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Do Place-Based Policies Promote Local Innovation and Entrepreneurship?*

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Abstract

This paper explores how a prominent place-based policy in China, the national high-tech zones, affects local innovation output and entrepreneurial activities. Making use of staggered establishments of national high-tech zones in various Chinese cities, we find that the establishment of national high-tech zones has positive effects on local innovation output and entrepreneurial activities. A number of additional tests suggest that the effects appear causal. Access to finance, reductions in administrative burdens, and talent cultivation are three plausible underlying economic channels. Our paper sheds new light on the evaluation of the effectiveness of China's place-based policies.

JEL Classifications: G24, G38, O38, L26

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1. Introduction

Technological innovation and entrepreneurial activities are key drivers of a nation's economic growth (e.g., Solow, 1957; Romer, 1986; Aghion and Howitt, 1992). Intensive studies have explored a variety of economic, institutional, and social determinants that could

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promote innovation and entrepreneurial activities.[1] Specifically, public policies, such as various government subsidiary programs, government-sponsored venture capital (VC), research and development (R&D) tax credit programs, and federal spending, have played important roles and attracted many discussions from researchers and regulators.[2] A fast-growing class of "place-based" policies, however, receives relatively little attention from financial economists although researchers have discovered significant effects of geography on corporate finance decisions and stock market performance.[3] In this paper, we focus on an emerging country, China, and study the effectiveness of place-based policies by examining how the establishment of national high-tech zones, a prominent place-based public policy in China, affects local innovation output and entrepreneurial activities.

Place-based policies are economic development policies that aim at fostering the economic growth of an area within their jurisdiction and explicitly target transfers toward specific geographical areas instead of particular groups of individuals. Based on studies using US and European data (e.g., Bartik, 2003; Glaeser and Gottlieb, 2008), economists generally find place-based policies are ineffective and hence express little support for such policies.[4] The situation, however, could be different in China. As the largest emerging country, while China suffers from poorly developed institutions and markets, its economic reforms launched in 1978 have catapulted China into a stellar growth trajectory: In nowadays, China has the second-largest Gross Domestic Product (GDP), the largest number of granted patents, and the most active entrepreneurial activities around the world. Because a variety of place-based policies (including China's famous special economic zones) have been introduced since 1978, it appears that, unlike the USA and Europe, place-based policies positively contribute to China's economic growth. However, there is no empirical research that evaluates the effectiveness of China's prominent place-based policy, national high-tech zones, on its innovation output and entrepreneurial activities. In this paper, we attempt to fill the gap and provide new evidence to evaluate the effectiveness of national high-tech zones.

China presents an ideal setting for carrying out research on place-based policies, in particular on national high-tech zones: In 1988, the Ministry of Science and Technology (MOST) of China implemented the "Torch Plan" with the main goal of establishing national high-tech zones. The policy aimed to develop China's high-tech industries and enhance economic growth. The first national high-tech zone, the ZhongGuan Village (Beijing) high-tech zone, was established in 1988. In 1990, the State Council approved the first wave of twenty national high-tech zones. After the early success, in 1991, the State Council promulgated preferential policies for national high-tech zones and approved the second wave of twenty-six high-tech zones. In 1992, the third wave of twenty-five high-tech zones was approved. By the end of 2016, there have been 146 national high-tech zones established in

1 See Decker *et al.* (2014), Da Rin, Hellmann, and Puri (2013), Chemmanur and Fulghieri (2014), and He and Tian (2018, 2020) for surveys of these two strands of literature.

2 A few recent examples of this literature include Audretsch, Link, and Scott (2002), Brander Du, and Hellmann (2015), Howell (2017), and Kong (2020).

3 Pirinsky and Wang (2006), Kedia and Rajgopal (2009), John, Knyazeva, and Knyazeva (2011), Tian (2011), Cai, Tian, and Xia (2016), and Bernile, Kumar, and Sulaeman (2015) show the effects of firms' locations on the comovement of stock returns, corporate stock option plans, dividend payout policy, VC stage financing, acquisition likelihood, and institutional investors' geographical bias.

4 One exception is Austin, Glaeser, and Summers (2018) who argue that place-based policies could insure residents against place-based economic shocks.

China across all provinces and autonomous regions. We discuss more institutional details on China's high-tech zones in Section 2.

We compile our data set from a few sources. We retrieve patent application and grant information from the State Intellectual Property Office (SIPO) of China and patent citation data from Google Patent. We obtain China's new firm registration data from the State Administration for Industry and Commerce (SAIC) of China and city-level characteristics from the China City Statistical Yearbook. We aggregate patent and new firm registration data up at the city level. Our sample includes 8,890 city-year observations from 473 unique cities over a 30-year period between 1985 and 2014.

A standard approach that assesses the consequences of high-tech zone establishments is to undertake the ordinary least squares (OLS) regressions that regress a city's innovation output and entrepreneurial activities on the city's high-tech-zone status and control variables. This approach, however, suffers from a few identification difficulties. First, the establishment of national high-tech zones and the city's innovation output and entrepreneurial activities could be driven by common characteristics that may not be observable to econometricians, which causes the omitted variable concern. Second, expected changes in a city's innovation output and entrepreneurial activities could lead to the establishment of national high-tech zones. This is the typical reverse-causality concern. Finally, a sample that includes all cities with high-tech zones is likely to bias toward large cities with more economic activities, which could bias the estimation. Hence, the results obtained from a standard OLS estimation may tell us little about the causal effect of national high-tech zones on local innovation output and entrepreneurial activities.

To tackle the endogeneity issue and establish causality, we use a difference-in-differences (DiD) approach that makes use of staggered establishments of national high-tech zones in various Chinese cities during our sample period. The DiD approach has two advantages when addressing the identification concerns. First, the DiD approach absorbs constant unobserved differences between the treatment group cities (i.e., cities that have national high-tech zones established) and the control group cities (i.e., cities that do not have national high-tech zones established). Second, the DiD approach stripes out omitted time trends that are correlated with the establishment of national high-tech zones and local innovation output and entrepreneurial activities. In addition, our research setting provides another advantage due to the fact that the establishment of national high-tech zones takes place at exogenously different times for different cities. Hence, this institutional feature represents multiple shocks to China's place-based policies and avoids a common identification difficulty faced by studies with a single shock: potential omitted variables coinciding with the shock could directly affect local innovation and entrepreneurial activities.

Our baseline DiD regressions suggest that the establishment of national high-tech zones has a positive, causal effect on local innovation output and entrepreneurial activities. Specifically, compared with cities without high-tech zones established, cities with high-tech zones exhibit a 36.9% larger increase in patent applications, a 50.3% larger increase in patent grants, a 17.5% larger increase in patent citations, and a 12.9% larger increase in new firm registrations. These effects are economically sizable and support the argument that China's place-based policies spur local innovation output and entrepreneurial activities.

While the DiD approach with multiple shocks is able to address the identification issue to a large degree, there still exist concerns that treatment cities could be different from control cities in many dimensions. We provide a number of additional tests to strengthen our causal argument. First, we use a propensity score matching algorithm that matches treatment and control cities based on important characteristics that could affect local innovation output and entrepreneurial activities. After ensuring the satisfaction of the parallel trend assumption, we find evidence consistent with our baseline DiD results.

Second, one reasonable concern is that the establishment of national high-tech zones could not be completely exogenous and suffers from a selection issue. The rationale is as follows: the establishment of many national high-tech zones goes through a two-step procedure in which the zone is established by the local government and later certified by the central government. Because the certification by the central government brings many preferential policies, such as discounted land-use fees, tax deductions, and special offers in bank loans, it is possible that local governments establish high-tech zones in cities with higher innovation potential and more active entrepreneurial activities so that it would be easier for these cities to get certified by the central government. To address this concern, we focus on a subsample of treatment cities in which the establishment of national high-tech zones is initiated directly by the central government rather than the local government. Hence, the establishment of high-tech zones in these cities is more exogenous. Our findings in this subsample are consistent with the baseline DiD results.

Third, to address the concern that our results could be driven by chance, we undertake two placebo tests. The first placebo test artificially moves the event time (high-tech zone establishment year) 3 years prior to the actual event year and repeats the baseline DiD analysis. We fail to observe that the falsely assumed establishment of high-tech zones exhibits any effect on local innovation output and entrepreneurial activities. The second placebo test is to artificially assign treatment and control city status in our sample and repeat the baseline DiD analysis. We do not find significant results either. Overall, these placebo tests suggest that our main results are unlikely driven by chance.

Fourth, one may concern that another contemporaneous place-based policy, the Economic Technological Development Zones (ETDZs), could affect our results. The ETDZ program is a place-based policy in China that is initiated and supervised by the Ministry of Commerce and is with the aim of attracting foreign direct investment and boosting export. There have been 219 ETDZs established in China, with more than half of the ETDZs located in coastal provinces. We address this concern by undertaking a test that excludes treatment cities where any ETDZ was established prior to the establishment of a national high-tech zone. The results suggest that our baseline DiD findings are not driven by the ETDZ policy.

Fifth, to alleviate the concern that our results could be driven by firms' increased exposure to foreign technologies (i.e., technology spillovers) from international trade, we focus on a sub-sample excluding observations after 2001 when China joins the World Trade Organization (WTO). The results suggest that our main findings are unlikely driven by technology spillovers from foreign companies due to expanded international trade.

Sixth, to alleviate the concern that our results could be driven by nearby cities due to common unobservable local economic conditions, we repeat out analysis in a sub-sample excluding nearby cities (within a 250-km radius of a treatment city) from the control group. The results suggest that our main results are unlikely driven by unobservable local economic conditions.

Finally, to mitigate the concern that resources such as capital and labor are mobile and respond to place-based policies, which make it hard to interpret the results, we conduct two tests in sub-samples of cities that have relatively lower mobility of resources. The first test restricts the sample to cities located in non-eastern regions in China and the second test excludes cities that have bullet-train access before the establishment of national high-tech zones. The results of the two tests suggest that, even in places with lower mobility of resources, the establishment of national high-tech zones still has a positive effect on local innovation and entrepreneurship.

Furthermore, we attempt to explore plausible underlying economic channels through which national high-tech zones affect local innovation output and entrepreneurial activities. First, we propose and test an access to finance channel. We find that cities with national high-tech zones exhibit significantly lower income tax and sales tax rates and fee rates after the establishment of the zones. In addition, cities with national high-tech zones experience a significantly higher increase in early-round VC investment after zone establishments. The average premium of land transactions in cities with national high-tech zones is significantly lower than that without high-tech zones. Second, we suspect that firms in high-tech zones enjoy lower administrative burdens imposed by local governments and term it as the reductions in administrative burdens channel. We find that firms located in cities with national high-tech zones have significantly lower administrative expenses. Third, cities with high-tech zones could attract more talent, which enhances innovation output and entrepreneurial activities. We find that cities with national high-tech zones have a larger number of college students, although the numbers of middle and high school students in these cities are similar to those without national high-tech zones. We also find that these three channels could explain a significant proportion (53–82%, depending on specifications) of the positive effect of national high-tech zones on local innovation output and entrepreneurial activities. Overall, these pieces of evidence suggest that access to finance, reductions in administrative burden, and talent cultivation and introduction could be three plausible underlying channels through which high-tech zones promote local innovation and entrepreneurship.

In the final part of the paper, we explore the spillover effects of national high-tech zones. Specifically, we look at how the establishment of national high-tech zones affects the innovation output and entrepreneurial activities of nearby cities. We find that, for cities that locate closer to the city with a national high-tech zone, they experience larger increases in patenting and new firm registrations than other cities that are located farther away from the city with a national high-tech zone, after the city establishes its high-tech zone. This finding suggests that, instead of increasing their own innovation output and entrepreneurial activities at the cost of nearby cities, national high-tech zones appear to have some positive spillover effects on nearby cities.

Our paper contributes to two strands of literature. It adds to the literature on the relation between governments and the private sector (Cohen, Coval, and Malloy, 2011; Houston *et al.*, 2014; Andonov, Hochberg, and Rauh, 2018; Huang and Xuan, 2019; Li, Lin, and Xu, 2020). In terms of entrepreneurial activities, earlier work such as Lerner (2000) and Audretsch, Link, and Scott (2002) show that R&D awards under the USA. Small Business Innovation Research (SBIR) program has positive effects on entrepreneurial firm growth. Howell (2017) finds that an early-stage award from the US Department of Energy's SBIR grant program approximately doubles the probability that a firm receives subsequent VC and has large, positive effects on patenting and revenue. Brander, Du, and Hellmann (2015) show that government-sponsored VC augments (instead of displaces) private VC and its investment are positively associated with entrepreneurial firms' success. Regarding the literature on government roles of promoting innovation: while Da Rin, Nicodano, and Sembenelli (2006) find no effect on government R&D support on innovation, Kong (2020) shows the federal government spending is detrimental to innovation. These findings, however, are consistent with the general consensus that the research is inconclusive regarding the effects of government spending on innovation (Klette, Moen, and Griliches, 2000). Our paper contributes to this literature by exploring the role played by the Chinese government, which is largely ignored by the existing literature but represents an important economic force, on promoting innovation and entrepreneurship.

