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Identifying Knowledge Spillovers from Universities: Quasi-experimental Evidence from Urban China*

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Abstract

This paper studies the impact of universities on local innovation activity by exploiting a unique university expansion policy in China as a quasi-experiment. We take a geographic approach, empowered by geocoded data on patents and new products at the address level, to identify knowledge spillovers as an important channel. We obtain three main findings. First, university expansion significantly increases universities' own innovation capacity, which results in a dramatic boom of local industry patents. Second, the impact of university expansion on local innovation activities attenuates sharply within 2 kilometers of the universities. Third, university expansion boosts nearby firms' new products and the number of times when nearby industry patents cite university patents but not the number of times when industry patents cite patents far away from universities.

Keywords: university expansion; knowledge spillovers; patents; new product

JEL classifications: I25, O33, R11, R12

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1. Introduction

Economists and policy makers have long stressed the importance of higher education institutions in fostering economic growth (Acemoglu 1995; Redding 1996; Andersson et al. 2004, 2009; Aghion et al. 2009). The common belief is that universities not only train high-skill labor, but also disseminate knowledge and promote productivity in local communities (Valero and Van Reenen 2019; Andersson et al. 2009). Whereas previous research has shown the impacts of universities on the development of certain industries and local productivity, we have limited understanding on the causal role that universities play in facilitating knowledge-based externalities and on the geographic scope of such externalities (Kantor and Whalley 2014, 2019). The central challenges that have limited progress in the literature are the endogeneity concerns and the difficulty in distinguishing knowledge spillovers from other potential channels. This paper takes a geographic approach, combined with a quasi-experimental setting, to resolve the challenges and identify the role of knowledge spillovers from universities.

We examine the causal impact of university activity on the creation of local patents and new products by taking advantage of a unique quasi-experiment in China that has exogenously expanded higher education institutions since 1999. We exploit a structural break in the university-innovation relationship induced by the policy shock to uncover the localized nature and striking geographic attenuation of university spillovers at a very refined geographic level (within 2-3 km).[1] We achieve this goal by utilizing novel datasets that contain comprehensive information on patents and new products of firms geocoded at the address level. The uncovered geographic nature of the impact allows us to identify knowledge spillovers from universities by building on the general consensus that idea flows rely heavily on spatial proximity.[2] By further merging our core datasets with patent citation information, we also reveal direct evidence of knowledge outflows from universities and striking spatial

[1]While previous studies have documented the localized nature of university spillovers at the scope of cities or counties (Jaffe 1989; Audretsch and Feldman 1996; Anselin et al. 1997; Andersson et al. 2004, 2009; Kantor and Whalley 2014; Liu 2015; Kantor and Whalley 2019; Hausman 2022), none has studied the spillover effects at the refined geographic level as we undertake in this paper. The extension to this geographic level is important in identifying knowledge spillovers as one of the mechanisms that contribute to the impact of universities on local innovation.

[2]An extensive literature emphasizes that knowledge spillovers decay rapidly within narrowly defined geographic space (Jaffe et al. 1993; Rosenthal and Strange 2003, 2005, 2008; Arzaghi and Henderson 2008; Combes and Gobillon 2015; Li et al. 2022; Baum-Snow et al. 2021). This is because gains from exchanging knowledge and information rely heavily on close-range face-to-face contact. The geographic approach to identify the mechanisms of agglomeration externalities has been emphasized in Rosenthal and Strange (2020) and validated in Li et al. (2022).

decay patterns of the citation links. Our findings unanimously point to the importance of knowledge spillovers in fostering innovation in close proximity to education and research institutions.

The evidence on knowledge spillovers from universities helps researchers better understand the role of universities in the economic growth process. It is widely acknowledged that research and development (R&D) played a central role in advancing the world technology frontier and contributed to continued economic growth over the past 200 years (Acemoglu 2008). However, in innovation-based growth models, the R&D production function has been taken as a reduced-form representation and the specific steps leading to practical innovations is not yet clear.[3] Presumably, research outputs from research institutions serve as a key first step leading to innovative ideas that are then converted into innovative products. By tracing the impact of university activities on patents, patent citations, and new products, we document the role of knowledge spillovers from universities in the innovation process. This process of transforming fundamental knowledge into patentable findings and practical products forms the cornerstone of the R&D production function that is at the center of innovation-based economic growth theory.

Understanding the presence and the spatial scope of university spillovers in promoting local innovation also has important policy implications. First, it justifies public investments on higher education that has witnessed enormous growth in recent decades (Schofer and Meyer 2005).[4] Second, the extent to which education investment spills over to benefit surrounding firms provides guidance for creating technology hubs near education institutions. Evidenced by the salient example of Cambridge's Kendall Square near Harvard University and the Massachusetts Institute of Technology, policy makers have formed a general consensus that proximity to universities is a key condition for a vibrant high-tech community. Yet, a careful policy design requires a good understanding on how quickly the positive externalities decay with geographic distance. If university spillovers decay slowly, social planners may not have to endure high congestion costs in close proximity to research institutions to exploit the spillover benefits. If, however, the positive externalities decay quickly, policy makers would need to carefully gauge policy parameters to balance the spillover benefits with rising conges-

[3]Externalities from human capital and innovation had a scientific revival with the endogenous growth models starting with Romer (1986, 1990), Lucas (1988), and Grossman and Helpman (1991). Jaffe (1986, 1989) modeled a simple production function using industry and university research as inputs. Both studies found significant and positive effects of university research on outputs.

