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Science Parks in Taiwan and Their Value-Adding Contributions[*]

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Abstract

The establishment and expansion of science parks have been pivotal to Taiwan's economic development. This study integrates administrative, financial, and patent data to evaluate the causal impact of Taiwan's three major science parks—Hsinchu, Central, and Southern—on tenant firms across three types of additionality: input, behavioral, and output. Specifically, it investigates whether relocating to science parks significantly enhances R&D investment, PhD employment, total factor productivity, and patent quality. To address challenges like staggered firm entry and selection bias, the study employs augmented inverse probability weighting combined with a difference-in-differences model for panel data with staggered treatments, ensuring robust causal inference. The findings reveal significantly positive effects across all three types of additionality, extending beyond the Hsinchu Science-based Industrial Park. By integrating multiple value-adding channels and expanding the analysis to all three major science parks, this research provides a comprehensive evaluation and extends the scope of previous studies. Additionally, it highlights heterogeneity in effects by firm size and industry, underscoring the need for tailored policies to maximize the benefits of science parks.

Keywords: science parks, Taiwan, additionality, R&D, TFP, patent quality, causal inference, panel data
JEL classification: O32, O38, C23, D22, L26, R58

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1. Introduction

Taiwan has experienced remarkable improvements in living standards since the 1980s. According to the World Economic Outlook (WEO), Taiwan's real GDP per capita surpassed $10,000 international dollars in 1984, a key milestone marking its escape from the middle-income trap. Over the following four decades, Taiwan maintained robust growth, with real GDP per capita exceeding $50,000 international dollars by 2019. From 1980 to 2020, Taiwan's real GDP per capita grew at an average annual rate of 4.6%, significantly outpacing Japan and the UK, both of which achieved around 1% annual growth during the same period (International Monetary Fund, 2024). By 2009 and 2012, Taiwan had overtaken Japan and the UK, respectively, in terms of living standards. Taiwan also demonstrated economic resilience during the COVID-19 pandemic, maintaining positive GDP growth driven by global demand for semiconductors amid disrupted supply chains.

Since the 1970s, Taiwan has strategically transitioned from an economy based on light industry to one driven by high technology, with the establishment of science parks playing a pivotal role in this transformation. The success of the Hsinchu Science-based Industrial Park (HSIP), established in 1980, exemplifies this shift. A key milestone was the founding of Taiwan Semiconductor Manufacturing Company (TSMC) in 1987 as a spinoff from the Industrial Technology Research Institute (ITRI), a national research institute established in 1973 and located within what would later become HSIP. TSMC's rise as a global semiconductor leader underscores the success of Taiwan's science park model. Today, HSIP is recognized as a global hub for semiconductor innovation, attracting major firms and generating significant agglomeration effects.

Internationally, science parks have been studied for their contributions to university-industry collaboration, R&D productivity, firm growth, and regional development. These studies align with the frameworks of innovation economics, emphasizing policy interventions that address both demand- and supply-side challenges to foster innovation. Early research relied on qualitative methods and matched-pair analyses, often without controlling for selection bias or unobserved heterogeneity. Over time, the field has advanced, with contemporary studies employing panel data and sophisticated econometric techniques to identify genuine causal effects.

In Taiwan, research has predominantly focused on HSIP due to its prominence and longer history compared to the Southern Taiwan Science Park (STSP) and the Central Taiwan Science Park (CTSP), which were established in the 1990s and 2000s, respectively. These eras marked Taiwan's transition from economic catch-up to global leadership in key high-tech industries. Given the critical role of science parks in Taiwan's economic trajectory, there is a growing need for rigorous causal analyses of all three major parks. Such analyses, grounded in robust theoretical frameworks and utilizing advanced panel data methods, can provide deeper insights into the contributions of science parks to innovation and economic growth.

This study aims to conduct causal inference to assess the true contributions of science parks to tenant firms in terms of input, behavioral, and output additionality. By integrating administrative, financial, and patent databases, this research evaluates whether tenant firms significantly increase their R&D investment, enhance university linkages, and improve productivity and patent quality after relocating to science parks.

The remainder of this paper is organized as follows: Section 2 outlines the theoretical framework for assessing the value-added contributions of science parks and derives hypotheses based on it. Section 3 reviews existing empirical research on science parks. Section 4 provides an overview of the historical background, selection criteria, and technological characteristics of Taiwan’s science parks. Section 5 introduces the data and variables used in econometric analysis and explains the econometric model applied for causal inference. Section 6 presents the estimation results. Section 7 discusses the research and policy implications of these findings, and Section 8 concludes by addressing limitations and suggesting directions for future research.

2. Theoretical framework for science parks

The International Association of Science Parks and Areas of Innovation (IASP) defines a science park as "an organisation managed by specialised professionals, whose main aim is to increase the wealth of its community by promoting the culture of innovation and the competitiveness of its associated businesses and knowledge-based institutions" (IASP, n.d.).[1] According to the IASP Global Survey, 72 percent of science parks that join IASP are located on land owned by governments or universities, while 14 percent are on land owned by private companies (International Association of Science Parks and Areas of Innovation [IASP], n.d.). This shows that in many countries science parks are established as a part of public policy for innovation and entrepreneurship.

From the perspective of the economics of innovation, science parks serve as a policy tool aimed at addressing market and innovation system failures, particularly those challenges most commonly faced by startups. First, startups often lack complementary assets, making it difficult for them to capture the full returns on their innovations. This, in turn, discourages investment in R&D. To mitigate this underinvestment, science parks offer demand-side support for innovation, including measures like R&D subsidies and tax credits, to stimulate greater R&D activity.

Second, startups with limited social capital often struggle to access external knowledge sources, particularly those requiring substantial cognitive bridging, such as universities. Science parks provide a locational advantage by fostering face-to-face interactions with university researchers. These

1 There is no uniform consensus on the definition of science parks. Institutions such as the American Association of University Research Parks (AURP), the United Kingdom Science Park Association (UKSPA), and the United Nations Educational, Scientific, and Cultural Organization (UNESCO) provide varying definitions. However, they generally agree that science parks are intended to foster high-tech agglomeration, innovation, and entrepreneurship, leveraging academic research.

interactions enable startups to collaborate with academic scientists through various channels. This supply-side support plays a crucial role in addressing innovation system failures.

Finally, by fulfilling these functions, science parks enhance the R&D productivity of their tenant firms, driving innovation and fostering growth. As a result, science parks deliver value-added benefits by improving innovative inputs, strengthening university-industry collaborations, and increasing innovative outputs. Figure 1 illustrates the theoretical implications of the roles science parks play within regional innovation systems.

Figure 1 Theoretical framework

This framework closely aligns with the concept of *additionality* in policy impact analysis. Input additionality examines whether public R&D support programs genuinely increase recipients' R&D expenditures or merely substitute for private R&D investments. Output additionality evaluates the extent to which these programs lead to measurable improvements in R&D outputs, such as patents, that can be directly attributed to the support received. Recognizing the need to capture broader qualitative impacts, the concept of behavioral additionality was introduced. This dimension accounts for changes in recipients' R&D strategies, the acquisition of new skills or technological competencies, enhanced collaboration with firms, universities, or public research institutions, and an increased willingness to undertake uncertain or long-term R&D projects (Falk, 2004; OECD, 2006; Gök & Edler, 2012; Kubera, 2021).

Empirical studies by Clarysse et al. (2009), Okamuro and Nishimura (2015), and Dai et al. (2020) have emphasized how public R&D support influences firm behavior, enhances organizational learning, and fosters collaboration and trust. These findings underscore the multifaceted impacts of R&D policies, extending beyond direct financial outcomes to encompass critical behavioral and strategic transformations.

In the context of science parks, behavioral additionality is reflected in tenant firms' evolving R&D strategies, the cultivation of high-skilled human capital, and the formation of direct linkages with universities and public research institutes. Tenant firms often prioritize hiring PhD-level talent to enhance their absorptive capacity for advanced knowledge and to strengthen connections with academic institutions. These behavioral shifts highlight the pivotal role of science parks in fostering transformative changes beyond financial or output-based metrics.

Building on these insights, this study defines behavioral additionality in science parks as tenant firms' increased emphasis on science-based R&D. This involves hiring scientifically qualified R&D personnel and engaging in research activities that advance cutting-edge technologies and foster deeper academic collaborations, driven by the support of science parks.

Within this framework, the study proposes the following hypotheses to evaluate the value-added contributions of science parks to tenant firms across input, behavioral, and output additionality:

Hypothesis 1: Relocating to science parks increases the R&D expenditure of tenant firms.
Hypothesis 2: Relocating to science parks increases the number of PhD holders in tenant firms.
Hypothesis 3: Relocating to science parks improves the productivity of tenant firms.
Hypothesis 4: Relocating to science parks enhances the patent quality of tenant firms.

3. Literature review

Table 1 summarizes findings from empirical studies on science parks. These studies often rely on performance indicators such as university linkages, innovation outcomes, and growth metrics. Few studies have specifically examined input additionality, such as the ATT on R&D expenditure. Monck et al. (1988), although not employing causal inference, surveyed R&D intensity among on-park and off-park firms in the UK, finding that on-park firms had a higher ratio of qualified scientists and engineers (QSE) to total employment. In Italy, subsequent studies by Liberati et al. (2016) and Lamperti et al. (2017) reported positive effects of science parks on the ratio of intangible assets to sales and on overall R&D expenditure, respectively.

Table 1 Literature review

Early research on the role of science parks in fostering university-industry collaborations[2] often relied on case studies or matched-pair analyses, which had limited generalizability and did not control for selection bias arising from unmatched factors. For instance, studies conducted in the UK (Monck et al., 1988; Massey et al., 1992; Quintas et al., 1992) and in Belgium and the Netherlands (Van Dierdonck et al., 1991) found no significant effects on university-industry knowledge interactions. When such interactions occurred, they were typically limited to informal contacts and shared facilities. These findings were attributed to the invalidity of the linear model of innovation in the context of science parks. This model assumes that simply co-locating tenant firms and academic research institutions automatically facilitates unidirectional knowledge flows, resulting in high-tech innovations. Alternatively, the lack of observed university-industry collaborations may be due to the immaturity of support programs in these regions or the limitations of the empirical methods used in these studies.