Second, our paper contributes to the literature on evaluating place-based policies. Existing literature on place-based policies in China focuses on these policies' effects on economic growth, employment, wage, and productivity. For example, Wang (2013) finds that the establishment of Special Economic Zones boosts the local economy by attracting foreign direct investment, achieving agglomeration economies, and generating wage increases. Alder, Shao, and Zilibotti (2016) show that the establishment of Special Economic Zones is associated with an increase in GDP. Lu, Wang, and Zhu (2019) document that Special Economic Zones have a positive effect on firm employment, output, capital, and labor productivity. These studies, however, ignore the effect of place-based policies on innovation and entrepreneurship. In this study, we evaluate how China's establishment of high-tech zones affects local innovation output and entrepreneurial activities.[5]

The rest of the paper is organized as follows. Section 2 discusses the institutional background of China's high-tech zones. Section 3 describes our sample selection procedure and variable constructions. Section 4 discusses the baseline DiD results. Section 5 reports additional identification tests. Section 6 explores plausible underlying economic channels. Section 7 discusses the spillover effects. We conclude in Section 8.

2. Institutional Background

Ever since China started its economic reform in 1978, the Chinese government has introduced several place-based policies to boost its economic growth. These policies have set up various types of special economic zones with different focuses and goals. Among them, the high-tech zones are implemented to promote high-tech industries and foster technological innovation.[6]

There are two main categories of high-tech zones established in China: national-level zones are approved by the central government and enjoy more privileged policies; province-level zones are initiated by the government at lower administrative levels (Lu, Wang, and Zhu, 2019). In this paper, we focus only on national-level high-tech zones for the following reasons. First, the preferential policies provided to provincial high-tech zones are prohibited to be the high level that is comparable to those given to national-level zones, so as to avoid excessive competition among high-tech zones.[7] Second, the certification criteria for firms in provincial

5 See, for example, Neumark and Simpson (2015) for a comprehensive review on place-based policies in the USA and Europe. Existing studies pertaining to place-based policies in the USA mainly focus on Round I of the federal urban Empowerment Zone program and the California Enterprise Zone program. For example, Busso, Gregory, and Kline (2013) find that the Empowerment Zone designation substantially increases employment in zone neighborhoods and generates wage increases for local workers. Neumark and Kolko (2010) show that the California Enterprise Zone program has no significant effect on local employment.

6 Other contemporaneous place-based policies include the ETDZs with the aim of attracting foreign direct investment and boosting exports, the Bonded Zones with the aim of expediting import and export faster, and the Export Processing Zones for importing and processing raw materials from abroad without entering the territory of China (Alder, Shao, and Zilibotti, 2016).

7 State Administration of Taxation (2004) states that "the policies given to the province-level development zones should not be comparable to those given to the national ones."

high-tech zones are lower than those for national zones.[8] As a result, Alder, Shao, and Zilibotti (2016) find an insignificant effect of provincial zones on local economic growth.

In 1988, the MOST of the central government launched the "Torch Plan" and established the ZhongGuan Village (Beijing) high-tech zone as a pilot.[9] In 1990, the State Council approved the first wave of twenty national high-tech zones. In 1991, the State Council promulgated preferential policies for national high-tech zones and approved the second wave of twenty-six national high-tech zones.[10] In 1992, the third wave of twenty-five national high-tech zones was approved. By the end of 2016, there have been 146 national high-tech zones in China. We list all the national high-tech zones by the end of 2016 in Online Appendix A. Figure 1 depicts the geographical distribution of these national high-tech zones. One can observe that all provinces (and autonomous regions) have established national high-tech zones by 2016 with the only exception of Tibet. Online Appendix B presents a brief summary of the development history of national high-tech zones in China.

The locations of national high-tech zones are mainly decided by the central government, which gives high priority to regional balance concerns, and therefore, bear mainly political missions to maintain social stability and development (Chen *et al.*, 2019). This institutional feature, to some extent, alleviates the endogeneity concern that the government may have selected the places for national high-tech zones based on local innovation and entrepreneurship. To further address the endogeneity concern, we differentiate between two types of national-level high-tech zones: Type I zones (empty dots in Figure 1) are initially established directly by the central government; Type II zones (solid dots in Figure 1) are initially established by local governments, and later certificated by the MOST and upgraded to the national level. In addition to promoting technological advancement, Type I national high-tech zones bear strategic missions to balance cross-region gaps and serve as pilots for policy experiments. Hence, the establishment of Type I national high-tech zones is less likely to be correlated with pre-existing local economic conditions and technological levels than Type

8 For national high-tech zones, the certification requires firms to have their main businesses involving high-tech industries, spend 3% or more of their revenue in R&D, and have 30% or more of employees with higher education backgrounds. Provincial high-tech zones, on the other hand, do not have any requirements on firms or they target certain industries based on local political or economic interests and are "a patchwork of different policies rather than a coherent policy instrument" (Alder, Shao, and Zilibotti, 2016). Note that the certification of firms and beneficial policies given to firms happen after a national high-tech zone is established and therefore has nothing to do with the concern that the approval of the central government could be related to a city's innovation capacity and industrial development.

9 On May 10 1988, the State Council of China initiated the "Interim Regulations of Beijing New Technology Industry Development Pilot Zone." The ZhongGuan Village (Beijing) became the first national high-tech zone initiated by the central government. For more details, see the Ministry of Science and Technology website: http://www.most.gov.cn/gxjscykfq/ldjh/.

10 On March 6 1991, the State Council approved twenty six national high-tech zones and issued the Notice on the National High-tech Zone and Related Policies with Three Annexes (Annex I, "Conditions and Measures for the Identification of High-tech Enterprises in National High-tech Zones," Annex II, "Interim Provisions on Certain Policies in National High-tech Zones," and Annex III, "Tax Policies for National High-tech Zones"). The full document (in Chinese) can be found from the website of the Ministry of Science and Technology: http://www.most.gov.cn/ztzl/jqzzcx/zzcxcxzzo/zzcxcxzz/zzcxgncxzz/200512/t20051230_27334.htm.

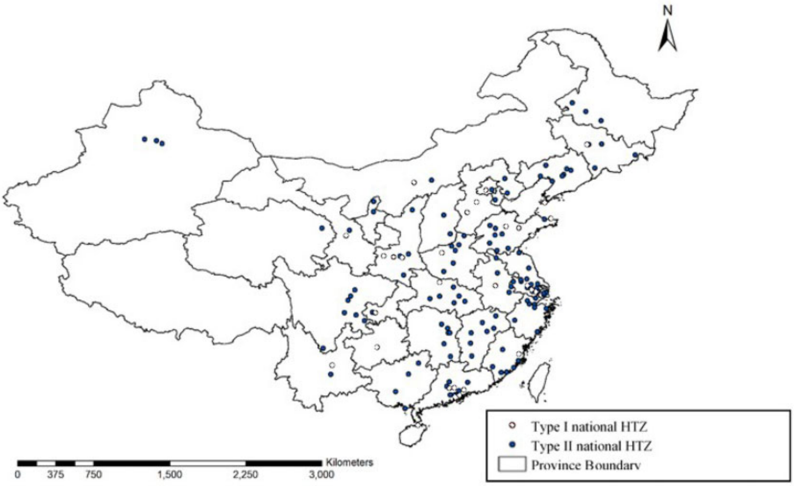

Figure 1. Geographical distribution of national high-tech zones. This figure exhibits the geographical distribution of national high-tech zones. Empty dots show the Type I national high-tech zones (i.e., zones initiated by the central government), while solid dots show the Type II national high-tech zones (i.e., those initially established by local governments and then certified by the MOST to be national-level zones).

II zones. In Section 5, we restrict our treatment group to cities with Type I zones for the robustness of our results.

National high-tech zones enjoy a certain degree of institutional autonomy to decide preferential policies for qualified firms (Lu, Wang, and Zhu, 2019). First, qualified firms in these zones are entitled to tax advantages including exemptions on corporate income tax; also, they can perform accelerated depreciation for tax-saving purposes according to Annex III, "Tax Policies for National High-tech Zones," issued in 1991 by the State Council.[11] Second, they enjoy discounted land-use fees. For example, certified high-tech firms in the Guiyang high-tech zone in the Guizhou province enjoy a 25–35% discount on regular land-use fees (Lu, Wang, and Zhu, 2019). Third, there are implicit benefits embedded in national high-tech zones. For instance, the administrative procedure is significantly simplified in national high-tech zones: the number of administrative staff per national high-tech zone is only 1/8 to 1/10 of that in other administrative regions in China.[12] The administrative approval for firm registration is much faster and easier in national high-tech zones than in other regions (Zheng *et al.*, 2017). In addition, being labeled as a high-tech zone firm brings

11 For example, if a firm is confirmed as a high-tech enterprise, its income tax is collected at a reduced rate of 15% since the date of confirmation. If the output value of export products of a certified high-tech enterprise in the high-tech zones accounts for more than 70% of the total output value in the same year, its income tax is collected at a reduced rate of 10%. A certified newly opened high-tech firm in the high-tech zones can be exempted from the income tax within 2 years after it is put into production.

12 According to the report given by the governor of the Minister of Science and Technology, Guanhua Xu, at the meeting of the national high-tech zone in August, 2005, the report (in Chinese) is available at http://www.most.gov.cn/ztzl/gjgxjskfq/gxhyfy/200508/t20050830_24388.htm.

high prestige and visibility that allow the firm to attract high-quality investors, partners, managers, employees, etc.

National high-tech zones have served as a major engine for China's economic growth. In 2015, national high-tech zones contribute 11.7% of GDP in China and 128 out of 146 national high-tech zones contribute 15% or above of their host city's GDP. National high-tech zones also contribute immensely to technological innovation. In 2015, firms located in national high-tech zones account for 44.3% of China's total R&D expenditures and 19.8% of China's total authorized invention patents (IPs). In addition, one-fifth of firms in national high-tech zones are newly registered, indicating active entrepreneurship within the zones. Currently, there are more than 1,170 publicly listed firms located in national high-tech zones, including Lenovo, Alibaba, Haier, and Baidu.

The national high-tech zone policy is different from another contemporaneous place-based economic policy in China, the ETDZs in a number of ways. First, ETDZs aim to attract foreign direct investment and boost export levels, while national high-tech zones intend to promote the advancement, commercialization, and internationalization of science and technology. Second, geographically speaking, the EDTZs concentrate more in eastern China, especially in coastal cities, while national high-tech zones are comparatively more scattered across the country.

3. Data and Summary Statistics

3.1 Sample Selection

Our data set mainly consists of three parts: patent application/grant information, new firm registration, and city-level characteristics. Patent application/grant information is retrieved from the SIPO of China, while the patent citation data are constructed based on information retrieved from Google Patent. We obtain China's new firm registration data from the State SAIC of China. We obtain city-level characteristics from the China City Statistical Yearbook. We aggregate firms' innovation output and entrepreneurial activity data up at the city level. Finally, we match patent data, entrepreneurship data, and city characteristics using city names, and manually check for matching accuracy.

The final sample includes 8,890 city-year observations for 473 unique cities over a 30-year period from 1985 to 2014.[13] As city characteristics are only available from 1987, we restrict our sample period between 1987 and 2014 when we run multivariate regressions with city characteristics as controls.

3.2 Variable Construction

3.2.a. Measuring innovation output and entrepreneurial activities

We collect patent application/grant data from the SIPO, which provides China patent information since 1985 and includes a patent's type, application year, and grant year (if granted), as well as the applicant's detailed address. Based on these pieces of information, we construct two measures that capture a city's innovation output level. We first use a city's total number of IP applications (in thousands) in a year to capture the local innovation

13 There are 333 prefectural-level municipalities/units (i.e., cities defined in this study) in China. We include both prefectural-level and county-level cities in our baseline regressions, but only include prefectural-level cities in our matched DiD analysis to further insure that the size of the treatment cities and control cities are comparable (in fact, the propensity matching procedure has taken the size factor into account and would also automatically drop the county-level cities if we do not impose this restriction).

productivity (*P_Apply*). We only consider IPs in our study because they are regarded as the most original patents and are the most difficult type of patents for inventors to apply.[14] We only include patents applied by firms and exclude others that are applied by universities, governments, individuals, and non-profit institutions. Second, as the SIPO also provides patent grant information, we use a city's total number of granted patents (in thousands) that are applied in the application year to capture the quality of innovation (*P_Grant*). To further evaluate the quality and influence of a patent, we obtain patent citation information from Google Patents between 1985 and 2014 and aggregate them up to the city-year level (in thousands). Following Hall, Jaffe, and Trajtenberg (2001), we adjust the truncation bias issue in the patent citation data. Specifically, we divide the number of citations per patent by the average number of citations per patent in the same patent technology class and the same year. We then aggregate adjusted numbers of citations up at the city-year level (in thousands) and construct the variable *P_Cite*.[15]

We measure a city's entrepreneurial activities by the number of new firms established. The new firm registration data are collected from the SAIC, which covers all records of new firm registrations in China since 1985. We aggregate the variable up to the city level and calculate the city's total number of new firm registrations (in thousands) in a year (labeled as *F_Est*) to capture the city's entrepreneurial activities.

