The impact of biopharmaceutical industrial parks on pharmaceutical innovation in China

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Abstract

Pharmaceutical innovation plays a pivotal role in improving human health. While prior research has examined the effects of market demand on drug innovation, evidence on whether industrial policy can stimulate pharmaceutical innovation remains limited. This paper investigates the impact of biopharmaceutical industrial parks on drug innovation in China. We construct a staggered difference-in-differences framework, exploiting variation in the timing of park establishment across cities to estimate causal effects on innovation outcomes. The establishment of biopharmaceutical industrial parks significantly increases the number of invention patents for both biologic and chemical drugs. Regarding mechanisms, the establishment of biopharmaceutical industrial parks led to an increase in the number of innovative firms, expanded the incidence and volume of government-backed venture capital financing, and reduced the average relative price of land transactions designated for biopharmaceutical use. In our heterogeneity analyses, we find that cities with stronger fiscal capacity, top-tier universities, a greater number of research hospitals, and presence of contract development and manufacturing service providers are associated with a higher number of patents. This suggests that fiscal support, scientific community, and complementary industrial infrastructure are important in facilitating the effectiveness of biopharmaceutical industrial parks. Regarding aggregate innovation, it is associated with a reduction in the number of patents in non-drug fields within the same city, but no reduction in drug-related patents in other cities within the same province. Lastly, we find suggestive evidence that biopharmaceutical industrial parks significantly increased development activity for biologic drugs, but had no comparable effect on chemical drugs. These findings point to the mixed effectiveness of place-based industrial policy in fostering drug innovation.

Key words: industrial policy; drug innovation; government guidance funds.

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INTRODUCTION

Pharmaceutical innovation can play a critical role in enhancing human health and longevity. However, the process of developing new drugs is highly costly, inherently uncertain, characterized by irregular scientific breakthroughs and unpredictable timelines (Petrova, 2013; Chandra et al., 2024). A substantial body of theoretical and empirical research suggests that expansions in expected market size can stimulate private-sector innovation efforts in healthcare (Acemoglu and Linn, 2004; Blume-Kohout and Sood, 2013; Agha et al., 2022; Zhang and Nie, 2021; Clemens, 2013; Dranove et al., 2020, Finkelstein, 2004; Kalcheva et al., 2018). Yet in developing countries, where consumer purchasing power remains limited, market incentives alone may be insufficient to induce pharmaceutical firms to invest adequately in research and development (Kremer, 2002; Lichtenberg, 2005).

When innovation is inefficiently underprovided by private markets, there is a potential role for government intervention to enhance efficiency (Bryan et al., 2021). Conceptually, governments can intervene by either reducing the costs of research or increasing the expected revenues from innovation. Prior studies have demonstrated that policy instruments aimed at lowering the effective costs of R&D, such as tax credits (McCutchen, 1993; Oliver et al., 2024), tax deductions for R&D expenditures (Mansfield, 1986), and targeted incentives for clinical trials (Yin, 2008), are effective in promoting innovation. Public funding for basic scientific research has also been found to play a significant role in fostering innovation (Ward and Dranove, 1995; Toole, 2012; Blume-Kohout and Sood, 2013; Agarwal and Gaule, 2022).

Beyond targeted fiscal incentives, broader industrial strategies, such as place-based initiatives that provide land and infrastructure subsidies, tax credits, and government-backed venture capital, may also play a critical role in promoting pharmaceutical innovation, particularly in settings where market failures are pronounced. A growing body of empirical work has examined place-based policies in recent years (e.g. Lu et al., 2019; Devereux et al, 2007), evidence on their effectiveness in inducing high-cost, high-risk innovation activities, such as drug development, remains limited. The challenges of applying place-based policies to pharmaceutical innovation are distinct from their application to traditional manufacturing sectors, which were the original focus of such strategies in early years of economic reform in China (Li and Branstetter, 2024). In highly uncertain fields such as pharmaceuticals, informational asymmetries between firms and policymakers can give rise to both moral hazard and adverse selection (Kremer, 2002). Moral hazard arises because policymakers cannot perfectly monitor recipients of policy support. Adverse selection occurs because researchers possess more information than policymakers about the true likelihood of success of their projects, while politicians often lack the expertise to evaluate which research proposals or disease targets are most promising (Kremer, 2002).

Hence, it remains unclear whether industrial policies such as place-based initiatives can effectively promote innovation. This paper examines the impact of biopharmaceutical industrial parks on pharmaceutical innovation in China. Biopharmaceutical industrial parks offer a bundle of explicit policy supports, including negotiated land and infrastructure subsidies, tax credits, and government-backed venture capital. In addition to these direct benefits, the concentration of firms and institutions within the parks facilitates the aggregation of skilled talent and the development of upstream and downstream supply chains. While many parks are established within existing national, provincial, and municipal industrial zones, some are created as entirely new developments (Zhao and Xu, 2021). Due to the absence of officially compiled records documenting the establishment year of biopharmaceutical industrial parks, we extract this information from city-level annual government work reports. Out of 286 cities in China, we identify 146 that established biopharmaceutical industrial parks between 2006 and 2020. We construct a multiple difference-in-differences framework, exploiting variation in the timing of biopharmaceutical park establishment across cities to estimate causal effects on innovation outcomes. Our specification includes city fixed effects to control for time-invariant differences across cities and province-by-year fixed effects to absorb unobserved shocks that vary across provinces over time, such as region-specific economic trends or policy shifts. We further control for a rich set of city-year level covariates to account for observable time-varying characteristics that may influence both treatment assignment and innovation performance.

Using patent data, we find that the establishment of biopharmaceutical industrial parks led to an increase in the number of patents for both biologic and chemical drugs, while having no impact on the average number of weighted citations those patents received. Second, to explore potential mechanisms, we find that industrial policies associated with the parks led to an increase in the number of newly established innovative firms, expanded both the incidence and volume of government venture capital financing, and reduced the average relative price of land transactions designated for biopharmaceutical use. In our heterogeneity analyses, we find that cities with stronger fiscal capacity, top-tier universities, a greater number of research hospitals, and presence of contract development and manufacturing service providers are associated with a higher number of patents. This suggests that fiscal support, scientific community, and complementary industrial infrastructure played an important role infacilitating the effectiveness of biopharmaceutical industrial parks.

Third, we find that the establishment of biopharmaceutical industrial parks is associated with a reduction in the number of patents in non-drug fields within the same city—possibly because local resources and attention were redirected toward drug-related innovation. This suggests a new type of diversion effect not previously documented in the industrial policy literature. Importantly, this also implies that our results are unlikely to be driven by omitted variable bias, as we observe reallocation within cities rather than broad increases across all sectors of innovation. On the other hand, we do not observe a reduction in drug-related patents in other cities within the same province, indicating no evidence of geographic diversion effects within the biopharmaceutical sector.

Lastly, we find suggestive evidence that biopharmaceutical industrial parks significantly increased the development of new drug pipelines as measured by clinical trials for biologic drugs, but had no comparable effect on chemical drugs. In China, biologic drug firms appear to operate in a favorable demand and supply conditions: they face less generic competition, enjoy broader international market access, and are more often led by globally trained, research-oriented entrepreneurs. In contrast, chemical-drug firms tend to operate in saturated, cost-competitive markets and possess weaker R&D capabilities. These differential findings highlight the need for further research to identify market conditions that can enable place-based interventions to enable innovation in high-risk, high-investment sectors.

Overall, our findings reveal a nuanced and mixed picture of the impact of biopharmaceutical industrial parks on pharmaceutical innovation, characterized by increases in patent quantity but not average citations per patent, trade-offs in innovation across sectors within cities, and heterogeneous effects by drug type. Together, these results help explain the recent surge in biologic drug pipelines in China and offer important lessons for other middle-income economies seeking to stimulate innovation in the life sciences.

This paper advances four strands of research. First, in developed countries, policy instruments aimed at lowering the effective costs of R&D—such as tax credits (McCutchen, 1993; Oliver et al., 2024), tax deductions for R&D expenditures (Mansfield, 1986), and tax incentives for clinical trial activities (Yin, 2008)—have been shown to significantly increase private-sector innovation. For example, Yin (2008) finds that the Orphan Drug Act (ODA), which provided tax incentives for rare disease drug development, led to a significant and sustained increase in new clinical trials, particularly for more prevalent rare diseases. In addition, public funding of basic scientific research has been demonstrated to spur downstream pharmaceutical innovation (Ward and Dranove, 1995; Kalcheva et al., 2018; Agarwal and Gaule, 2022). However, existing evidence primarily draws on advanced economies characterized by strong market incentives, robust intellectual property protection, and well-established regulatory institutions. Our paper extends this literature by focusing on place-based initiatives that bundle multiple forms of policy support and by providing new evidence from a middle-income country context characterized by weaker market incentives and price regulation.

Second, our study contributes to the growing literature on the efficacy of placed-based industrial policy (Lu et al., 2019; Wang, 2014; Zheng et al., 2017; Tian and Xu, 2022; Lu et al., 2023; Fang et al., 2024; Alder et al., 2016). By design, place-based policies can influence the amount of economic activity through agglomeration effects and human capital spillovers (Combes and Gobillon, 2015; Glaeser and Gottlieb, 2008). Existing research has primarily focused on outcomes such as foreign direct investment (Wang, 2014), firm productivity (Lu et al., 2019; Fang et al., 2024), total factor productivity growth (Alder et al., 2016; Wang, 2014; Zheng et al., 2017), output (Lu et al., 2019), wages (Lu et al., 2019; Wang, 2014), employment (Lu et al., 2019; Zheng et al., 2017), and human capital (Lu et al., 2023). In contrast, relatively few studies examine the impact of industrial policy on innovation. Tian and Xu (2022) find that national high-tech zones positively affect local innovation output, as measured by patent counts, forward citations, and entrepreneurial activity. However, their paper do not distinguish between different types of innovation, and hence we still know relatively little about the effectiveness of industrial policy in promoting innovation in high-risk, capital-intensive sectors such as pharmaceuticals. In addition, our analysis highlights a key mechanism—government guidance fund investment—that has received limited attention in the existing literature on place-based industrial policy.