Subsequent research conducted in broader regions, utilizing panel data on firms both inside and outside science parks, has provided better control over unobserved heterogeneity and selection bias. Studies

2 Some studies have examined how science parks facilitate inter-firm relationships through trade, research, and resource sharing. Phillimore (1999), criticizing the focus of existing studies on formal research links, explored this phenomenon in Australia, while Koçak and Can (2014) analyzed the determinants of such relationships in Turkey.

in Israel (Felsenstein, 1994), the UK (Westhead & Storey, 1994, 1995), Italy (Colombo & Delmastro, 2002), Sweden (Löfsten & Lindelöf, 2002; Lindelöf & Löfsten, 2004), Japan (Fukugawa, 2006, 2015), Spain (Vázquez-Urriago et al., 2016), and China (Gao et al., 2024) consistently confirm positive or complementary effects on university linkages. These impacts are demonstrated through collaborative research, consulting, co-authorship, and joint patent applications. This evidence highlights the role of science parks as intermediaries that facilitate knowledge interactions between academic research institutes and tenant firms.

Early studies on science parks based on cross-sectional data, such as those in the UK (Westhead & Storey, 1994; Westhead, 1997), Italy (Colombo & Delmastro, 2002), and Sweden (Lindelöf & Löfsten 2004), found no significant impact on innovation outcomes measured by new products, services and patents. However, subsequent research, including some studies using panel data, has confirmed positive impacts on innovation. Evidence comes from studies conducted in Israel (Felsenstein, 1994), the US (Link & Scott, 2003), the UK (Siegel et al., 2003; Helmers, 2019), Finland (Squicciarini, 2008, 2009), Spain (Díez-Vial & Fernández-Olmos, 2015; Albahari et al., 2017, 2018; Antón-Tejón et al., 2024), Italy (Lamperti et al., 2017; Corrocher et al., 2019), China (Xiong & Li, 2022; Wei et al., 2023), and Belgium, Denmark, and Spain (Lecluyse et al., 2023). Additionally, recent European studies suggest that science parks enhance not only the volume but also the quality of patents (Helmers, 2019, UK; Antón-Tejón et al., 2024, Spain).

The evidence on the effects of science parks on the growth of tenant firms remains mixed. Most studies have evaluated firm growth using employment or sales data. Several studies conducted in the UK (Monck et al., 1988), Sweden (Ferguson and Olofsson, 2004; Löfsten and Lindelöf, 2002), Italy (Lamperti et al., 2017), the US (Gwebu et al., 2019), and Portugal (Martins et al., 2023a; 2023b) found no significant impact of science parks on firm growth. In contrast, other studies, including early research, have identified a positive effect of science parks on firm growth. These findings were observed in studies conducted in the UK (Westhead and Storey, 1994), Italy (Colombo and Delmastro, 2002; Liberati et al., 2016), China (Wright et al., 2008), and Spain (Díez-Vial and Fernández-Olmos, 2017).

Empirical studies on science parks have evolved from cross-sectional analyses to panel data approaches and, more recently, to causal inference methods such as the generalized method of moments and difference-in-differences models combined with propensity score matching (e.g., Martins et al., 2023a, 2023b in Portugal; Xiong & Li, 2022; Gao et al., 2024 in China). These advancements emphasize the importance of addressing selection bias and unobserved heterogeneity to enhance the reliability of findings. Building on this foundation, this study adopts a difference-in-differences model designed for staggered treatment timings in panel data, incorporating the inverse probability of entering science parks to adjust covariates.

While firm-level analysis can highlight value-adding impacts through specific performance indicators, it often falls short of capturing the broader success of science parks. To achieve a comprehensive assessment, some studies have used science park-level data to account for a wider range of contributions. They examined agglomeration externalities that contribute to productivity growth (Ratinho & Henriques, 2010), the social value generated by science parks (Blázquez et al., 2023), and the overall effects on innovation and entrepreneurship (Ferrara et al., 2016) across various European countries, including Denmark, Italy, Portugal, Spain, Sweden, and the UK.

In addition, efforts, particularly in Asia, have focused on quantitatively assessing the technical efficiency of science parks and the allocation of innovation resources. Notable studies in this area include Chen et al. (2006) and Sun (2011) in Taiwan, as well as Hu (2007), Hu et al. (2010), and Yang et al. (2021) in China.[3] These studies provide essential insights into the overall efficiency of science parks and highlight challenges in optimizing innovation resources across different tasks.

Building on this strand of research, some studies have utilized community- or county-level data to explore the agglomeration facilitation effect of science parks as key actors in regional innovation systems. For instance, Appold (2004) found that science parks in the United States do not exhibit significant agglomeration effects. In contrast, Cheng et al. (2013) demonstrated that such effects are evident in China's Shenzhen High-tech Industrial Park (SHIP). Similarly, Xiong and Li (2022) identified positive agglomeration effects in China.

Another trend observed in the literature is a shift in research focus from whether science parks are effective to when they are most effective. Recent studies, grounded in contingency theory, have explored the conditions under which science parks deliver the most significant benefits. A key mediating factor identified is absorptive capacity: spillovers contribute to innovation only when recipients possess the capability to evaluate, assimilate, and exploit external knowledge. For instance, Díez-Vial and Fernandez-Olmos (2015) found that tenant firms with high absorptive capacity and strong university-industry collaborations experienced greater innovation benefits. Similarly, Hasan et al. (2018) observed that total factor productivity improvements depended on the technological intensity of tenant firms' production processes. Corrocher et al. (2019) further highlighted the combined roles of absorptive capacity and social capital in driving innovation outcomes.

The role of science parks as intermediaries has also been emphasized, particularly through incubators. Koçak and Can (2014) demonstrated the positive network effects arising from science parks' intermediation roles. Fukugawa (2015) examined how the human capital of incubators contributed to

3 In China, the R&D efficiency of science parks has declined since 2011, following the science park boom driven by national policy (Yang and Lee, 2021). Larger, older science parks with a higher proportion of highly educated workers and strong university-industry collaborations are more efficient compared to younger science parks established during or after the boom. Their counterfactual analysis shows that R&D efficiency would have been significantly higher if the boom had not occurred.

fostering university-industry linkages. Helmers (2019) showed that improvements in patent quality were most pronounced when tenant firms and universities were within walking distance. Additionally, Gao et al. (2024) highlighted complementary effects between public subsidies, park location, and university-industry joint patent applications. Finally, Gwebu et al. (2019) demonstrated that sales growth benefits were closely tied to the strategic alignment between tenant firms' business focus and the park's objectives.

Lastly, despite being officially defined as seedbeds for entrepreneurial firms, science parks have surprisingly received little research attention regarding their impact on entrepreneurship. One notable exception is Yang et al. (2009), who examined the effect of spin-offs created by ITRI researchers or Silicon Valley returnee engineers on R&D productivity. They found a positive effect for spin-offs in general but failed to observe the same for those spawned within HSIP.[4] Studies by Chan and Lau (2005) in Hong Kong, Salvador and Rolfo (2011) in Italy, and Fukugawa (2015) in Japan have explored the role of incubators associated with science parks. However, these studies do not directly assess how science parks accelerate entrepreneurship or the performance of high-tech spin-offs. The extent to which science parks foster science-based entrepreneurship remains an underexplored area in the field.

A detailed review of the literature on science parks in Taiwan will be provided in the next section.

4. Science parks in Taiwan

4-1. History of Taiwan's science parks

HSIP was established in 1980 with the dual goals of promoting high-tech industries and fostering technological innovation. It has successfully attracted major players, including TSMC, solidifying Taiwan's position as a global leader in the semiconductor industry. Over the decades, HSIP has transformed into one of the world's leading semiconductor hubs. According to the Industry and Service Census 2021, 27.4% of the 804 semiconductor firms in Taiwan are based in science parks (Statistical Bureau, n.d.). Of these, 83.6% are located in HSIP (National Science and Technology Council, 2024), suggesting the significant agglomeration externalities generated by the park. As discussed later, research has consistently identified the semiconductor industry as the most technically efficient sector in HSIP, further emphasizing the park's critical role in driving semiconductor innovation. Moreover, HSIP demonstrates a high level of technological specialization in related industries such as telecommunications and computers, as summarized in Table 2.[5]

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4 The authors interpret the absence of a productivity effect among spin-offs as evidence of international inter-firm spillovers in the semiconductor sector. This suggests that semiconductor firms surrounding spin-offs benefit from the new knowledge and networks that spin-offs bring to HSIP.

5 Table 2 shows that technological specialization decreases over time, which may impact MAR (Marshall–Arrow–Romer) agglomeration externalities within the same industry.

Table 2 The number of companies in science parks and location quotients based on the distribution of these firms as of December 2014 (upper section) and November 2024 (lower section)

The concentration of innovative and entrepreneurial activities within the semiconductor industry is evident in national statistics. According to the Indicators of Science and Technology 2023, the semiconductor sector contributed an average of 76.5% to R&D expenditures and 67.6% to sales between 2013 and 2022 (National Science and Technology Council 2023). These figures strongly corroborate the dominance of the semiconductor industry in driving Taiwan's innovation and economic growth.

