Do place-based policies promote local innovation and entrepreneurial finance?

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Abstract

This paper explores how a prominent place-based policy in China, the national high-tech zones, affects local innovation and entrepreneurial activities. Relying on plausible exogenous variation in place-based policies caused by staggered establishments of national high-tech zones and using a difference-in-differences approach, we find that the establishment of national high-tech zones has a positive effect on early-round venture capital investment, local innovation output, and the number of new firms established. A number of additional tests suggest that the effects appear causal. Favorable tax treatments, talent cultivation, and land price reductions are three plausible underlying mechanisms. Our paper provides new evidence to the debate about the real effects of place-based policies on corporate innovation and entrepreneurial finance.

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

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 U.S. and European data (e.g., Bartik, 2002; Glaeser and Gottlieb, 2008), economists generally express serious concerns and hence little support for such policies, because they argue that these policies generate large distortions in economic behavior.[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 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 U.S. and Europe, place-based policies positively contribute to China' economic growth. The goal of this paper is to explore the real effects of a prominent place-based

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[1] See Decker et al. (2014), Kerr et al. (2014), and He and Tian (2018) for surveys of these two strands of literature.

[2] A few recent examples of this literature include Audretsch, Link, and Scott (2002), Brander et al., (2015), Cumming and Maclntosh (2006), Howell (2017), and Lerner (1999).

[3] Pirinsky and Wang (2006), Kedia and Rajgopal (2009), John et al. (2011) and Bernile et al. (2015) show the impact of firms' location on the comovement of stock return, corporate stock option plans, dividend payout policy and institutional investors' geographical bias.

[4] One exception is Austin et al. (2018) who argue that place-based policies could insure residents against place-based economic shocks.

policy, national high-tech zones, on China's local innovation and entrepreneurial activities, and provide new evidence to the debate about the real effect of place-based policies.

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 of China (MOST henceforth) 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, ZhongGuan Village (Beijing) high-tech zone, was established in 1988. After its early success, in 1991, the State Council promulgated preferential policies for national high-tech zones and approved the second wave of 26 national high-tech zones. In 1992, the third wave of 25 national high-tech zones was approved. By the end of 2016, there have been 146 national high-tech zones established in China across all provinces and autonomous regions. We provide more institutional details on China's high-tech zones in Section 2.

We compile our data set from a few sources: We retrieve the patent application and grant information from the State Intellectual Property Office of China (SIPO) and the patent citation data from Google Patent. We obtain China's new firm registration data from the State Administration for Industry and Commerce of China (SAIC) and city-level characteristics from the China City Statistical Yearbook. The data on venture capital (VC henceforth) investment are retrieved from CVSource, the largest dataset that covers Chinese VC activities. We aggregate patent and new firm registration data up at the city level. Our sample includes 8,933 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 run 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' innovation 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 towards 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 zone establishments on local innovation and entrepreneurial activities.

To tackle the endogeneity issue and establish causality, we use a difference-in-differences (DiD) approach that relies on plausible exogenous variation in place-based policies generated by staggered establishments of national high-tech zones in 473 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 and entrepreneurial finance. 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 and entrepreneurial activities. Specifically, compared to cities without high-tech zones established, cities with high-tech zones exhibit a 34.2% larger increase in patent applications, a 49.6% larger increase in patent grants, a 23.0% larger increase in patent citations, a 12.3% larger increase in new firm registrations, and more than two times of increase in early-stage VC investment amount one year surrounding the establishment of high-tech zones. These effects are economic sizable and support the argument that China's place-based policies spur local innovation 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 three sets 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 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 may not be completely exogenous and suffers from a selection issue. The rationale is the 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 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 output and more active entrepreneurial activities so that it would be easier for these cities 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. We find that 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 years) three 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 and entrepreneurial activities. The second placebo test is to artificially assign treatment city and control city status in our sample and repeat the baseline DiD analysis. We do not find significant results. Overall, these placebo tests suggest that our main results are unlikely driven by chance.

In the final part of the paper, we attempt to explore plausible economic underlying mechanisms through which the establishment of national high-tech zones affects local innovation and entrepreneurial activities. We find that cities with national high-tech zones exhibit significantly lower income tax rate and sales tax and fee rate. These cities also have a larger number of college students although the number of middle school students in these cities is similar to those without national high-tech zones. Finally, the average premium of land transactions in the cities with national high-tech zones is significantly lower than those without high-tech zones. Overall, these pieces of evidence suggest that favorable tax treatments, talent cultivation, and land price reductions could be three plausible underlying mechanisms.

Our paper contributes to two strands of literature. It adds to the growing literature on the government's role in promoting entrepreneurial activities and innovation. In terms of entrepreneurial activities, earlier work such as Lerner (1999) and Audretsch, Link, and Scott (2002) show that the R&D awards made under the U.S. Small Business Innovation Research (SBIR) program have positive effects on entrepreneurial firm growth. Howell (2017) shows that an early-stage award from the U.S. 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 (2014) find that government-sponsored venture capital (VC) augments (instead of displaces) private VC and its investment is 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 of government R&D support on innovation, these findings are consistent with the general consensus discussed in a review by Klette, Moen, and Griliches (2000) in the sense that the research is inconclusive regarding the effect of government R&D subsidies on innovation. Our paper contributes to this literature by exploring the role played by Chinese governments, which are largely ignored by the existing literature but represent an important economic force, on promoting innovation and entrepreneurial activities.

Second, our paper contributes to the literature on evaluating the consequences of place-based policies. Existing studies pertaining to place-based policies in the U.S. 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. Existing literature pertaining to 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 (2015) 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 entrepreneurial activities. In this study, we evaluate how China's establishment of high-tech zones affects local innovation and entrepreneurial activities.

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 our baseline DiD results. Section 5 reports additional identification tests. Section 6 explores plausible underlying mechanisms. We conclude the paper in Section 7.

2. Institutional Background

Since China's economic reform in 1978, the Chinese government has introduced several place-based policies to boost economic growth, attract foreign direct investment, and promote technological innovation. In 1988, the MOST implemented the Torch Plan with the main goal of establishing national high-tech zones. That policy serves to develop China's high-tech industries and enhance economic growth.[5]

The first national high-tech zone, ZhongGuan Village (Beijing) high-tech zone, was established in 1988. In 1991, the State Council promulgated preferential policies for national high-tech zones and approved the second wave of 26 national high-tech zones. In 1992, the third wave of 25 national high-tech zones was approved. By the end of 2016, there have been 146 national high-tech zones in China. Figure 1 depicts the geographical distribution of national high-tech zones. One can observe that all provinces (and autonomous regions) have national high-tech zones established with the only exception of Tibet.