[4]For example, in 2017, the Ministry of Education of China spent 1,110.9 billion yuan (about US$170.9 billion using the exchange rate in December 2017) on higher education (http://www.moe.gov.cn/).

tion costs.

Empirically, it is challenging to identify the causal impact of university spillovers on local innovation activities. One possible endogeneity concern resides in the presence of persistent local unobserved amenities that attract both premier universities and productive firms. In addition, business activities also reversely impact nearby universities and academic research through collaborations with or donations to universities (Bils and Klenow 2000). We address the concerns by exploiting a unique national university expansion policy resulted from an unanticipated economic stimulus plan from the central government in China. The policy introduced an exogenous structural break in city-specific university capacity that is presumably independent of local economic conditions. We make use of the kinked relationship created by the shock to identify the impact of the university expansion in a difference-in-differences framework, drawing on cross-sectional variations in the exposure to the shock determined by the university capacity prior to the shock.

More important, the core element of our empirical analysis is the focus on within-city variations to characterize the geographic nature of university spillovers and to identify the role of knowledge spillovers. This within-city focus allows us to adopt a triple-differences approach in which we control for a rich set of interacting fixed effects to tighten our identification. Specifically, to capture the spatial attenuating features at very refined geographical levels, we examine the impact of university expansion on surrounding industrial innovation activities within 0.5 km, between 0.5 km and 1 km, between 1 km and 1.5 km, and so on, extending up to 5 km or 10 km, depending on the specific model. We control for year by ring, year by city, and city by ring fixed effects to absorb unobserved local demand shocks or factors related to either China's World Trade Organization (WTO) accession or reduction in internal migration and trade costs.[5] Our focus on the localized geographic nature of the impact allows us to shed light on the geographic scope and the underlying mechanism of university spillovers. As existing studies have shown how fast knowledge spillovers decay over space, taking the analysis to this level of geography is essential.

In the empirical analysis to follow, we document the extent to which proximity to academic universities in China affects nearby patent generation and cross-patent citations. We utilize detailed

[5] We address further concerns on the possible presence of city- and location(distance)-specific unobserved time-varying factors by taking advantage of information on nearby patents that cite university patents. We elaborate on this point in Section 3.

patent-level data between 1995 and 2007 from the National Intellectual Property Administration of China and patent citation links scraped from Google Patents to achieve this focus. Patenting is one of the best proxies for innovation and is widely used to capture knowledge creations. Since Jaffe et al. (1993), the literature has taken advantage of patent citation links to trace the paper trails of knowledge flows.[6] We rely on citation links to highlight direct knowledge flows from universities to nearby industrial firms. Moreover, a comparison between nearby patents that cite university patents and those that cite patents far away from universities helps address concerns on the possible presence of city- and location (distance)-specific unobserved time-varying factors that may contaminate our triple-differences identification.

Despite the benefit of detailed information on patents, patenting represents an intermediate step rather than the final economic output in the process of converting new ideas to new products. To mitigate this concern, we take advantage of previously under-explored information on new firm product sales reported in the Annual Survey of Industrial Firms (ASIF). According to ASIF, "products included in the category of new product sales are those that are new in relation to the reporting firm's prior product mix." Hence, new product sales in ASIF better reflect the ultimate outcome of the innovation process: the commercialization of technical ideas. Other firm-level surveys rarely capture this information on new product.[7] It provides a unique opportunity to examine the impact of university expansion on a direct measure of downstream outputs produced using knowledge and ideas.

We obtain the following results. First, university innovation activities increase nearby patents, and the impact decays sharply with geographic distance. In particular, we find that the level of patenting activities reduces by about 80 percent when moving from within 0.5 km to 0.5-1 km of a university. The impact reduces by another 65 percent when moving from 0.5-1 km to 1-1.5 km of a university. The sharp decline stops roughly at 2 km away, and the attenuation slope flattens out thereafter. Second, we find that the spatial attenuation of university spillovers is ubiquitously present in different regions and industries in China but is more pronounced in the Eastern region and for industries more reliant on high-skilled labor. Third, we find that university expansion increases nearby industry patents that

[6] Although the case-control approach in Jaffe et al. (1993) faces challenges and is refined in several follow-up efforts, the approach of following patent citations to trace knowledge flows is widely recognized (Thompson and Fox-Kean 2005; Thompson 2006; Murata et al. 2014; Figueiredo et al. 2015).

[7] A few studies use new product announcement data from the U.S. Small Business Administration to examine innovation (Acs and Audretsch 1988; Acs et al. 1994; Feldman and Audretsch 1999; Acs et al. 2002). That data, however, are only available for 1982 and are also limited in scope.

cite university patents. The knowledge outflows captured by citation links also decay quickly across space and stabilize beyond the 2 km radius. The spatial attenuation pattern, however, is not present for the number of times when nearby industry patents cite patents far away from universities. Last, further analysis suggests that university expansion boosts new products from firms and that the impact follows a similar spatial decay. This effect is more pronounced for high-skilled intensive industries and private firms than for low-skilled intensive industries and state firms.