Third, this paper contributes to the broader literature on technological progress in emerging markets like China. Prior studies have explored China's innovation trajectory through various lenses, including rising wages and expanding domestic demand (Wei et al., 2017), international trade integration (Shu and Steinwender, 2019), human-capital accumulation (Kong et al., 2022), intellectual-property protection (Fang, 2017), institutional change (Rong, 2017), and wide-ranging industrial-policy instruments (Fang et al., 2025; Tian and Xu, 2022; König et al., 2022; Li et al., 2022). By contrast, the pharmaceutical sector has received surprisingly limited empirical attention, despite extensive media coverage and drug-review commentary on the sharp rise in global drug development activity involving Chinese firms (Li et al., 2022). Only recently have scholars begun to examine this domain. Jia (2023) shows that expedited drug-approval timelines stimulate innovation in drug development as measured by development pipelines, while Zhang and Nie (2021) find that the expansion of public health insurance boosts pharmaceutical patenting. Yet most existing work centers on regulatory reforms and other demand-side mechanisms. Our paper fills this gap by focusing on a supply-side institutional mechanism.

Fourth, this paper contributes to the broader literature on the mixed outcomes of industrial policy. Economic theory offers contrasting predictions regarding the effectiveness of such interventions. On the one hand, industrial policy can mitigate market failures or generate positive externalities through mechanisms such as agglomeration economies (Kline and Moretti, 2014a). On the other hand, critics argue that it risks distorting resource allocation and supporting inefficient firms (Juhasz et al., 2023; Glaeser and Gottlieb, 2008), and therefore the success of industrial policies can be limited or mixed. Empirically, studies have documented that industrial policy often increases the quantity of innovation, but sometimes has limited impact on quality as measured by citations (Sun et al., 2021). Moreover, the literature highlights trade-offs: while targeted support can boost innovation in specific sectors or locations, it may also divert resources from other areas (Kline and Moretti, 2014b). The effectiveness of industrial policy also appears to be context-dependent, shaped by firm capabilities, market structures, and supply-side constraints (Barwick et al., 2019; Kalcheva et al., 2018). By systematically identifying and demonstrating these three interrelated patterns within a single empirical setting, our study advances the literature by offering a more nuanced understanding of the trade-offs, unintended consequences, and sectoral heterogeneity that condition the success or failure of innovation-focused industrial policy interventions.

INSTITUTIONAL DETAILS

China’s Strategic Focus on Drug Industry

The Chinese government has identified the biopharmaceutical industry as one of the most strategically important sectors since the early 2000s (The State Council, 2015; The State Council, 2006). This recognition reflects the industry's multifaceted potential to advance critical national objectives. First, the development of a robust domestic pharmaceutical sector is essential for improving public health outcomes and ensuring equitable access to essential medicines. Second, it reduces China's reliance on imported drugs, which are often expensive and subject to supply chain risks. Third, the biopharmaceutical industry is characterized by high R&D intensity, substantial intellectual property content, making it a promising engine of high-value, innovation-driven economic growth. Promoting this industry therefore aligns with broader national goals of industrial upgrading, technological self-sufficiency, and long-run productivity growth (The State Council, 2006).

Recognizing its strategic value, the Chinese central government began actively promoting the development of the biopharmaceutical sector in the early 2000s, with significant policy signals articulated in the 11th Five-Year Plan (2006–2010) (The State Council, 2006). A key subdocument, the 11th Five-Year Plan for the Development of the Bioindustry, marked the first time that China formally designated the bioindustry as a strategic sector within its national economic and social development framework. Since then, a series of high-level policy documents—including the Made in China 2025 strategy and the Healthy China 2030 blueprint—have explicitly prioritized the biopharmaceutical sector as a key area for industrial upgrading, innovation, and national self-reliance (The State Council, 2015; The State Council, 2016).

In China's administrative system, formal policy documents serve as key mechanisms for articulating national priorities and triggering implementation at lower levels of government (Wang, 2024; Fang, 2025). Their issuance often shape resource allocation and bureaucratic incentives. Under China's "tournament-style" system of cadre evaluation, local officials are rewarded for initiatives that closely align with central policy priorities (Zhou, 2007). While industrial policies usually leave local governments ample room for discretion, after the biopharmaceutical industry was designated a strategic sector, local governments responded with tangible implementation efforts, although the timing and intensity of these responses varied by locality.

Biopharmaceutical Industrial Parks

One of the important vehicles through which local officials have implemented central directives is the establishment of dedicated industrial parks (Fang, 2025). These parks serve as institutional platforms for directing land, capital, and resources toward sector-specific development. These parks may be located within pre-existing zones to leverage shared infrastructure and administrative capacity, or may be developed in new areas when existing sites face land constraints. They offer both physical infrastructure and a policy environment conducive to innovation. They also provide the bureaucratic scaffolding necessary to implement targeted instruments such as milestone-based subsidies, tax credits, and expedited regulatory approvals. Biopharmaceutical industrial parks that are within pre-existing zones include those in the Suzhou Industrial Park, Shanghai’s Zhangjiang Hi-Tech Park, and Beijing’s Zhongguancun Life Science Park. Independent biopharmaceutical industrial parks include Foshan Yundonghai Biopharmaceutical Industrial Park, the Jinan Qilu Pharmaceutical Biopharmaceutical Park, and the Chongqing International Biocity.

The creation of biopharmaceutical industrial parks is part of a broader utilization of place-based economic policy in China. Place-based policies are development strategies designed to stimulate growth in specific geographic areas by directing resources and administrative support to targeted localities (Neumark and Simpson, 2014; Austin et al., 2018). Since the beginning of the economic reform era, China has launched a series of place-based initiatives to accelerate regional development and industrial upgrading (Tian and Xu, 2022). These zones were initially designated with a specific industrial focus, such as advanced manufacturing, renewable energy, or digital technologies. However, their priorities often evolve over time in response to changes in national development strategy, industrial upgrading goals, or local comparative advantages. The industrial composition of national-level development zones in China has undergone significant restructuring over the past two decades. Initially dominated by labor-intensive manufacturing and traditional sectors, many of these zones have shifted toward high-tech, innovation-driven industries in response to evolving national strategies (Li and Branstetter, 2024; Wang, 2013; State Council, 2006).

Because many biopharmaceutical industrial parks are located within high-tech industrial development zones or economic and technological development zones (See Supplementary File A for explanations about these zones), it is useful to review the institutional features of these zones. They typically involve large-scale investments in land, infrastructure, and facilities designed to attract firms and foster local agglomeration economies (Wang, 2013). In addition to physical infrastructure, local governments offer a suite of policy supports. These include generous tax incentives (Wang, 2013; Alder et al., 2016), below-market land-use rights with flexible payment terms (Zheng et al., 2017), and, in some cases, direct discounts of 25–35% on land-use fees (Lu, Wang & Zhu, 2019). Access to finance is also improved through collaboration with state-owned banks, which provide preferential loan terms and simplified approval processes (Wang, 2013; Alder et al., 2016). Many cities have also established government-backed venture capital and industrial development funds to support early-stage, high-potential firms, particularly those engaged in R&D (Tian & Xu, 2022). Administrative efficiency is another distinguishing feature. For example, in national high-tech zones, administrative staffing levels are significantly lower than in comparable districts, resulting in faster and more predictable approval processes. These streamlined procedures help reduce regulatory burdens and lower transaction costs for firms (Tian & Xu, 2022; Zheng et al., 2017).

Compared to traditional industrial parks, biopharmaceutical parks benefit from additional subsidies and policy instruments tailored to the sector's unique needs (Zhao and Xu, 2021). For example, some of the local governments provide milestone-based grants to firms that enter clinical trials, obtain FDA or EMA certification, or achieve key commercialization outcomes. Other targeted support includes one-time subsidies for technological breakthroughs, expedited approval processes for importing innovative drugs and medical devices, and prioritized access to pilot programs for medical innovation. Informed by an understanding of upstream and downstream supply chains, local governments also actively promote industrial clustering by attracting firms across the biopharmaceutical value chain.

Differences in Chemical versus Biologic Drugs

We distinguish between chemical and biologic drug patents, along with their corresponding development pipelines, due to several differences between these two drug types. First, the discovery process differs by these two types of drugs and hence the inherent risk differ (Lakdawalla, 2018; Petrova, 2013). The discovery processes for chemical (small-molecule) and biologic (large-molecule) drugs share a common staged structure but differ significantly in technological complexity, risk profile, and R&D investment intensity. Small-molecule drug discovery typically begins with identifying a disease-related biological mechanism, followed by screening and optimizing chemical compounds to modulate that mechanism. These drugs are chemically synthesized, allowing for more standardized production and lower marginal costs once developed. In contrast, biologic drug discovery involves engineering molecules to interact with biological targets such as proteins or genes, using advanced biotechnological methods. Biologics are inherently more complex, resulting in higher production costs, greater regulatory uncertainty, and higher attrition rates throughout the R&D pipeline (Lakdawalla, 2018; Petrova, 2013).