National high-tech zones serve as a major engine for China's economic growth. In 2015, national high-tech zones account for 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 with national high-tech zones account for 44.3% of China's total R&D expenditures and 19.8% of China's total invention patents authorized then. In addition, one-fifth of national high-tech zone firms 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 top firms like Lenovo, Alibaba, and Huawei.

Qualified firms in national high-tech zones enjoy preferential policies. First, they are entitled to tax advantages including exemptions on income tax, and they can perform accelerate

[5] For more details, see the Ministry of Science and Technology website: http://www.most.gov.cn/gxjscykfq/ldjh/.

depreciation.[6] Second, they are privileged in a few dimensions including land use, talent recruitment, and government funding application. Third, there are also implicit benefits. For instance, the administrative procedure is simplified in national high-tech zones: the number of administrative staff per national high-tech zone is only 1/8th to 1/10th of that in other administrative regions in China.[7] Also, being labeled as a high-tech zone firm brings good reputation that allows the firm to attract high-quality investors, partners, employees, etc.

The national high-tech zone policy is different from another placed-based economic policy in China, the Economic Technological Development Zones (ETDZ henceforth). First, ETDZs aim to attract foreign direct investment and boost export, while national high-tech zones intend to promote the advancement, commercialization, and internationalization of science and technology. Second, EDTZs concentrate more in eastern China geographically, especially in coastal cities, while national high-tech zones are comparatively more scattered across the country.

There are two types of national high-tech zones. Type I national high-tech zones (empty dots in Figure 1) are initially established directly by the central government; Type II national high-tech zones (solid dots in Figure 1), though initially established by local government, are later certificated by the MOST and upgraded to the national level. In addition to promoting technological advancement, the 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 are less correlated with local economic conditions and technological level. This feature helps to alleviate the endogeneity concern when we restrict our sample to the Type I national high-tech zones later in Section 5.

We do not consider provincial high-tech zones in our study for several reasons. First, to avoid excessive competition among high-tech zones, it is prohibited that preferential policies given to provincial economic zones are comparable to those given to national economic zones.[8] Second, the certification criteria implemented for firms in provincial high-tech zones are lower than those

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[6] If a firm is confirmed as a high-tech enterprise, its income tax will be collected at a reduced rate of 15% since the date of confirmation. If the output value of export products of a confirmed 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 will be collected at a reduced rate of 10%. A confirmed newly opened high-tech enterprise in the high-tech zones can be exempted from the income tax within two years after it is put into production.

[7] More related details are available from the website of China Ministry of Science and Technology at http://www.most.gov.cn/ztzl/gjgxjskfq/gxhyfy/200508/t20050830_24388.htm.

[8] 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."

for national ones.[9] As a result, Alder, Shao, and Zilibotti (2016) find an insignificant effect of provincial zones on local economic growth.

3. Data and Summary Statistics

3.1 Sample selection

Our dataset mainly consists of three parts: patent application/grant information, new firm registration, and city-level characteristics. Patent application/grant information is retrieved from the State Intellectual Property Office of China (SIPO), 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 Administration for Industry and Commerce of China (SAIC). We retrieve city-level characteristics from the China City Statistical Yearbook. We aggregate firm patent and entrepreneurial activities data up at the city level. Finally, we match patent data, entrepreneurship data, VC investment data and city characteristics using city name, and manually check for matching accuracy.

The final sample includes 8,933 city-year observations for 473 unique cities over a 30-year period from 1985 to 2014. 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

3.2.1 Measuring innovation 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 level. We first use a city's total number of invention patent applications (in thousands) in a year to capture the local innovation productivity (*P_Apply*). We only consider invention patents in our study because they are regarded as the most original

[9] For national high-tech zones, the certification requires firms to have their main business 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.

patents and are the most difficult type of patents for inventors to apply.[10] Second, as the SIPO also provides patent grant information, we use a city's total number of granted patents (in thousands) in a year (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 add them up at the city-year level (in thousands) to construct our second measure of innovation quality (*P_Cite*).

We measure a city's entrepreneurial activities by the number of new firms established and the amount of VC investment in early-stage start-ups. The new firm registration data are collected from the SAIC, which covers all records of new firm registrations in China since 1985. We retrieve VC investment data from CVSource. We aggregate the two variables 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*) and use the natural logarithm of VC investment amount in seed stage and series-A stage start-ups (*VC_Seed&A_AMNT*) to capture the city's entrepreneurial activities.

As the distribution of the firm registration sample and the patent sample are 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_PCite*, *ENTREPRE_FEst*, and *VC_Seed&A_AMNT*, respectively.

3.2.2 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 Ministry of Science and Technology (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

[10] There are three types of patents in China: invention patents, utility model patents, and design patents. The Chinese invention patents (IP) are granted for a new technical solution relating to a product, a process, or an improvement, the Chinese utility model patents (UMP) are granted for new and practical technical solutions related to the shape and/or structure of a product, and the Chinese design patents (DP) 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 utility model patent and an invention patent, followed by the abandonment of the UMs once the invention patent is officially granted. On the other hand, only IPs requires "substantive examination", indicating stricter grant standards and higher "inventiveness".

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 1. Panel A shows that more than 80% of national high-tech zones were established before 2000. As China had not joined the World Trade Organization 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.[11] Therefore, we can observe from the statistics that the aim for 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 1985 to 2014. We mainly control for economic variables including the natural logarithm of the city' population (*Population*), natural logarithm of the city's GDP (*GDP*), the percentage of GDP from secondary industry (*GDP2_%*), percentage of GDP from the service sector (*GDP3_%*), natural logarithm of average wage in the city (*AvgWage*), and the Customer Price Index (*CPI*). We replace missing values of these control variables with the average value of the city-year observations one year before and one year after the missing value year. Table 1 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 1 Panel D. To alleviate the concern that our results could be driven by outliers, we winsorize all variables at the 1st and 99th percentiles.