Our study contributes to two sets of literature. First, this paper joins the literature on knowledge spillovers and agglomeration economies. Since Marshall (1890), researchers have attributed the micro-foundations of agglomeration externalities to the sharing of goods, people, and ideas—otherwise labeled as intermediate input sharing, labor market pooling, and knowledge spillovers (Duranton and Puga 2004; Holmes 1999; Glaeser and Maré 2001; Moretti 2004; Ellison et al. 2010). It is also recognized that different microfoundations are associated with different spatial attenuation of agglomeration externalities (Rosenthal and Strange 2004; Combes and Gobillon 2015; Li et al. 2022).[8] Rosenthal and Strange (2020), in particular, emphasizes the convenience of identifying the nature of agglomeration externalities by relying on the observed attenuation patterns. Baum-Snow et al. (2021) interprets the micro-geographic level rapid spatial decay in productivity spillovers as explained by learning or knowledge transfer. Hence, the fast attenuation speed documented in our paper points to the important role of knowledge spillovers in university spillover benefits.

Second, we contribute to the literature on the impact of research institutions and academic research on local economic outcomes. Previous studies have focused on a range of economic outcomes in the context of developed countries. For instance, Jaffe (1989) and Anselin et al. (1997) examine the effects of university research on local innovations in the United States. Andersson et al. (2004, 2009) investigate the impact of educational investment on productivity and innovation in Sweden. Kantor and Whalley (2019) uses historical establishment of agricultural experiment stations in the United States to evaluate the impact of proximity to research on agricultural productivity.[9] However, the geographic unit of analysis is mostly at the city, county, municipality, state, or region level,

[8]For instance, industries that rely heavily on knowledge spillovers as the main agglomeration force often require close-range face-to-face contact, which implies a rapid spatial decay of agglomeration spillovers; industries that cluster mainly because of input-output linkages could have agglomeration externalities decay slowly and extend to a larger spatial scale.

[9]Other studies in this strand of literature include Aghion et al. (2009), Kantor and Whalley (2014), Liu (2015), Andrews (2019), and Hausman (2022).

which prohibits researchers from understanding the micro-geographic scope of university spillovers and drawing conclusions on the channel through which the localized spillovers take place. We extend the literature by focusing on a developing country context and documenting a sharp spatial attenuation of the impact of university expansion on intermediate innovation outcomes (patents and citation links) and final output measures (new products).

The rest of the paper is organized as follows. Section 2 introduces the institutional background of the university expansion in China. Section 3 lays out the empirical framework and identification strategies. Section 4 describes data and variables. Section 5 presents the empirical results on patents. Section 6 presents the results on patent citations and new products. We conclude in Section 7.

2. Institutional Background

In this section, we introduce China's higher education system and discuss the policy background of the university expansion that started in 1999.

China's higher education system is under central planning since its establishment in the 1950s. The Ministry of Education (MOE) in the central government is the sole entity that makes admission plans for all universities based on the national economic development plan. High school graduates are admitted to different universities based on their performance on a unified national college entrance examination. This central planning feature governs that the implementation of higher education policies follows a top-down approach, and the intensity of the policy is usually not responsive to economic environment at the local level.[10] The radical university expansion that started in 1999 is one such example and was unanticipated at the time.

Before 1999, the development of China's higher education institutions was steady and smooth.[11] However, the onset of the 1997 Asian financial crisis and the massive layoffs resulted from the state-owned enterprise (SOE) reforms in the late 1990s raised concerns about a recession and triggered

[10]China's higher education system is different from the systems in many Western countries, such as the United States. or example, almost all prestigious universities in China are public universities, whereas many prestigious universities in the United States are private. In addition, the financial support for higher education is almost entirely provided by the MOE in China, whereas fundraising plays a significant role in financing the universities in the United States.

[11]China's higher education system went back to normal after the Cultural Revolution ended in 1976. In the 1990s, the Ministry of Education guided China's higher education sector under a theme called "steady development." The number of enrolled students increased with an average growth rate of 7 percent between 1977 and 1998. From 1990 to 1998, the number of university students increased from 2.06 million to 3.41 million, and the number of university teachers rose slightly from 0.395 million to 0.407 million.

a need to expand the higher education sector to stimulate the domestic demand for educational services and other related consumption.[12] University expansion was also believed to postpone the entry of high school graduates into the labor market, which may otherwise exacerbate the already-high unemployment rate (Che and Zhang 2018).

In June 1999, the MOE and the National Development and Planning Commission jointly announced a new higher education recruitment plan, with expected new students of 1.53 million in 1999—a 42 percent year-on-year increase. In the meantime, college tuition fees increased by 15-20 percent across different regions. The revenue from tuition became an important financial resource for universities. The central government also shifted more resources to higher education to accommodate the huge increase in university scale. From 1998 to 2000, the science and technology funding and national expenditure on higher education increased from 8.2 billion yuan to 14.3 billion yuan and from 33.6 billion yuan to 49.1 billion yuan, respectively. From 1998 to 2000, the number of university teachers also rose by 55,519, more than fourfold of the increase from 1990 to 1998.