Second, market opportunities differ significantly between these two types of drugs. In international markets, chemical drugs face intense competition. Mature regulatory frameworks, low production costs, and long-established multinational firms have created highly competitive markets for chemical drugs (Yina et al., 2023). By contrast, biologic drugs encounter relatively less competition globally. Many biologic therapies target emerging or specialized therapeutic areas, such as oncology and autoimmune diseases, where competition remains less saturated (Li et al., 2022).

As a result, biologic drugs offer firms better market opportunities and possibility of premium pricing both domestically and internationally.

Firm characteristics differ substantially between the chemical and biologic drug sectors in China. Chemical drug firms are generally older, having grown during earlier phases of China's pharmaceutical industry expansion focused on generic production and chemical synthesis (Shen et al., 2025). Many of these firms have limited R&D capabilities and historically prioritized manufacturing efficiency and cost competitiveness over innovation. In contrast, firms specializing in biologic drugs are often newer entrants founded during the 2000s and 2010s, many led by entrepreneurs with many years of scientific and industry experience (Han et al., 2021; Xu et al., 2024). These biologic firms tend to emphasize research and development and often adopt business models geared toward international regulatory approval and global market participation.

DATA AND RESEARCH DESIGN

Establishment of Biopharmaceutical Industrial Parks

This paper leverages city-level government work reports from 2006 to 2020 to measure whether municipal governments announced the establishment of biopharmaceutical industrial parks in a given year. Government work reports are among the most authoritative and standardized official documents at the municipal level in China. Typically delivered in the first quarter of each year by the mayor to the local People's Congress and the Chinese People's Political Consultative Conference, these reports summarize the city's major socio-economic achievements over the past year and outline key policy priorities and development targets for the year ahead. Extracted policy commitments and development targets from these reports have been widely used in prior research to examine the effects of local policy priorities and targets on economic and social outcomes (Chen et al., 2018; Yu et al., 2019). Prior research has used policy documents issued governmental agencies to quantify the intensity and target of industrial policy (Mao et al., 2021; Juhasz et al., 2023; Fang et al., 2025). Government work reports are available for most cities from 2006 onward, enabling consistent tracking of policy announcements over time.

We intend to identify the establishment of biopharmaceutical industrial parks which would involve the planning, construction, or expansion of dedicated zones for pharmaceutical innovation and production. To systematically identify these policy announcements, we employed a multi-step approach. First, we used ChatGPT 4.0 and DeepSeek to generate a comprehensive list of keywords related to pharmaceuticals and industrial parks (see Supplementary File C Table 1 for details). Second, we extracted all municipal government work reports containing these keywords. Third, our team of co-authors and research assistants manually interpret and filter the relevant passages, distinguishing substantive policy actions—such as the establishment of biopharmaceutical industrial parks—from rhetorical references. Common phrases identified include statements such as “this year we will finish building a biopharmaceutical industrial park,” “the construction of the biopharmaceutical industrial park will soon be completed,” or “we will accelerate the development of the biopharmaceutical industrial park this year.” All outputs are then manually reviewed and verified by co-authors to ensure accuracy and consistency in coding.

We then aggregate the extracted information to the city-year level. A city is coded as treated (i.e., assigned a value of one) starting from the first year the establishment of a biopharmaceutical industrial park is mentioned in the report; all subsequent years are also coded as one, following a standard treatment-onset convention in difference-in-differences designs.

While it is possible that some municipal governments established biopharmaceutical industrial parks prior to 2006, such early cases are not captured in our dataset due to the lack of systematically archived reports before that year. However, it is more likely that most cities initiated these efforts after 2006, driven by shifts in national development strategy, particularly the increased emphasis on science and innovation-led growth outlined in the country's 11th Five-Year Plan (2006–2010).

Earlier efforts had primarily focused on positioning China as a global manufacturing hub with a comparative advantage in the production of inexpensive commodity goods, rather than on innovation-driven production of technologically sophisticated products (Li and Branstetter, 2023).

We measure the establishment of biopharmaceutical industrial parks using city-level government work reports because there is no publicly available, centralized dataset that documents the exact timing and nature of these park establishments. While records on special economic zones (SEZs) indicates the year of establishment, the designated zone type, and the target industries, relying on these records presents significant limitations in our context. First, the industry focus listed in SEZ documentation covers multiple sectors simultaneously. For example, many of the tech including electronics, manufacturing, logistics, materials, and pharmaceuticals. As a result, it is difficult to determine whether the biopharmaceutical sector was prioritized in practice or merely mentioned as part of a general development agenda. Second, many national and provincial-level SEZs were designated in the 1990s or early 2000s, during a period when industrial policy primarily targeted manufacturing, export-oriented production, and traditional sectors. As such, even when pharmaceuticals were included in SEZ mandates, most of the focus was on the production of generic drugs rather than on high-risk, innovation-intensive R&D. China shifted toward an innovation-driven development strategy under the 11th Five-Year Plan. Thus, during this period, biopharmaceutical industrial parks were developed to explicitly support novel drug development and were often accompanied by tailored policy instruments. Therefore, relying solely on SEZ records would introduce substantial measurement error. Lastly, commonly used SEZ datasets typically cover only national and provincial-level zones. However, a number of biopharmaceutical industrial parks have been launched at the municipal level. Relying solely on SEZ records would therefore result in incomplete coverage and would systematically omit an important subset of relevant policy interventions. By drawing from city-level government work reports, we are able to identify a more comprehensive and policy-relevant sample of biopharmaceutical park establishments.

Measurement of Outcome Variables

We conduct our analysis at the municipal-year level. Our main outcome of interest is the number of approved invention patent at the city level. Pharmaceutical R&D follows a structured but highly uncertain pipeline. After the discovery of a new compound, firms typically file for a patent well before clinical validation or market approval. Hence, patents have often been used in the literature as an early and observable indicator of innovative activity. While not all patents lead to commercially viable products, the decision to file a patent reflects a firm's intention to protect novel intellectual property and signals a commitment to further development (Gadiya, 2023).

Our patent record is obtained from the State Intellectual Property Office (SIPO). For each patent, we extract essential information including the patent title, application date, applicant name and address, and legal status indicators such as grant, renewal, and expiration dates. We restrict the sample to drug-related patents granted to firms as the first assignee and exclude those filed by individuals or academic institutions as the first assignee. Each granted patent is assigned to the municipality of the first-listed applicant. Furthermore, we limit the analysis to invention patents, excluding utility models and design patents, which typically reflect lower levels of technological novelty. The final dataset spans the years 2006 to 2020.

Our primary variables of interest focuses on the primary set of drug-related patents which were classified as new chemical or biological entities, new therapeutic indications, combination therapies, or formulation enhancements. We exclude this set of drug patents from those limited to manufacturing or technical process claims, specifically, patents whose claims pertain primarily to bioprocess methods, polymorphs, salts, API synthesis routes, chemical manufacturing processes, or excipient-related technologies. We primarily relied on large language behavior models to classify patents based on their titles and descriptions. We employed two independent models and obtained consistent results across both. In addition, we conducted a complementary classification using IPC codes and found similar patterns.

To distinguish between biologic and chemical drugs, we classify patents using a combination of International Patent Classification (IPC) codes, keyword-based filters, and manual validation. We supplement the SIPO dataset with forward citation data obtained via web scraping from Google Patents. Forward citations are widely used in the innovation literature as a proxy for patent quality and technological impact. Following Hall, Jaffe, and Trajtenberg (2001), we correct for truncation bias in the patent citation data. Specifically, for each patent, we divide its number of citations by the average number of citations for patents within the same technology class and grant year. We then aggregate these adjusted citation counts at the city–year level to obtain a normalized measure of innovative activity.

Control Variables

We obtained information on GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries from the China City Statistical Yearbook, published by the National Bureau of Statistics of China. In addition, we extract information on the establishment year of the national or provincial special economic zones and information on whether the zone is a high-tech industrial development zones or economic and technological development zones and whether they are established at national or provincial level from the Bulletin List for the Official Boundaries of Chinese Industrial Parks published by Ministry of Land and Resources in China.

Multiple Differences-in-differences Specification

To understand the impact of the establishment of biopharmaceutical industrial parks on innovation activity, we construct a multiple differences-in-differences specification using the following specification, where

$$Outcomes_{it} = \beta_0 + \beta_t Treatment_{it} + X_{it} + \gamma_i + \omega_{jt} + e_{it} \quad (1)$$

where $Outcomes_{it}$ is the sum of patents measured at the city level at time t. To accommodate zero values in patent applications and citation counts, we apply a log transformation after adding one to each count. $Treatment_{it}$ equals one if the city announced the establishment of a new industrial park for the first time (and remains one thereafter), and zero otherwise.

Our identifying assumption is that the timing of biopharmaceutical industrial park establishment is uncorrelated with unobserved factors that simultaneously affect our outcomes of interest. First, Figure 1 depicts the geographic rollout of biopharmaceutical industrial parks across Chinese cities from 2006 to 2020. Each shaded area in the figure corresponds to a city where a new park was established during a two to three year period. This temporal and spatial visualization illustrates both the progressive expansion of the program and the breadth of geographic coverage it achieved. A key feature revealed by Figure 1 is the relatively even distribution of parks across coastal and inland areas in each wave of implementation. Second, we control for a set of city-year level characteristics, including GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, share of employment in agriculture, share of employment in manufacturing, land area, shares of secondary and tertiary industries. Third, we include city fixed effects to absorb time-invariant unobserved heterogeneity across cities. We incorporate province-by-year fixed effects, which allow us to control for all time-varying shocks at the provincial level. This approach ensures that identification is based solely on within-province, across-city variation in the timing of park establishment. Moreover, we explicitly control for the establishment of other industrial policy instruments, including the creation of national or provincial industrial zones and the types of zones, to isolate the independent contribution of biopharmaceutical park policies. Additionally, we conduct event-study analyses to test for pre-treatment trends in outcomes, providing a direct assessment of the parallel trends assumption and further reinforcing the credibility of our identification strategy.