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

On average, a sample city has 188 invention patent applications per year, among which 67 patent applications are granted. These granted patents per year for an average city receive a total of 46 citations subsequently. Cornaggia et al. (2015) report that an average U.S. state in their sample receives 2,988 granted patents in three years and these patents receive a total of 39,085 citations. From our summary statistics, a province in China on average has 19 cities, and so it has (67*19)*3=3,819 granted patents and these patents receive (46*19)*3=2,622 subsequent citations in three years. Thus, the total number of granted patents generated in a certain region is similar between the U.S. and China, while Chinese patents enjoy much fewer citations on average. Regarding entrepreneurial activities, an average city has 3,650 new firm registrations per year.

[Insert Table 1 about Here]

4. Baseline Results

A standard approach to assess the effect of high-tech zone establishments is to run OLS regressions that regress a city's innovation and entrepreneurial activities on a dummy variable that represents the city's high-tech-zone status. This approach, however, suffers from endogeneity concerns. First, the establishment of national high-tech zones and the city's innovation output and entrepreneurial activities could be driven by common characteristics that are unobservable to econometricians, which causes the omitted variable concern. Second, reverse-causality concern worries that expected changes in a city' innovation and entrepreneurial activities could lead to the establishment of national high-tech zones. Finally, a sample that includes all cities with high-tech zones is likely to bias towards large cities, 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 zone establishments on local innovation and entrepreneurial activities.

To address the endogeneity concern, we use a difference-in-differences (DiD) approach that relies on plausible exogenous variation in place-based policies caused by staggered establishments of high-tech zones in 473 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 entrepreneurial activities. 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 and entrepreneurial activities.

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

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

where i denotes city, and t denotes year. There are two sets of dependent variables used in our regressions. One is related to innovation output and the other is related to entrepreneurial activities. To capture the innovation quantity and quality, we use the natural logarithm of one plus city i's total number of invention patent applications in year $t+1$ ($INNOV\_PApply_{i,t+1}$) , the natural logarithm of one plus city i's total number of invention patents granted in year $t+1$ ($INNOV\_PGrant_{i,t+1}$), and the natural logarithm of one plus city i's total number of citations from invention patents that are granted 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 $t+1$ ($ENTREPRE\_FEst_{i,t+1}$) city i's natural logarithm of one plus the VC investment amount in seed stage and series-A stage start-ups in year $t+1$ ($VC\_Seed\&A\_AMNT_{i,t+1}$). $HTZone_{i,t}$ 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. We also include year and city fixed effects to account for time-specific shocks and time-invariant unobservable city characteristics that may affect the relations between the establishment of high-tech zones and local innovation (and entrepreneurship). In all regressions, we cluster standard errors at the city level.

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 facilitates 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.

[Insert Table 2 about Here]

In Table 2, 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 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 34.2% more than that of a control city in one year after the establishment of the national high-tech zone, compared to 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 49.6% larger increase in the number of patents grants and a 23.0% larger increase in the number of future citations of granted patents after the high-tech zone is established, compared to those prior to the establishment.

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 12.3% larger increase in the number of new firm registrations one year after the establishment, compared to that before the establishment. Column (5) demonstrates that the establishment of a national high-tech zone leads to 2.5 times of larger increase in the early-stage VC investment amount one year after the establishment, compared to that before the establishment.

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

5. Addressing additional concerns

While the DiD approach with multiple shocks provide strong support that the establishment of high-tech zones has a positive effect on local innovation and entrepreneurial activities, there still exist concerns that treatment cities may not be comparable to control cities in many dimensions. Hence, our results could be driven by the differences in these cities' local economic 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 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 if otherwise (control city). Independent variables are the same as those in equation (1) measured in year *t-1*, including 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 three years prior to the establishment of a national high-tech zone, $PApply\_Growth_{i,-3\ to\ -1}$, $PGrant\_Growth_{i,-3\ to\ -1}$, $PCite\_Growth_{i,-3\ to\ -1}$ (i.e., the growth in the number of patent applications, the growth in the number of patents grants and the growth in the number of total patent citations) as well as the entrepreneurship growth variable over three 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 3.[12]

[Insert Table 3 about Here]

Column (1) of Table 3 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 48% 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 propensity scores calculated from the first step to perform the nearest-neighbor propensity score matching without replacement. We set the caliper of the matching to 0.7, which means that the propensity score distance between two cities can be no more than 0.7 if they are to be matched observations, to

[12] We didn't include the early-stage VC investment variable in the propensity score matching because the decision of building a high-tech zone mainly relies on the evaluation of regional economic outcomes and concerns and VC investment is far from a first-order issue. This can be observed by the data that VC deals only appears in a small proportion of cities in our sample that it hardly can become an valid standard for the decision of establishing a high-tech zone.

further assure that matched observations are similar in all dimensions. We obtain 95 unique pairs of matched cities.

To ensure that the parallel trends 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 5.9% and the p-value of the χ^2 test suggests 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 3 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 observable 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 group. We obtain the average change by subtracting the average number of patent applications (number of grants, citations, new firm registrations, and early-stage VC investment amount) over the four-year period just preceding the establishment of the national high tech zone from the average number of patent applications (number of grants, citations, new firm registrations, and early-stage VC investment amount) over the four-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 columns (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 9.1 more patent applications for the treatment cities than for the control cities per year. Similarly, the treatment cities exhibit 3.7 more granted patents, 14.3 more total citations, 497 more new firm registrations, and 53.1% more early-stage VC investment 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 nine-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 citations; Panel D illustrates the number of new firm registrations; Panel E depicts the early-stage VC investment amount in million for both groups over the same period. We observe from figure 2 that the lines for the treatment group and control group trend closely in parallel in years preceding the establishment of high-tech zones.[13] After the establishment of a high-tech zone, however, the two lines start to diverge, indicating that the treatment group enjoys a larger increase in innovation output and entrepreneurial activities.

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 in the regression framework. We use city-year observations for both treatment group and control group for a 9-year window centered on the establishment year and estimate the following model:

$$P\_Apply^{*}\ (P\_Grant^{*}, P\_Cite^{*}, F_{Est}{}^{*}, VC\_Seed\&A\_AMNT^{*}) = \alpha_i + \beta_1 Before^{-1} + \beta_2 Treat * Current^{0} + \beta_3 Treat * After^{1} + \beta_4 Treat * After^{234} + \beta_5 Treat + \beta_6 Before^{-1} + \beta_7 Current^{0} + \beta_8 After^{1} + \beta_9 After^{234} + \varepsilon$$

(2)

[13] The exception in Panel E that the control group cities have higher early-stage VC investment than treatment group cities three years before the establishment of high-tech zones does not work against our argument: Even in a certain year control cities have higher early-stage VC investment before the establishment of a high-tech zone, treatment cities still receive more early-stage VC investment after the establishment.