As the distribution of the firm registration sample and the patent sample is right-skewed, we take the natural logarithm of patent application counts, patent grant counts, patent citation counts, and new firm registration counts. To avoid losing observations, we add one to the actual number of all measures when calculating the natural logarithm. We label these variables as *INNOV_PApply*, *INNOV_PGrant*, *INNOV_Cite*, and *ENTREPRE_FEst*, respectively.

14 There are three types of patents in China: IPs, utility model patents (UMPs), and design patents (DPs). The Chinese IPs are granted for a new technical solution relating to a product, a process, or an improvement, the Chinese UMPs are granted for new and practical technical solutions related to the shape and/or structure of a product, and the Chinese DPs are granted for new designs related to the shape, pattern or their combinations, or the combination of color, shape, and/or pattern that is aesthetically pleasing and industrially applicable. On the one hand, computation of both IPs and UMPs would have an overlap, as there is the parallel filing of a UMP and an IP, followed by the abandonment of the UMs once the IP is officially granted. On the other hand, only IPs requires "substantive examination," indicating stricter grant standards and higher "inventiveness."

15 We adjust the number of patent grants to address the truncation bias concern as well, following Hall, Jaffe, and Trajtenberg (2001) by dividing each patent by the average number of patents applied from firms in the same technology class as the patent in that year. We do not report the results using the adjusted number of patent grants in the paper because of several reasons. First, our 30-year sample period ends in 2014. As the patent examination period is usually 2 years in China, the truncation bias for patent grants is unlikely to be serious. Second, there is no unique firm identification number available in the Chinese patent dataset, which creates problems for the adjustment as the number of firms in each technology class is required when adjusting the number of patent grants. Third, only the number of patent grants might be affected by the truncation bias, but not the number of applications. Unlike US patent data in which only granted patents are included, we can observe both the number of patent applications and the number of patent grants in the Chinese patent dataset. We show that both innovation quantity variables have significant results. Our results are robust to the adjustment and available upon request. Other papers that study the innovation output of Chinese firms have used similar measures, see, for example, Fang, Lerner, and Wu (2017) and Cong and Howell (2021).

3.2.b. Defining national high-tech zones and other control variables

We obtain a list of 136 China national high-tech zones from the website of the MOST, available at http://www.most.gov.cn/gxjscykfq/ldjh/. We then manually collect the precise date when these zones were established and certified by the MOST at the national level (rather than at the province level). By combining the list and the establishment timetable of national high-tech zones, we are able to define a city's national high-tech zone status.

We provide summary statistics on national high-tech zones in Table I. Panel A shows that more than 80% of national high-tech zones were established before 2000. As China had not joined the WTO until 2001, most national high-tech zones were established when the cities where they located had not experienced much technological spillover from foreign companies. Panel B shows that the geographical distribution of national high-tech zones is more similar to the geographical distribution of population than that of GDP.[16] Therefore, we can observe from the statistics that the aim of the policy of establishing national high-tech zones was more to balance regional economic differences than to select regions that had better economic conditions. For cities that have more than one national high-tech zone, we consider the year when the first zone was established in the city.

Following the existing literature, we control for a vector of city characteristics that could affect a city's innovation output and entrepreneurial activities. All city-level control variables are collected from the China City Statistical Yearbook from 1987 to 2014. We mainly control for economic variables including the natural logarithm of the city's population (*Population*), the natural logarithm of the city's GDP (*GDP*), the natural logarithm of the average wage in the city (*AvgWage*), and the Consumer Price Index (*CPI*).[17] To control for the industrial structure of a city, we include the percentage of GDP from the manufacturing sector (*GDP2_%*), percentage of GDP from the service sector (*GDP3_%*) in the regressions. We replace missing values with the average value of the city-year observations 1 year before and 1 year after the missing value year. Table I Panel C provides detailed definitions of the variables used in our tests.

3.3 Summary Statistics

We report summary statistics of all variables discussed above in Table I Panel D. To alleviate the concern that our results could be driven by outliers, we winsorize all variables at the 1st and 99th percentiles.

On average, a sample city has 181 IP applications per year, among which 64 patent applications are granted. These granted patents for an average city receive a total of fifty raw citations (not reported) or ten truncation adjusted citations subsequently. Cornaggia *et al.* (2015) report that an average US state in their sample receives 2,988 granted patents in 3 years and these patents receive a total of 39,085 citations. From our summary statistics, a province in China on average has nineteen cities, and so it has 3,648 (=64*19*3) granted patents, and these patents receive 2,850 (=50*19*3) subsequent citations in 3 years. Thus,

16 According to the Fifth National Population Census of China conducted in 2000, 39% of the population is located in the eastern China, 33% in the middle China, and 28% in the western China; while eastern China generates 58% of total GDP, middle China generates 24% and western China generates 18%, according to the National Bureau of Statistics of China.

17 We also add past 1- or 3-year GDP growth rate for a city to the regressions as a control variable. Our main findings are robust to adding the growth rate variable and the coefficient estimate on growth rate is statistically insignificant. The results are available upon requests.

Table I. Summary statistics on national high-tech zones

This table presents variable definitions and descriptive statistics for the sample cities and national high-tech zones. Panel A lists national high-tech zones in the sample by the establishment year. Panel B reports national high-tech zones in the sample by geographical area. Panel C defines all variables used in our analyses. Panel D reports the descriptive statistics for the sample cities. The sample consists of 8,890 city-year observations for 473 cities over a 30-year period from 1985 to 2014. All variables are winsorized at the 1st and 99th percentiles.

Panel A: Number of national high-tech zones established by year

Est. year	Freq.	Percent	Cum.
1988	15	11.03	11.03
1989	1	0.740	11.76
1990	6	4.410	16.18
1991	19	13.97	30.15
1992	50	36.76	66.91
1993	5	3.680	70.59
1994	3	2.210	72.79
1995	2	1.470	74.26
1996	1	0.740	75
1997	2	1.470	76.47
1999	4	2.940	79.41
2000	4	2.940	82.35
2001	8	5.880	88.24
2002	5	3.680	91.91
2003	5	3.680	95.59
2005	1	0.740	96.32
2006	2	1.470	97.79
2010	2	1.470	99.26
2012	1	0.740	100
Total	136	100	

Panel B: Number of national high-tech zones established by region

Geog.	Freq.	Percent	Cum.
Eastern	65	47.79	47.79
Middle	40	29.41	77.21
Western	31	22.79	100
Total	136	100	

Panel C: Definition of variables

Variable	Definition
Measures of innovation	
$INNOV\_PApply_{i,t+1}$	Natural logarithm of one plus a city i's total number of IP applications in year $t+1$
$INNOV\_PGrant_{i,t+1}$	Natural logarithm of one plus a city i's total number of IPs applied in year $t+1$ and finally got granted

(continued)

Table I. Continued

Panel C: Definition of variables

Variable	Definition
$INNOV\_PCite_{i,t+1}$	Natural logarithm of one plus a city i's total number of citations adjusted for truncation bias on city i's IPs applied for in year $t+1$
Measure of entrepreneurship	
$ENTREPRE\_FEst_{i,t+1}$	Natural logarithm of one plus a city's total number of new firms registrations in year $t+1$
Measures of innovation growth	
$PApply\_Growth_{i,-3\ to\ -1}$	Change in the number of patent applications over the 3-year period before the establishment year
$PGrant\_Growth_{i,-3\ to\ -1}$	Change in the number of granted patents which are applied over the 3-year period before the establishment year
$PCite\_Growth_{i,-3\ to\ -1}$	Change in the number of adjusted patent citations over the 3-year period before the establishment year
Measure of entrepreneurship growth	
$FEst\_Growth_{i,-3\ to\ -1}$	Change in the number of new firm registrations over the 3-year period before the establishment year
Control variables used in baseline specifications	
$Population_{i,t}$	Natural logarithm of city i's total population at the end of year t
$GDP_{i,t}$	Natural logarithm of city i's total GDP in year t
$GDP2\_\%_{i,t}$	City i's % GDP from the secondary industry in year t
$GDP3\_\%_{i,t}$	City i's % GDP from the tertiary industry in year t
$AvgWage_{i,t}$	Natural logarithm of city i's average wage in year t
$CPI_{i,t}$	City i's CPI in year t

Panel D: Summary statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
P_Apply	8,890	0.181	0.712	0.000	5.342
P_Grant	8,890	0.064	0.243	0.000	1.777
P_Cite	8,890	0.001	0.002	0.000	0.015
F_Est	8,045	3.632	5.976	0.049	37.729
Population	8,890	5.436	1.027	−0.211	8.124
GDP	8,890	5.068	1.880	−2.356	10.068
GDP2_%	8,890	46.417	12.330	0.400	93.407
GDP3_%	8,890	32.943	9.115	0.200	85.340
AvgWage	8,890	8.998	1.110	5.540	11.451
CPI	8,890	106.631	7.290	96.400	133.057

the total number of granted patents generated in a certain region is similar between the USA and China, while Chinese patents enjoy fewer citations on average. Regarding entrepreneurial activities, an average city has 3,632 new firm registrations per year.

4. Baseline Results

A standard approach to assess the effect of national high-tech zone establishments is to run OLS regressions that regress a city's innovation output and entrepreneurial activity variables on a dummy variable that represents the city's high-tech-zone status. This approach, however, suffers from endogeneity concerns as we described before.

To address the endogeneity concern, we use a DiD approach that makes use of staggered establishments of national high-tech zones in various Chinese cities during our sample period. The DiD approach has two advantages in addressing the concerns discussed above. First, the DiD approach absorbs constant unobserved differences between the treatment group cities (that have national high-tech zones established) and the control group cities (that do not have national high-tech zones established). Second, the DiD approach stripes out omitted time trends that are correlated with the establishment of high-tech zones and local innovation and entrepreneurship. In addition, our setting provides another advantage. Because the establishment of national high-tech zones takes place at exogenously different times for different cities, which represents multiple shocks to China's place-based policies, it avoids a common identification difficulty faced by studies with a single shock: potential omitted variables coinciding with the shock could directly affect local innovation output and entrepreneurial activities.

We undertake the DiD approach following Bertrand and Mullainathan (2003) by estimating the following model:

$$Y_{i,t+1} = \alpha + \beta HTZone_{i,t} + \gamma' CONTROLS_{i,t} + \delta YEAR_t + \theta CITY_i + \varepsilon_{i,t}, \tag{1}$$

where i indexes city and t indexes year. Y represents innovation output and entrepreneurial activity variables used in our regressions. To capture the innovation quantity and quality, we use the natural logarithm of one plus city i's total number of IP applications in year $t+1$ ($INNOV\_PApply_{i,t+1}$), the natural logarithm of one plus city i's total number of granted patents that are applied in year $t+1$ ($INNOV\_PGrant_{i,t+1}$), and the natural logarithm of one plus city i's total number of citations from IPs that are applied in year $t+1$ ($INNOV\_PCite_{i,t+1}$). We proxy entrepreneurial activities by using the natural logarithm of one plus city i's total number of firms registered in year $t+1$ ($ENTREPRE\_FEst_{i,t+1}$). $HTZone_{i,t}$ is the key variable of interest, which is a dummy variable that equals one if a national high-tech zone has been established by the end of year t in city i, and zero otherwise. $CONTROLS_{i,t}$ includes several control variables that could affect local innovation and entrepreneurship as described before. We include year and city fixed effects to account for time-specific shocks and time-invariant unobservable city characteristics that may affect the relation between the establishment of high-tech zones and local innovation and entrepreneurship.[18] In all regressions, we cluster standard errors at the city level.[19]

18 In unreported tests, we include province-by-year fixed effects in the regressions, in addition to year fixed effects and city fixed effects, to capture the regional trends and other contemporaneous events in a given province year. The coefficient estimates on *HTZone* are all positive and statistically significant under this specification at the 5% or 1% level. The results are available upon requests.

19 We are aware of the issue pointed out by De Chaisemartin and D'Haultfoeuille (2020) that DiD estimates could be affected in a two-way fixed effect setting when the treatment effect is heterogeneous between groups, or over time, and causes a significant amount of weights to be negative. We find that most of the weights in our regressions are positive (93% in the baseline regressions and 100% propensity-score-matched regressions). In the case of the baseline regressions in which the weights are not all positive, we check the standard errors of the treatment effect that lead the DiD estimators to change signs, and find that they are 20–353 times larger than the standard errors of our DiD estimates. The above statistics suggest that our results are unlikely to be affected by the negative-weight issue in the two-way fixed effect setting.