The expansion was unanticipated by the general public and local governments. The new plan would impose huge impacts on the college entrance examination in July (one month later) and the new academic semester starting in September (three months later). The time left for the government to distribute the enrollment quota was pressing. Official documents suggest that the quota allocation across cities mainly depended on the national expansion plan and existing universities' physical and logistical capacity at the city level. The quota allocation rules also present strong inertia as the radical expansion continued in the following years. Therefore, the expansion led to an exogenous structural break in a city's higher education scale, and the magnitude of the structure break depended on the city's university resources prior to the shock.

Figure 1 depicts various aspects of the structural break in China's higher education sector induced by the policy shock. Panels A-D present the numbers of university teachers, university students, university entrants, and university graduates from 1990 to 2010. Before 1999, the growth rate of those numbers was low and steady. However, a clear trend break exists in the time series of the

[12] Min Tang, a famous economist in the Development Research Center of the Asian Development Bank, originally proposed the university expansion policy. In November 1998, Mr. Tang, along with his wife Xiaolei Zuo, wrote an open letter to the central government, in which they appealed for doubling the higher education enrollment in three years. They also suggested that China stop offering free higher education and require students to pay tuition fees. They believed that those actions would help generate demands in relevant economic sectors and stimulate the nation's economy. The letter can be viewed at http://finance.sina.com.cn/review/20041023/15201102716.shtml.

numbers of university teachers, university students, and university entrants in 1999 and the number of university graduates in 2003. The scale of universities in China increased dramatically after 1999. In particular, the number of university teachers in 2010 was more than three times of the number in 1998. In Panel E, the national higher education expenditure increased more than threefold from 1998 to 2006. Panel F shows that the science and technology funding for the higher education sector increased by a factor of over 11 from 1998 to 2010. The expansion dramatically increased the research resources to universities, at both the aggregate and per teacher level.

In Figure 2, we plot the correlation between the extent of university expansion from 1999 to 2007 and the scale of higher education before the expansion at the city level. Specifically, in Panel A, we plot the increase in the number of university teachers between 1999 and 2007 in each city against the number of university teachers in each city in 1990. We do the same for the number of university students in Panel B. There is a clear positive correlation between the expansion in university scale and the pre-existing university students and teachers before the expansion at the city level. The pattern confirms that, during the expansion period, the enrollment quota was allocated to different cities mainly based on the city-level pre-existing physical and logistical capacity of the higher education sector. The increase in enrollment quota further induces universities to gain more funding, upscale the teachers, and eventually expand the research capacity.

In sum, the higher education expansion policy followed a top-down approach and created a positive exogenous shock to university scale. The extent of the expansion in each city was largely determined by the national expansion plan and existing universities' capacity before the expansion. Several studies find support for the exogeneity of this national policy to the local economic environment (Che and Zhang 2018; Li et al. 2017; Rong and Wu 2020).[13] We provide similar evidence in Appendix Figure A1 that the extent of university expansion in a city is not predicted by the growth of patents, GDP and firm TFP in the city before the expansion. We use this policy shock to form a difference-in-differences and a triple-differences research design.

[13]Che and Zhang (2018) shows that the annual growth rates of gross domestic product and annual admission are uncorrelated at the provincial level for the period of 1995-2011. They also show that the correlations between the growth of new college graduates in 2001-2003 and the growth of provincial GDP and firm TFP are small and statistically insignificant.

3. Empirical Framework

We face three empirical challenges. The first challenge pertains to the identification of the impact of university activity on local economic outcomes. An endogeneity concern arises from that university activity does not occur randomly. For instance, there may exist location-specific unobserved characteristics that attract innovative firms and research-oriented universities simultaneously. Alternatively, the nearby presence of innovative firms may reversely affect the activities of universities through knowledge spillovers from industrial firms to universities, through donations to universities and collaborations, or through increased local demand for a university-trained labor force.

We address the endogeneity concern by utilizing the university expansion policy in China as a quasi-experiment. As explained in Section 2, the policy created an unanticipated structural break in the intertemporal development of universities, which allows us to identify the causal impact of the university expansion in a difference-in-differences framework. We examine the extent to which the policy shock induces an expansion in university patenting and the extent to which it spills over to affect citywide industrial patenting activities. The regression equation is specified as follows:

$$Outcome_{c,t} = \beta \times (Treatment_c \times Post_t) + \alpha_c + \gamma_t + \varepsilon_{c,t}, \tag{3.1}$$

where $Outcome_{c,t}$ represents $UniversityScale_{c,t}$, the numbers of university teachers, university students, or university patents in city c and year t, or $IndustryInno_{c,t}$, the number of collaboration patents or industry patents in city c and year t. $Treatment_c$ is the number of university teachers (or students) in city c in year 1990, a proxy for treatment intensity. $Post_t$ is a dummy variable that equals 1 if year t is 2000 or after. α_c and γ_t are city and year fixed effects, and $\varepsilon_{c,t}$ is the error term.