We report the results in Table 3 Panel D. The dependent variable is *P_Apply**, city *i*'s number of applied patents in a year, or *P_Grant**, city *i*'s number of granted patents in a year, or *P_Cite**, the number of citations of granted patents in a year, or *F_Est**, the number of new firm registrations in a year, or *VC_Seed&A_AMNT**, the natural logarithm of one plus a city's total VC investment in seed stage and series-A stage start-ups in a year. *Treat* is a dummy that equals one for treatment cities and zero for control cities. $Before^{1}$ is a dummy that equals one if a city-year observation is from the year that immediately before the establishment year and zero otherwise. $After^{1}$ is a dummy that equals one if a city-year observation is from the year that immediately after the establishment year and zero otherwise. $After^{234}$ equals one if a city-year observation is from the period that two to four years after the establishment year and zero otherwise. The benchmark group comprises of city-year observations that are two to four years before the establishment year.

We report the results of estimating equation (2) in Table 3 Panel D. In all columns, the coefficient estimates on β_1 and β_2 are statistically insignificant, suggesting that treatment cities and control cities do not exhibit significantly different trends in innovation output and entrepreneurial activities prior to the establishment of national high-tech zones. On the contrary, we observe β_4 in columns (1) to (3) are all positive and significant at the 1% level, suggesting that treatment cities, compared to control cities, have more patent applications, patents grants, and patent citations after the establishment of national high-tech zones. The coefficient estimate on β_4 in column (4) is positive and significant at the 10% level, suggesting a larger increase in new firm registrations in treatment cities than control cities. The coefficient estimate on β_3 is only significantly positive in column (1). The results suggest that patent applications respond immediately in the following year after the establishment of high-tech zones, but patents grants, patent citations, and new firm registrations start to increase significantly in two years after the establishment. This observation is consistent with the fact that it takes time for inventors and entrepreneurs to respond to policy changes, and hence we observe rises in innovation output and entrepreneurial activities with a two-year lag.

The evidence from the DiD tests using matched control group cities lends further support to our baseline results that the establishment of national high-tech zones has a positive, causal effect on local innovation output and entrepreneurial activities.

5.2 Additional identification tests

In this subsection, we perform a few additional tests to further address the concern that our baseline DiD results may not reflect a causal link between the establishment of national high-tech zones and local innovation 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 et al. 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 (Montinola, Qian, and Weingast, 1995) while central government would focus more on gross economic growth and cross-region economic disparity. 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 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 initiated 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 4.1 and report the results in Table 4. We observe that all of the coefficient estimates on *Enforced_HTZone*$_{i,t}$ are statistically significant, suggesting that the positive effect 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.

[Insert Table 4 about Here]

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 time, the possibility that unobservable omitted variables affecting local innovation 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 three years backward so they are three 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 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 5. 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 and entrepreneurial activities. Therefore, our results are not driven by omitted variables that coincide with the establishment of national high-tech zones.

[Insert Table 5 about Here]

Finally, 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 6. In all regressions, we observe insignificant DiD estimators. This finding suggests that our main results are unlikely driven by chance.

[Insert Table 6 about Here]

6. Plausible Mechanisms

Our evidence so far suggests that the establishment of high-tech zones has a positive, causal effect on local innovation and entrepreneurial activities. In this section, we explore plausible underlying mechanisms through which the establishment of national high-tech zones affects local innovation output and entrepreneurial activities. Specifically, we provide suggestive evidence on three plausible underlying mechanisms: favorable tax treatments, talent cultivation, and land price reductions.

6.1 Favorable tax treatment

The first plausible mechanism that allows the establishment of national high-tech zones to promote local innovation and entrepreneurial activities is favorable tax treatment in the zones. 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) suggests that corporate taxes hinder future innovation. There is also a large strand of literature arguing that taxation could discourage potential entrepreneurs from registering their our businesses (Djankov et al. 2002; Webb et al. 2009). Hence, we conjecture that favorable tax treatment in high-tech zones could be a plausible mechanism.

As stated in the official document by MOST, firms that 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. Therefore, tax benefits could be a plausible economic mechanism through which the establishment of a national high-tech zone promotes local innovation and entrepreneurial activities.

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 income tax rate and the sales tax and fee rate at the firm level from the database. Specifically, a firm’s income tax rate is computed by using its paid income taxes divided by the summation of net income and 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 income tax rate in a city (*Income_Tax_Rate*) and the annual mean of sales tax & fee rate (*Sales_Tax&fee_Rate*) during the 9-year window period 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 3 Panel C.

Table 7 reports the DiD estimators. Column (1) presents the average change in the income tax rate and sales tax and fee rate four years for treatment cities after the establishment of national high-tech zones and four years prior to the establishment. Column (2) presents the average change in control group 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 income tax rate of treatment group cities decreases 1.6% (significant at the 1% level) more than that of control group cities. The estimator on *Sales_Tax&fee_Rate* shows that the sales tax and fee rate of treatment group cities decreases 0.3% (significant at the 1% level) more than the sales tax and fee rate of control group cities.

[Insert Table 7 about Here]

Our evidence suggests that more favorable tax treatments, especially income tax cuts, in national high-tech zones could be a plausible underlying mechanism through which the establishment of high-tech zones positively affects local innovation and entrepreneurial activities.

6.2 Talent cultivation

A second plausible mechanism is the cultivation of talent. Human capital is crucial to innovation and high-skilled talent inflow may boost regional innovation output and productivity (Kerr et al., 2016). Researchers using U.S. data find that high-skilled immigrant inflows can raise human capital and the stock of ideas in the host country (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 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 could be an underlying channel for the establishment of high-tech zones to enhance local innovation and entrepreneurial activities.

To test this conjecture, we use the number of college students as a proxy for talents. College students could be potential 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 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 school students (in thousands) during the 9-year window centered on the event year, respectively. We calculate the change in the number of college and middle school students for treatment and control group cities, from its average over the four years before the establishment of national high-tech zones to its average over the four years after, and report the results in Table 8.