RESULTS

Main Results

Table 1 presents a set of baseline covariates used as controls in the empirical analysis. These variables allow us to control for key dimensions of local development that may influence both the likelihood of park establishment and innovation outcomes.

Figure 2 presents event-study estimates of patenting outcomes disaggregated by drug type. The results show no discernible pre-treatment trends prior to the establishment of biopharmaceutical industrial parks, lending support to the validity of the parallel trends assumption. Beginning approximately three to four years after park establishment, we observe a statistically significant increase in the number of overall patents, as well as in patents for both biologic and chemical drugs. This upward trajectory persists for at least a decade following the park's inception.

We address recent econometric concerns with staggered difference-in-differences research designs by showing robustness to the use of a variety of alternative estimators. We report OLS estimates under the homogeneous treatment effect assumption, as well as adjusted event study estimators that are robust to heterogeneous treatment effects over time or across groups in Figure 2 and Supplementary File C Table 6 (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; De Chaisemartin & D'Haultfoeuille; Cengiz et al,2019).

We further evaluate the robustness of our estimates using the Honest DiD sensitivity framework, which quantifies how treatment effect identification weakens under increasing levels of allowable violation of the parallel trends assumption. Supplementary File Figure 2 plots Honest DiD confidence intervals for a range of sensitivity parameters MMM, with M=0M = 0M=0 representing the benchmark assumption and larger values permitting progressively greater deviations from parallel trends.

Across all three outcomes, the honest DiD point estimates remain positive and stable as MMM increases. As expected, the confidence intervals widen with larger MMM, reflecting the more conservative design-based uncertainty inherent in the

Honest DiD approach. Importantly, for moderate levels of sensitivity, the lower bounds of the confidence intervals remain above or very close to zero, indicating that the estimated effects are not driven by small departures from the identifying assumptions. Even under relatively large violations (M=0.20M = 0.20M=0.20), the confidence intervals remain centered on positive effects, suggesting that substantial deviations from parallel trends would be required to change our main findings.

Table 2 presents the corresponding regression estimates, quantifying the effects illustrated in Figure 2. Specifically, the establishment of a biopharmaceutical industrial park is associated with a 15.3% increase in total drug patents, a 10.3% increase in biologic drug patents, and a 14.2% increase in chemical drug patents, controlling for city fixed effects and province-year fixed effects. We added additional city-level covariates in Column 2.In Column 3, we further control for the timing of Special Economic Zones (SEZs), distinguishing by SEZ level (national versus provincial) and SEZ type (whether the zone is a high-tech industrial development zones or economic and technological development zones), to ensure that the observed effects are not confounded by broader industrial policy trends or earlier waves of spatial economic planning. The treatment effects remain stable and statistically significant across these specifications. The corresponding estimated effects are 14.1%, 9.2%, and 14%, respectively. In Supplementary Table 2, we examine patent outcomes using total patent applications. The results are consistent with those obtained using the number of approved patents.

Supplementary File Table 3–4 examines patent outcomes that include patents representing marginal improvements to drug innovation, as well as all drug-related patents. We find essentially similar results.

Table 3 presents the regression results for average forward citations, a commonly used proxy for the quality and impact of innovation. We do not find any statistically significant effect of biopharmaceutical industrial park establishment on the average number of citations per patent. This suggests that while the parks stimulate an increase in the quantity of patenting activity, they do not appear to influence the average technological significance or scientific impact of those patents as measured by citation counts. This result is consistent with previous findings that industrial policy interventions often increase the quantity of innovation outputs but have limited impact on innovation quality (Sun et al., 2021). One possible explanation is that parks may incentivize strategic patenting without necessarily fostering substantive technological breakthroughs. Alternatively, the support provided by parks may encourage marginal or incremental innovations and follow-on improvements, rather than enabling truly groundbreaking discoveries. It is also possible that in the pharmaceutical sector, many patents are often filed for strategic or regulatory purposes (Gurgula, 2020). In such cases, citation counts may not fully capture the economic or clinical significance of the underlying innovation.

In Supplementary File C Table 2, we examine total citations and find that park establishment increases total citations. This result aligns with our earlier findings: while there is an increase in the total number of patents, the average citation per patent remains unchanged.

Robustness Tests

To ensure the validity of our findings, we conduct a series of robustness checks. First, we estimate poisson and negative binomial regressions to account for the count nature and skewed distribution of our dependent variables. As shown in Supplementary File C Table 5, the positive treatment effect on patent outcomes remains statistically significant under this specification.

Second, we assess the sensitivity of our results to variable selection procedures. To this end, we employ the post-double selection LASSO method (Belloni et al., 2014), which leverages machine learning to identify the most relevant control variables while mitigating the risk of overfitting. As reported in Supplementary File C Table 7, we include the original control variables along with their square and third polynomial terms. The estimated treatment effects remain robust after adjusting for the covariates selected through this procedure.

Third, we assess the robustness of our findings to sample composition by excluding municipalities directly administered by the central government—Beijing, Shanghai, Tianjin, and Chongqing—which may possess disproportionately large innovation systems or administrative privileges. In addition, we also conducted an analysis excluding Guangzhou and Suzhou which are known for their innovation capacity in drugs. Supplementary File C Table 8 shows that the treatment effects remain stable and statistically significant, suggesting that our results are not driven by these outlier cities.

Lastly, in Supplementary File B Figure 3, we randomly assigned treatment years to cities and found that the resulting placebo estimates were centered around zero and statistically insignificant.

Possible Mechanisms

To better understand the mechanisms through which biopharmaceutical industrial parks influence innovation outcomes, we focus on three key channels: the entry of innovative firms, venture capital investment, and relative land price (Table 4 to Table 6).

Table 4 presents evidence on firm creation, finding that the number of innovative firms—measured by the number of pharmaceutical firms that have ever filed for patents—increases significantly following the establishment of a biopharmaceutical industrial park. We created this variable based on the patent dataset. We find similar effects using data from the list of pharmaceutical firms that are recognized as national high-tech firms. To qualify for this recognization, firms must hold core intellectual property—such as invention patents or software copyrights, employ at least 10% of staff in R&D or technical roles, invest a required share of annual revenue in R&D over the past three years, and show evidence of successfully commercializing new technologies. Hence, the number of pharmaceutical firms that are qualified for high-tech firms are much smaller than the percentage of pharmaceutical firms that hold patents. Overall, these finding suggests that the parks may serve as effective incubators for innovative firms.

Table 5 examines the impact of biopharmaceutical industrial parks on venture capital activity. To measure venture capital activity, we use data from Zero2IPO, a leading venture capital and private equity service provider in China. Founded in 2000, Zero2IPO offers one of the most comprehensive commercial datasets on venture capital and private equity activity in the country (Beraja et al., 2024). While total VC investment does not show a statistically significant change following park establishment, we find a robust increase in government venture capital fund capital, both in the number of investments and in total capital deployed. Here, we define a government venture capital fund to include both government venture firms and government guidance funds, whose main purpose is to invest in sectors prioritized by the state (Wei et al., 2023). Specifically, the number of deals invested by government venture capital funds increases by 4.2%, and investment funding grows by 10%. In contrast, there is no significant change in private-sector VC activity, suggesting that public capital is playing a central role in financing early-stage drug development.

Table 6 examines the impact of biopharmaceutical industrial parks on land market dynamics using data from the China Land Transfer Database compiled by the China Land Market Network. One of the key instruments in industrial park policy is the provision of discounted land purchases, as lower land prices reduce firms' fixed costs of entry and expansion. Using national land sales data, we find that the establishment of biopharmaceutical industrial parks is associated with a significant increase in the number of land sales designated for biopharmaceutical use, accompanied by a reduction in the average relative price of land sold for biopharmaceutical use. This pattern likely reflects local governments' active reallocation and subsidization of land resources to support the development of targeted industries.

Hetergeneity Analysis

To further explore the conditions under which biopharmaceutical industrial parks are most effective, we examine heterogeneity in treatment effects across cities with differing levels of scientific and fiscal capacity. Specifically, we focus on three dimensions: the presence of top-tier universities, the number of research hospitals, local fiscal capacity, and the prescence of contract development and manufacturing service providers. The corresponding results are presented in Supplementary File C Tables 9–15.

Second, we assess heterogeneity by fiscal capacity, measured as the ratio of government expenditure to government revenue from the *China City Statistical Yearbook* (Supplementary File C Table 10). The results indicate that cities with greater fiscal capacity experience significantly stronger increases in pharmaceutical patenting following the establishment of biopharmaceutical industrial parks. This pattern may be a result of the ability of fiscally stronger local governments to provide matching funds, targeted subsidies, and administrative support when they establish industrial park.

Next, we examine whether the effects of biopharmaceutical industrial park establishment vary with the presence of top-tier universities. To do so, we construct indicators for whether a city hosts a university ranked among the top 50 or top 30 in the Shanghai Ranking's Academic Ranking of World Universities (ARWU), which serves as a proxy for local higher education and research quality (Supplementary File C, Table 11). The results indicate that cities with top-ranked universities experience significantly larger increases in invention patenting following the establishment of biopharmaceutical industrial parks. This pattern is likely driven by the role of universities as key sources of knowledge creation, talent, and collaboration opportunities between firms and academia. We explicitly test this collaboration channel in Supplementary File C, Table 12, and find that cities hosting biopharmaceutical industrial parks alongside top universities exhibit a higher share of university–industry collaborative patents. Hence, this suggests that the presence of leading universities amplifies the innovation benefits of biopharmaceutical industrial parks by fostering stronger knowledge exchange and collaborative research linkages between academia and industry.

