2017)	-0.0272***	-0.0204***
	(0.0064)	(0.0071)
Number of International (PCT) Filing (log)	0.0953***	0.0955***
	(0.0093)	(0.0088)
Share of International (PCT) Filing (%)	-0.0438	-0.0514
	(0.1011)	(0.1033)
City-industry Fixed Effect	✓	✓
Year Fixed Effect	✓	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation quantity and quality, using a balanced panel where all outcome variables have the same non-missing observations. Column (1) reports estimates from the outcome regression model in Eq. (1); column (2) shows doubly robust estimates using Eq. (3). All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 14. Robustness Check: Average Impact of SEI on Innovation Quantity and Quality (Accounting for Sectoral Heterogeneity)

Dependent Variable	Doubly Robust Average Treatment Effect
I. Innovation Quantity	
Number of Granted Patent (log)	1.0662***
	(0.0176)
Number of Patenting Firm (log)	0.1208***
	(0.0066)
II. Innovation Quality: Patent Citation	
Total Citation (log)	0.2706***
	(0.0076)
Average Citation (log)	0.0012
	(0.0013)
Number of Patent Cited by Foreign Source (log)	0.0449***
	(0.0025)
Share of Patent Cited by Foreign Source (%)	-0.5791**
	(0.2259)
III. Innovation Quality: Patent Lifespan and Global Reach	
Number of Durable Patent (Lifespan $\geq$ 3 yrs, log)	1.0665
	(0.0166)
Share of Durable Patent (Lifespan $\geq$ 3 yrs, %)	-0.1855
	(0.1601)
Total Patent Lifespan (log, capped at 2017)	1.3517***
	(0.0301)
Avg. Patent Lifespan (log, capped at 2017)	-0.0135**
	(0.0059)
Number of International (PCT) Filing (log)	0.0836***
	(0.0070)
Share of International (PCT) Filing (%)	0.0065
	(0.0858)
City–Industry Fixed Effect	✓
Year Fixed Effect	✓

Notes: This table presents the average treatment effect on the treated (ATT) of the SEI initiative on innovation quantity and quality, estimated via the doubly robust difference-in-differences estimator (Equation 3). The propensity score model augments baseline covariates with: (1) a green sector dummy and (2) the RCA index, accounting for heightened policy effects in environmentally targeted sectors and those with pre-existing innovation advantages. All specifications include year and city-industry fixed effects. Standard errors are bootstrapped (999 iterations) and clustered at the city-industry level. *** p<0.01, ** p<0.05, * p<0.1.