This identification strategy draws on cross-sectional variation in the exposure to the shock determined by the university capacity prior to the shock. The identification assumption is that the evolution of outcome variables in cities with larger expansions should not vary systematically from cities with smaller expansions in the absence of the expansion, conditional on included control variables. In other words, any pre-existing trends should be properly controlled for. We discuss the validity of the identification assumption in more detail below. Also note that if we are willing to make additional assumption that the expansion impacts industry innovation only through increasing university scale, we can consider the impact of the expansion on $UniversityScale_{c,t}$ as the first-stage effect, and the impact on $IndustryInno_{c,t}$ as the reduced-form effect, in a standard Wald difference-in-differences setup (Duflo 2001; Bhuller et al. 2013).[14]

The second empirical challenge hinges on the core of the paper—identifying the role of knowledge spillovers as an important channel contributing to the impact of universities. That is, even if the causal impact of university activity on local economy is convincingly justified, it is not clear whether the impact is channeled through knowledge spillovers. For example, an increase in university scale may accompany an increase in the supply of college graduates if graduates prefer to work in the area where they attend college (Card 1995). Increased high-skilled labor could improve local economic outcomes directly (Che and Zhang 2018). Hence, the challenge is how to safely disentangle the role of knowledge spillovers from other mechanisms.

We tackle this challenge by focusing on the extremely localized effects of universities. Previous studies have shown that knowledge spillovers tend to decay rapidly across space, while other benefits of agglomeration, such as labor market pooling, operate at a much larger geographic scope (Rosenthal and Strange 2003, 2005; Arzaghi and Henderson 2008; Li et al. 2022). In particular, Arzaghi and Henderson (2008) depict sharply attenuating knowledge spillovers and networking benefits that deplete at 750 meters away. As noted in Carlino and Kerr (2015), this spatial approach "represents an important precedent for future research related to innovation more directly." Indeed, the focus on the geographic nature of university spillovers is convenient to disentangle the important role of knowledge spillovers. It is difficult to imagine that alternative channels, such as the labor market channel, would dissipate dramatically at a short distance away from a university.[15] In the online appendix, we present a simple conceptual framework to formalize the identification of knowledge spillovers by drawing on the localized nature of knowledge spillovers.

We achieve this geographic focus econometrically by specifying a rich set of concentric ring

[14]The effect of university innovation capacity on industrial innovation activities can be retrieved by taking the ratio of the reduced-form and the first-stage estimates or by two-stage-least-squares (2SLS) estimation with direct inference. Because the assumption of exclusion restriction is harder to justify, we focus on the difference-in-differences model, but we also report the 2SLS estimates in the appendix tables.

[15]It is possible that highly innovative firms are attracted to the close proximity of research universities to draw on the spillover benefits. As a result, firms closer to universities may disproportionately hire university graduates. However, we should be careful and not interpret the increased innovation activities near universities as a mere consequence of disproportionately allocated high-skilled labor since the latter is an equilibrium outcome of knowledge spillovers and serves as a channel through which knowledge spillovers benefit nearby innovation in a self-reinforcing process.

variables that capture innovation activities at various distances from research universities. Each concentric ring spans 500 meters. We include 10 or 20 rings to cover places up to 5 km or 10 km away from a university, depending on the specific model.[16] This additional source of within-city variation allows us to identify the spatial attenuation of university spillovers in a triple-differences framework, specified as follows:

$$IndustryInno_{c,r,t} = \sum_{r=1}^{9} \beta_r \times (Treatment_c \times Post_t \times Ring_r) + d_{c,r} + d_{c,t} + d_{r,t} + \varepsilon_{c,r,t}, \tag{3.2}$$

where $IndustryInno_{c,r,t}$ represents the number of industry patents in city c, ring r, and year t; $Treatment_c$ and $Post_t$ are defined the same as before; $Ring_r$ is a dummy variable that equals 1 if the patents are in the concentric ring r and 0 otherwise (ring 10 is set as the reference group and is omitted); $d_{c,r}$, $d_{c,t}$, and $d_{r,t}$ are city by ring, city by year, and ring by year fixed effects, respectively.

The ability to include all interactive fixed effects is crucial for identifying the geographic nature of university spillovers. China experienced dramatic economic reforms in the past few decades. For instance, since the early 2000s, the Chinese government has undertaken policy reforms and infrastructure investments that have substantially reduced the costs of internal migration and trade. China also joined the WTO at the end of 2001, which led to large reductions in international trade costs. Those reforms contributed to a significant growth in aggregate productivity and may drive increases in innovation activities (Brandt et al. 2017; Tombe and Zhu 2019). We address those potential confounding factors by including city by year, ring by year, and city by ring fixed effects in a generalized triple-differences framework. In particular, city-level time-varying unobservables, the main confounding factor in the difference-in-differences model, are controlled for by city by year fixed effects. The remaining unobserved factors conditional on those demanding interacting fixed effects are unlikely to systematically impact innovation activities at different distances from universities. Thus, the triple-differences strategy relies on weaker identification assumption than the difference-in-differences strategy.

The third empirical challenge is the measurement of innovation. Conceptually, innovation should comprise generation of new ideas and conversion of ideas into commercial products. The new ideas generated could sometimes result in patents. Therefore, it is natural to use patent as a proxy for inno-

[16] Section 4.2 provides a detailed explanation on the construction of the rings.

vation. Plus, patent data are also publicly available and contain rich details. However, two potential concerns exist: (1) patents do not directly reflect knowledge flows and (2) they are an intermediate step in the innovation process and do not capture the ultimate economic value of the invention (Acs et al. 2002).[17] Because patents and new products do not necessarily collocate, we need to interpret the patent-based evidence with caution (Feldman and Kogler 2010).