Third, we examine heterogeneity by the number of research hospitals within a city, using data on the number of tertiary hospitals from the *China Health Statistical Yearbook* (Supplementary File C Table 13). Tertiary hospitals in China are large, research-oriented institutions that also attract the largest share of outpatient and inpatient care patients. Cities with a greater number of research hospitals are defined as those whose number of tertiary hospitals exceeds the sample median. We find that cities with a greater number of research hospitals experience significantly larger increases in pharmaceutical patenting following park establishment (Supplementary File C Table 14). This pattern may be explained by the presence of research hospitals that expand the pool of biomedical knowledge and foster collaboration between clinicians and researchers.

Lastly, we examine whether the effects of biopharmaceutical industrial parks differ in cities that host major contract development and manufacturing organizations (CDMOs) or contract research organizations (CROs). We obtained the list of the top 20 CDMOs and CROs in China from a public ranking that accounts for firms' research capacity and revenue. Data on the locations of their headquarters and branch offices were compiled from firm registration records. As shown in Supplementary File C Table 15, the interaction term between park establishment and the presence of a top 20 Chinese CDMO or CRO enterprise is positive and statistically significant across all drug categories. The estimated coefficients suggest that cities with such firms experience larger increases in patenting activity following park establishment—by approximately 0.10 to 0.15 log points, depending on drug type. These results indicate that the presence of specialized service providers may complement policy interventions by reducing coordination costs and facilitating access to technical and manufacturing capabilities. However, the findings should be interpreted as suggestive rather than causal, as cities with CDMO or CRO enterprises may differ systematically in their pre-existing industrial composition or innovation capacity.

Overall, these results suggest that fiscal support, scientific, and complementary industrial infrastructure are important in facilitating the effectiveness of biopharmaceutical industrial parks. However, the findings should be interpreted as suggestive rather than causal, as cities with better fiscal resources or scientific community or major contract CDMOS and CROs differ systematically in their pre-existing industrial composition or innovation capacity.

Aggregate Innovation: Effects on Other Innovation

Because the city has to allocate substantial fiscal and policy resources to support the biopharmaceutical park—including land, infrastructure investment, subsidies, and administrative capacity—it may divert attention and funding away from other types of innovation. We examine this empirically in Supplemental File C Table 16 and find that the establishment of the park is correlated with a statistically significant reduction in other innovation activities, as measured by non-drug invention patents. This result helps rule out the possibility that our findings are driven by general upward trends in innovation or by omitted variables affecting all sectors equally.

In addition, it suggests that cities may face an innovation trade-off when adopting targeted industrial policies. This crowding-out effect underscores the importance of considering opportunity costs in the design and evaluation of place-based innovation policies.

Aggregate Innovation: Creation versus Diversion Effects?

It is possible that part of the observed increase in pharmaceutical innovation reflects firm relocation rather than net new firm creation (Glaeser and Gottlieb, 2008). To test this possibility, we follow the approach of Zhang (2014) and examine whether a city's pharmaceutical innovation outcomes are affected by the presence of a neighboring city that establishes a biopharmaceutical park. Specifically, we estimate a specification that includes an indicator for whether any city within the province initiated a park policy during the observation window. We find no statistically significant decline in pharmaceutical patenting in cities within the same province, suggesting that the observed innovation gains in treated cities are not merely the result of displacement from nearby locations (Supplementary File C Table 17). This finding supports the interpretation that the biopharmaceutical industrial parks generate net positive effects on innovation, rather than simply redistributing existing activity within a region.

Additional Outcomes

In addition to patent data, we collect information on clinical trials from the registry maintained by the National Medical Products Administration (NMPA). This registry includes detailed clinical trial application information on applicant names, application dates, purpose of clinical trials, drug types with all applications classified as either biologic or chemical drugs, and locations of application. We measure development activity using the aggregate number of clinical trials at the level.

A key limitation is that systematic drug development data on clinical trials are only available beginning in 2012. This creates a potential source of bias: a number of cities (66 out of the full sample) had already established biopharmaceutical industrial parks prior to 2012 and thus appear as treated throughout our entire sample window. These "always-treated" cities would cause bias because always-treated units lack a pre-treatment period, so their observed outcomes cannot be cleanly used to estimate counterfactual trends. In addition, if their treatment effects evolve over time, they contaminate the control comparisons used to estimate effects for later-treated groups (Goodman-Bacon, 2021). To mitigate this concern, following Braghieri et al. (2022), we conduct our analysis on a restricted sample that excludes early-treated cities and includes only those cities that established biopharmaceutical industrial park in or after 2011. This approach ensures a valid comparison group and sufficient pre-treatment periods for identification. The corresponding results are presented in Supplemental File C Table 18. We find no statistically significant effect of biopharmaceutical industrial park establishment on total development activity. However, the estimated effect on biologic drug development activity is positive and statistically significant. The coefficient of 0.349 suggests that park establishment is associated with an average increase of 0.349 biologic development activity per city-year. In contrast, the effect on chemical drug development pipeline is positive but statistically insignificant, suggesting that the treatment effect is concentrated in biologics.

This progression along the R&D pipeline highlights that the parks not only stimulate early discovery (as reflected in patenting) but also facilitate clinical development for biologic drugs. In contrast, we do not observe statistically significant effects on chemical drug trials.

By separately analyzing biologic and chemical drugs, we find that industrial policy efforts are more effective in promoting innovation in the biologics sector. These additional findings provide a more nuanced understanding of the conditions under which policy interventions yield differential impacts. Kalcheva et al. (2018) emphasized the dual importance of demand-side triggers and a conducive supply-side environment. Chinese biologics firms appear to benefit from both dimensions. On the demand side, they face limited generic competition and enjoy broader global commercialization opportunities—such as licensing products to advanced markets like the United States. On the supply side, many biologics firms are younger, research-intensive ventures led by returnee scientists and internationally trained entrepreneurs. In contrast, chemical-drug firms operate in more mature and price-competitive markets and often face constraints in global talent acquisition and innovation capacity.

DISCUSSION AND CONCLUSION

China has made remarkable strides in biologics drug innovation in recent years. Major international outlets such as The Wall Street Journal and CNN have referred to these developments as “Deepseek moments” for China”s pharmaceutical sector, underscoring the industry’s progress in drug innovation (Wainer, 2025; Chang, 2025). The findings of this paper help illuminate some of the institutional underpinnings of this growth.

Overall, we present a mixed assessment of industrial policy effects in the context of pharmaceutical innovation. Exploiting variation in the timing of park establishment across cities and drawing on a city-year panel, we estimate the causal impact of these place-based industrial policies on a range of pharmaceutical innovation outcomes. We find that park establishment leads to significant increases in invention patenting for overall drugs and for both biologic and chemical drugs, but have no impact on the number of forward citations of the patents.

Second, we find a significant reduction in non-pharmaceutical patenting within treated cities. This intra-jurisdictional reallocation may have resulted from the diversion of public resources, land allocation, and administrative capacity away from broader innovation efforts and toward the prioritized sector.

Third, we also explored the effects on new drug development activity clinical trials and found that the effects are concentrated in biologics, suggesting that the parks not only boost early-stage idea generation but also help translate promising discoveries into more advanced pipeline development in the biologic domain. This differential impact likely reflects the specific scientific, market, and institutional conditions under which such policies are implemented.

The mixed findings of industrial policy effects have important policy implications for middle-income countries seeking to stimulate innovation in the life sciences. Because biopharmaceutical industrial parks are predominantly subnational initiatives, they offer a transferable model for other countries facing similar challenges of underinvestment in high-risk, capital-intensive R&D sectors. The findings also highlight the need for careful policy design: interventions should consider balance support for targeted sectors with the potential crowding-out of other innovative activities, and should account for sector-specific factors, such as market structures, to ensure that public investments translate into meaningful innovation gains

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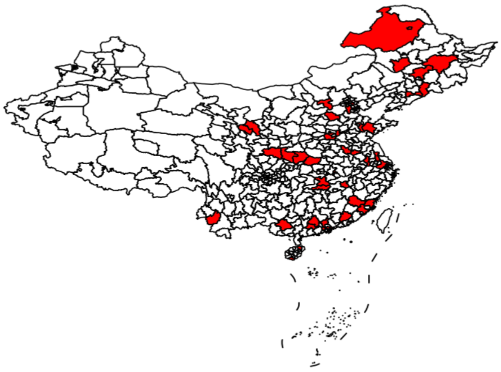
Figures and Tables