As previously discussed, one of the key value-added contributions of science parks is their ability to facilitate knowledge spillovers from universities and public research institutes located within the parks. HSIP is closely connected with National Tsing Hua University (NTHU) and National Yang Ming Chiao Tung University (NYCU). NTHU, a premier research university in Taiwan, is renowned for its groundbreaking research in semiconductor technology, often collaborating with industry leaders such as TSMC. Similarly, the Chiao Tung campus of NYCU, which resulted from the recent merger of National Yang Ming University and National Chiao Tung University, has a strong focus on advanced engineering education and research across various fields. The robust scientific research and engineering programs at these universities have enabled them to produce skilled R&D personnel who meet the demands of ITRI and high-tech companies operating within HSIP.

STSP, established in 1996, was designed to foster high-tech development in southern Taiwan and balance the economic landscape between the island's northern and southern regions. Since its inception, STSP has evolved into a prominent hub for biotechnology, achieving the highest relative specialization index among Taiwan's three science parks, as indicated in Table 2. This strategic focus on biotechnology aligns with the Biotechnology Industry Promotion Program established in 1995, which includes initiatives such as the establishment of the Biomedical Research Center by ITRI and the National Science and Technology Program for Biotechnology and Pharmaceuticals led by the National Science Council (Dodgson et al., 2008; Kuo, 2005).[6] In addition to biotechnology, precision machinery is another major focus of STSP, with a location quotient of 1.45 in 2014 and 1.41 in 2024, as highlighted in Table 2.

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6 Taiwan's commitment to developing its biotechnology and pharmaceutical industries was sparked by the success of pioneering U.S. firms like Genentech, whose commercial breakthroughs in recombinant DNA technology in the 1970s demonstrated the vast economic potential of the biotechnology sector. This success motivated Taiwan to identify biotechnology as one of its eight key areas for technology development in the 1980s. Recognizing the strategic importance of biotechnology, the government began laying the groundwork for long-term development through the establishment of institutions like the Development Center for Biotechnology in 1984.

CTSP, established in 2003, was designed to decentralize Taiwan's high-tech industries from the northern regions. Strategically situated in Taichung, the geographic center of Taiwan, CTSP places a strong emphasis on precision machinery. As shown in Table 2, its location quotient was 2.15 in 2014 and 2.04 in 2024, with the higher value in 2014 closely linked to the establishment of the Taichung City Precision Machinery Innovation Technology Park in 2013.

The government of Taiwan has disclosed findings from a benefit-cost analysis of individual science parks. According to Lee and Lu (2022), the self-liquidating ratio (SLR)—calculated as the present value of revenues divided by the present value of costs—for each science park is as follows: HSIP (97.2%–122.8%), CTSP (94.8%), and STSP (35.8%–67.0%). STSP faces challenges in recovering its costs through operational revenues, potentially requiring additional financial support to maintain sustainability. This highlights the need for a detailed analysis of individual science parks, partially addressed by the comparison of HSIP and non-HSIP tenant firms, with the results presented in the next section.

In 2003, HSIP accounted for 20.93 percent of private R&D spending in Taiwan, a significant increase from 4.79 percent in 1990 (Yang et al., 2009). Recent data indicate that Taiwan’s three major science parks collectively accounted for 27.1 percent of private R&D spending in 2013 and 40.7 percent in 2022 (National Science and Technology Council, 2023). Additionally, these three science parks generated 18.7 percent of Taiwan’s GDP in 2022, up from 14.3 percent in 2013. Table 3 presents these data. While international comparisons of science parks' contributions to national statistics can be challenging, these figures appear to be among the highest for industrialized nations.

Table 3 The presence of three major science parks in Taiwan

Yang et al. (2009) demonstrated that the average R&D intensity of firms located in HSIP from 1990 to 2003 was five times greater than that of all manufacturing firms in Taiwan. While the R&D intensity of on-park firms continued to grow from 2013 to 2022, the R&D intensity of all manufacturing firms in Taiwan increased at a faster rate during the same period. This resulted in a lower ratio between the two compared to the 1990–2003 period, as shown in Table 3. Additionally, the total number of patents granted in Taiwan decreased between 2013 and 2022. This trend was also observed in patents granted to on-park firms, though the rate of decline was slower for these firms. Consequently, the ratio reflected in the last column of Table 3 shows a slight increase.

To further promote technological innovation and attract a diverse range of industries, the Act for the Establishment and Administration of Science Parks was amended in 2018, introducing flexible policies aimed at boosting R&D activities, supporting talent development, and optimizing land use (Ministry of Justice, 2018). Among other changes, the 2018 amendments significantly impacted firms’ incentives for R&D. Before 2018, companies were required to invest twice the national average R&D

intensity of the manufacturing sector, calculated over "the last three consecutive years." After 2018, this threshold was raised, requiring firms to invest more than three times the national average R&D intensity of the manufacturing sector, now calculated over "the first three years" of operation. This adjustment substantially raised the initial R&D investment benchmark, encouraging companies to prioritize R&D from the outset of their operations. This policy change applies to firms that entered science parks after September 2022. Conducting a rigorous analysis of its impact requires longitudinal data over a longer time span than what is available in this study.

4-2. Previous studies on Taiwan's science parks

Previous studies on Taiwan's science parks began with qualitative assessments, focusing mainly on the tenants of HSIP. A case study on HSIP highlights its unique role in fostering regional innovation systems, a role not initially planned (Lin, 1997). Lin attributes this to the market-driven R&D activities within HSIP, especially in the semiconductor industry. Hu et al. (2005), based on interviews with 268 technology professionals, support Lin’s findings, indicating that HSIP's regional innovation systems fostered MAR (Marshall–Arrow–Romer) agglomeration externalities within the same industry through labor, intermediate goods, and capital markets. Hu's (2011) patent analysis by sector further supports this view. Additionally, Lai and Shyu (2005) compared 162 tenants from Zhangjiang High-Tech Park (ZHTP) with 101 HSIP tenants, finding that HSIP held an overall advantage. In a comparison of HSIP and STSP, Hu (2008) identified a positive network effect, which was more pronounced in HSIP.

Chen et al. (2006) and Sun (2011) both analyze the efficiency of six high-tech industries in HSIP, using Data Envelopment Analysis (DEA) and the Malmquist Productivity Index to evaluate performance across two periods: 1991–1999 and 2000–2006, respectively. Both studies consistently identify the semiconductor industry as the most efficient, attributed to strong R&D investments and advanced infrastructure. Chen et al. (2006) highlight that precision machinery and telecommunications could benefit from enhanced infrastructure and workforce development, while Sun (2011) points to optoelectronics and biotechnology as lagging in efficiency, recommending resource reallocation to support balanced growth.

The shared use of DEA and the Malmquist index across consecutive periods reinforces the findings, revealing disparities in sectoral efficiency that persist over time. Combined, these studies suggest that HSIP can enhance its competitiveness by maintaining R&D incentives for high-performing sectors like semiconductors and tailoring support for lower-performing industries. By addressing specific infrastructure and workforce needs in these sectors, Taiwan’s science parks could foster a balanced, sustainable growth environment across its high-tech industries, aligning with both studies’ insights on industry-specific policy measures.

One of the earliest econometric evaluations of Taiwan's science parks was conducted by Yang et al. (2009), using data from the Taiwan Economic Journal (TEJ). Their findings indicated a positive effect of the HSIP on R&D productivity. Hasan et al. (2018) analyzed panel data from Emerging Markets Information Services (EMIS) for 2009–2011 and found that Taiwan's science parks positively impacted total factor productivity (TFP), measured using the Levinsohn and Petrin method (2003). This effect was influenced by the technological intensity of the production process. They found that urban areas hosting science parks demonstrated the highest TFP in science and technical services, including biotechnology. In contrast, computer and electronics firms in large cities, such as Taipei, exhibited the highest TFP.

In a subsequent study using EMIS data from 2010 to 2012, Hasan et al. (2020) compared science parks in South Korea and Taiwan, uncovering a significant finding: in Taiwan, urban areas housing science parks showed the highest TFP, as measured by the Olley and Pakes method (Olley and Pakes, 1996), especially among small firms. The authors interpreted this as evidence of a selective process, where high-productivity small firms are attracted to science parks, while low-productivity small firms are pressured to exit due to competitive selection forces, indicating a one-sided sorting process as opposed to the case where both types of firms are attracted to science parks.

5. Method

5-1. Data

This study integrates data from TEJ, Orbis, and the Taiwan Science Park Bureau. TEJ provides consolidated data on all listed companies in Taiwan, encompassing 1,909 firms as of 2024, with the analysis covering the period from 2002 to 2023. Orbis Intellectual Property (Orbis IP) complements TEJ by offering detailed patent information for both listed and unlisted firms. Additionally, data from the Taiwan Science Park Bureau includes records of the years when current tenants moved into their respective science parks.

Seventy-seven percent of the sample consists of tenant firms where the parent companies are located in a science park. For firms with multiple establishments or subsidiaries, the designated science park corresponds to the location of the parent company. If the parent company is not located in a science park, but a subsidiary is—for instance, in CTSP—and another establishment is in STSP, the subsidiary's science park (CTSP) is designated. Lastly, if neither the parent company nor its subsidiaries are located in a science park but an establishment is, the science park where the establishment first moved in is designated.

This approach introduces potential biases in estimating science park spillovers due to the use of consolidated data, which aggregates financial outcomes from organizations in diverse locations. Specifically, the localized effects of science park activities may be diluted or obscured, as the consolidated data does not distinguish between the performance of parent companies, subsidiaries, or establishments located outside the park. The inability to capture establishment-level data limits the study's ability to identify true spillover effects.

Ideally, a more refined approach would involve the development of a tenant firm dummy variable to represent companies without multiple establishments or subsidiaries—typically startups that may experience the most direct impact from science park spillovers. However, since TEJ provides only consolidated data for all listed companies in Taiwan, such a treatment dummy could not be incorporated in this study. Future research should prioritize the use of data from non-listed companies to better capture startups and their unique characteristics, thereby improving the accuracy of spillover estimation.