Table II. Baseline DiD specification

This table reports pooled OLS regression results of the following model:

$INNOV\_PApply\ (INNOV\_PGrant, INNOV\_PCite,\ ENTREPRE\_FEst)_{i,t+1} = \alpha + \beta HTZone_{i,t} + \gamma' CONTROLS_{i,t} + \delta YEAR_t + \theta CITY_i + \varepsilon_{i,t}.$

Variable definitions are provided in Table I Panel C. Year fixed effects, $YEAR_t$, and city fixed effects, $CITY_i$, are included in all regressions. Coefficient estimates are shown, and their standard errors are clustered by city and displayed in parentheses below. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) $INNOV\_PApply_{i,t+1}$	(2) $INNOV\_PGrant_{i,t+1}$	(3) $INNOV\_PCite_{i,t+1}$	(4) $ENTREPRE\_FEst_{i,t+1}$
HTZone	0.369***	0.503***	0.175***	0.129**
	(0.082)	(0.089)	(0.032)	(0.058)
Population	−0.099*	−0.156**	−0.076***	0.192***
	(0.057)	(0.062)	(0.019)	(0.050)
GDP	0.054	0.041	0.055***	−0.034
	(0.042)	(0.042)	(0.017)	(0.040)
GDP2_%	0.003	−0.000	−0.003**	0.001
	(0.004)	(0.004)	(0.001)	(0.003)
GDP3_%	0.012**	0.012**	0.001	−0.004
	(0.006)	(0.006)	(0.001)	(0.004)
AvgWage	0.045	0.158**	0.042**	0.086
	(0.071)	(0.066)	(0.019)	(0.071)
CPI	0.002	0.001	0.002	0.015*
	(0.005)	(0.005)	(0.002)	(0.008)
Constant	−0.598	−1.584	−0.376	0.182
	(0.990)	(1.001)	(0.294)	(1.112)
Observations	8,351	8,351	8,351	7,780
R-squared	0.906	0.883	0.838	0.860
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

The coefficient estimate on *HTZone* in Equation (1) is the DiD estimator that captures the causal effect of the establishment of national high-tech zones on local innovation and entrepreneurship. If the establishment of high-tech zones promotes local innovation output and entrepreneurial activities, we should observe positive and significant coefficient estimates on *HTZone*. Note that we only include *HTZone* but not the treatment dummy and time dummy in the regressions, because the two dummies are absorbed by city and year fixed effects, respectively.

In Table II, we examine the effect of national high-tech zone establishments on a city's patent applications, patent grants, patent citations, and new firm registrations per year by estimating Equation (1). In Column (1), the dependent variable is the patent application quantity variable, *INNOV_PApply*. The coefficient estimate on *HTZone* is positive and significant at the 1% level. The economic effect is sizable: the magnitude of the coefficient estimate in Column (1) suggests that the number of patent applications of a treatment city increases by 36.9% more than that of a control city in 1 year after the establishment of national high-tech zones, compared with the number prior to the establishment. In Column (2), we replace the dependent variable with *INNOV_PGrant*. In Column (3), we use the patent citation quantity variable *INNOV_PCite* as the dependent variable. The coefficient estimates on *HTZone* in Columns (2) and (3) are both positive and significant at the 1% level. The magnitudes of the coefficient estimates suggest that a treatment city exhibits a 50.3% larger increase in the number of patent grants and a 17.5% larger increase in the number of future citations after the national high-tech zone is established, compared with those of the control cities surrounding the high-tech zone establishments.

In Column (4), we replace the dependent variable with the number of new firm registrations, *ENTREPRE_FEst*. The coefficient estimate on *HTZone* in Column (4) is positive and significant at the 5% level. The coefficient magnitude suggests that the establishment of a national high-tech zone leads to a 12.9% larger increase in the number of new firm registrations 1 year after the establishment, compared with that of the control cities surrounding the high-tech zone establishments.

Our baseline DiD results show that the establishment of national-level high-tech zones appears to have a positive, causal effect on cities' local innovation output and entrepreneurial activities.

5. Addressing Various Concerns

While the DiD approach with multiple shocks provides strong support that the establishment of high-tech zones has a positive effect on local innovation output and entrepreneurial activities, there still exist concerns that treatment cities may not be comparable to control cities in some dimensions. Hence, our results could be driven by the differences in these cities' local conditions rather than the establishment of national high-tech zones. We address this concern in a few ways in this section.

5.1 Did Approach with Propensity Score Matching

To eliminate the possibility that our results are driven by differences in other characteristics between treatment and control cities, we match cities in the treatment and control groups using the propensity score matching algorithm. First, we estimate a probit model in which the dependent variable equals one if city *i* has a national high-tech zone established in year *t* (treatment city) and zero otherwise (control city). Independent variables are the same as those in Equation (1) measured in year $t-1$, including $Population_{-1}$, GDP_{-1}, $AvgWage_{-1}$, $GDP2\_\%_{-1}$, $GDP3\_\%_{-1}$, and CPI_{-1}. To ensure the satisfaction of the parallel trend assumption, a key identification assumption of the DiD approach, we include innovation growth variables over 3 years prior to the establishment of national high-tech zones, $PApply\_Growth_{i,-3\ to\ -1}$, $PGrant\_Growth_{i,-3\ to\ -1}$, $PCite\_Growth_{i,-3\ to\ -1}$ (i.e., the growth in the number of patent applications, the growth in the number of patent grants, and the growth in the number of total patent citations, respectively) as well as the entrepreneurship growth variable over 3 years prior to the establishment of a national high-tech zone, $FEst\_Growth_{i,-3\ to\ -1}$ (i.e., the growth in the number of new firm registrations). We also include province and year fixed effects in the regressions and report the results in Table III.

Column (1) of Table III Panel A presents the estimates of the probit model. The results show that our specification captures a large proportion of variation in the dependent variable, as the pseudo-R^2 is 42% with a *p*-value from the χ^2 test below 0.001. Hence, we are able to reject the null hypothesis that all independent variables are jointly zero. We next use the

Table III. DiD tests with PSM

This table reports the diagnostics and results of the DiD tests on the effect of the establishment of national high-tech zones on local innovation and entrepreneurship. We match cities using a one-to-one nearest neighbor propensity matching, without replacement, on a set of observable city characteristics. Panel A reports parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. The dependent variable in the probit model is the *HTZone* dummy. Column (1) contains the parameter estimates of the probit model estimated using the sample prior to matching. These estimates are then used to generate the propensity scores for matching treatment cities and control cities. Column (2) contains the parameter estimates of the probit model estimated using the subsample of matched treatment–control pairs after matching. Definitions of all other variables are listed in Panel C of Table I. The models in both columns of Panel A are estimated with province and year fixed effects. Coefficient estimates are reported and standard errors are displayed in parentheses below. Panel B reports the univariate comparisons between the treatment and control cities' characteristics and their corresponding *t*-statistics. Panel C provides the DiD test results. Standard errors are given in parentheses below the mean differences in innovation and entrepreneurial activities. The dependent variable is *P_Apply**, city *i*'s total number of patent applications in a given year, or *P_Grant**, city *i*'s total number of granted patents that are applied in a given year, or *P_Cite**, city *i*'s total number of patent adjusted citations generated by patent applied in a given year, or *F_Est**, city *i*'s total number of new firm registrations in thousands in a given year. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pre-match propensity score regression and post-match diagnostic regression

	(1) Pre-match	(2) Post-match
$PApply\_Growth_{-3\ to\ -1}$	0.004	0.006
	(0.007)	(0.015)
$PGrant\_Growth_{-3\ to\ -1}$	0.015	0.000
	(0.023)	(0.041)
$PCite\_Growth_{-3\ to\ -1}$	−0.005	−0.021
	(0.015)	(0.032)
$FEst\_Growth_{-3\ to\ -1}$	0.000	−0.000
	(0.000)	(0.000)
$Population_{-1}$	1.173***	0.310
	(0.242)	(0.382)
GDP_{-1}	0.705***	0.091
	(0.194)	(0.308)
$AvgWage_{-1}$	−0.177	0.381
	(0.357)	(0.541)
$GDP2\_\%_{-1}$	0.084***	0.010
	(0.015)	(0.022)
$GDP3\_\%_{-1}$	0.117***	0.033
	(0.022)	(0.030)
CPI_{-1}	−0.103	−0.054
	(0.073)	(0.122)
Constant	−15.409*	−0.340
	(8.717)	(13.746)
Observations	2,690	210

(continued)

Table III. Continued

Panel A: Pre-match propensity score regression and post-match diagnostic regression

	(1) Pre-match	(2) Post-match
Province FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R-squared	0.42	0.055

Panel B: Differences in pre-establishment characteristics

	Treatment	Control	Difference	*t*-statistics
GDP	4.408	4.206	0.202	1.206
Population	5.549	5.472	0.077	0.659
AvgWage	48.053	48.233	−0.180	−0.100
GDP2_%	29.362	28.743	0.619	0.547
GDP3_%	8.169	8.096	0.073	0.689
CPI	105.039	104.896	0.143	0.175
PApply_Growth	10.519	8.074	2.444	0.709
PGrant_Growth	3.102	2.611	0.491	0.338
PCite_Growth	−0.081	0.008	−0.089	−0.632
FEst_Growth	−0.126	0.006	−0.133	−0.999

Panel C: DiD test

	Mean treatment difference (after-before)	Mean control difference (after-before)	Mean DiD estimator (treat-control)	*t*-statistic for DiD
P_Apply	24.159	11.399	12.760	2.390
	(2.433)	(4.752)	(5.339)	
P_Grant	9.476	4.370	5.106	1.862
	(1.138)	(2.495)	(2.742)	
P_Cite	0.560	0.094	0.466	3.962
	(0.029)	(0.114)	(0.118)	
F_Est	1.638	0.801	0.837	2.860
	(0.157)	(0.247)	(0.293)	

propensity scores calculated from the probit regression to perform the nearest-neighbor propensity score matching without replacement in a dynamic manner. Specifically, for each treatment city i in an event year t, we pick the control city as the one with the highest propensity score and has not been designated as a high-tech zone in year t. We set the caliper of the matching to 0.6, which means that the propensity score distance between two cities can be no more than 0.6 if they are to be matched observations, to further assure that matched observations are similar in all dimensions.[20] We obtain 105 unique pairs of matched cities.

20 The choice of calipers reflects the tradeoff between matching precision and statistical power. Our results are robust to alternative caliper choices.

To ensure that the parallel trend assumption is not violated, we perform a few diagnostic tests. First, we observe that the coefficient estimates on the growth variables in Panel A Column (1) are not statistically significant, suggesting that there is no obvious difference in the trend of pre-treatment innovation and entrepreneurship growth even before we do the match. Next, we re-run the probit regression on the matched sample and report the results in Column (2). We observe that the coefficient estimates on the growth variables are not significant either. In addition, the pseudo-R^2 drops dramatically to 5.5% and the p-value of the χ^2 test suggest that we cannot reject the null hypothesis that all of the coefficient estimates in the regressions are jointly equal to zero.

Third, since the validity of the DiD estimator relies on the satisfaction of the parallel trend assumption, we make comparisons of cities' characteristics before the establishment of a national high-tech zone between the treatment group and the control group. Table III Panel B shows that none of the univariate comparisons before the establishment of high-tech zones is statistically significant. To be concrete, the differences in innovation and entrepreneurship growth variables are not statistically significant between treatment and control groups, suggesting once again that the parallel trend assumption is not violated. In addition, the univariate comparisons in population, GDP, the industry structure of GDP, average wage, and CPI between the two groups of cities suggest that there are no differences in these characteristics between the two groups of cities.

Panel C reports the DiD estimators. Column (1) presents the average change in the number of patent applications, patent grants, patent citations, and the number of new firm registrations (in thousands) for the treatment cities. We obtain the average change by subtracting the average number of patent applications (number of grants, citations, and new firm registrations) over the 4-year period just preceding the establishment of the national high-tech zone from the average number of patent applications (number of grants, citations, and new firm registrations) over the 4-year period after establishment. We calculate the average change in the control group in a similar way and report the results in Column (2). Column (3) reports the DiD estimators (the difference between Column (1) and Column (2)). Column (4) reports the corresponding two-tailed t-statistics.

There are two main findings observed from Panel C. First, we find that both treatment cities and control cities experience an increase in innovation output and entrepreneurial activities after the (pseudo) establishment of high-tech zones, which is consistent with the results of our baseline regressions. Second and more importantly, the DiD estimators are positive and statistically significant, which suggests that the increases in innovation output and entrepreneurial activities for the treatment group are larger than those for the control group. The magnitude of the DiD estimators on *P_Apply* indicates that the establishment of a national high-tech zone, on average, results in 12.8 more patent applications for the treatment cities than for the control cities per year. Similarly, the treatment cities exhibit 5.1 more granted patents, 0.5 more citations, and 837 more new firm registrations per year than the control cities.