[Insert Table 8 about Here]

In Table 8, the DiD estimator on *College Students* is positive and significant at the 5% level. The magnitude of the DiD estimator suggests that the number of college students for treatment group cites rises 4,064 more than that for control group cities 9 years surrounding the establishment of high-tech zones. To address the concern that the increased number of college students are due to China's education promotion policy rather than the supporting policy for national high-tech zones, we use the change in the number of middle school students as a benchmark comparison. If the change in college students is induced by policies related to the development of national high-tech zones, we should not observe an increase in middle school students soon after the establishment of the high-tech zone. Table 8 shows that the DiD estimator of *Mid School 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 a college education.

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

6.3 Land price reduction

The third plausible mechanism through which the establishment of national high-tech zones positively affects local innovation and entrepreneurial activities is land price reductions. Previous research suggests that real estate and collateral have significant effects on corporate investment and entrepreneurial activities (e.g., Chaney, Sraer, and Thesmar, 2012; Schmalz, Sraer, and Thesmar, 2017). 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. Also, lower costs of establishing new firms induced by discounted land prices would boost local entrepreneurial activities.

If land price reduction is an underlying mechanism, we expect to observe land prices in cities with national high-tech zones exhibit a lower premium in land transaction deals than that 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 the period from 1989 to 2014. We use the average land transaction premium ratio (*AvgPremiumRat*), which equals the transaction price minus the land cost divided by the land cost, provided in the dataset to measure the cost in land transactions. Since land transactions do not frequently happen in cities, we conduct regressions in the baseline DiD framework in equation (1).[14] The key variable of interest, $HTZone_{i,t}$, is defined in the same way as before while the control group cities only include the matched ones. We report the results in Table 9.

[Insert Table 9 about Here]

The results in Table 9 indicate that the average premium of land transactions for the treatment group cities decreases about 0.65% (0.69% in column (1) without control variables and 0.62% in column (2) with control variables) more than that in the control group cities. The economic impact 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 decreases the premium of land transactions. Hence, land price reductions could be a mechanism through which the establishment of national high-tech zones promotes local innovation and entrepreneurial activities.

7. Conclusion

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 and entrepreneurial activities. Relying on plausible exogenous variation in place-based policies caused by staggered establishments of national high-tech zones in 473 Chinese cities and using a DiD approach, we find that the establishment of national high-tech zones has a positive effect on early-stage VC investment, local patents quantity and quality, and new firm registration. A number of additional

[14] This specification allows us to include more city-year observations.

tests suggest that the results are likely causal and unlikely driven by chance. Favorable tax treatments, talent cultivation, and land price reductions offered by national high-tech zones are three plausible underlying mechanisms through which high-tech zones promote local innovation and entrepreneurial activities. Our paper sheds new light on the impact of China's national high-tech zones and provides new evidence to the debate about the real effect of place-based policies.

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Table 1 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 8,933 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 invention patent applications in year *t+1*
$INNOV\_PGrant_{i,t+1}$	Natural logarithm of one plus a city *i*'s total number of invention patents grants in year *t+1*
$INNOV\_PCite_{i,t+1}$	Natural logarithm of one plus a city *i*'s total number of citations on city *i*'s invention patents filed 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*
$VC\_Seed\&A\_AMNT_{i,t+1}$	Natural logarithm of one plus a city *i*'s total VC investment in seed stage and series-A stage start-ups in year *t+1*
Measures of Innovation Growth	
$PApply\_Growth_{i,-3\ to\ -1}$	Change in the number of patent applications over the three-year period before the establishment year
$PGrant\_Growth_{i,-3\ to\ -1}$	Change in the number of patents grants over the three-year period before the establishment year
$PCite\_Growth_{i,-3\ to\ -1}$	Change in the number of patent citations over the three-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 three-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 Gross Domestic Product in year *t*
$GDP2\_\%_{i,t}$	City *i*'s % GDP from the second-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 Consumer Price Index (CPI) in year *t*

Panel D: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
P_Apply	8,933	0.188	0.765	0.000	6.033
P_Grant	8,933	0.067	0.267	0.000	2.107
P_Cite	8,933	0.046	0.173	0.000	1.328
F_Est	8,290	4.000	6.840	0.056	44.906
VC_Seed&A_AMNT	8,933	2.096	5.758	0.000	23.587
Population	8,933	5.440	1.021	-0.211	8.124
GDP	8,933	5.069	1.874	-2.356	10.068
GDP2_%	8,933	46.456	12.319	0.400	93.407
GDP3_%	8,933	32.946	9.129	0.200	85.340
AvgWage	8,933	9.002	1.110	5.540	11.451
CPI	8,933	106.610	7.275	96.400	133.057

Table 2 Baseline DiD Specification

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

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

Variable definitions are provided in Table 1 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.

VARIABLES	*INNOV_PApply* $_{i,t+1}$	*INNOV_PGrant* $_{i,t+1}$	*INNOV_PCite* $_{i,t+1}$	*ENTREPRE_FEst* $_{i,t+1}$	*VC_Seed&A_AMNT* $_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
HTZone	0.342***	0.496***	0.230***	0.123**	2.518***
	(0.092)	(0.094)	(0.074)	(0.059)	(0.386)
Population	-0.088	-0.145**	-0.036	0.195***	-1.473***
	(0.060)	(0.063)	(0.048)	(0.050)	(0.284)
GDP	0.059	0.039	0.036	-0.036	0.766***
	(0.043)	(0.042)	(0.034)	(0.040)	(0.166)
GDP2_%	0.004	-0.000	0.021***	0.001	-0.073***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.020)
GDP3_%	0.014**	0.012**	0.002	-0.004	0.030
	(0.005)	(0.006)	(0.005)	(0.004)	(0.022)
AvgWage	0.057	0.178***	0.010	0.084	0.675**
	(0.071)	(0.066)	(0.054)	(0.069)	(0.296)
CPI	0.000	0.001	-0.002	0.015**	0.028
	(0.005)	(0.005)	(0.005)	(0.007)	(0.032)
Constant	-0.716	-1.873*	-1.060	0.215	-3.151
	(0.967)	(0.988)	(0.810)	(1.030)	(5.369)
Observations	8,394	8,394	8,394	8,020	8,394
R-squared	0.895	0.876	0.791	0.868	0.435
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 3 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. Sample selection begins with all cities with non-missing matching variables and non-missing outcome variables in the year prior to the share reform. 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. The 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 group cities and control group cities. The 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 1. The models in both columns of Panel A are estimated with province and year fixed effects. Coefficient estimates are reported and t-statistics 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. Panel D reports regression estimates of the innovation and entrepreneurship dynamics of treatment and control cities surrounding establishment of national high-tech zones. 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 patent grants in a given year, or *P_Cite**, city *i*'s total number of patent citations generated by patent applied in a given year, *F_Est**, city *i*'s total number of new firm registrations in a given year, or *VC_Seed&A_AMNT**, city *i*'s natural logarithm of total VC investment amount in the seed stage or in series-A stage start-ups 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