As of 2024, there are 995 firms operating within science parks, according to the Science Park Bureaus. Figure 2 illustrates the distribution of entry years for these firms, highlighting a growing trend in relocations, with notable peaks in 1997, 2003, and 2022. The peaks in 1997 and 2003 appear to be linked to the establishment of new science parks.

Figure 2 Distribution of years of entry

This study utilizes four performance indicators as dependent variables: R&D expenditure to capture input additionality; number of PhD holders (sourced from TEJ) to measure behavioral additionality; and TFP, calculated via the Olley and Pakes method,[7] alongside total IP quality (sourced from Orbis IP) to assess output additionality. Recruiting PhD holders and encouraging employees to pursue PhDs help firms build connections with universities and public research institutes, enhancing the firm's reputation within the scientific community. This, in turn, increases the likelihood of collaborations with highly productive scientists. Total IP quality is a composite indicator, encompassing 27 factors[8] and rated on a scale from 1 to 100, where 1 represents low quality and 100 denotes superior quality. This measure is used by recent studies that assess patent quality (Fukugawa, 2023; European Commission, 2024). This study controls for value-added for the model where the dependent variable is R&D expenditure, labor for the model where the dependent variable is PhD holders, and R&D expenditure for the models where the dependent variable represents TFP and patent quality.

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7 The Olley-Pakes (1996) method addresses simultaneity and selection biases in production function estimation by employing investment as a proxy for unobservable productivity shocks and accounting for firm exit.

8 Examples of these factors include family size, examiner citations, forward citations by foreign applicants, claim width and coverage, detectability of infringement, and oppositions. For more details, see Fukugawa (2023). These components have been utilized individually in prior research, such as patent litigation (Nakanishi & Yamada, 2007), patent scope or diversity (Chen & Chang, 2010), and patent family size (Fischer & Leidinger, 2014). Additionally, other studies have developed composite indicators integrating aspects like forward citations, backward citations, patent family size, and claims to offer a more comprehensive measure of patent quality and its impact on firm value (Lanjouw & Schankerman, 2004).

The matching of the TEJ and Orbis databases was carried out using the unique identification number assigned to all firms in Taiwan. However, the number of observations for the patent quality variable decreases due to unmatched records between the two databases. This mismatch underscores the absence of corresponding data in one or both databases for certain firms.

Descriptive statistics for the variables are provided in Table 5.

Table 5 Descriptive statistics

5-2. Model

The decision to locate in a science park is a choice variable for both science parks and potential tenants. Additionally, firms relocate to science parks at different times, which implies staggered treatment timings in a difference-in-differences (DID) model using panel data. This study employs the augmented inverse probability weighting (AIPW) approach to address selection bias, adjusting the entire sample by applying the inverse provability weights. In the first stage of the AIPW method, weights are generated for control units based on the inverse of the propensity score, *e*, which is defined as $ei = P(Di=1 \mid Xi)$, where *D* is a binary variable indicating whether firm *i* is located in a science park, and *X* represents covariates that determine science park location. Following Yang et al. (2009), this study incorporates R&D expenditure, labor, regional dummies, and industry dummies as factors influencing whether firms are located in science parks. The inverse provability weights, *w*, are defined as follows. For treated units (D=1): $w1=1/e$. For control units (D=0): $w0=1/(1-e)$. Treated units with low propensity scores and untreated units with high propensity scores are assigned higher weights, ensuring greater comparability in terms of covariate distribution.

The second stage incorporates staggered treatment timings within the DID framework using Stata's *xthdidregress* command with the AIPW option. The parsimonious form of the two-way fixed-effects (TWFE) model for the outcome *Y* of a group *g* in a period *t* is: $Y_{g,t}=\alpha_g+\beta_{fe}D_{g,t}+\gamma_t+\epsilon_{g,t}$, where α denotes group fixed effects, β_{fe} is the group-specific treatment effects, γ denotes time fixed effects, and ϵ is the error term. When treatment effects are homogeneous across groups and time, β_{fe} is interpreted as the average treatment effect on the treated (ATT). However, under heterogeneous treatment effects,[9] TWFE-DID estimators may be biased due to contaminated comparisons. This occurs when early-treated units serve as controls for later-treated units, potentially leading to estimates with the opposite sign of the true ATT (Gardner, 2021; Baker et al., 2022).

Recent studies have introduced models for panel data with staggered treatments to address this bias (Borusyak et al. 2021; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2020; Sun

9 This occurs when treatment effects are correlated with treatment timing. Fukugawa (2024) examined a scenario where later program participants experienced smaller treatment effects and identified underlying sources of this correlation.

and Abraham 2021). Analyzing the same dataset with six alternative estimation methods, de Chaisemartin and D'Haultfoeuille (2022) found that these models produce consistent results. The *xthdidregress* command implements Callaway and Sant'Anna's (2021) model to estimate the true ATT, using never-treated units as the control group.[10] This approach ensures unbiased and reliable ATT estimates, even with staggered treatments. The AIPW estimator is considered doubly robust, as it produces consistent estimates if either the treatment assignment model or the outcome regression model is correctly specified.

Goodman-Bacon's (2021) decomposition theorem explains that β_{fe} is a weighted average of all possible two-by-two DID estimators, with some comparisons potentially assigned negative weights.[11] The results of the decomposition will be discussed in the next section.

Following Hasan et al. (2018), who presented heterogeneous treatment effects of Taiwan's science parks across different technologies, this study estimates the aforementioned models for subsamples consisting of semiconductor (M2324 in the Taiwan Stock Exchange classification system) and biotechnology (M1722) firms. Furthermore, in line with Hasan et al. (2020), who found heterogeneous treatment effects of Taiwan's science parks based on firm size, this study also estimates the models for subsamples of firms with fewer than 200 employees.

6. Results

6-1. Findings from AIPW models

The Goodman-Bacon decomposition results indicate that 90% of the weight in the treatment effect estimate comes from comparisons between never-treated groups and timing groups, which are typically reliable as never-treated groups provide a proper control. Comparisons between timing groups (2.3% weight) raise concerns about contaminated comparisons, as early-treated groups may already reflect treatment effects while late-treated groups might be influenced by anticipation effects, violating the parallel trends assumption. However, as shown later, treatment timing is not correlated with treatment effects, reducing the risk of bias from these comparisons. Comparisons involving always-treated groups (7.7% weight) are excluded in the Callaway and Sant'Anna (2021) model, as discussed in the preceding section.

Table 5 presents the estimation results for the entire sample, demonstrating significantly positive ATTs for R&D expenditure, the employment of PhD holders, productivity, and patent quality. For instance, relocating to science parks is associated with a 1.215% increase in TFP. By pooling information across time, the aggregated ATT accounts for variability in individual time periods, yielding a consistent and

10 Accordingly, firms that were always treated—those that entered the science parks before 2002—are excluded from the econometric analysis. This exclusion affects approximately 20% of science park tenants.
11 They include pairs between early-treated and never-treated groups, late-treated and never-treated groups, early-treated and late-treated groups (before the late-treated group receives treatment), and late-treated and early-treated groups (after the early-treated group receives treatment).

reliable estimate of the treatment effect. These findings highlight the cumulative effect of the treatment over the analyzed period.

Table 5 Estimation results of the entire sample

A cohort-level analysis shows no correlation between treatment timings and the ATTs, suggesting the robustness of the aggregate measure. Figure 3 depicts the ATTs on R&D expenditure across different time points for the entire sample. This visualization reinforces the stability and reliability of the estimated effects.

Figure 3 The ATTs on R&D expenditure across different time points. The estimation results of the entire sample.

Additionally, this study estimates the same model for non-HSIP tenant firms,[12] with the results presented in Table 6. Tenant firms in CTSP and STSP experienced a significant increase in R&D investment, PhD holder employment, and improvements in TFP. Relocating to CTSP or STSP is associated with a 1.39% increase in TFP, a result slightly higher than that observed for the entire sample. However, no significant effect was observed on patent quality, suggesting that improvements in patent quality are primarily driven by HSIP tenant firms.

Table 6 Estimation results of the non-HSIP sample

These results support all proposed hypotheses. Subsequent subsample analyses further confirm the robustness of these findings. More specifically, they validate the hypotheses on input additionality and output additionality. Overall, the results provide compelling evidence of the value-added contributions of Taiwan's science parks. This study extends the findings and insights of previous research, such as Yang et al. (2009), which focused on the impact of HSIP on R&D productivity, to encompass three major science parks and three dimensions of additionality.

Table 7 presents the estimation results for the semiconductor industry. The ATTs are significantly positive for R&D expenditure and TFP, aligning with the findings of Chen et al. (2006) and Sun (2011), which identified the semiconductor industry as the most technically efficient sector. However, the ATT for PhD holders was not statistically significant. Moreover, the magnitude of the ATTs is smaller than those observed in the full sample. This may be attributed to the reduced number of observations or the industrial characteristics, which may necessitate a larger dataset for more robust results.

Table 7 Estimation results of semiconductor firms

12 Due to limitations in sample size, park-specific estimations were not feasible, leaving this as a promising avenue for future research.

Although the model for total IP quality did not yield a significant ATT, the results indicate that the technical quality variable—an alternative indicator of patent quality used for robustness checks—improved by ten points following firms' relocation to science parks. As total IP quality encompasses broader dimensions, such as market attractiveness, these findings suggest that the value-added contributions of science parks are more pronounced in the technological aspects of patents. This underscores the nuanced impact of science parks on various dimensions of innovation and performance within the semiconductor industry.

Table 8 presents the estimation results for the biotechnology industry, highlighting that the number of cohorts analyzed was limited due to the small sample size of biotechnology firms. Most models include only two distinct cohorts—firms entering science parks at two specific time points—compared to never-treated units.[13] While this reduction in cohorts does not necessarily undermine robustness, it introduces sensitivity to cohort-specific characteristics, potentially limiting the generalizability of the results. These limitations will be explored in detail in the next section.