Figure 2 depicts the trends. Panel A shows that the number of patent applications for the treatment and control groups over a 9-year period centered on the zone establishment year (denoted as year 0). Panel B shows the number of granted patents; Panel C depicts the total number of citations; and Panel D illustrates the number of new firm registrations. We observe that the two lines representing outcome variables in each of these panels are trending closely in parallel in the 4 years leading to the national high-tech zone establishment year. After the establishment of a high-tech zone, however, the two lines start to diverge,

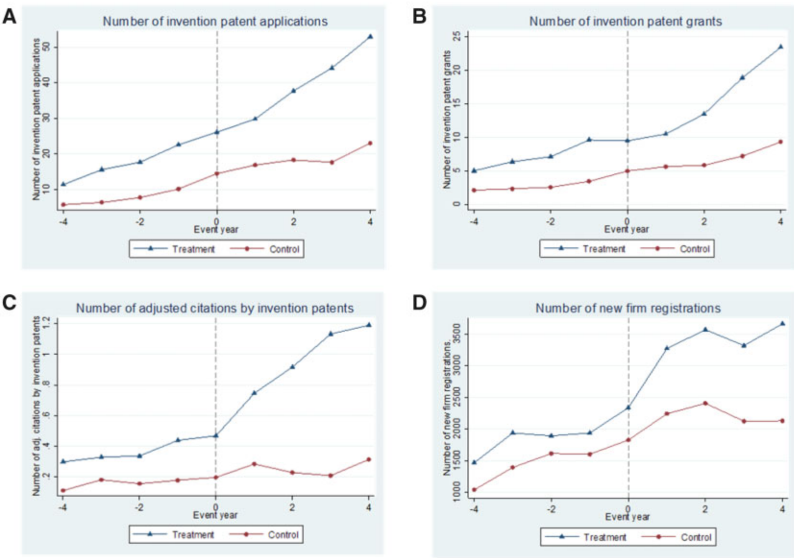

Figure 2. Patent and firm registration dynamics surrounding establishment of zones. This figure shows the mean difference in innovation and entrepreneurship captured by an average number of patent applications, patent grants, patent citations, and new firm registrations for treatment and control cities from 4 years before the establishment of national high-tech zones to 4 years after the establishment of zones. The sample consists of 105 treatment cities and 105 unique control cities matched. Year 0 is defined as the event year when zones are established. Panel A shows the difference in patent applications (*P_Apply*), Panel B shows the difference in patents applied and finally granted (*P_Grant*), Panel C shows the difference in adjusted patent citations (*P_Cite*), and Panel D shows the difference in new firm registrations (*F_Est*). (A) Number of patent applications. (B) Number of patents grants. (C) Number of patent citations. (D) Number of new firm registrations.

indicating that the treatment group cities enjoy a larger increase in innovation output and entrepreneurial activities than control group cities.

To further ensure that our results are not driven by reverse causality, following Bertrand and Mullainathan (2003), we next examine the dynamics of the effect of establishments of national high-tech zones in a regression framework illustrated by the following equation:

$$P\_Apply(P\_Grant,\ P\_Cite,\ F\_Est)_{i,t}=\alpha+\sum_{t=-4}^{4}\beta_t Treat_i * Period_t+\sum_{t=-4}^{4}Period_t+\varepsilon_{i,t}, \qquad (2)$$

where we use a set of dummy variables (*Period*) to interact with the treatment dummy variable (*Treat*). $Period_{-4}$, $Period_{-3}$, $Period_{-2}$, and $Period_{-1}$ correspond to 4, 3, 2, and 1 year, respectively, before the establishment of national high-tech zones; $Period_0$ is the year when national high-tech zones are established; $Period_1$, $Period_2$, $Period_3$, and $Period_4$ correspond to 1, 2, 3, and 4 years, respectively, after the establishment of national high-tech zones. To avoid multicollinearity problems, we drop the dummy variable, Treat, in the regressions.

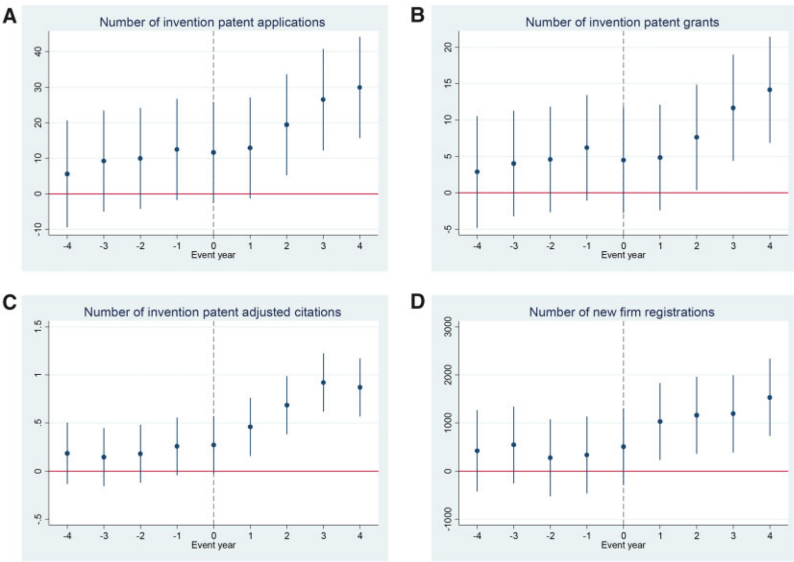

Figure 3. The dynamics of national high-tech zone establishments on local innovation and entrepreneurship. This figure plots the coefficient estimates of β_t in the following model in a 9-year window centered on the establishment years:

$$P\_Apply(P\_Grant,\ P\_Cite, F\_Est)_{i,t} = \alpha + \sum_{t=-4}^{4} \beta_t Treat_i * Period_t + \sum_{t=-4}^{4} Period_t + \varepsilon_{i,t}$$

where $Period_t$ is a set of dummy variables. $Period_{-4}$, $Period_{-3}$, $Period_{-2}$, and $Period_{-1}$ corresponds to 4, 3, 2, and 1 year, respectively, before the establishment of the national high-tech zones; $Period_0$ is the year when the national high-tech zones are established; $Period_1$, $Period_2$, $Period_3$, and $Period_4$ corresponds to 1, 2, 3, and 4 years, respectively, after the establishment of the national high-tech zones. The sample consists of 105 treatment cities and 105 unique control cities matched. Year 0 is defined as the event year when zones are established. We plot the coefficient estimates of β_t when the dependent variable is the number of patent applications in Panel A, the number of patents applied and finally granted in Panel B, the number of adjusted citations of granted patents in Panel C, and the number of new firm registrations in Panel D. The center points show the point estimates of β_t and the vertical lines denote the 95% confidence intervals of β_t estimates. (A) Number of patent applications. (B) Number of patent grants. (C) Number of patent citations. (D) Number of new firm registrations.

Figure 3 plots the coefficient estimates of β_t in Equation (2) over a 9-year period centered on the zone establishment year (denoted as year 0). We plot the coefficient estimates of β_t when the dependent variable is the number of patent applications in Panel A, the number of granted patents in Panel B, the number of patent citations in Panel C, and the number of new firm registrations in Panel D. In Figure 3, the center points show the point estimates of β_t and the vertical lines denote the 95% confidence intervals of β_t estimates. Figure 3 shows that the coefficient estimates of β_t are not statistically significant from zero before the establishment of national high-tech zones. This observation suggests that there are no significant differences in the outcome variables before the establishments of high-tech zones and hence our framework satisfies the parallel trend assumption of the DiD analysis. After the establishment of a high-tech zone, however, one can observe upward trends in the coefficient estimates in all four panels and the coefficient estimates are significant at the 5% level. This observation confirms our previous results that the establishment of national high-tech zones has positive effects on local innovation output and entrepreneurial activities.

Overall, the evidence from the DiD tests using matched control cities lends further support to our baseline results that the national high-tech zones appear to have positive, causal effects on local innovation output and entrepreneurial activities.

5.2 Additional Identification Tests

In this subsection, we perform a number of additional tests to further address the concern that our baseline DiD results may not reflect a causal link between national high-tech zones and local innovation output and entrepreneurial activities.

First, because national high-tech zones need to be certificated by China's central government and the certification could bring many preferential policies, such as discounted land-use fees, tax deductions, and special offers in bank loans (Wang, 2013; Alder, Shao, and Zilibotti, 2016; Zheng *et al.*, 2017), there still exists a possibility that local governments choose to establish high-tech zones in cities that enjoy higher innovation output and more active entrepreneurial activities so that it would be easier for them to get the certification by the central government (although we undertake the propensity score matching approach to ensure that our DiD results are not driven by differences in city characteristics). If this argument is true, our previous results could be driven by the selection of local governments rather than the establishment of a national high-tech zone itself.

To address this concern, we use a subsample of treatment cities in which the establishment of national high-tech zones is initiated directly by the central government rather than the local government (the Type I national high-tech zones). Hence, high-tech zones in these treatment cities do not go through the typical two-step procedure in which the zone is first established by the local government and later certified by the central government. China's economic and political reforms starting from 1978 provide more incentives for local governments to promote local economic prosperity while the central government would focus more on gross economic growth and cross-region economic disparity (Montinola, Qian, and Weingast, 1995). Therefore, high-tech zones that are established directly by the central government do not suffer from the local government selection concern as we mentioned above.

We identify Type I national high-tech zones by looking at the date when the high-tech zone is established and the date when it is approved by the MOST as a national high-tech zone. A national high-tech zone is defined as the Type I zone if the above two dates coincide. In other words, the high-tech zone does not go through the two-step procedure and is established directly by the central government. We perform tests using the same framework from the baseline regressions and substitute the key variable with $Enforced\_HTZone_{i,t}$, which equals one if the high-tech zone is initia6ted directly by the central government by the end of year t in city i, and zero otherwise. We use the same matched control cities as in Section 5.1 and report the results in Table IV. We observe that all of the coefficient estimates on $Enforced\_HTZone_{i,t}$ are statistically significant, suggesting that the positive effect

Table IV. Excluding type II high-tech zones

This table shows the results for analyses that exclude type II high-tech zones. We only include treatment cities where the establishment of a national high-tech zone was initiated by the central government rather than the local government. The regression framework is the same as that in Equation (1), while the key variable is substituted with *Enforced_HTZone*. The variable *Enforced_HTZone* equals one when a zone has been initiated by the central government by year *t* in city *i*, and zero otherwise. Definitions of all other variables are listed in Table I Panel C. Coefficient estimates are shown below, and their standard errors are clustered by city and displayed in parentheses below. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *INNOV_PApply*	(2) *INNOV_PGrant*	(3) *INNOV_PCite*	(4) *ENTREPRE_FEst*
Enforced_HTZone	0.871***	1.039***	0.409**	0.399**
	(0.297)	(0.310)	(0.179)	(0.178)
Population	0.156	0.094	0.028	0.241**
	(0.130)	(0.126)	(0.030)	(0.111)
GDP	−0.023	−0.051	−0.001	−0.025
	(0.096)	(0.090)	(0.028)	(0.086)
GDP2_%	0.020***	0.019**	0.004*	0.001
	(0.008)	(0.008)	(0.002)	(0.008)
GDP3_%	0.016	0.015	0.001	0.000
	(0.013)	(0.012)	(0.003)	(0.009)
AvgWage	0.265	0.338	0.073	0.213
	(0.204)	(0.209)	(0.052)	(0.141)
CPI	−0.008	−0.013	−0.008	0.031***
	(0.012)	(0.013)	(0.007)	(0.009)
Constant	−4.724**	−3.999	−0.086	−1.531
	(2.261)	(2.477)	(0.917)	(1.536)
Observations	3,382	3,382	3,382	3,303
R-squared	0.870	0.840	0.679	0.807
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
PSM	Yes	Yes	Yes	Yes

of the national high-tech zone establishments on local innovation output and entrepreneurial activities are robust even if we restrict the treatment cities to those that have national high-tech zones initiated directly by the central government.

Second, one concern is that some unobservable omitted variables coinciding with the establishment of national high-tech zones could drive our results. As we discussed before, since the establishments of high-tech zones happen in different cities at different times, the possibility that unobservable omitted variables affecting local innovation output and entrepreneurial activities coincide with the establishments of high-tech zones is very small.