VARIABLES	(1) Pre-match	(2) Post-match
PApply_Growth $_{-3\ to\ -1}$	0.012	0.030
	(0.012)	(0.031)
PGrant_Growth $_{-3\ to\ -1}$	-0.024	0.005
	(0.022)	(0.055)
PCite_Growth $_{-3\ to\ -1}$	0.011	-0.015
	(0.009)	(0.025)
FEst_Growth $_{-3\ to\ -1}$	0.000	-0.000
	(0.000)	(0.000)
Population $_{-1}$	-0.043	-0.208
	(0.498)	(0.462)
GDP $_{-1}$	2.158***	0.903*
	(0.542)	(0.485)
AvgWage $_{-1}$	1.756*	-0.247
	(0.948)	(1.208)
GDP2_% $_{-1}$	0.049**	0.015
	(0.020)	(0.023)
GDP3_% $_{-1}$	0.096***	0.042
	(0.021)	(0.032)
CPI $_{-1}$	-0.091	-0.047
	(0.068)	(0.151)
Constant	-17.654*	3.359
	(9.611)	(18.627)
Observations	2,434	190
Province FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R-squared	0.48	0.059

Panel B Differences in Pre-establishment Characteristics

	Treatment	Control	Difference	t-statistics
GDP	4.345	4.152	0.193	1.116
Population	5.518	5.456	0.062	0.507
AvgWage	8.176	8.160	0.015	0.15
GDP2_%	48.403	47.815	0.588	0.312
GDP3_%	29.078	28.389	0.689	0.565
CPI	104.826	104.719	0.107	0.125
PApply_Growth	7.042	3.906	3.135	1.676
PGrant_Growth	2.031	0.906	1.125	1.336
PCite_Growth	6.760	3.635	3.125	1.546
FEst_Growth	478.833	377.260	101.573	0.473

Panel C Difference-in-Differences Test

	Mean treatment Difference (after-before)	Mean Control Difference (after-before)	Mean DiD Estimator (treat-control)	t-statistic for DiD
P_Apply	17.396	8.272	9.124	2.728
	(1.224)	(3.112)	(3.344)	
P_Grant	7.398	3.732	3.666	1.970
	(0.614)	(1.757)	(1.861)	
P_Cite	20.626	6.346	14.280	2.270
	(0.846)	(6.235)	(6.292)	
F_Est	1.208	0.711	0.497	1.679
	(0.159)	(0.250)	(0.296)	
VC_Seed&	0.646	0.115	0.531	1.924
A_AMNT	(0.164)	(0.222)	(0.276)	

Panel D Difference-in-Differences Analysis for Dynamics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	P_Apply*	P_Grant*	P_Cite*	F_Est*	VC_Seed&A _AMNT*
*Treat*Before^{-1}*	2.640	1.106	1.349	-0.063	0.480
	(5.218)	(2.872)	(9.681)	(0.480)	(0.379)
*Treat*Current^{0}*	4.338	1.533	3.692	0.150	0.290
	(5.218)	(2.872)	(9.681)	(0.480)	(0.442)
*Treat*After^{1}*	7.083*	1.867	6.953	0.406	0.465*
	(4.152)	(2.285)	(7.703)	(0.382)	(0.281)
*Treat*After^{234}*	12.568***	6.054***	22.323***	0.554	0.715*
	(4.152)	(2.285)	(7.703)	(0.382)	(0.394)
Before^{-1}	1.439	0.270	1.459	0.161	-0.183
	(3.691)	(2.031)	(6.847)	(0.339)	(0.214)
Current^{0}	3.564	0.916	3.449	0.376	0.292
	(3.691)	(2.031)	(6.847)	(0.339)	(0.276)
After^{1}	6.528**	2.483	6.267	0.768***	-0.330**
	(2.937)	(1.616)	(5.449)	(0.270)	(0.153)
After^{234}	10.783***	5.124***	7.204	0.740***	0.202
	(2.937)	(1.616)	(5.449)	(0.270)	(0.201)
Treat	7.099***	2.956**	6.870	0.346	-0.119
	(2.693)	(1.482)	(4.996)	(0.247)	(0.185)
Constant	5.727***	1.595	4.447	1.437***	0.330**
	(1.906)	(1.049)	(3.536)	(0.175)	(0.153)
Observations	1,681	1,681	1,681	1,681	1,681
R-squared	0.084	0.057	0.035	0.036	0.014

Table 4 Placebo Tests: Subsample Analysis

This table shows the results for subsample analysis. 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 1 Panel C. Coefficient estimates are shown as 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.

VARIABLES	(1) INNOV_PApply	(2) INNOV_PGrant	(3) INNOV_PCite	(4) ENTREPRE_FEst	(5) VC_seedA_AMNT
Enforced_HTZone	0.929**	1.100***	0.632*	0.507**	5.220***
	(0.357)	(0.353)	(0.350)	(0.201)	(1.345)
Population	0.229**	0.152	0.155	0.209*	-0.0499
	(0.112)	(0.109)	(0.119)	(0.123)	(0.497)
GDP	0.000	0.0378	0.00376	-0.0853	0.557
	(0.089)	(0.0824)	(0.0861)	(0.100)	(0.363)
GDP2_%	0.028***	0.0249***	0.0316***	-0.00131	0.0171
	(0.007)	(0.00760)	(0.00738)	(0.00766)	(0.0323)
GDP3_%	0.029***	0.0310***	0.0106	-0.00685	0.0999**
	(0.009)	(0.00993)	(0.00798)	(0.00889)	(0.0433)
AvgWage	-0.154	-0.158	0.129	0.323	-0.293
	(0.205)	(0.211)	(0.204)	(0.218)	(0.603)
CPI	-0.024*	-0.0362***	-0.0192	0.0256***	-0.0335
	(0.012)	(0.0116)	(0.0178)	(0.00808)	(0.0539)
Constant	0.657	1.829	-1.917	-1.329	-1.427
	(2.539)	(2.426)	(2.415)	(1.902)	(8.887)
Observations	3,064	3,064	3,064	2,982	3,064
R-squared	0.861	0.834	0.735	0.826	0.369
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
PSM	Yes	Yes	Yes	Yes	Yes

Table 5 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 three 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 year *t-3* in city *i*. Definitions of all other variables are listed in Table 1 Panel C. Coefficient estimates are shown as 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.