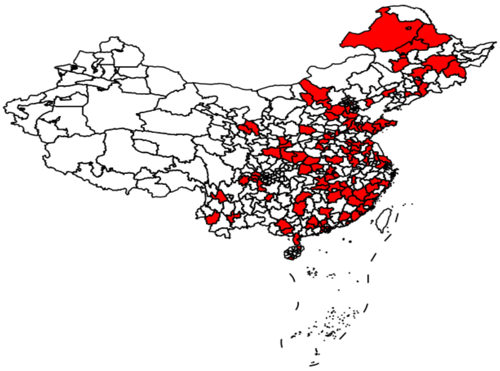
Figures

Figure 1. Spatial distribution of biopharmaceutical industrial parks

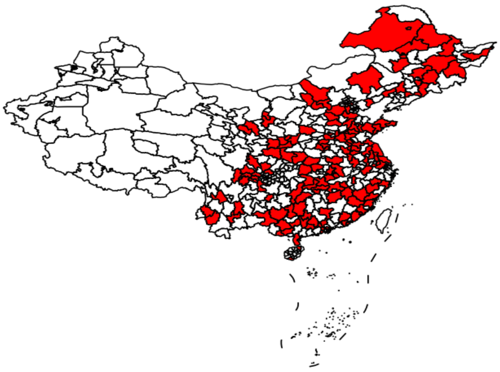
Panel A. 2006-2010



Panel B. 2011-2015

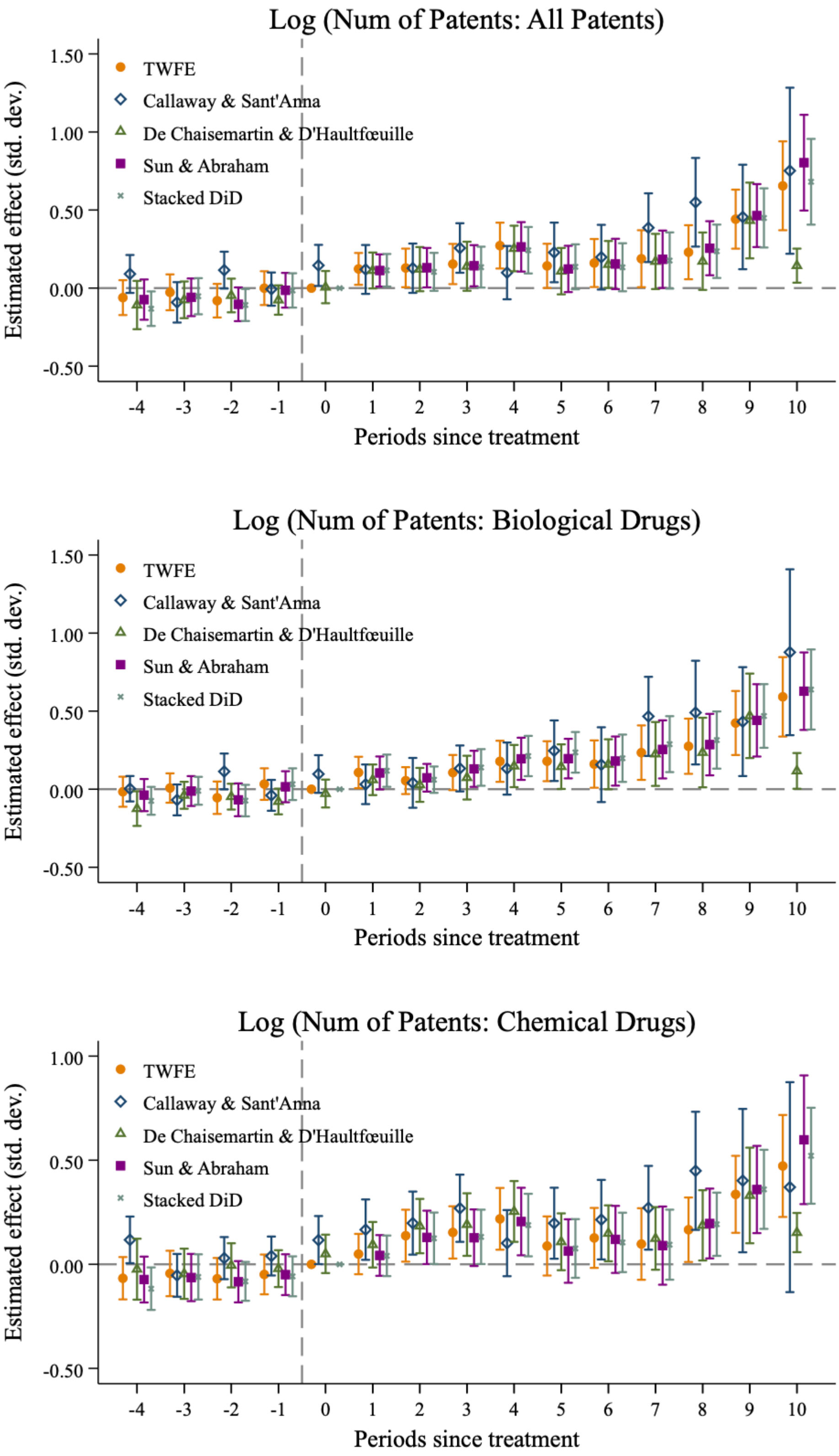


Panel C. 2016-2020



Notes: The figure shows China's biopharmaceutical industrial parks established in the period of 2006–2010, 2011–2015, and 2016–2020. Cities where new parks were established are highlighted in red.

Figure 2. Event study analysis of patents



Note: This figure presents event-study estimates for the drug patents using four different estimators: TWFE OLS (orange circles), Callaway and Sant'Anna (2021) (blue diamonds), De Chaisemartin and D'Haultfœuille (2020) (green triangles), Sun and Abraham (2021) (purple squares), and Stacked DiD (gray crosses). The coefficients are plotted along with their corresponding 95% confidence intervals.

Tables

Table 1. Descriptive Statistics

Variable Names	Mean	SD
Log GDP	7.083	1.019
Log population	5.871	0.699
Log employment	3.483	0.813
Ratio of government expenditure to revenue	2.948	2.013
GDP growth rate	10.121	4.533
Share of employment in agriculture	2.718	6.523
Share of employment in manufacturing	42.994	14.942
Log land area	9.357	0.810
Share of secondary industries	0.465	0.112
Share of tertiary industries	0.407	0.103
National economic development zones	0.347	0.476
Provincial economic development zones	0.276	0.447

Note: Information on GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries from the China City Statistical Yearbook are published by the National Bureau of Statistics of China. Development zones information are sourced from the Bulletin List for the Official Boundaries of Chinese Industrial Parks published by Ministry of Land and Resources in China. N=4290

Table 2. Impact of biopharmaceutical industrial parks on patents

	Panel A. Log (Num of Patents: All Drugs)		
Biopharmaceutical industrial parks	0.154***	0.147***	0.151***
	(0.055)	(0.050)	(0.049)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel B. Log (Num of Patents: Biologic Drugs)		
Biopharmaceutical industrial parks	0.103**	0.092**	0.092**
	(0.051)	(0.046)	(0.045)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel C. Log (Num of Patents: Chemical Drugs)		
Biopharmaceutical industrial parks	0.142***	0.139***	0.140***
	(0.043)	(0.040)	(0.040)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In Column 1, we included city fixed effects and province-year fixed effects. In Column 2, we added a set of rich city-year level covariates which include GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries. In Column 3, we additionally add dummies that indicated whether the zone is a high-tech industrial development zones or economic and technological development zones and whether they are established at national or provincial level. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 3. Impact of biopharmaceutical industrial parks on patent citations

	Panel A. Log (Average Citations Per Patent: All Drugs)		
Biopharmaceutical industrial parks	-0.022	-0.021	-0.020
	(0.016)	(0.016)	(0.016)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel B. Log (Average Citations Per Patent: Biologic Drugs)		
Biopharmaceutical industrial parks	-0.002	-0.005	-0.005
	(0.023)	(0.023)	(0.023)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel C. Log (Average Citations Per Patent: Chemical Drugs)		
Biopharmaceutical industrial parks	-0.008	-0.007	-0.005
	(0.020)	(0.020)	(0.020)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In Column 1, we included city fixed effects and province-year fixed effects. In Column 2, we added a set of rich city-year level covariates which include GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries. In Column 3, we additionally add dummies that indicated whether the zone is a high-tech industrial development zones or economic and technological development zones and whether they are established at national or provincial level. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 4. Test for the mechanism: innovative firms

	Log (Number of Innovative Firms)		
	Panel A.Innovative firms measured by patents related to durgs		
	All	**Biologic**	**Chemical**
Biopharmaceutical industrial parks	0.190***	0.090*	0.170***
	(0.071)	(0.047)	(0.054)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel B.Innovative firms measured by nationally certified high-tech firms		
	All	**Biologic**	**Chemical**
Biopharmaceutical industrial parks	0.061***	0.024*	0.039**
	(0.021)	(0.012)	(0.020)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. **p* < .10; ***p* < .05; ****p* < .01.

Table 5. Test for the mechanism: venture capital

	All Venture Capital	Government Venture Capital	Private Venture Capital
	Panel A. Log (Counts of VC investment)		
Biopharmaceutical industrial parks	0.041	0.042**	0.010
	(0.030)	(0.019)	(0.025)
Mean of dependent variables	0.938	0.170	0.769
City FEs	Y	Y	Y
Year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel B. Log (Mean amount of VC investment)		
Biopharmaceutical industrial parks	0.053	0.100*	0.018
	(0.070)	(0.053)	(0.063)
Mean of dependent variables (hundred millon)	4.204	1.763	3.522
City FEs	Y	Y	Y
Year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 6. Mechanism tests: land sales in the biopharmaceutical sector

	Panel A. Number of Land Sales in the Biopharmaceutical Sector
Biopharmaceutical industrial parks	0.983*
	(0.544)
Mean of dependent variables	8.379
City FEs	Y
Year FEs	Y
City controls	Y
SEZ controls	Y
N	4,215

	Panel B. Average Relative Price of Land Sales in the Biopharmaceutical Sector
Biopharmaceutical industrial parks	-0.027*
	(0.015)
Mean of dependent variables	0.269
City FEs	Y
Year FEs	Y
City controls	Y
SEZ controls	Y
N	4,215

Note: The relative price of land sales in the biopharmaceutical sector is calculated as the ratio of the price of land sold for the biopharmaceutical sector to the price of land sold for other uses. All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Supplementary Files

The impact of biopharmaceutical industrial parks on pharmaceutical innovation in China

Supplementary File A. Special Economic Zones

China's place-based policy efforts have included the establishment of various types of Special Economic Zones (SEZs), each with specific policy objectives. The most relevant ones to us are the high-tech industrial development zones that were introduced to promote advanced technology sectors and foster innovation. Economic and Technological Development Zones (ETDZs) were designed to attract foreign direct investment and support export-oriented industries (Alder et al., 2016). High-tech industrial development zones and economic and technological development zones often serve overlapping functions, making the distinction between the two less distinctive in practice. Both types of zones are designed to attract investment, promote industrial upgrading, and support innovation, and they frequently adopt similar policy tools and institutional structures (Lu et al., 2019). In addition, these zones can be classified as either national-level or provincial-level. National-level zones are approved by the central government and typically benefit from more generous policy incentives, stronger administrative support, and greater visibility in national development plans. In contrast, provincial-level zones are established by subnational governments and generally operate with more limited resources, fewer preferential policies, and lower levels of central oversight.