To further address this concern, we conduct a placebo test by randomly assigning fictitious event time in our sample. Specifically, we first obtain the distribution of event time (high-tech zone establishment year). We then move event time 3 years backward so that they are 3 years prior to the true event year. We repeat the baseline DiD regressions based on the fictitious event time. Specifically, we replace the key variable of interest with a

Table V. Placebo tests using pseudo-event year

This table reports the results of identification tests using a pseudo-event year for the DiD analysis. We first obtain the distribution of the event years and then move back the event years 3 years before the real event year while keeping the same distribution. The key variable of the regressions is *HTZone_3y_Before*, a dummy equals one when a national high-tech zone is established by 3 years prior to the actual event year (year *t*–3) in city *i*. Definitions of all other variables are listed in Table I Panel C. Coefficient estimates are shown below, and their standard errors are clustered by city and displayed in parentheses below. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *INNOV_PApply*	(2) *INNOV_PGrant*	(3) *INNOV_PCite*	(4) *ENTREPRE_FEst*
HTZone_3y_Before	0.058	0.114	0.022	0.043
	(0.068)	(0.070)	(0.021)	(0.063)
Population	−0.065	−0.095	−0.041*	0.173***
	(0.061)	(0.061)	(0.023)	(0.060)
GDP	0.025	0.026	0.031*	−0.028
	(0.039)	(0.039)	(0.017)	(0.063)
GDP2_%	−0.000	−0.000	−0.001	−0.005
	(0.004)	(0.004)	(0.002)	(0.005)
GDP3_%	−0.004	−0.001	−0.002	−0.018*
	(0.005)	(0.005)	(0.002)	(0.011)
AvgWage	0.230*	0.233*	0.152***	0.268**
	(0.130)	(0.126)	(0.040)	(0.122)
CPI	−0.008	−0.005	−0.006*	−0.001
	(0.006)	(0.006)	(0.003)	(0.006)
Constant	−2.482*	−2.432*	−0.776	2.165*
	(1.401)	(1.299)	(0.521)	(1.267)
Observations	2,291	2,291	2,291	2,231
R-squared	0.852	0.801	0.637	0.846
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
PSM	Yes	Yes	Yes	Yes

dummy, $HTZone\_3y\_Before_{i,t}$, that equals one when a national high-tech zone is established by year $t-3$ in city i and zero otherwise, and report the results in Table V. We observe that none of the coefficient estimates on $HTZone\_3y\_Before_{i,t}$ is statistically significant. The results show that falsely assumed high-tech zone establishments do not exhibit any effect on local innovation output and entrepreneurial activities. Therefore, our results are not driven by omitted variables that coincide with the establishment of national high-tech zones.

Third, we undertake another placebo test by randomly assigning treatment and control cities. The rationale of this test is that if the establishment of national high-tech zones indeed promotes local innovation output and entrepreneurial activities, the effect should only exist in real treatment cities. In other words, we shall not expect to observe any effect in a city if it is not a treatment city. We repeat the baseline DiD results in a sample in which treatment and control cities are randomly assigned and report the results in Table VI. In all

Table VI. Placebo tests using randomly assigned treatment and control cities

This table reports the results of identification tests using randomly assigned treatment and control cities for the DiD analysis. We re-estimate the DiD estimators in Table III Panel C. Definitions of variables are listed in Table I Panel C. Standard errors are given in parentheses below the mean differences in innovation and entrepreneurial activities. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Mean treatment difference (after-before)	Mean Control difference (after-before)	Mean DiD estimator (treat-control)	*t*-statistic for DiD
P_Apply	18.161	19.078	−0.917	−0.167
	(4.165)	(3.591)	(5.499)	
P_Grant	7.260	7.430	−0.170	−0.061
	(2.197)	(1.737)	(2.801)	
P_Cite	0.303	0.377	−0.074	−0.625
	(0.094)	(0.072)	(0.118)	
F_Est	1.269	1.133	0.136	0.452
	(0.217)	(0.206)	(0.300)	

regressions, we observe insignificant DiD estimators. This finding suggests that our main results are unlikely driven by chance.

Fourth, we address the concern that other contemporaneous place-based policies might affect our results. Among all other place-based policies initiated in China during the sample period, the most important one is the ETDZ program. However, as we mentioned in Section 2, ETDZs have different policy goals than the national high-tech zones and they are not as widespread across China as the national high-tech zones. Nevertheless, to address the concern, we still perform a test by excluding treatment cities in which any ETDZ is established prior to the establishment of a national high-tech zone. We use the same baseline regression framework and substitute the key variable with $HTZone\_only_{i,t}$, which equals one if a national high-tech zone is established by the end of year t in city i and no ETDZ has been established in the same city by then, and zero otherwise. We use the same matched control cities as in Section 5.1. The results are reported in Table VII. We observe that all of the coefficient estimates on $HTZone\_only_{i,t}$ are statistically significant, suggesting that the positive effect of the national high-tech zone establishments on local innovation output and entrepreneurial activities is robust after we restrict the treatment cities to those where national ETDZs are not established prior to the establishment of national high-tech zones.

Fifth, we repeat our analysis in sub-sample excluding observations after 2001 to alleviate the concern that our results could be driven by firms' increased exposure to foreign technologies (i.e., technology spillovers) from international trade. China's accession to the WTO in 2001 is an important event in changing China's international trade activity (Brandt *et al.*, 2017) and draw foreign direct investment into the manufacturing sector (Whalley and Xian, 2010). Given that the manufacturing sector is more patent-intensive than other sectors, one concern could be that it is China's WTO entry instead of the establishment of national high-tech zones that drives our main findings. Hence, we perform a

Table VII. Excluding treatment cities with ETDZ established

This table reports the results of the tests excluding treatment cities where the ETDZs have been established prior to the establishment of the earliest national high-tech zones. $HTZone\_only_{i,t}$ is a dummy that equals one if a national high-tech zone is established by the end of year t in city i and no ETDZ has been established in that city by then, and zero otherwise. Definitions of variables are listed in Table I Panel C. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *INNOV_PApply*	(2) *INNOV_PGrant*	(3) *INNOV_PCite*	(4) *ENTREPRE_FEst*
HTZone_only	0.219*	0.277**	0.123**	0.174*
	(0.125)	(0.132)	(0.049)	(0.099)
Population	0.029	−0.064	−0.026	0.215**
	(0.097)	(0.093)	(0.027)	(0.090)
GDP	0.056	0.055	0.040	0.046
	(0.072)	(0.070)	(0.029)	(0.068)
GDP2_%	0.013**	0.010	0.001	−0.002
	(0.006)	(0.007)	(0.002)	(0.007)
GDP3_%	0.018**	0.016*	0.001	−0.003
	(0.009)	(0.008)	(0.003)	(0.009)
AvgWage	0.066	0.115	0.062	0.226
	(0.183)	(0.166)	(0.046)	(0.141)
CPI	−0.022***	−0.023***	−0.010*	0.025***
	(0.008)	(0.008)	(0.005)	(0.007)
Constant	0.452	0.192	0.198	−0.606
	(1.951)	(1.834)	(0.704)	(1.741)
Observations	5,441	5,441	5,441	5,339
R-squared	0.881	0.857	0.725	0.817
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
PSM	Yes	Yes	Yes	Yes

subsample test excluding treatment cities where their national high-tech zones are established after 2001 as well as their matched control cities. We report the results in Table C1 in Online Appendix C. In all DiD tests, we observe positive and significant DiD estimators, suggesting that our main results are unlikely driven by technology spillovers from foreign companies due to expanded international trade.

Sixth, to alleviate the concern that our results could be driven by nearby cities due to common unobservable local economic conditions, we repeat out analysis in a sub-sample excluding nearby cities (within a 250-km radius of a treatment city) from the control group. We report the results in Table C2 in Online Appendix C. In all DiD tests, we observe positive and significant DiD estimators, suggesting that our main results are unlikely driven by unobservable local economic conditions.

Finally, one concern is that resources such as capital and labor are mobile and respond to place-based policies, which makes it hard to interpret the results. To mitigate this concern, we conduct two tests in sub-samples of cities that have relatively lower mobility of resources. The first test restricts the sample to cities located in non-eastern regions in

China. The main rationale is that, due to the under-development of infrastructure and public transportation systems (air, train, and bus), the mobility of factors is lower compared with those cities located in eastern China. Hence, if the positive effects of national high-tech zone establishment on local innovation output and entrepreneurial activities are still present in this subsample, it supports the conjecture that these place-based policies are effective in promoting innovation and entrepreneurship. We report the results in Table C3 in Online Appendix C. Based on the same rationale, the second test excludes cities that have bullet-train (i.e., high-speed train) access before the establishment of national high-tech zones and we report the results in Table C4 in Online Appendix C. The results of the two tests suggest that, even in places with lower mobility of resources, the establishment of national high-tech zones still has a positive effect on local innovation and entrepreneurship.[21]

6. Plausible Underlying Channels

Our evidence so far suggests that the establishment of high-tech zones has a positive, causal effect on local innovation output, and entrepreneurial activities. In this section, we explore plausible underlying economic channels through which national high-tech zones promote local innovation output and entrepreneurial activities. Specifically, we provide supportive evidence on three plausible channels: access to finance, reductions in administrative burden, and talent cultivation and introduction.

6.1 Access to Finance

In this subsection, we provide a few pieces of evidence suggesting that better access to finance could be a plausible underlying channel through which national high-tech zones promote local innovation output and entrepreneurial activities.

6.1.a. Favorable tax treatment

The first test we undertake is to explore whether the establishment of national high-tech zones allows firms to enjoy favorable tax treatment. Previous studies have explored how fiscal policies affect corporate innovation. For example, regarding innovation input, Mansfield (1986) and Wilson (2009) show that tax credits have a significant positive effect on firm R&D investment. In terms of innovation output, Mukherjee, Singh, and Zaldokas (2017) suggest that corporate taxes hinder future innovation. There is also a large strand of literature arguing that taxation could discourage potential entrepreneurs from registering their businesses (Djankov *et al.*, 2002; Webb *et al.*, 2009).

As stated in the official document by the MOST, firms located in national high-tech zones would enjoy more favorable tax treatment. As a result, they could invest more in R&D and generate more innovation output, while entrepreneurs may reduce their initial cost for business and later continuous cost for operations. Hence, we conjecture that favorable tax treatment in high-tech zones could be a plausible underlying channel.

21 In unreported results, we conduct an analysis on the impact of provincial high-tech zones on local innovation and entrepreneurship, and fail to find any significant results. This observation is a validation of what we have discussed regarding institutional background in Section 2 that policies given to provincial high-tech zones are not be comparable to those in national high-tech zones. The results are available upon requests.

If our conjecture is supported, we expect to observe significantly different tax rates of firms located in cities with high-tech zones and those without. We obtain firm-level data from annual surveys conducted by the National Bureau of Statistics (NBS) of China from 1998 to 2011. The database covers all industrial firms with sales above 5 million RMB, which are also referred to as the "above-scale" firms. We first compute the corporate income tax rate and the sales tax and fee rate at the firm level from the database. Specifically, the corporate income tax rate of a firm is computed by using its paid corporate income taxes divided by the summation of net income and corporate income taxes, while the firm's sales tax and fee rate is computed by using its sales tax and fee expenses divided by its sales revenue. We then calculate the annual mean of the corporate income tax rate in a city (*Income_Tax_Rate*) and the annual mean of sales tax and fee rate (*Sales_Tax&fee_Rate*) during the 9-year window centered on the event year. We examine the effect of the establishment of national high-tech zones on tax rates in the DiD framework using the matched sample constructed in Table III Panel C.

Table VIII reports the DiD estimators. Column (1) presents the average change in the corporate income tax rate and sales tax and fee rate in treatment cities 4 years after the establishment of national high-tech zones and 4 years prior to the establishment. Column (2) presents the average change in control cities. Column (3) shows the DiD estimators and Column (4) presents the corresponding *t*-statistics. The DiD estimator on *Income_Tax_Rate* shows that the corporate income tax rate of treatment cities decreases by 1.6% (significant at the 1% level) more than that of control cities. The estimator on *Sales_Tax&fee_Rate* shows that the sales tax and fee rate of treatment cities decreases by 0.3% (significant at the 1% level) more than the sales tax and fee rate of control cities.

Our evidence suggests that firms in cities with national high-tech zones enjoy more favorable tax treatments, especially corporate income tax cuts, compared with those without national high-tech zones.

6.1.b. Increases in early-stage venture capital investment

The second test we perform is to explore whether the establishment of national high-tech zones increases early-stage VC investment. Samila and Sorenson (2011) show that increases in the supply of VC investment positively affect entrepreneurship due to the anticipation of would-be entrepreneurs and the demonstration effect of funded startups on their employees. There is also a large strand of literature showing how VC investment positively contributes to corporate innovation (He and Tian, 2018, 2020).

If the establishment of national high-tech zones promotes local innovation output and entrepreneurial activities through better access to finance, we expect to observe a significantly larger increase in early-stage VC investment in cities after the establishment of national high-tech zones than cities without national high-tech zones. We retrieve Chinese VC investment data from CVSource, the largest dataset that covers Chinese VC funding raising and investment activities. We define *VC_Seed&A_AMNT* as the natural logarithm of one plus a city *i*'s total amount of VC investment in the seed stage and series-A stage start-ups in a year.

The third row in Table VIII reports the DiD estimator on *VC_Seed&A_AMNT*. The DiD estimator is positive and statistically significant, suggesting that treatment cities enjoy 53.1% more early-stage VC investment per year than the control cities. Our evidence suggests that cities with national high-tech zones enjoy a larger increase in early-stage VC

Table VIII. Plausible channels: access to finance

This table reports the results for DiD tests on the average city tax rate, early-stage VC investment, and average premium of land transactions. *Income_Tax_Rate* equals the mean of the corporate income tax rate of firms in a city during the 9-year window period centered on the event year, which is computed by using the corporate income tax divided by the summation of its net income and the corporate income tax. *Sales_Tax&fee_Rate* equals the mean of firms' sales tax & fee divided by its sales revenue during the 9-year window period centered on the event year. The firm-level data is retrieved from annual surveys conducted by the NBS of China from 1998 to 2011. *VC_Seed&A_AMNT* is defined as the natural logarithm of one plus a city's total amount of VC investment in seed-stage and series-A stage start-ups. The data on VC investment are retrieved from CVSource, the largest dataset that covers Chinese VC activities. *Avg_Premium_Rate* equals the transaction price minus the land cost divided by the land cost. The land transaction records are obtained from the CSMAR, which covers the period from 1989 to 2014.