To mitigate measurement concerns associated with using patent counts as proxies for innovation, we supplement our patent analysis with subsidiary analyses on two additional measures: patent citation links and new commercial products. We examine the incidences when industry patents cite university patents as direct evidence of knowledge transfers from universities. We also take advantage of previously under-explored information on firms' new commercial products to reveal the impact of university spillovers on the final products.

We estimate the following triple-differences specification to capture the spatial decay of patent citations:

$$Cite_{c,r,t} = \sum_{r=1}^{9} \beta_r \times (Treatment_c \times Post_t \times Ring_r) + d_{c,r} + d_{c,t} + d_{r,t} + \varepsilon_{c,r,t}, \tag{3.3}$$

where $Cite_{c,r,t}$ represents the number of cases when industry patents in city c, ring r, and year t cite university patents. The rest variables are defined in the same way as in Equation (3.2).

To explore the impact of university expansion on nearby new products at the firm level, we estimate the following specification:

$$\begin{aligned} NewProduct_{i,c,r,t} = & \sum_{r=1}^{9} \beta_r \times (Treatment_c \times Post_t \times Ring_r) \\ & + d_{c,r} + d_{c,t} + d_{r,t} + \boldsymbol{X}_{i,c,r,t}\boldsymbol{\rho} + \varepsilon_{i,c,r,t}, \end{aligned} \tag{3.4}$$

where $NewProduct_{i,c,r,t}$ represents the new commercial product ratio of firm i in city c, ring r, and year t; $\boldsymbol{X}_{i,c,r,t}$ is a set of firm-specific controls, including the age of a firm, fixed assets, a dummy for whether a firm is an SOE, and the employment size; and $\varepsilon_{i,c,r,t}$ is a firm-specific error term. We define the rest variables in the same way as in Equation (3.2).

[17] Based on Acs and Audretsch (1988), Griliches (1979) and Pakes and Griliches (1980), "patents are a flawed measure (of innovative output) particularly since not all new innovations are patented and since patents differ greatly in their economic impact."

The set of differencing strategies stated above relies on the identifying assumption that, conditional on included fixed effects and other controls, the evolution of the outcome variables in cities with larger expansions should not vary systematically from cities with smaller expansions in the absence of the expansion (difference-in-differences setup), and, in the event that there exist systematic variations across cities, such counterfactual differences do not vary across rings (triple-differences setup). A natural check on the validity of such assumption is whether the pre-trends are parallel. We perform event-study analyses to check on this assumption and also to capture the dynamics of the treatment effects. The event-study specification for the city-level analysis is as follows:

$$\begin{aligned} Outcome_{c,t} = & \sum_{t=1995}^{1998} \beta_t \times (Treatment_c \times Year_t) \\ & + \sum_{t=2000}^{2007} \beta_t \times (Treatment_c \times Year_t) + \alpha_c + \gamma_t + \varepsilon_{c,t}, \end{aligned} \tag{3.5}$$

where $Outcome_{c,t}$ represents $UniversityScale_{c,t}$ or $IndustryInno_{c,t}$; $Year_t$ is a set of year dummies that equals 1 if year equals t and 0 otherwise. Year 1999 is set as the base year and is omitted. We define the rest variables the same as in Equations (3.1).

We also estimate event-study model for the ring-level analysis as follows:

$$\begin{aligned} IndustryInno_{c,r,t} = & \sum_{r=1}^{9} \sum_{t=1995}^{1998} \beta_{r,t} \times (Treatment_c \times Year_t \times Ring_r) \\ & + \sum_{r=1}^{9} \sum_{t=2000}^{2007} \beta_{r,t} \times (Treatment_c \times Year_t \times Ring_r) + d_{c,r} + d_{c,t} + d_{r,t} + \varepsilon_{c,r,t}, \end{aligned} \tag{3.6}$$

where $Year_t$ is a set of year dummies that equals 1 if year equals t and 0 otherwise. We define the rest variables in the same way as in Equation (3.2).

However, as discussed in detail in Section 5, the event study analysis reveals that the pre-treatment trends seem to be not sufficiently controlled for by the included fixed effects and controls in both the city-level and ring-level analyses. This could be explained by that cities experiencing more intensive university expansions may also have been adopting more innovation-promoting and growth-enhancing policies before the expansion and such efforts could be more directed towards areas close to existing innovations than far-away areas.

We undertake a collection of efforts to address this concern. First, we examine whether the university expansion induces a slope change in variables of interest by estimating a trend break model, following Almond et al. (2019). As the policy created an unanticipated structural break in the intertemporal development of universities and the magnitude of the structural break is independent of unobserved local economic conditions, we rely on a kinked relationship to identify the impact of universities on local innovation through the channel of knowledge spillovers. The model at the city level is specified as follows.

$$\begin{aligned} IndustryInno_{c,t} = {} & \beta \times (Treatment_c \times Trend_t) \\ & + \gamma \times (Treatment_c \times Trend_t \times Post_t) + \alpha_c + \gamma_t + \varepsilon_{c,t}, \end{aligned} \tag{3.7}$$

where $Trend_t$ is a trend variable defined as the patent application year minus 1999; The rest variables are defined the same as in Equation (3.1). The coefficient β measures the difference in trends associated with cities of different treatment intensity prior to the university expansion. The coefficient γ measures the post-expansion slope change in the outcome variable relative to the pre-expansion trend.