VARIABLES	(1) INNOV_PApply	(2) INNOV_PGrant	(3) INNOV_PCite	(4) ENTREPRE_FEst	(5) VC_seedA_AMNT
HTZone_3y_Before	-0.058	0.046	-0.029	0.116	0.456
	(0.095)	(0.095)	(0.056)	(0.078)	(0.334)
Population	0.029	-0.087	-0.040	0.110	-0.385*
	(0.067)	(0.066)	(0.053)	(0.075)	(0.217)
GDP	-0.016	0.026	-0.002	-0.101	0.226*
	(0.047)	(0.046)	(0.042)	(0.074)	(0.115)
GDP2_%	0.006	0.002	0.008**	-0.008*	-0.004
	(0.005)	(0.005)	(0.003)	(0.004)	(0.015)
GDP3_%	0.009*	0.008	0.008*	-0.021***	0.016
	(0.005)	(0.006)	(0.005)	(0.008)	(0.021)
AvgWage	0.349***	0.304***	0.328***	0.401***	0.374
	(0.110)	(0.110)	(0.094)	(0.147)	(0.298)
CPI	-0.014*	-0.018***	-0.015*	0.010*	-0.028**
	(0.007)	(0.007)	(0.009)	(0.006)	(0.014)
Constant	-2.132	-1.274	-2.025	1.517	-0.448
	(1.297)	(1.114)	(1.341)	(1.257)	(2.951)
Observations	2,845	2,845	2,845	2,779	2,845
R-squared	0.777	0.721	0.683	0.833	0.351
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
PSM	Yes	Yes	Yes	Yes	Yes

Table 6 Tests Using Randomly Assigned Treatment and Control Group Cities

This table reports the results of identification tests using randomly assigned treatment and control group cities for the DiD analysis. We re-estimate the DiD estimators in Table 3 Panel C. Definitions of variables are listed in Table 1 Panel C. ***, **, 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	10.611	14.890	-4.279	-1.271
	(2.783)	(1.896)	(3.367)	
P_Grant	4.388	6.653	-2.265	-1.225
	(1.595)	(0.934)	(1.848)	
P_Cite	8.805	17.800	-8.995	-1.462
	(5.911)	(1.711)	(6.154)	
F_Est	1.078	0.851	0.227	0.753
	(0.173)	(0.247)	(0.301)	
VC_Seed&	0.358	0.400	-0.042	-0.153
A_AMNT	(0.208)	(0.180)	(0.275)	

Table 7 Possible Mechanism: Tax Benefit

This table reports the results for DiD tests on average city tax rate. *Income_Tax_Rate* equals the mean of firms' income tax rate in a city during the nine-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 income tax. *Sales_Tax&fee_Rate* equals the mean of firms' sales tax & fee divided by its sales revenue during the nine-year window period centered on the event year. The firm-level data is retrieved from annual surveys conducted by the National Bureau of Statistics (NBS) of China from 1998 to 2011. ***, **, 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
Income_Tax_Rate	-0.023	-0.007	-0.016	-2.828***
	(0.004)	(0.004)	(0.006)	
Sales_Tax&fee_Rate	-0.003	0.000	-0.003	-2.121***
	(0.001)	(0.001)	(0.001)	

Table 8 Possible Mechanisms: Talent Introduction and Cultivation

This table reports the results for DiD tests on the average number of a city's college students and a city's middle school students. The variable *College_Students* expresses the average number of a city's college students per year in thousand during the nine-year window period centered on the event year, while the variable *MidSchool_Students* per year expresses the number of a city's middle school students in thousand during the nine-year window period centered on the event year. The education data are collected from China City Statistics Yearbook. ***, **, 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
College_Students	8.150	4.086	4.064	2.121**
	(1.075)	(1.586)	(1.916)	
MidSchool_Students	51.517	37.501	14.016	0.674
	(13.618)	(15.734)	(20.809)	

Table 9 Possible Mechanism: Land Price Deduction

This table reports the results for DiD tests on the average premium of the land transaction. The land transaction records are obtained from the China Stock Market & Accounting Research (CSMAR), which covers the period from 1989 to 2014. *AvgPremiumRat* equals the transaction price minus the land cost divided by the land cost. Definitions of other variables can be found in Table 1 Panel C. Coefficient estimates are shown as 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.

VARIABLES	(1) *AvgPremiumRat* $_{i,t+1}$	(2) *AvgPremiumRat* $_{i,t+1}$
HTZone	-0.689**	-0.620**
	(0.284)	(0.286)
Population		-24.739***
		(3.731)
GDP		4.023*
		(2.296)
GDP2_%		-0.511**
		(0.199)
GDP3_%		-0.632***
		(0.228)
AvgWage		0.000**
		(0.000)
CPI		-0.079
		(0.290)
Constant	-20.657***	138.181***
	(4.077)	(46.877)
Observations	19,482	19,482
R-squared	0.148	0.153
City FE	Yes	Yes
Year FE	Yes	Yes

Figure 1 Geographical distribution of national high-tech zones

This figure exhibits the geographical distribution of national high-tech zones. Empty dots shows 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).