Table 8 Estimation results of biotechnology firms

With this caution in mind, the results indicate significantly positive ATTs for R&D expenditure, PhD holders, and productivity, underscoring the strong impact of science parks on these outcomes. The findings for PhD holders emphasize the science-based nature of innovation in the biotechnology sector, consistent with the observations of Hasan et al. (2018). This sectoral characteristic makes PhD holders particularly important as human capital, acting not only as a skilled workforce but also as entrepreneurs and as a bridge between research institutes, venture capitalists, and the biotechnology industry (Hsu et al., 2005).

Although the model for total IP quality did not yield a significant ATT, technical quality increased by three points following firms' relocation to science parks. Cohort-level analysis shows that firms entering science parks in 2011 recorded an ATT of 2.405, while the 2022 cohort achieved a higher ATT of 6.266. However, the 2011 cohort accounts for approximately 86.67% of the total observations, which shifts the overall ATT closer to the 2011 cohort's estimate.

Table 9 presents the estimation results for firms with fewer than 200 employees. While the model for patent quality did not converge, the ATTs for R&D expenditure and TFP are significantly positive. Relocating to science parks is associated with a 5.435% increase in TFP. These findings are consistent

13 An extreme case is observed for PhD holders, where 19 biotechnology firms that entered science parks in 2011 are compared to never-treated units. Plotting the ATT for this cohort reveals significantly positive effects in 2013, from 2015 to 2017, and in 2020.

with Hasan et al. (2020), who highlighted the positive effects of science parks on TFP, particularly for smaller firms.

Table 9 Estimation results of firms with fewer than 200 employees

The larger magnitude of ATTs for small firms underscores the pivotal role of science parks in fostering growth and innovation in these enterprises. However, the ATT for PhD holders is statistically insignificant, suggesting that science parks do not have a substantial impact on this variable for small firms. This outcome may be partially explained by the reduced sample size for PhD-related data, a limitation discussed in the conclusion section.

6-2. Robustness checks

To address concerns about potential biases introduced by using consolidated financial data, a robustness check was conducted by restricting the analysis to a subsample where 77% of the firms were tenant firms whose parent companies were located in a science park, but their establishments and subsidiaries were not. This approach mitigates the risk of dilution or misattribution of science park spillovers that might arise due to the inclusion of subsidiaries and establishments located in diverse regions. The regression results from this restricted subsample were consistent with those obtained from the full sample, suggesting that the findings are not solely driven by the aggregation of data across different organizational units but reflect genuine spillover effects associated with science park locations.

The first stage of the AIPW process is critical because it determines the weights. Even though AIPW can correct for some deficiencies in the first-stage model via the outcome model, poorly estimated propensity scores can lead to inefficiency or instability. This study tests the robustness for the first stage by overlap diagnostics, weight stability, and covariate balance. First, a very small proportion of the sample (47 out of 14,086) falls outside the common support. This suggests that common support is largely acceptable, with the overlap region covering most treated and untreated units. Second, the mean weight is 0.993, which is ideal as it indicates the weights are appropriately scaled to reflect the marginal probabilities of treatment and control. The median is 0.923, indicating that half of the observations have weights below this value. The majority of weights are reasonable, as seen in the percentiles (e.g., 90% of weights are below 1.2). Lastly, covariate balance between treatment and control groups was evaluated using the Standardized Mean Difference (SMD). As shown in Table 10, all variables achieved SMDs below the 10% threshold, indicating an acceptable balance. This confirms that confounding variables were effectively controlled, enhancing confidence that observed differences in outcomes can be attributed to the treatment effect rather than pre-existing baseline differences.

Table 10 Covariate balance

A key assumption in causal inference, especially with the DID method within the AIPW model, is that in the absence of treatment, the treated and control groups would have exhibited parallel trends in the outcome variable. Figure 4 integrates 14 graphs depicting dynamic trends from the estimation results. As shown in the dynamic graphs, no systematic trends appeared before treatment, which supports the model's validity. This implies that observed differences in post-treatment outcomes are attributable to the treatment itself rather than to any pre-existing differences in the trajectories of the treated and control groups.

Figure 4 Combined dynamic graphs of the ATTs

In addition, using alternative indicators for productivity and patent quality provides an additional robustness check, ensuring that the results are not overly reliant on a single measure of success. The results of these checks are presented in Tables 5 to 9. Alternative models incorporating labor productivity and technical quality[14] (sourced from Orbis IP) yielded consistent findings,[15] further strengthening the robustness of the analysis. Notably, technical quality showed a significantly positive ATT for semiconductor and biotechnology firms, indicating that science parks have enhanced the technological aspects of high-tech tenants' patents. However, for small firms, the ATT for labor productivity was not statistically significant, suggesting that capital deepening is more critical than innovation for improving labor productivity in these firms.

7. Discussion

This study's theoretical framework highlights how science parks address systemic and market failures through demand-side measures (e.g., R&D subsidies) and supply-side interventions (e.g., university collaborations). The findings confirm this, showing that Taiwan's science parks enhance tenants' R&D investment, attract high-quality talent, and boost productivity. While earlier research primarily focused on HSIP and its productivity gains and network effects, this study expands the analysis to CTSP and STSP, demonstrating positive impacts across three types of additionality.

HSIP has long been recognized for its advantages in fostering connections with NTHU and the Chiao Tung campus of NYCU. The findings further suggest that tenant firms in CTSP and STSP also enhance their human capital with scientific expertise, albeit with characteristics distinct from those of HSIP. This development may stem from opportunities to establish university linkages, which requires further park-level analysis using direct measurements to better understand university-industry collaboration dynamics.

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14 Technical quality represents the degree of innovation that can be derived from a company's IP, which includes the width and coverage of independent claims, detectability of infringement, difficulty in inventing around, and forward citations by foreign assignees.

15 The result for technical quality in the entire sample is positive, with a statistical significance of 11 percent, closely aligning with the findings for total IP quality.

The varying ATTs across subsamples reveal that the impacts of science parks differ by industry and firm size, emphasizing the importance of tailored strategies to meet specific industry needs and foster sustained innovation and economic growth. Previous studies have identified the semiconductor industry as the most technically efficient sector within Taiwan's science parks. Consistent with this, the present study shows that semiconductor firms significantly benefit from the parks' R&D and productivity-enhancing features. These features should be leveraged to strengthen their competitive edge, drive technological innovation, and develop strong proprietary technologies. These contributions not only boost firm-level competitiveness but also reinforce Taiwan’s global leadership in semiconductors, with potential spillover benefits to other industries.

The biotechnology sector also benefits significantly from the collaborative environment fostered within science parks. By fostering close collaborations with universities, the parks bridge cognitive and social distances between firms and researchers, spurring innovation. A positive ATT on PhD-level talent underscores the parks' role in cultivating a highly skilled workforce critical for the biotechnology industry. Moreover, such a high-quality talent pool is particularly important in the biotechnology sector, where PhD-level professionals can serve as entrepreneurs and intermediaries between the realms of science and technology and the financial domain, such as venture capitalists. A positive ATT on the technical quality of patents further illustrates the parks’ contribution to helping tenants develop strong proprietary technologies. These findings align with the Biotechnology Industry Promotion Program, which focuses on talent cultivation, patent enhancement, and technology transfer in knowledge-intensive industries. However, these results must be interpreted cautiously due to the limited number of cohorts analyzed within the biotechnology subsample. Expanding longitudinal data in future studies will address this limitation and provide deeper insights into the long-term impacts of science parks on the biotechnology sector.

Smaller firms showed stronger gains in R&D and TFP but did not exhibit comparable increases in high-skill employment. This pattern, consistent with prior research, suggests that science parks create competitive environments that selectively benefit high-productivity small firms. However, these firms often lack the social capital necessary for effective collaboration with academic institutions. Challenges such as insufficient mentorship, training, and networking opportunities may limit their ability to fully utilize science park resources. Strengthening public policies to address these gaps can enhance university collaborations and support small firms' growth, further solidifying the role of science parks in advancing Taiwan's high-tech startup sector.

Prior studies have noted that science parks increase the volume of patents, but patent quality tends to be highly uneven. While most patents are of lower quality, basic patents exhibit higher value. This study advances the literature by focusing on high-value innovations and considering factors such as forward non-self citations, family size, litigation, and scope. The results highlight a positive impact of science parks on fostering university linkages, enabling tenants to produce high-quality, basic patents. These collaborations between tenants and universities or public research institutes drive competitive technological advancements in Taiwan's knowledge-intensive industries.

This research contributes to the global discussion on measuring the impact of science parks by highlighting the limitations of traditional metrics, such as sales or employment growth, which often produce mixed results. Instead, TFP emerges as a more reliable measure of science parks' success. The findings demonstrate that science parks significantly enhance TFP, particularly for small firms. Future evaluations should prioritize TFP metrics to better assess the role of science parks in regional innovation systems.

8. Conclusion

This study underscores the pivotal role of Taiwan's science parks (HSIP, CTSP, and STSP) in fostering innovation through input, behavioral, and output additionality. Firms relocating to these parks exhibited increased R&D expenditure, higher employment of PhD holders, improved productivity, and enhanced patent quality. By leveraging the AIPW model with robust checks, including covariate balance, pre-treatment trend tests, and alternative indicators, the study ensures credible and reliable causal inferences. These findings align with global trends, demonstrating the effectiveness of science parks in driving university-industry collaboration and innovation, while highlighting their unique contributions in the Taiwan-specific context.

The study faced several data limitations that constrained its analysis. Voluntary responses to the TEJ questionnaire limited the accuracy of variables such as PhD holder employment, while the absence of direct measures of university linkages, such as joint research project data, hindered the assessment of tenant-university collaborations. The limited sample size also precluded park-specific analyses, and the lack of longitudinal data restricted insights into long-term impacts, particularly in sectors like biotechnology. Future research should address these gaps by incorporating non-listed companies, expanding longitudinal datasets, and employing direct measures of university linkages to enhance the understanding of science parks' role in innovation.