Reference

Lu, Y., Wang, J., & Zhu, L. (2019). Place-based policies, creation, and agglomeration economies: Evidence from China's economic zone program. American Economic Journal: Economic Policy, 11(3), 325-360.

Supplementary File B: Figures

Figure 1. Cumulative timeline of biopharmaceutical industrial parks establishment

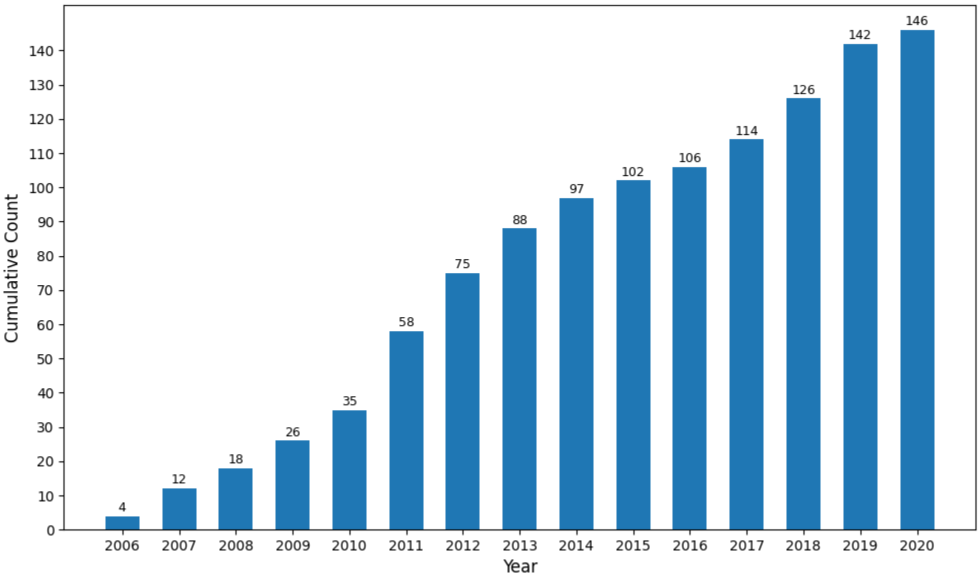
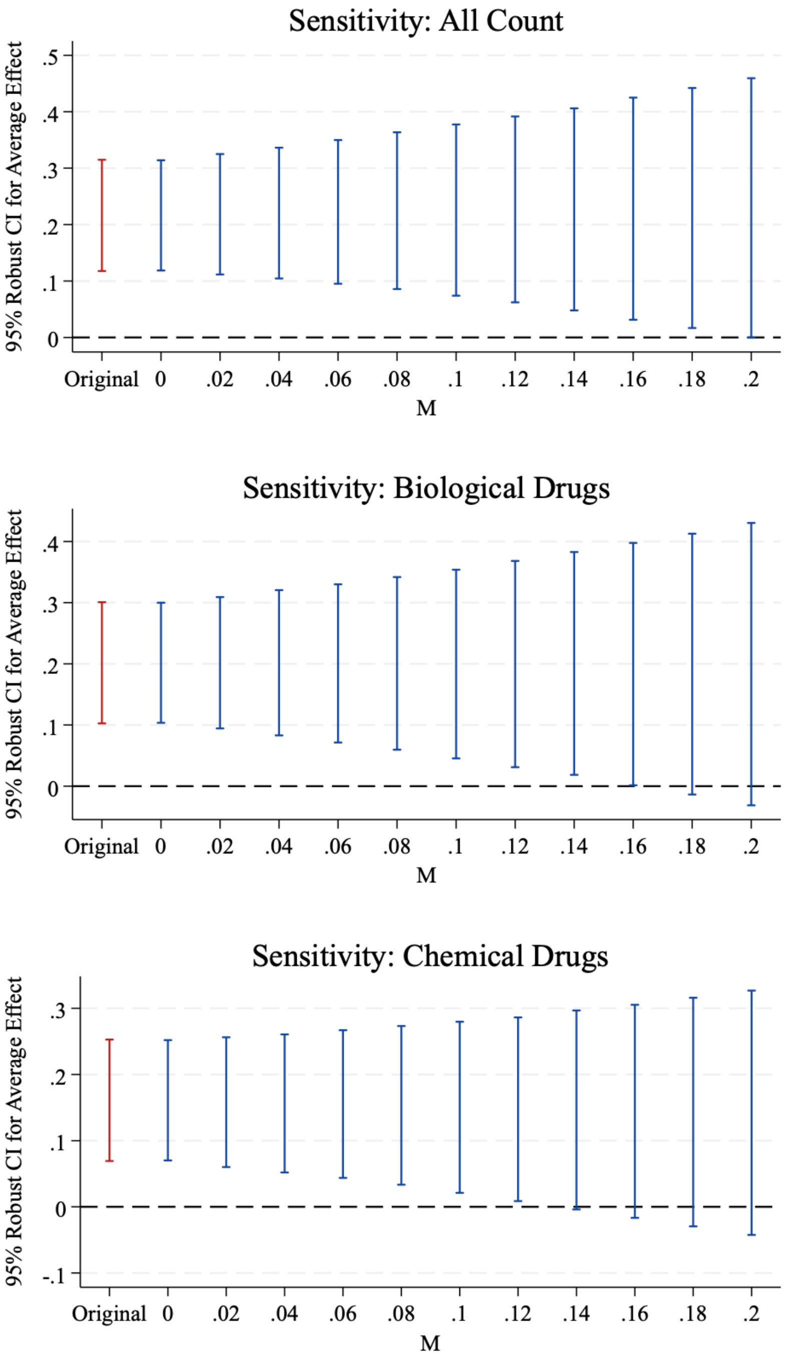
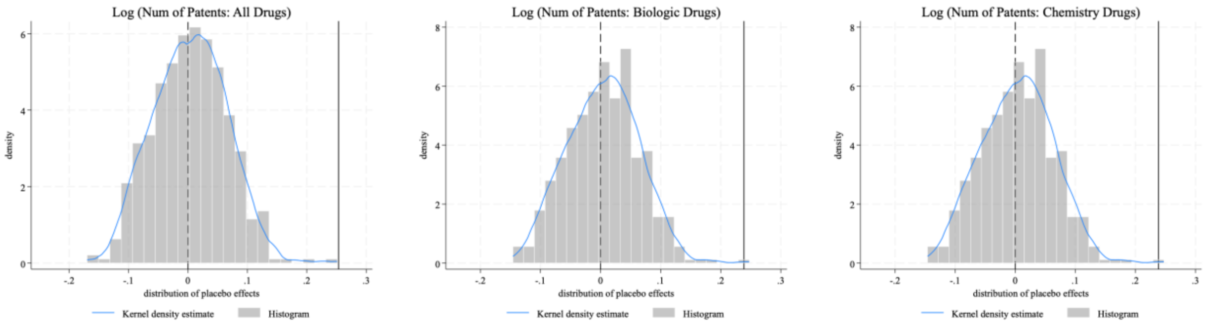


Figure 2. Honest DiD estimates



Note: This figure presents sensitivity analyses following the methodology of Rambachan and Roth (2023). We report the confidence sets for the average treatment effect across all post-treatment periods when allowing for violations of the parallel trends assumption. The horizontal axis represents varying values of the smoothness parameter M (ranging from 0 to 0.2), which bounds the potential change in trend between consecutive periods. The vertical axis displays 95% robust confidence intervals for the average effect.