	Mean treatment difference (after-before)	Mean control difference (after-before)	Mean DiD estimator (treat-control)	*t*-statistic for DiD
Income_Tax_Rate	−0.023	−0.007	−0.016	−2.667
	(0.004)	(0.004)	(0.006)	
Sales_Tax&fee_Rate	−0.003	0.000	−0.003	−3.000
	(0.001)	(0.001)	(0.001)	
VC_Seed&A_AMNT	0.646	0.115	0.531	1.924
	(0.164)	(0.222)	(0.276)	
Avg_Premium_Rate	−0.017	0.001	−0.018	−1.617
	(0.003)	(0.010)	(0.011)	

investment, which supports the conjecture that access to finance could be a plausible underlying channel.

6.1.c. Land price reduction

The third test we undertake is to examine whether the establishment of national high-tech zones helps reduce land prices, an important part of preferential policies given to firms located in national high-tech zones. Previous research suggests that real estate and collateral have significant effects on corporate innovation and entrepreneurial activities (e.g., Chaney, Sraer, and Thesmar, 2012; Schmalz, Sraer, and Thesmar, 2017; Mao, 2021). Chen *et al.* (2015) show that the real-estate price shock has a crowding-out effect on firms' investment and financing in the Chinese market. Hence, if firms in national high-tech zones could enjoy land price reductions, they may invest more in R&D, and therefore promote local innovation output. Also, lower costs of establishing new firms induced by discounted land prices would boost local entrepreneurial activities.

If the land price reduction is an underlying channel, we expect to observe land prices in cities with national high-tech zones exhibit a lower premium in land transaction deals than those in cities without high-tech zones. We examine this conjecture by obtaining land transaction records from the China Stock Market & Accounting Research (CSMAR), which covers land transaction information starting from 1989. We use the average land transaction premium ratio (*Avg_Premium_Rate*), which equals the transaction price minus the land cost divided by the land cost. We report the results in Table VIII.

The last row in Table VIII indicates that the average premium of land transactions for the treatment cities decreases by about 1.8% more than that in the control cities. The economic effect is sizable because the mean premium of all land transactions is around 3.3%.

Overall, we find that the establishment of national high-tech zones allows firms to enjoy more favorable tax treatments, receive more early-stage VC investment, and decrease the premium of land transactions they have to pay. Taken together, all these pieces of evidence suggest that access to finance is a plausible underlying channel through which the establishment of national high-tech zones promotes local innovation output and entrepreneurial activities.

6.2 Reductions in Administrative Burden

The second plausible underlying channel we propose is the reductions in administrative burden. Firms in developing countries often have to spend extra resources to survive in a legal environment in which regulatory procedures are burdensome and governance is weak in implementation (Hallward-Driemeier and Pritchett, 2015). In China, anecdotal evidence suggests that an entrepreneur has to go through burdensome procedures and collect at least fifty approvals from various government agencies before her startup is allowed to be founded. As we discussed in Section 2 on the institutional background of national high-tech zones, administrative procedures are significantly simplified in national high-tech zones, which could save significant resources that startups have to spend on building relationships with government officers.

We expect to observe a larger decrease in firms' administrative expenses in cities with national high-tech zones than cities without high-tech zones after the establishment. Cai, Tian, and Xia (2011) use entertainment and travel costs expenditures, which are part of administrative expenses recorded in annual accounting books, as a measure of corruption and government relationship building in Chinese firms. Following the spirit of Cai, Tian, and Xia (2011), we construct two administrative burden measures. The first measure is computed by using a firm's total administrative expenses divided by its sales and the second measure is computed by using the firm's administrative expenses excluding administrative taxes divided by its sales. We then calculate the annual mean of the first measure of all sample firms in a city to get *Gross_Adm_Exp* and the annual mean of the second measure to get *Net_Adm_Exp*. The firm-level administrative data are obtained from annual surveys conducted by the NBS of China from 1998 to 2011.

Table IX reports the DiD estimators. Column (1) presents the average change in administrative expenses between 4 years for treatment cities prior to the establishment of national high-tech zones and 4 years after the establishment. Column (2) presents the average change in control cities. Column (3) shows the DiD estimators and Column (4) presents the corresponding *t*-statistics. The DiD estimator on *Gross_Adm_Exp* shows that the total administrative expenses of treatment cities decrease by 1.8% more than that of control cities and the difference is significant at the 1% level. The estimator on *Net_Adm_Exp* shows that the administrative expenses excluding administrative taxes of treatment cities decrease by 1.7% (significant at the 1% level) more than that of control cities.

In summary, we find that the establishment of national high-tech zones significantly reduces administrative expenses of firms. Given that administrative expenses represent a

Table IX. Plausible channels: reductions in administrative burden

This table reports the results for DiD tests on the average administrative expenses of firms in a city. The variable *Gross_Adm_Exp* expresses the average administrative expenses of firms divided by their sales in a city per year during the 9-year window period centered on the event year, while the variable *Net_Adm_Exp* expresses administrative expenses excluding administrative taxes of firms divided by their sales in a city per year during the 9-year window period centered on the event year. The data are collected from annual surveys conducted by the NBS of China from 1998 to 2011. Standard errors are given in parentheses below the mean differences in innovation and entrepreneurial activities.

	Mean treatment difference (after-before)	Mean control difference (after-before)	Mean DiD estimator (treat-control)	*t*-statistic for DiD
Gross_Adm_Exp	−0.034	−0.016	−0.018	−2.250
	(0.006)	(0.006)	(0.008)	
Net_Adm_Exp	−0.033	−0.016	−0.017	−2.125
	(0.006)	(0.006)	(0.008)	

significant proportion of Chinese firms' operating costs, reductions in administrative burden are a plausible underlying channel through which national high-tech zones promote local innovation output and entrepreneurial activities.

6.3 Talent Cultivation and Introduction

A third plausible underlying channel is the cultivation and introduction of talent. Human capital is crucial to innovation and high-skilled talent inflow could boost regional innovation output and productivity (Kerr *et al.*, 2016). Researchers using US data find that high-skilled immigrant inflows can raise human capital and the stock of ideas in the host country (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Akcigit, Grigsby, and Nicholas, 2017). The establishment of high-tech zones is often accompanied by favorable policies that intend to attract talents and more government expenditure in promoting higher education. Therefore, we propose that talent cultivation and introduction could be an underlying channel through which the establishment of high-tech zones enhances local innovation output and entrepreneurial activities.

To test this conjecture, we first use the number of college students as a proxy for talent. College students could be potential high-skilled employees of firms located in high-tech zones. They could also initiate startups as entrepreneurs. Thus, the increase in college students could lead to growth in local innovation output and entrepreneurial activities. We collect education data from China City Statistics Yearbook and construct two variables, College Students and Mid School Students. These two variables represent the average number of college and middle and high school students (in thousands) during the 9-year window centered on the establishment year, respectively. We calculate the change in the number of college and middle and high school students for treatment and control cities, from its average over the 4 years before the establishment of national high-tech zones to its average over the 4 years after, and report the results in Table X. The DiD estimator on College Students is positive and significant at the 5% level. The magnitude of the DiD estimator suggests

Table X. Plausible channels: talent cultivation

This table reports the results for DiD tests on the average number of a city's college students and a city's middle and high school students. The variable *College_Students* expresses the average number of a city's college students per year (in thousands) during the 9-year window period centered on the event year, while the variable *MidSchool_Students* expresses the number of a city's middle and high school students per year (in thousands) during the nine-year window period centered on the event year. The variable *Executives_Graduate* expresses the average number of a city's executives at listed companies with a graduate degree per year during the nine-year window period centered on the event year. The education data are collected from China City Statistics Yearbook, which covers the full sample period (from 1985 to 2014). The education information on the executives working for listed firms is collected from CSMAR, which covers the period from 1999 to 2014.

	Mean treatment difference (after-before)	Mean control difference (after-before)	Mean DiD estimator (treat-control)	*t*-statistic for DiD
College_Students	9.556	3.381	6.175	3.328
	(0.877)	(1.635)	(1.855)	
MidSchool_Students	52.208	27.888	24.320	1.519
	(11.465)	(11.173)	(16.009)	
Executives_Graduate	3.215	1.303	1.912	1.828
	(0.867)	(0.585)	(1.046)	

that the number of college students for the treatment group rises 6,175 more than that for control cities 9 years surrounding the establishment of high-tech zones.

One concern about our above test is that the increased number of college students is due to China's education promotion policy starting in the late 1990s rather than the establishment of national high-tech zones. To address this concern, we use the change in the number of middle and high school students as a benchmark comparison. If the change in college students is induced by policies related to the establishment of national high-tech zones, we should not observe an increase in middle and high school students soon after the establishment of the high-tech zone. Table X shows that the DiD estimator of MidSchool_Students is not statistically significant. Therefore, the establishment of national high-tech zones is accompanied by high-skilled talent cultivation that significantly increases the number of students pursuing college education.

We also use the number of executives with graduate degrees (either a master or a Ph.D.) as a proxy for talent. We are able to observe education information of executives who are working at public firms from the CSMAR database between 1999 and 2014. It is not common for executives to have graduate degrees during our sample period: only about 18% of executives in the CSMAR database have a master's degree and 7% of them have a Ph.D. degree. The DiD estimator reported in Table X shows that the number of executives with graduate degrees increases significantly for treatment cities than control cities after the establishment of national high-tech zones, suggesting that the establishment of national high-tech zones helps firms attract talents.

Our results suggest that the cultivation and introduction of talent appears a plausible underlying channel through which the establishment of national high-tech zones positively affects local innovation output and entrepreneurial activities.

6.4 Channels and Explanatory Power

In Sections 6.1–6.3, we provide evidence showing that access to finance, reductions in administrative burdens, and talent cultivation are three plausible underlying channels through which the establishment of national high-tech zones positively affects local innovation and entrepreneurship. In this section, we study to what extent these three plausible underlying channels could explain the positive effect of national high-tech zones on local innovation output and entrepreneurial activities. Specifically, we examine whether the DiD estimators, which capture the causal effect of the establishment of national high-tech zones on innovation output and entrepreneurial activities, remain positive and statistically and economically significant after controlling for hypothesized underlying channel variables. Using the matched sample described in Section 5, we estimate the following model.

$$\begin{aligned} &P\_Apply(P\_Grant,\ P\_Cite,\ F\_Est)_{i,t} \\ &= \alpha + \beta_1 Treat_i * Post_t + \beta_2 Treat_i + \beta_3 Post_t + \gamma Channels_{i,t} + \varepsilon_{i,t}\ , \end{aligned} \tag{3}$$

where i indexes city and t indexes year. The dependent variable is the number of patent applications (*P_Apply*), the number of granted patents (*P_Grant*), the number of patent citations (*P_Cite*), or the number of new firm registrations (*F_Est*) in city i and year t. *Treat* is a dummy that equals one for treatment cities and zero for control cities. *Post* is a dummy that equals one if a city-year observation is from the period after the establishment year, and zero otherwise. Channels is a vector of variables that proxies for the three underlying channels we discussed previously. For the access to finance channel, we use *Income_Tax_Ratio* to capture favorable tax treatments received by local firms, *VC_seed&A_AMNT* to capture early-stage VC investments, and *Avg_Premium_Rate* to capture land prices. We use the average administrative expenses (*Gross_Adm_Exp*) to represent the administrative burden of firms and the number of college students (*College_Student*) to represent the level of talent cultivation for a city.[22] These measures are defined in detail in Sections 6.1–6.3.

The key variable of interest is the DiD estimator, β_1. If the establishment of national high-tech zones affects local innovation and entrepreneurship only through the three channels we documented before, we should observe that β_1 loses its significance once the above channels are controlled. If, however, there is a residual treatment effect of the establishment of national high-tech zones on local innovation and entrepreneurship, we should observe that β_1 continues to be positive and significant even after controlling for the three underlying channels.

We report the results in Table XI. The dependent variable is *P_Apply* in Columns (1) and (2). In Column (1), we estimate Equation (3) without controlling for any channel variables to get the benchmark DiD estimator. The magnitude of the coefficient estimate of β_1 is 115.2 and significant at the 1% level.[23] In Column (2), we estimate Equation (3) and include all the channel variables. The coefficient estimate of β_1 is no longer statistically

22 To avoid multicollinearity, we do not include Sales_Tax&fee_Rate and Net_Adm_Exp in the regression. The results are similar if we include these two variables.