Moreover, as illustrated in the case of China (Yang and Lee, 2021), while Taiwan's science parks have made overall positive contributions to university spillovers and innovation, this does not necessarily imply that creating more science parks will always yield better outcomes. Future research should focus on identifying the optimal size and number of science parks that operate most efficiently under specific economic conditions. The findings from such studies could provide more targeted and meaningful insights for policymakers, not only in Taiwan but also globally.

Finally, as noted in the literature review, little research has focused on how science parks accelerate entrepreneurship or influence the performance of high-tech spin-offs. Future studies should establish panel data on entrepreneurial firms to explore the role of science parks in fostering entrepreneurship and supporting spin-off success.

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Table 1 Literature review

Author(s)	Data	Method	Period	Region	N	Results
Monck et al. 1988	Firm	Matched-pair	1986	UK	183 and 101	Ge, Gs, Q(+), U
Van Dierdonck et al. 1991	Science park	Descriptive	1988	Belgium, Netherlands	68(B) and 71(N)	U
Felsenstein 1994	Firm	Log-linear	Unknown	Israel	73 and 89	I(+), U(+)
Westhead and Storey 1994	Firm	Matched-pair	1986, 1992	UK	75 and 62	G(+), I, S, U(+)
Westhead and Storey 1995	Firm	Matched-pair	1986, 1992	UK	75 and 62	S(+), U(+)
NISTEP 1996	Science park	Descriptive	1994	Japan	111	U
Vedovello 1997	Science park	Case study	1993	UK	1(SRP)	U(+)
Westhead 1997	Firm	Matched-pair	1986, 1992	UK	75 and 62	I, S
Phillimore 1999	Science park	Case study	1998	Australia	1(WATP)	N(+)
Colombo and Delmastro 2002	Firm	Matched-pair, Tobit	2000	Italy	45 and 45	Ge(+), I, F(+), U(+)
Lofsten and Lindelof 2002	Firm	Matched-pair, OLS	1999	Sweden	134 and 139	Ge, Gs, U(+)
Link and Scott 2003	University	Ordered probit	2001	US	28	I(+), R(-)
Siegel et al. 2003	Firm	SFE	1992	UK	89 and 88	I(+)
Appold 2004	County	ESR	1960–1985	US	3024	A
Ferguson and Olofsson 2004	Firm	Matched-pair	1995, 2002	Sweden	30 and 36	Ge, Gs, S(+)
Lindelof and Lofsten 2004	Firm	Matched-pair	1999	Sweden	134 and 139	I, U(+)
Durao et al. 2005	Science park	Case study	Unknown	Portugal	1(Taguspark)	Complementarity of cyber and real parks
Hu et al. 2005	Individual	Case study	2001	Taiwan	268(HSIP)	A(+)
Lai and Shyu 2005	Individual	ANOVA	2003	China, Taiwan	162(ZJHP) and 101(HSIP)	Overall advantage of HSIP
Chen et al. 2006	Industry	DEA	1991–1999	Taiwan	54	TE(Computer and semiconductor industries remain the benchmarks.)
Fukugawa 2006	Firm	Bivariate probit	2001–2003	Japan	74 and 74	U(+)
Hu 2007	Science park	OLS	1992–2000	China	52 and 52	LPG(converging)
Hu 2008	Individual	OLS	2001–2005	Taiwan	HSIP(243) and TSIP (172)	N(+, greater in HSIP)
Squicciarini 2008	Firm	Duration model	1970–2002	Finland	48 and 72	I(+)
Wright et al. 2008	Firm	OLS	2005	China	53(USP) and 296(non-USP)	Ge(+, non-USP)

Author(s)	Data	Method	Period	Region	N	Results
Squicciarini 2009	Firm	Duration model	1970–2002	Finland	252	I(+)
Yang et al. 2009	Firm	Heckit, FE	1998–2003	Taiwan	57 and 190	RDP(+)
Hu et al. 2010	Science park	DEA	2004–2006	China	53	TE(Beijing, Shanghai, and Hangzhou remain the benchmarks.)
Ratinho and Henriques 2010	Science park	Case study	2006	Portugal	15(including incubators)	A
Salvador 2011	Firm	Case study, OLS	2007	Italy	30(case), 20 and 91(OLS)	R, V(-)
Salvador and Rolfo 2011	Firm	OLS	2007	Italy	65 and 90	E(+)
Sun 2011	Industry	DEA	2000–2006	Taiwan	42	TE(Computer and semiconductor industries remain the benchmarks.)
Cheng et al. 2013	Community	ZIP	2007	China	601	A(+, only SHIP)
Koçak and Can 2014	Firm	Negative binomial	2008	Turkey	136	N(+, contingent on intermediary)
Díez-Vial and Fernandez-Olmos 2015	Firm	RE Tobit	2007–2011	Spain	11201	I(+, contingent on absorptive capacity and UI collaboration)
Fukugawa 2015	Firm	Heckit	2000–2002	Japan	7330	U(+, contingent on intermediary)
Ferrara et al. 2016	Science park	MAVT	2012	Italy	56	I, E
Liberati et al. 2016	Firm	DID	2009–2011	Italy	65 and 63	Gs(+, old, public, and non-specialized SP, small and old firms), I, RD(+)
Vasques-Uriaggo et al. 2016	Firm	Heckit	2007	Spain	39722	U(+)
Albahari et al. 2017	Firm	OLS	2009	Spain	849	I(+)
Díez-Vial and Fernandez-Olmos 2017	Firm	RE Tobit	2007–2012	Spain	11594	Ge(+), Gs(+), I(+)
Lamperti et al. 2017	Firm	CEM	2004–2012	Italy	147 and 146	Gs, I(+), RD(+)
Albahari et al. 2018	Firm	Tobit, OLS	2009	Spain	849	I(+)
Hasan et al. 2018	Firm	2SLS with IV	2009–2011	Taiwan	4655	TFP(+, contingent on technological intensity of production process)
Corrocher et al. 2019	Firm	CEM, Heckit	2006–2013	Italy	470 and 511	I(+, absorptive capacity, social capital)
Gwebu et al. 2019	Firm	OLS	2008–2010	US	205	Gs(+, contingent on business focus shared with the park)
Helmers 2019	Firm	FE	2000–2014	UK	241	PQ(+, walking time distance)
Hasan et al. 2020	Firm	2SLS with IV	2010–2012	South Korea, Taiwan	5066(SK) and 4646(TW)	TFP(+, for both countries)
Yang and Lee 2021	Science park (NHIZ)	KPF	2007–2014	China	145	RDP dropped since 2011
Xiong and Li 2022	City	PSM-DID	1999–2017	China	293	A(+), I(+, big cities)

Author(s)	Data	Method	Period	Region	N	Results
Blazquez et al. 2023	Science park	Descriptive	2021	Denmark, Italy, Portugal, Spain, Sweden, UK	14	SV(+)
Lecluyse et al. 2023	Firm	SEM	2018	Belgium, Denmark, Spain	201	I(+), N(+)
Martins et al. 2023a	Firm	PSM, GMM	2006–2014	Portugal	553 and 553	Ge
Martins et al. 2023b	Firm	PSM, GMM	2002–2014	Portugal	553 and 553	Gs
Wei et al. 2023	Firm	CEM, ZINB, Heckit	2016–2020	China	911 and 861	I(+)
Anton-Tejon et al. 2024	Patent	OLS, Poisson	2004–2012	Spain	1102 and 5783	PQ(+)
Gao et al. 2024	Firm	PSM, RE Tobit, GMM with IV	2010–2014	China	1271	U(+, complementary effect of subsidy and park location on science linkage and university-industry joint patent applications)

Note
The number of observations (N) represents the count of on-park firms and off-park firms, respectively.

Method
ANOVA: Analysis of variance
CEM: Coarsened exact matching
DEA: Data envelopment analysis
DID: Difference-in-differences
ESR: Endogenous switching regression
FE: Fixed-effects model
GMM: Generalized method of moments
Heckit: Heckman selection model
IV2SLS: Instrumental variable two-stage least squares
KPF: Knowledge production function, used to evaluate innovation resource misallocation
MAVT: Multi-attribute value theory
OLS: Ordinary least squares
PSM: Propensity score matching
RE: Random-effects model
SEM: Structural equation model
SFE: Stochastic frontier estimation
ZINB: Zero-inflated negative binomial model

ZIP: Zero-inflated Poisson model

Results
A: High-tech agglomeration
E: Entrepreneurship, such as spinoffs
F: Funding
Ge: Employment growth
Gs: Sales growth
I: Innovation output, such as new products and patents
LPG: Labor productivity growth
N: Networking
PQ: Patent quality, represented by forward citations and renewals
Q: qualified scientists and engineers
R: Reputation
RD: R&D or intangible assets
RDP: R&D productivity
S: Survival
SV: Social value
TE: Technical efficiency
TFP: Total factor productivity
U: University linkage
V: Value added

Signs in parentheses indicate the positive or negative effects of science parks, with the items following each sign specifying the conditions under which these effects are observed.