The trend break model at the ring level is specified as follows.

$$\begin{aligned} IndustryInno_{c,r,t} = {} & \sum_{r=1}^{9} \beta_r \times (Treatment_c \times Trend_t \times Ring_r) \\ & + \sum_{r=1}^{9} \gamma_r \times (Treatment_c \times Trend_t \times Ring_r \times Post_t) + d_{c,r} + d_{c,t} + d_{r,t} + \varepsilon_{c,r,t}, \end{aligned} \tag{3.8}$$

The variables are defined the same as before. The coefficient β_r measures the difference in trends for ring r associated with cities of different treatment intensity prior to the university expansion. The coefficient γ_r measures the post-expansion slope change in the outcome variable relative to the pre-expansion trend for ring r.

Second, we strip away the city-specific or city-ring-specific pre-expansion linear time trend as a control strategy before we run difference-in-differences and triple-differences specifications, following the approach in Bhuller et al. (2013), Monras (2019) and Garcia-López et al. (2020).[18] Specifically, we estimate a city-specific or city-ring-specific linear trend using the pre-expansion sample (namely, 1995-1999) for our city-level and ring-level regressions, respectively. We then extrapolate

[18] As stated in Monras (2019), this is a valid identification strategy if in the absence of the treatment the outcome variables would have evolved following the linear trend implied by the periods preceding the treatment event.

pre-expansion time trends to the post-expansion sample and subtract out the estimated linear trend from the observations after treatment. We use the trend-free outcome measures as the dependent variables in the city-level and the ring-level analyses. We re-estimate a trend-free event study model to verify that the residualized pre-trends are parallel and also to depict the intertemporal dynamics of the impact. The event study model further tightens our identification by leveraging on the sharp timing of the university expansion and high frequency measurement of the outcomes.

Third, we conduct a set of robustness checks to corroborate our main results. In the first robustness check, we follow Dobkin et al. (2018)'s parametric event study approach to augment our baseline city-level and ring-level specifications with city-specific and city-ring-specific linear trends, respectively. This approach is conceptually the same as subtracting out the estimated linear trend elaborated above (Goodman-Bacon 2018, 2021; Rambachan and Roth 2022). In the second robustness check, we follow Rambachan and Roth (2022) to obtain robust inference after specifying how different the post-treatment violations of parallel trends can be from the pre-treatment differences in trends. This approach also allows us to conduct sensitivity analyses showing whether a causal conclusion can be drawn under various restrictions on possible violations of the parallel trend assumption. Details are discussed in Section 5.

Last, we further tighten our identification by drawing on variations in different types of citation flows. A possible argument against the identification of knowledge spillovers even with our most sophisticated generalized triple-differences model is that there may exist unobserved city- and location (distance)-specific time-varying factors that are correlated with the increase in location-specific innovation activities after the university expansion. Such a hypothetical scenario is possible but very unlikely given the rare coincidence of multiple co-evolving factors after controlling for a demanding set of fixed effects. Despite so, we address this concern by drawing on the information on patent citation links to show that the spatial pattern persists only for citation links of industry patents citing university patents but not for citation links of industry patents citing patents far away from universities. Otherwise, if unobserved co-evolving factors drive the spatial pattern of overall patenting activities and citation behaviors, we would observe similar patterns for both types.

4. Data, Variables, and Summary Statistics

4.1. Data

We use four primary datasets. The first dataset is a patent database obtained from the National Intellectual Property Administration of China (CNIPA). This dataset covers a complete list of patents granted between 1995 and 2007 in China. The data provide detailed information for each patent, such as inventor's name and affiliation, address of the patent, application date, approval date, patent ID, International Patent Classification (IPC) number, and patent type. There are three types of patents in the database: invention patent, utility model patent, and design patent.[19] We focus on invention patents because they represent the most innovative type. Overall, there were 553,248 invention patents granted in China between 1995 and 2007. We use invention patents to measure innovation activities inside and outside of universities.

The second dataset is extracted and compiled from four different statistical yearbooks of China. The first source is the China City Statistical Yearbook between 1996 and 2008 from the National Bureau of Statistics (NBS) of China. This collection provides information on various prefecture-city-level attributes by year, such as the number of university teachers and students.[20] The second source is the Educational Statistics Yearbook of China. We obtain the number of university entrants and graduates at the provincial and national level for each year from this yearbook. The third source is the Educational Finance Statistical Yearbook of China, which reports the higher education expenditures from 1995 to 2006. The fourth source is the Compilation of Statistical Data on University Science and Technology Resource, which provides information on the science and technology funding for higher education from 1991 to 2010. We use the number of university teachers and students from the first source as proxies for university scale or research capacity. The other three sources help us summarize aggregate trends for various aspects of the university expansion.

The third dataset is a patent citation database that is scraped from Google Patents. Google Patents is a search engine from Google that indexes patents and patent applications from all around the world.