23 The magnitudes of β_1 are different from the DiD estimator reported in Table III Panel C because we use the full sample for this test while we use the 9-year window centered at the event year for the DiD estimation in Table III Panel C. We need the full sample for this test to ensure that we have enough non-missing channel variables, that is, the data for calculating the tax treatments and the administrative burden are only available from 1998.

Table XI. Controlling for plausible underlying channels

This table reports the results for the DiD test after controlling for plausible underlying channels through which the establishment of national high-tech zones affects local innovation and entrepreneurship. *Treat* is a dummy that equals one for treatment cities and zero for control cities. *Post* is a dummy that equals one if a city-year observation is from the period after the establishment year and zero otherwise. Channel variables including *Income_Tax_Ratio*, *VC_seed&A_AMNT*, *Avg_Premium_Rate*, *Gross_Adm_Exp*, and *College_Student* are introduced in Tables VIII–X. Coefficient estimates are shown below, and their standard errors are clustered by city and displayed in parentheses below. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *P_Apply*	(2) *P_Apply*	(3) *P_Grant*	(4) *P_Grant*	(5) *P_Cite*	(6) *P_Cite*	(7) *F_Est*	(8) *F_Est*
Treat_Post	115.207***	21.354	44.731***	14.066	0.266**	0.125	5.883***	2.326
	(33.036)	(26.710)	(11.479)	(9.219)	(0.117)	(0.100)	(1.628)	(1.455)
Treat	−3.283	28.148	−0.426	7.032	0.190*	0.093	−1.970	−1.010
	(32.312)	(26.125)	(11.227)	(9.017)	(0.115)	(0.098)	(1.592)	(1.423)
Post	61.047**	35.262*	16.190*	8.468	−0.004	−0.053	−1.616	−2.221**
	(25.228)	(20.253)	(8.766)	(6.990)	(0.090)	(0.076)	(1.243)	(1.103)
Income_Tax_Ratio		−8.460***		−2.211***		0.001		−0.127**
		(0.953)		(0.329)		(0.004)		(0.052)
VC_seed&A_AMNT		4.108***		1.938***		0.015***		0.226***
		(0.364)		(0.126)		(0.001)		(0.020)
Avg_Premium_Rate		2.608***		1.010***		0.014***		0.097***
		(0.417)		(0.144)		(0.002)		(0.023)
Gross_Adm_Exp		−2.838***		−0.196		0.030***		−0.085
		(0.963)		(0.333)		(0.004)		(0.052)
College_Student		0.724***		0.240***		0.002***		0.027***
		(0.026)		(0.009)		(0.000)		(0.001)
Constant	40.255	189.652***	17.745**	48.782***	0.280***	−0.028	5.362***	6.825***
	(24.722)	(26.532)	(8.590)	(9.158)	(0.088)	(0.099)	(1.218)	(1.446)
Observations	2,770	2,770	2,770	2,770	2,770	2,770	2,770	2,770
R-squared	0.104	0.429	0.125	0.450	0.114	0.374	0.048	0.258
PSM	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

significant and its magnitude goes down to 21.4, reflecting an approximately 82% drop from the magnitude of the benchmark DiD estimator in Column (1). This result suggests that the proposed underlying channels are able to explain about 82% of the total effect of the establishment of national high-tech zones on local innovation output measured by the number of patent applications.

In Columns (3) and (4), we replace the dependent variable with *P_Grant* and repeat the analysis above. The DiD estimator β_1 is significant at the 1% level in Column (3), but not statistically significant in Column (4) after controlling for the channel variables. The magnitude of β_1 drops from 44.7 in Column (3) to 14.1 in Column (4), suggesting that the channel variables explain about 69% of the total effect of the establishment of a national high-tech zone on local innovation output measured by the number of granted patents. We replace the dependent variable with *P_Cite* in Columns (5) and (6) and *F_Est* in Columns (7) and (8). We observe similar patterns for the DiD estimator β_1. It is positive and significant at the 1% level in Columns (6) and (7), but becomes statistically insignificant in Columns (6) and (8) when channel variables are included in the regressions. The magnitude of β_1 drops by about 53% from Column (5) to Column (6) and by about 60% from Column (7) to Column (8). The results suggest that the proposed underlying channels can explain a large proportion (i.e., 53–82%) of the total effect of the national high-tech zones on local innovation and entrepreneurship.[24]

We also perform a Shapley–Owen decomposition of R^2 to compare the explanatory power of each underlying channel, and report the results in Table C5 in Online Appendix C. The results suggest that talent cultivation has the largest explanatory power of the effects (with a Shapley–Owen value of more than 50%), which is consistent with the existing literature that human capital plays important roles in enhancing innovation and entrepreneurship (Bradley, Kim, and Tian, 2017; Chemmanur *et al.*, 2019; Liu, Mao, and Tian, 2020, Gu *et al.*, 2021). The second most important channel that drives our main results is early-stage VC investment (with a Shapley–Owen value of around 25%), which has also been shown by the existing literature to have positive effects on innovation and entrepreneurship (e.g., Samila and Sorenson, 2011; Chemmanur, Loutskina, and Tian, 2014; Tian and Wang, 2014).

Overall, we observe that the DiD estimators lose their statistical and economic significance once the proposed underlying channels are controlled. Our findings suggest that the national high-tech zones seem to affect local innovation output and entrepreneurial activities mainly through the three proposed underlying channels.

7. Spillover Effects

So far, we have shown the positive, causal effect of national high-tech zones on local innovation output and entrepreneurial activities and its plausible underlying channels. In this section, we discuss potential spillover effects of national high-tech zones. We address the question of whether increases in local innovation and entrepreneurship induced by the establishment of national high-tech zones are generated at the cost of nearby cities without such high-tech zones.

To examine whether the establishment of national high-tech zone brings costs to or generates positive spillover effects on the innovation and entrepreneurship of nearby cities, we conduct a test using a sample of nearby (within a 250-km radius) cities without national high-tech zones established during the sample period by estimating the following equation:

$$\begin{aligned} &INNOV\_PApply(INNOV\_PGrant, INNOV\_PCite,\ ENTREPRE\_FEst)_{i,\ t+2} \\ &\quad = \alpha + \beta CloseHTZ{*}Post_{i,t} + \gamma' CONTROLS_{i,t} + \delta YEAR_t + \theta CITY_i + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where *CloseHTZ* is defined as the natural logarithm of the reciprocal of city *i*'s distance to the closest city with a national high-tech zone within the province. *Post* is a dummy

24 The results are similar if we include the access to finance channel variables individually instead of all together.

that equals one if a city-year observation is from the period after the year when the closest national high-tech zone is established, and zero otherwise. Dependent variables and control variables are defined in the same way as those in Equation (1) with the only exception that the dependent variables are now in year $t+2$ (instead of year $t+1$) to address the fact that spillover effects could take longer time than the main effects. We control for year-fixed effects and city-fixed effects. If the benefits of the national high-tech zone policy come at the cost of nearby cities, we expect to observe a significant and negative coefficient estimate on β in Equation (4), that is, after a national high-tech zone is established in a city, the closer another city to the national high-tech zone, the lower growth in innovation and entrepreneurship the city would expect in the next year, compared with the growth in the city before a nearby national high-tech zone is established. If, however, the establishment of national high-tech zones generates positive spillover effects to nearby cities, we expect to observe a positive and significant coefficient estimate on β.

Table XII reports the results. The dependent variable in Column (1) is *INNOV_PApply*. The coefficient estimate on β is positive and significant at the 1% level, suggesting that if a city locates closer to the city with national high-tech zones, it experiences a larger increase in the number of patent applications compared with that in cities that are further away from the national high-tech zones within the same province after the zone establishment. We replace the dependent variable with *INNOV_PGrant* in Column (2) and observe a positive and significant coefficient estimate on β as well. We replace the dependent variables in Columns (3) and (4) with *INNOV_PGrant* and *F_Est*, respectively. The coefficient estimates on β in these two columns are also positive, statistically significant at 10% level in Column (3) though insignificant in Column (4).

The results in Table XII suggest that increases in innovation output and entrepreneurial activities caused by the establishment of national high-tech zones in the host city do not come at the cost of nearby cities. Instead, the establishment of high-tech zones even generates some positive spillover effects in innovation output to nearby cities.

8. Conclusion and Discussion

In this paper, we have explored the effects of an important place-based program in China, the establishment of national high-tech zones, on local innovation output and entrepreneurial activities. We use a DiD approach that makes use of staggered establishments of national high-tech zones in various Chinese cities, and find that national high-tech zones have positive effects on local innovation output and entrepreneurial activities. A number of additional tests suggest that the results are likely causal. Access to finance, reductions in administrative burdens, and talent cultivation offered by national high-tech zones are three plausible underlying channels through which national high-tech zones promote local innovation output and entrepreneurial activities. Our paper sheds new light on the evaluation of the effectiveness of China's place-based policies in terms of promoting local innovation and entrepreneurship.

Unlike previous literature that studies place-based policies in developed countries and suggests insignificant effects of these policies (Glaeser and Gottlieb, 2008; Kline and Moretti, 2014), we find generally positive effects of national high-tech zones on local innovation and entrepreneurship in China. We acknowledge that some of the results could be particular to

Table XII. Spillover effects of national high-tech zones

This table reports for the test examining the spillover effects of national high-tech zones on nearby cities by estimating the following model:

$$INNOV\_PApply(INNOV\_PGrant, INNOV\_PCite, \ ENTREPRE\_FEst)_{i,\ t+2} = \alpha + \beta CloseHTZ*Post_{i,t} + \gamma' CONTROLS_{i,t} + \delta YEAR_t + \theta CITY_i + \varepsilon_{i,t}.$$

CloseHTZ is the natural logarithm of the reciprocal of city *i*'s distance to the closest city with a national high-tech zone in the province. We only include cities that are within a 250-km radius of a city with a national high-tech zone. *Post* is a dummy variable that equals one if a city-year observation is from the period after the year when the closest national high-tech zone is established and zero otherwise. The definitions of other variables are provided in Table I Panel C. Year fixed effects, $YEAR_t$, and city fixed effects, $CITY_i$, are included in all regressions. Coefficient estimates are shown, and their standard errors are clustered by city and displayed in parentheses below. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *INNOV_PApply*	(2) *INNOV_PGrant*	(3) *INNOV_PCite*	(4) *ENTREPRE_FEst*
CloseHTZ _Post	0.212***	0.270***	0.020*	0.052
	(0.073)	(0.084)	(0.011)	(0.082)
Population	0.078	0.018	0.001	0.140**
	(0.064)	(0.063)	(0.010)	(0.064)
GDP	−0.015	−0.001	0.007	−0.017
	(0.042)	(0.037)	(0.007)	(0.044)
GDP2_%	0.016***	0.012***	0.000	0.002
	(0.004)	(0.004)	(0.001)	(0.004)
GDP3_%	0.016***	0.015***	0.001	−0.000
	(0.005)	(0.005)	(0.001)	(0.005)
AvgWage	−0.024	0.051	0.019	−0.070
	(0.078)	(0.064)	(0.013)	(0.074)
CPI	0.004	0.001	0.002	0.018***
	(0.007)	(0.006)	(0.002)	(0.006)
Constant	−1.272	−1.741*	−0.571**	2.029*
	(1.107)	(0.994)	(0.238)	(1.047)
Observations	4,154	4,154	4,154	3,763
R-squared	0.839	0.774	0.324	0.781
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

China and we propose two explanations. First, unlike in developed countries where place-based policies target areas with lower income or employment rates, China's national high-tech zone policy serves the goal of experimenting with market reforms. By reducing administrative burdens and pre-existing distortions under the old central planning system, cities in China can exploit more benefits from the agglomeration brought by the national high-tech zone program (Alder, Shao, and Zilibotti, 2016). Second, the Chinese government has played an active role in implementing the national high-tech zone program and its accompanying preferential policies. The active involvement and intervention of the government can be unnecessary and unimaginable in most developed economies where cities are featured with pre-existing durable structures and may face more "Not In My Back Yard" opposition

(Zheng *et al.*, 2017). The lessons from China's national high-tech zone policy, however, could be valuable at least for other developing economies with a more centralized government system.

We acknowledge that, while we find China's place-based policies, that is, the establishment of national high-tech zones, are effective in promoting local innovation output and entrepreneurial activities, we are agnostic about the aggregate welfare effect of these place-based policies and hence our results should be interpreted with cautions. Put differently, our evidence merely suggests that placed-based policies are effective at promoting local innovation and entrepreneurship, but it does not speak to whether these policies are welfare-enhancing for the nation as a whole or not. To understand how place-based government policies affect social welfare at the aggregate level, one needs to measure if there are surpluses created net of shifting resources around across locations by the pace-based policies, which is empirically challenging. For example, the input of innovation and entrepreneurial activities, such as capital and labor, could move from an immediate neighborhood or from a very distant area, making a reduced-form approach like ours hard to capture the real effects of place-based policies. We acknowledge this limitation of our study and highlight this issue as an interesting and important area for future research.

Data Availability Statement

The data underlying this article will be shared on reasonable request to the corresponding author.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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