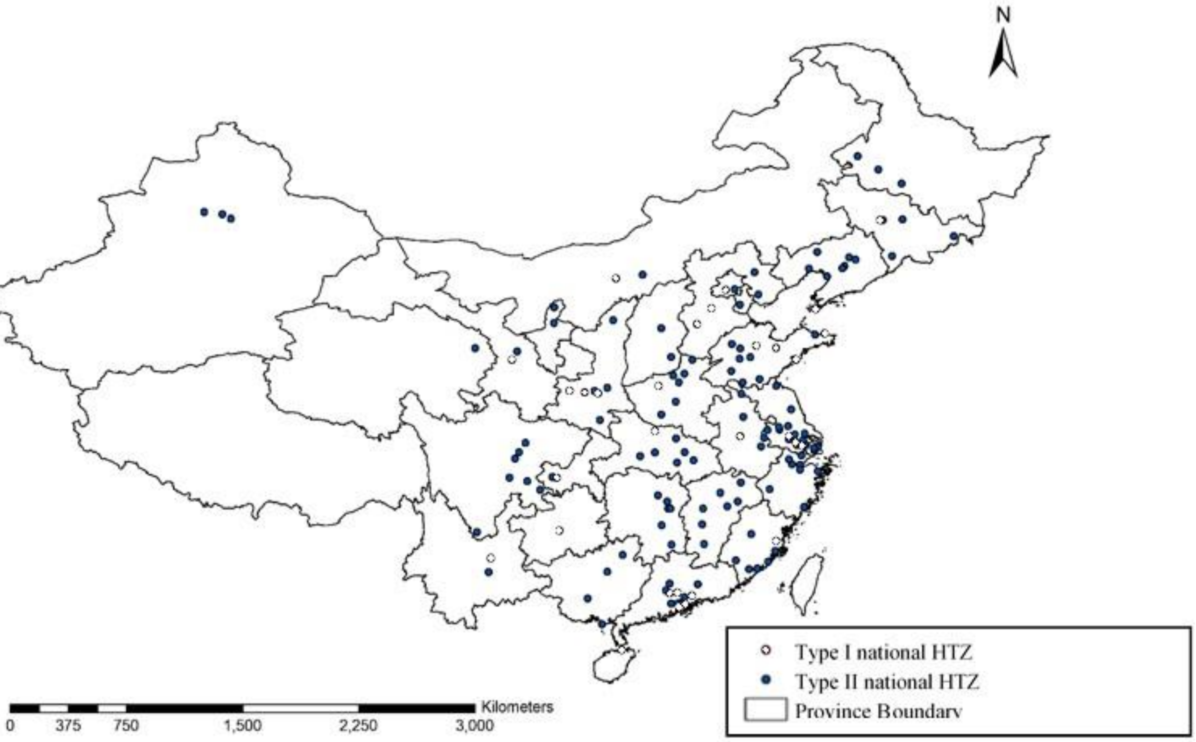
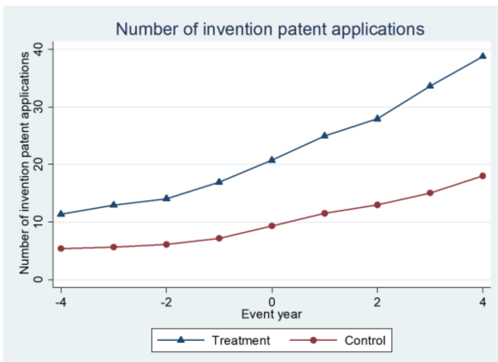
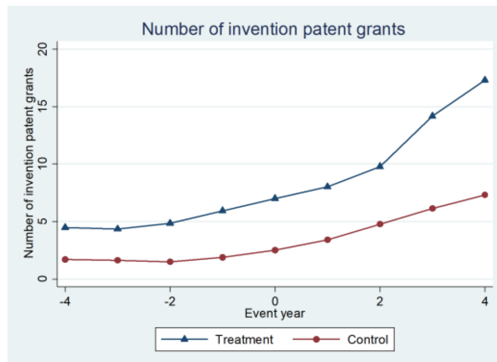


Figure 2 Patent and firm registration dynamics surrounding establishment of zones

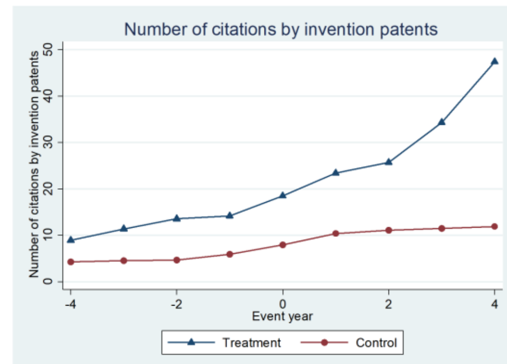
This figure shows the mean difference in innovation and entrepreneurship captured by an average number of patent applications, patent grants, patent citations and new firm registrations for treatment and control cities from four years before the establishment of national high-tech zones to four years after the establishment of zones. The sample consists of 95 treatment cities and 95 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 grants (*P_Grant*), Panel C shows the difference in patent citations (*P_Cite*), Panel D shows the difference in new firm registrations (*F_Est*), and Panel E shows the difference in VC investment amount in seed stage and series A stage (*VC_Seed&A_AMNT*).



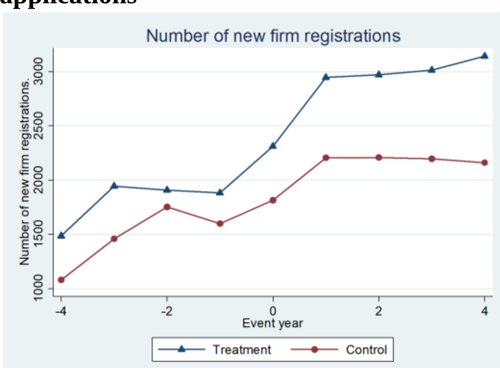
Panel A Number of invention patent applications



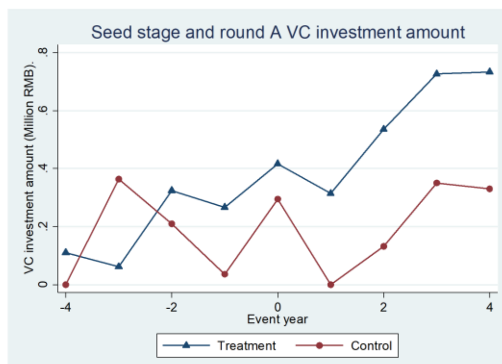
Panel B Number of invention patents grants



Panel C Number of citations by invention patents



Panel D Number of new firm registrations



Panel E Amount of VC investment in seed stage and series A stage