Figure 3. Time placebo effects



Supplementary File C: Tables

Table 1. Terms related to industrial parks

Terms related to industrial parks	Industrial park, industrial base, industrial zone, industry valley, biopharmaceutical port, medical city, biopharmaceutical park, healthcare industry park, biotechnology park, life science park, innovation park, industrial cluster zone, healthcare industrial platform, science and innovation park, functional industrial zone, biomedical harbor, health and medical city, smart healthcare park, bio-industry cluster zone, health valley, medical valley

Table 2. Impact of biopharmaceutical industrial parks on patent citations and applications

	Log (Total Citations)	Log (Patent applications)
	Panel A. All drugs	
Biopharmaceutical industrial parks	0.080	0.212***
	(0.056)	(0.053)
City FEs	Y	Y
Province-year FEs	Y	Y
City controls	Y	Y
SEZ controls	Y	Y
N	4,215	4,215
	Panel B. Biological drugs	
Biopharmaceutical industrial parks	0.036	0.089**
	(0.047)	(0.044)
City FEs	Y	Y
Province-year FEs	Y	Y
City controls	Y	Y
SEZ controls	Y	Y
N	4,215	4,215
	Panel C. Chemical drugs	
Biopharmaceutical industrial parks	0.059	0.170***
	(0.039)	(0.040)
City FEs	Y	Y
Province-year FEs	Y	Y
City controls	Y	Y
SEZ controls	Y	Y
N	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 3. Impact of biopharmaceutical industrial parks on patents representing marginal improvements to drug innovation

	Panel A. Log (Num of Patents: All Drugs)		
Biopharmaceutical industrial parks	0.175***	0.167***	0.169***
	(0.055)	(0.050)	(0.049)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel B. Log (Num of Patents: Biologic Drugs)		
Biopharmaceutical industrial parks	0.101**	0.089**	0.088**
	(0.050)	(0.045)	(0.044)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
	Panel C. Log (Num of Patents: Chemical Drugs)		
Biopharmaceutical industrial parks	0.170***	0.166***	0.166***
	(0.045)	(0.042)	(0.041)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In Column 1, we included city fixed effects and province-year fixed effects. In Column 2, we added a set of rich city-year level covariates which include GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries. In Column 3, we additionally add dummies that indicated whether the zone is a high-tech industrial development zones or economic and technological development zones and whether they are established at national or provincial level. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 4. Impact of biopharmaceutical industrial parks on all drug-related patents

		Panel A. Log (Num of Patents: All Drugs)	
Biopharmaceutical industrial parks	0.174***	0.166***	0.170***
	(0.054)	(0.049)	(0.049)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
		Panel B. Log (Num of Patents: Biologic Drugs)	
Biopharmaceutical industrial parks	0.104**	0.092**	0.091**
	(0.050)	(0.045)	(0.044)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215
		Panel C. Log (Num of Patents: Chemical Drugs)	
Biopharmaceutical industrial parks	0.171***	0.167***	0.168***
	(0.046)	(0.042)	(0.042)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	N	N	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In Column 1, we included city fixed effects and province-year fixed effects. In Column 2, we added a set of rich city-year level covariates which include GDP, population, employment, the ratio of government expenditure to revenue, GDP growth rate, the share of employment in agriculture and manufacturing, land area, and the shares of secondary and tertiary industries. In Column 3, we additionally add dummies that indicated whether the zone is a high-tech industrial development zones or economic and technological development zones and whether they are established at national or provincial level. Robust standard errors clustered at the city level are reported in parenthesis. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 5. Poisson and negative binomial regression estimates

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
	Panel A. Poisson regression estimates		
Biopharmaceutical industrial parks	0.251**	0.395***	0.222**
	(0.109)	(0.124)	(0.090)
City FEs	Y	Y	Y
Year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel B. Negative binomial regression estimates		
Biopharmaceutical industrial parks	0.113*	0.227**	0.227**
	(0.067)	(0.103)	(0.103)
City FEs	Y	Y	Y
Year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 6. Alternative Difference-in-differences estimates

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
	Panel A. Callaway-Sant' Anna		
Biopharmaceutical industrial parks	0.277***	0.235***	0.238***
	(0.071)	(0.072)	(0.064)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel B. DeChaisemartin-D' Haultfeuille		
Biopharmaceutical industrial parks	0.234***	0.195***	0.223***
	(0.063)	(0.063)	(0.057)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel C. Sun and Abraham		
Biopharmaceutical industrial parks	0.264***	0.249***	0.193***
	(0.063)	(0.062)	(0.062)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel D. Stacked DID		
Biopharmaceutical industrial parks	0.219***	0.243***	0.167***
	(0.063)	(0.062)	(0.062)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: This table presents robustness of our baseline estimate to using the alternative difference-in-differences estimators introduced in Callaway and Sant' Anna (2021), De Chaisemartin and d' Haultfoeuille (2020), Sun and Abraham (2021) and Cengiz et al. (2019). All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 7. Lasso regression estimates

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical	0.142***	0.070***	0.122***
industrial parks	(0.023)	(0.017)	(0.022)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In the lasso regression, we included the same set of controls used for Table 2 Column 3 as well as their square and third polynomial terms. Robust standard errors clustered at the city level are reported in parenthesis. **p* < .10; ***p* < .05; ****p* < .01.

Table 8. Excluding the municipalities directly under the central government

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical	0.150***	0.093**	0.140***
industrial parks	(0.049)	(0.045)	(0.039)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,185	4,185	4,185

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 10. Heterogeneity effects by city's fiscal support

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical industrial parks	0.327***	0.274***	0.259***
	(0.076)	(0.074)	(0.062)
Biopharmaceutical industrial parks*Fiscal support	0.097***	0.100***	0.066***
	(0.024)	(0.025)	(0.020)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Notes: We calculate a city’ s fiscal support as the ratio of government expenditure to government revenue, using data from the China City Statistical Yearbook. This measure reflects the extent of fiscal capacity and local government support available for industrial and innovation-related activities.All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *p < .10; **p < .05; ***p < .01.

Table 11. Heterogeneity effects by presence of top-ranked universities

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
	Panel A. Top 50 university		
Biopharmaceutical industrial parks	0.094*	0.021	0.090**
	(0.049)	(0.042)	(0.039)
Biopharmaceutical industrial parks*Top 50university	0.334***	0.418***	0.292***
	(0.090)	(0.099)	(0.070)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215
	Panel B. Top 30 university		
Biopharmaceutical industrial parks	0.094*	0.017	0.093**
	(0.049)	(0.041)	(0.040)
Biopharmaceutical industrial parks*Top 30university	0.596***	0.784***	0.494***
	(0.104)	(0.114)	(0.092)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: We construct indicators for whether a city hosts a university ranked among the top 50 or top 30 in the Shanghai Ranking’s Academic Ranking of World Universities (ARWU), which proxies for local higher-education and research quality. All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 12. Heterogeneity effects by presence of top-ranked universities on collaborative patents

	Log (Num of Patents)	
	Firm-only patents	Collaborative patents
Biopharmaceutical industrial parks	0.109**	0.000
	(0.052)	(0.010)
Biopharmaceutical industrial parks*Top 50university	0.306***	0.195***
	(0.084)	(0.046)
City FEs	Y	Y
Province-year FEs	Y	Y
City controls	Y	Y
SEZ controls	Y	Y
N	4,215	4,215

Notes: Firm-only patents are those owned exclusively by firms. Collaborative patents refer to patents jointly filed by firms and universities. All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *p < .10; **p < .05; ***p < .01.

Table 13. Heterogeneity effects by the number of research hospitals

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical industrial parks	-0.021	-0.072	0.001
	(0.053)	(0.044)	(0.047)
Biopharmaceutical industrial parks*Tier 3 hospitals	0.336***	0.320***	0.270***
	(0.087)	(0.082)	(0.072)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Notes: Research hospitals in China are typically classified as Tier 3 hospitals. We obtain the number of Tier 3 hospitals from the China Health Statistical Yearbook.All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *p < .10; **p < .05; ***p < .01.

Table 14. Heterogeneity effects by the number of research hospitals on collaborative patents

	Log (Num of Patents)	
	Firm-only patents	Collaborative patents
Biopharmaceutical industrial parks	0.001	-0.000
	(0.056)	(0.001)
Biopharmaceutical industrial parks*Tier 3 hospitals	0.314***	0.009*
	(0.092)	(0.005)
City FEs	Y	Y
Province-year FEs	Y	Y
City controls	Y	Y
SEZ controls	Y	Y
N	4,215	4,215

Notes: Firm-only patents are those owned exclusively by firms. Collaborative patents refer to patents jointly filed by firms and hospitals.All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *p < .10; **p < .05; ***p < .01.

Table 15. Heterogeneity Effects by the presence of contract development and manufacturing service providers

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical industrial parks	0.073	-0.013	0.063
	(0.051)	(0.044)	(0.041)
Biopharmaceutical industrial parks*Top 20 Chinese CDMO or CRO Enterprises	0.129***	0.174***	0.127***
	(0.027)	(0.027)	(0.025)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Notes: We sourced the location of contract development and manufacturing service providers from firm registration data. All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *p < .10; **p < .05; ***p < .01.

Table 16. Effects on other types of patents (non-drug patents)

	Log (Num of Other Patents)		
Biopharmaceutical industrial parks	-0.070* (0.040)	-0.074* (0.039)	-0.074* (0.039)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	N	Y	Y
SEZ controls	Y	N	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 17. Creation or diversion effects

	Log (Num of Patents)		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical industrial parks	0.215***	0.138***	0.188***
	(0.051)	(0.047)	(0.042)
Have any biopharmaceutical industrial parks in the same province	-0.034	-0.025	-0.025
	(0.045)	(0.043)	(0.038)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	4,215	4,215	4,215

Note: All observations are at the city-year level. In all regressions, we included year fixed effects, province fixed effects as well as a rich set of covariates listed in Table 1. Robust standard errors clustered at the city level are reported in parenthesis. *$p < .10$; **$p < .05$; ***$p < .01$.

Table 18. Additional results

	Development activity		
	All Drugs	**Biologic Drugs**	**Chemical Drugs**
Biopharmaceutical industrial parks	0.563 (0.339)	0.349** (0.168)	0.214 (0.211)
City FEs	Y	Y	Y
Province-year FEs	Y	Y	Y
City controls	Y	Y	Y
SEZ controls	Y	Y	Y
N	1,672	1,672	1,672

Note: All observations are at the city-year level. In all regressions, we included the same set of controls used for Table 2 Column 3. Robust standard errors clustered at the city level are reported in parenthesis. **p* < .10; ***p* < .05; ****p* < .01.