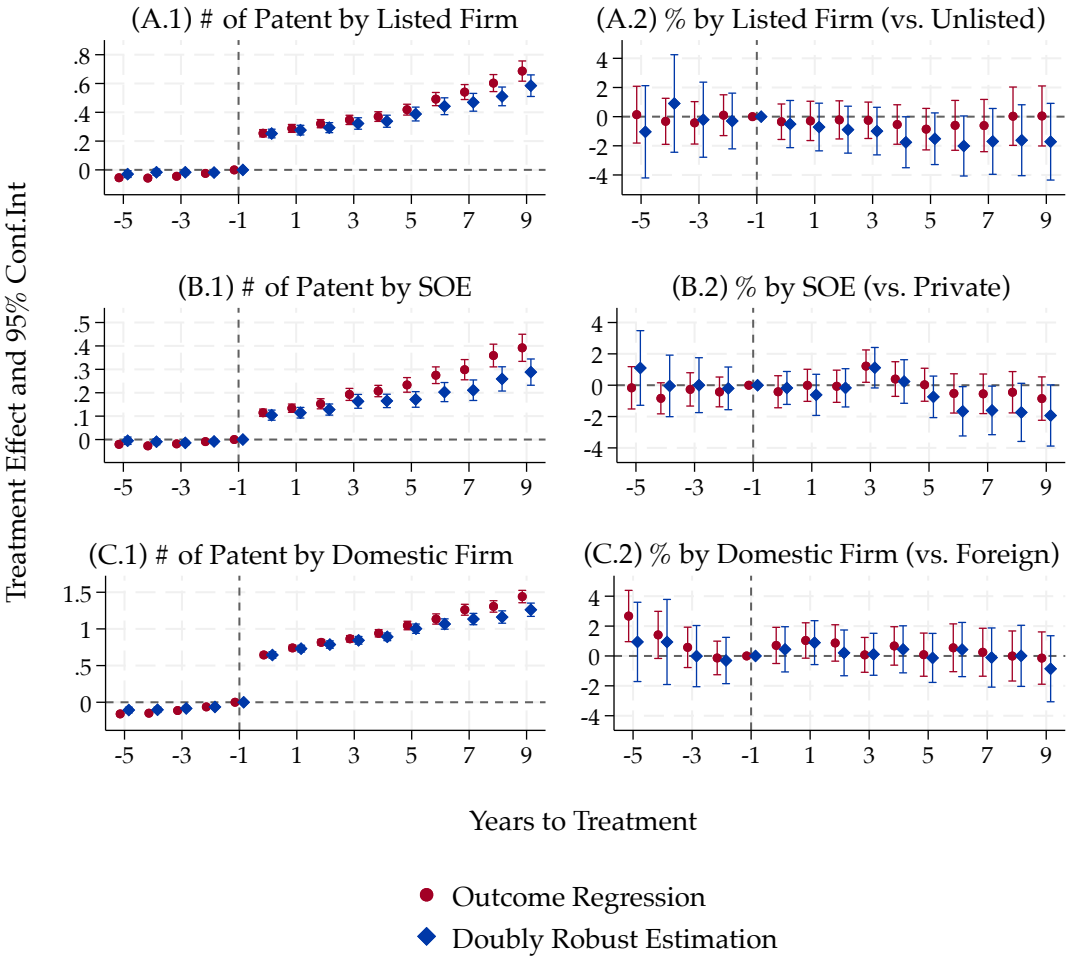
E. Impact of SEI on Innovation by Firm Types

Table 15. Average Impact of SEI on Patenting Firm's Participation by Ownership Type

Dependent Variable	(1) Outcome Regression	(2) Doubly Robust
Firm Innovation by Ownership Type		
Number of Patent by Listed Firm (log)	0.4321***	0.3877***
	(0.0119)	(0.0142)
Share of Patent by Listed Firm (vs. Unlisted, %)	-0.3637	-1.3420**
	(0.4476)	(0.5361)
Number of Patent by SOE (log)	0.2359***	0.1807***
	(0.0103)	(0.0105)
Share of Patent by SOE (vs. Private, %)	-0.1219	-0.7284*
	(0.3164)	(0.3756)
Number of Patent by Domestic Firm (log)	1.0200***	0.9527***
	(0.1728)	(0.0191)
Share of Patent by Domestic Firm (vs. Foreign, %)	0.4093	0.1443
	(0.3914)	(0.4863)
City-industry FE	✓	✓
Year FE	✓	✓

Notes: This table reports the average treatment effect on the treated (ATT) of the SEI initiative on innovation activity by firm ownership type, estimating both: (1) changes in absolute patent counts for listed vs. unlisted, state-owned vs. private, and domestic vs. foreign firms; and (2) shifts in their relative shares of total patenting. The analysis examines whether SEI preferentially stimulates innovation in strategically targeted firm types. The SEI impacts are estimated using difference-in-differences models in Equations (1) and (3), corresponding to columns (1) and (2), respectively. All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 24. Impact of SEI on Patent Shares by Firm Type



Notes: This figure displays dynamic differences-in-differences estimates of SEI's impact on innovation activity by firm ownership type, estimating both: (1) changes in absolute patent counts for listed vs. unlisted, state-owned vs. private, and domestic vs. foreign firms; and (2) shifts in their relative shares of total patenting. The analysis examines whether SEI preferentially stimulates innovation in strategically targeted firm types. The SEI impacts are estimated using difference-in-differences models in Equations (1) and (3), corresponding to the red (outcome regression) and blue (doubly robust) markers, respectively. All regressions include year and city-industry fixed effects. Bootstrapped standard errors (999 iterations) are clustered at the city-industry level. The error bars represent 95% confidence intervals.