Others
CTSP: Central Taiwan Science Park
HKSP: Hong Kong Science Park
HSIP: Hsinchu Science-based Industrial Park
NHIZ: National High-tech Industrial Zones
SHIP: Shenzhen High-tech Industrial Park
SRP: Surrey Research Park
TSIP: Tainan Science-based Industrial Park
WATP: Western Australian Technology Park
ZJHP: Zhangjiang High-Tech Park

Table 2 The number of companies in science parks and location quotients based on the distribution of these firms as of December 2014 (upper section) and November 2024 (lower section)

	Integrated circuits	Optoelectronics	Computers and peripherals	Telecommunications	Precision machinery	Biotechnology	Others	Total
The number of companies in science parks in 2014								
HSIP	202	101	55	45	39	73	9	524
CTSP	8	43	15	1	62	32	13	174
STSP	16	56	2	11	47	59	5	196
Total	226	200	72	57	148	164	27	894
LQ								
HSIP	1.52	0.86	1.30	1.35	0.45	0.76	0.57	
CTSP	0.18	1.10	1.07	0.09	2.15	1.00	2.47	
STSP	0.32	1.28	0.13	0.88	1.45	1.64	0.84	
The number of companies in science parks in 2024								
HSIP	184	94	60	45	53	133	8	577
CTSP	9	29	14	2	56	33	21	164
STSP	27	44	6	10	51	68	10	216
Total	220	167	80	57	160	234	39	957
LQ								
HSIP	1.39	0.93	1.24	1.31	0.55	0.94	0.34	
CTSP	0.24	1.01	1.02	0.20	2.04	0.82	3.14	
STSP	0.54	1.17	0.33	0.78	1.41	1.29	1.14	

Source: National Science and Technology Council 2024

Note

The Location Quotient (LQ) is defined as $LQ = (Xir/Xr) / (Xi/X)$ where Xir represents the economic activity in industry i within region r, Xr is the total economic activity in region r, Xi is the economic activity in industry i at the national level, and X is the total economic activity at the national level.

Table 3 The presence of three major science parks in Taiwan

	On-park firms' revenue / Taiwan's GDP (%)	On-park firms' R&D / Taiwan's R&D (%)	On-park firms' R&D intensity / Taiwan's R&D intensity	On-park firms' patents granted / Taiwan's patents granted (%)
2013	14.3	27.1	1.9	6.3
2014	14.2	27.9	1.9	4.8
2015	13.5	28.6	2.1	6.3
2016	13.5	28.7	2.1	6.8
2017	13.6	30.8	2.3	5.8
2018	14.1	31.4	2.2	5.0
2019	13.9	32.2	2.3	5.6
2020	15.1	35.0	2.3	6.4
2021	17.1	38.3	2.2	7.3
2022	18.7	40.7	2.2	7.5

Note

Patents include invention, utility model, and design.

Source: Indicators of Science and Technology 2023

Table 4 Descriptive statistics

Variable	N	Mean	Standard deviation	Min	Max
R&D expenditure	24,419	3.413	2.264	0	12.113
Labor	24,529	6.433	1.600	0.693	13.775
PhD holders	16,168	0.797	1.007	0	6.775
Capital	24,529	6.624	1.957	0	14.935
Value-added	23,724	6.326	1.633	-2.385	14.114
Total IP quality	15,355	50.454	15.691	13	92
Technical quality	15,355	74.752	15.088	36	100
TFP	22,651	1.57e-10	1.078	-7.829	5.128
Labor productivity	23,724	-0.129	1.224	-7.550	5.469

Note

All variables, except total IP quality and technical quality, are log-transformed.

Table 5 Estimation results of the entire sample

Additionality	Dependent variable	N	ATT	Significance
Input	ln(R&D)	21,850	3.339	***
Behavioral	ln(PhD holders)	14,680	4.871	*
Output	TFP	20,771	1.215	**
Output	Labor productivity	21,850	1.136	*
Output	Total IP quality	12,677	42.397	*
Output	Technical quality	12,677	47.354	

Note

Levels of statistical significance: *** 1%, ** 5%, * 10%.

Table 6 Estimation results of the non-HSIP sample

Additionality	Dependent variable	N	ATT	Significance
Input	ln(R&D)	21,600	3.622	***
Behavioral	ln(PhD holders)	14,499	5.239	*
Output	TFP	20,481	1.390	*
Output	Labor productivity	21,600	0.795	
Output	Total IP quality	12,596	77.808	
Output	Technical quality	12,596	0.435	

Note
Levels of statistical significance: *** 1%, ** 5%, * 10%.

Table 7 Estimation results of semiconductor firms

Additionality	Dependent variable	N	ATT	Significance
Input	ln(R&D)	1,337	0.364	*
Behavioral	ln(PhD holders)	925	0.342	
Output	TFP	1,259	0.296	***
Output	Labor productivity	1,386	0.419	***
Output	Total IP quality	893	5.254	
Output	Technical quality	893	10.365	*

Note

Levels of statistical significance: *** 1%, ** 5%, * 10%.

Table 8 Estimation results of biotechnology firms

Additionality	Dependent variable	N	ATT	Significance
Input	ln(R&D)	961	0.075	***
Behavioral	ln(PhD holders)	722	0.117	***
Output	TFP	917	0.278	***
Output	Labor productivity	968	0.491	***
Output	Total IP quality	641	0.502	
Output	Technical quality	641	2.919	***

Note

Levels of statistical significance: *** 1%, ** 5%, * 10%.

Table 9 Estimation results of firms with fewer than 200 employees

Additionality	Dependent variable	N	ATT	Significance
Input	ln(R&D)	6,307	15.163	***
Behavioral	ln(PhD holders)	3,802	-0.220	
Output	TFP	5,835	5.435	***
Output	Labor productivity	6,307	-5.152	

Note

Levels of statistical significance: *** 1%, ** 5%, * 10%.

The models for patent quality did not converge.

Table 10 Covariate balance

Variable	Treated Mean	Control Mean	% Bias	t-Test (p-value)
ln(R&D)	5.565	5.537	1.5	0.54
ln(labor)	6.914	6.898	1.0	0.30
Propensity Score	0.3448	0.3447	0.0	0.01
Regional and industry dummy (all)	N/A	N/A	<10	N/A

Figure 1 Theoretical framework

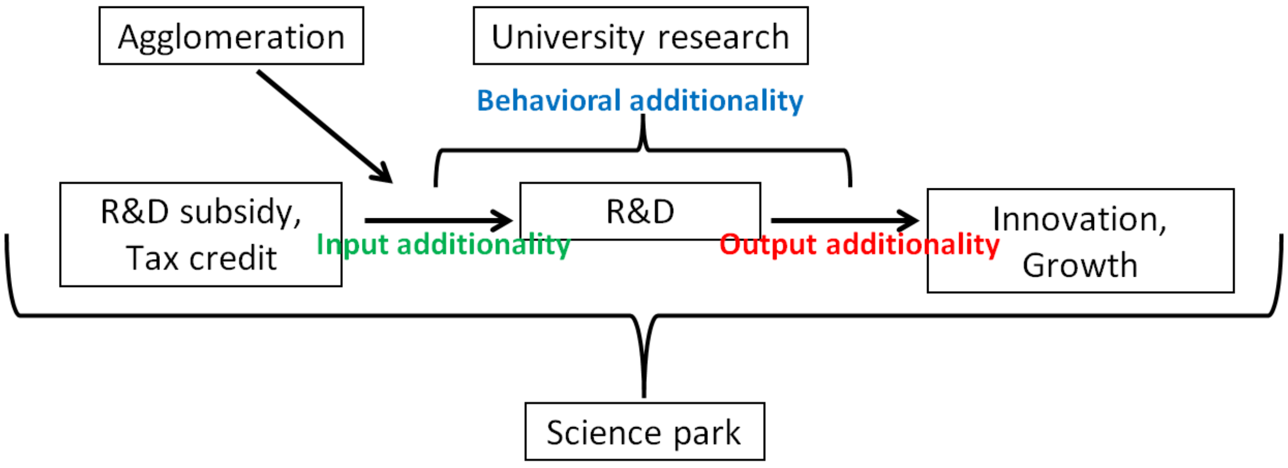
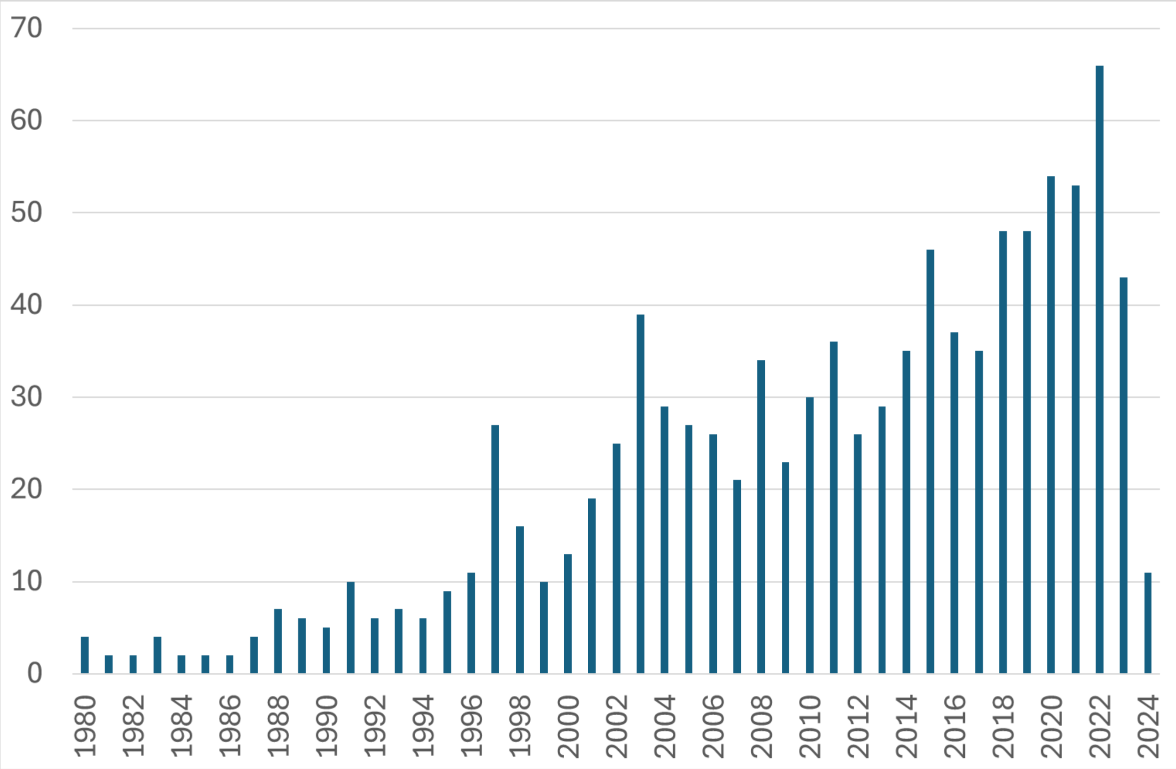


Figure 2 Distribution of years of entry



Source: Science Park Bureaus of Taiwan

Note

The vertical axis represents the number of firms that entered science parks.

Figure 3 The ATTs on R&D expenditure across different time points. The estimation results of the entire sample.

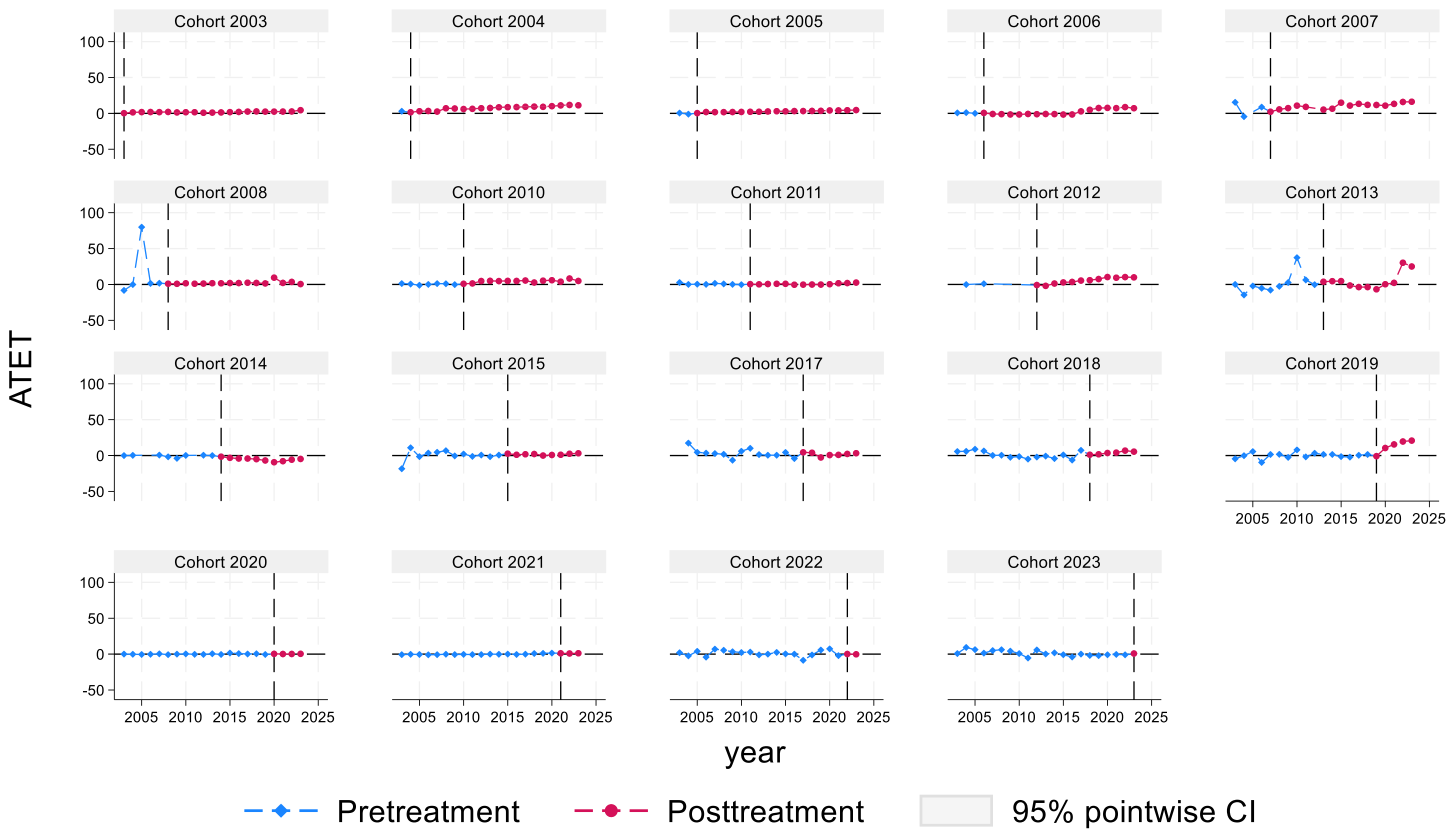
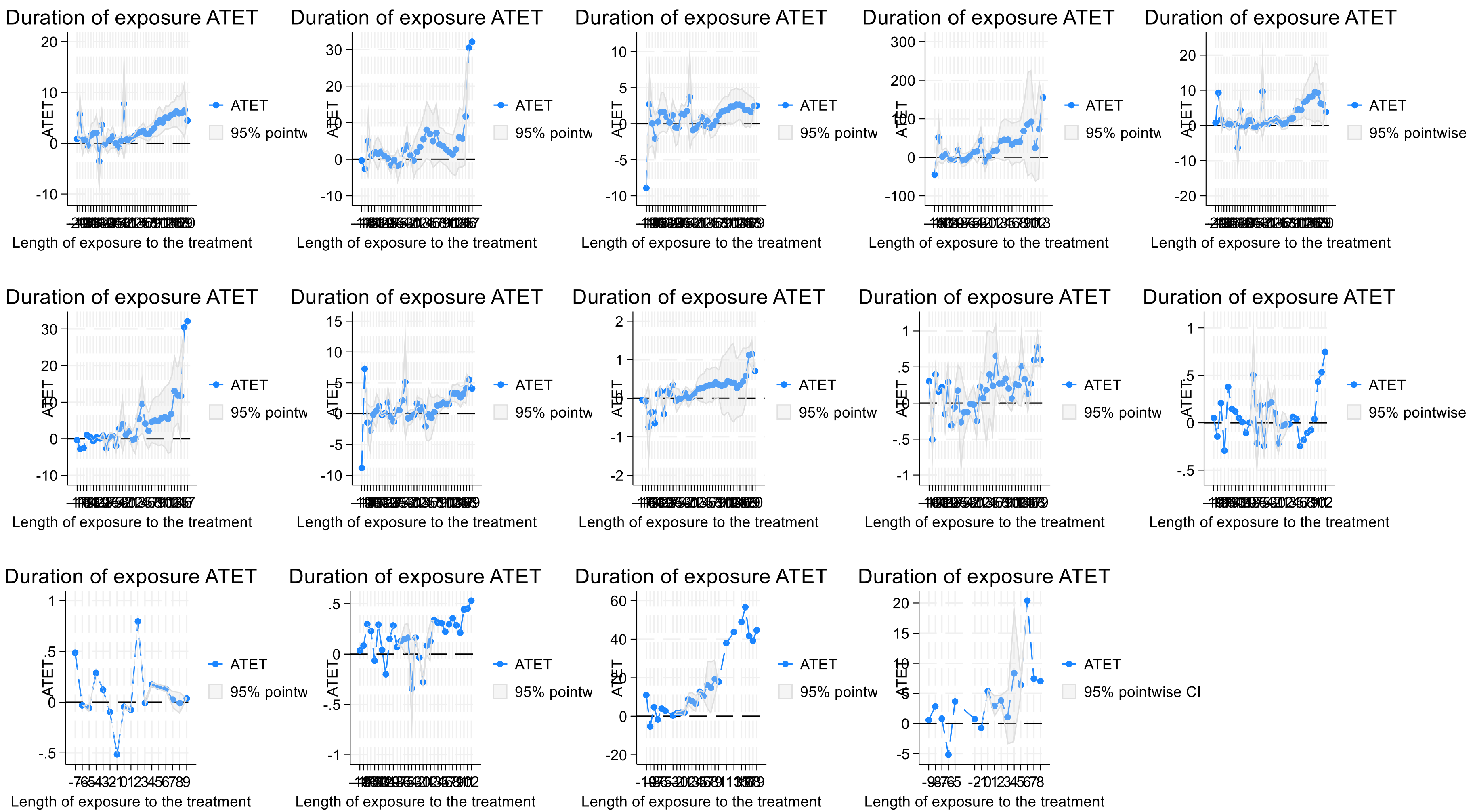


Figure 4 Combined dynamic graphs of the ATTs



From left to right:

Figure 4 Dynamic graph of the ATT on R&D expenditure based on the estimation results of the entire sample

Figure 5 Dynamic graph of the ATT on PhD holders based on the estimation results of the entire sample

Figure 6 Dynamic graph of the ATT on TFP based on the estimation results of the entire sample

Figure 7 Dynamic graph of the ATT on total IP quality based on the estimation results of the entire sample

Figure 8 Dynamic graph of the ATT on R&D expenditure based on the estimation results of the non-HSIP sample

Figure 9 Dynamic graph of the ATT on PhD holders based on the estimation results of the non-HSIP sample

Figure 10 Dynamic graph of the ATT on TFP based on the estimation results of the non-HSIP sample

Figure 11 Dynamic graph of the ATT on R&D expenditure based on the estimation results of semiconductor firms

Figure 12 Dynamic graph of the ATT on TFP based on the estimation results of semiconductor firms

Figure 13 Dynamic graph of the ATT on R&D expenditure based on the estimation results of biotechnology firms

Figure 14 Dynamic graph of the ATT on PhD holders based on the estimation results of biotechnology firms

Figure 15 Dynamic graph of the ATT on TFP based on the estimation results of biotechnology firms

Figure 16 Dynamic graph of the ATT on R&D expenditure based on the estimation results of firms with fewer than 200 employees

Figure 17 Dynamic graph of the ATT on TFP based on the estimation results of firms with fewer than 200 employees