[19] Invention patents require inventive technological improvements or new uses. Thus, invention patents have the highest standard of novelty. The other two types of patents are related more to the structure (utility model patent), shape (utility model and design patent), and design (design patent) of an object and have fewer requirements for inventiveness.

[20] The statistical yearbooks report the statistics for the previous year.

We searched for all patents granted in China. For each patent, we collect its basic information and patent citations. Then, we match the data to our patent database from CNIPA. This gives us a patent citation matrix about whether a patent cites another patent. We treat the patent citation links as the paper trail of knowledge flows and use them to identify knowledge spillovers from universities.

The final dataset is the ASIF of China from 1998 to 2007. This dataset is also from the NBS of China. The ASIF is an annual panel that covers all SOEs and the non-SOEs with annual sales exceeding 5 million yuan.[21] The data provide detailed firm-level attributes, including firm name, firm address, legal unit code, legal representative name, industry classification, opening year, ownership type, fixed capital, output value, and employment size, among others.[22] A unique advantage of the ASIF is the exact firm addresses provided in the data. We geocode the addresses and pin the firms into the concentric rings that we create.

We use the previously under-explored information on firm new products in the ASIF to measure the final commercialized outputs with new knowledge and ideas as inputs. The NBS defines a new product as a product that is produced for the first time at least within a province (Lu and Tao 2009). Based on an email correspondence with an officer at the NBS, "products included in the category of new product sales are those that are new in relation to the reporting firm's prior product mix. Products that involve the use of new principles, incorporate design improvements, utilize new materials, or embody new techniques constitute new products; existing products that are used for new functions or expand capabilities (e.g., production or speed) also constitute new products. Changes in a product's shape or minor changes in functionality do not constitute new products" (Jefferson et al. 2003). Other firm-level surveys rarely capture this measure of new product. It provides a unique opportunity to study final outputs from innovation. We use a firm's new product ratio as a proxy for innovation output and define it as the ratio of the dollar value of new products to the dollar value of total outputs.

4.2. Variables and Summary Statistics

In this section, we describe how we prepare our data for the empirical analysis and present the basic summary statistics. For the city-level analysis, we create a city by year panel by matching patent

[21]The ASIF contains many missing values after 2007. In addition, starting in 2011, the sampling cut-off increased to 20 million yuan of annual sales, which changes the sample composition and makes comparisons across years challenging.

[22]In the empirical analysis, we adjust all dollar variables using the national Consumer Price Index (CPI) so that they are comparable across years.

counts at the city level to city-level attributes from the statistical yearbooks. The year of patenting refers to the year when the patent application is filed, as opposed to the year when the patent is granted. Our goal is to trace how the flow of knowledge impacts the creation of new ideas, and the application year is closer to the timing of new knowledge creation (Moretti 2021). We have 184 cities in the panel after removing observations with missing information.

Table 1 presents the summary statistics for the numbers of university teachers, university students, and the total and sub-classifications of patents at the city level in each year. Columns (2) and (3) show the average number of university teachers and students. The city-average growth trends are similar to the national trends in Figure 1, showing a dramatic boom in university scale after 1999. Column (4) reports the average number of patents at the city level in each year. The number of patents also increased dramatically from 2000, which matches the timing of the university expansion. We further decompose patents into three mutually exclusive categories. Column (5) shows the average number of university patents, which we define as patents filed solely by inventors affiliated with universities. Column (6) reports the average number of collaborative patents between universities and the private sector. Column (7) reports the average number of patents that are filed solely by inventors from non-university entities. The three types of patents all experienced a sharp increase from 2000.

For the ring-level analysis, we create a panel at the city-year-ring level. To construct the rings, we compile a list of university locations as the centers of the rings in three steps. First, we manually search the locations for an exhaustive list of universities that are classified as "*Yiben*" universities in each city.[23] Second, we supplement the list with the locations of institutions in CNIPA that are classified as universities during our sample period.[24] Third, we add to the list the locations of other institutions or companies that have ever filed a joint patent application with a university during our sample period. This third step allows us to include possible university spin-offs in the university locations and avoids treating industry-university partnerships as spillovers.[25]

Then, we define the rings as a set of concentric rings around the universities locations. Specif-

[23]In China, universities are classified into several tiers. The tier of a university determines whether the university has priority when recruiting students. In general, "*Yiben*" (first tier) universities have the highest priority when recruiting students. "*Yiben*" universities also conduct the majority of research because they have better research and teaching capacity.

[24]This procedure may lead to multiple locations within the same university as the address filed in a patent application points to the exact building.

[25]Hall et al. (2003) documents industry-university research partnerships and suggests that the involvement of universities in industrial innovation benefits the outcome. However, we recognize that the patents generated from such partnerships should not be interpreted as spillovers from universities.

ically, we define one concentric ring for every 500 meters away from the center locations and have the rings extend up to 5 km or 10 km, depending on the specific model.[26] To identify the innovation activities within each concentric ring, we geocode the locations of patents and companies in CNIPA and ASIFs, and pinpoint them to the corresponding ring area. The patents generated at the center locations are not included in any rings. In the baseline ring-level analysis, variable $Inno_{c,r,t}$ is the number of patents in city c, ring r, and year t, where ring r refers to the concentric ring between the buffer zones $r-1$ and r.

We provide a graphic illustration in Appendix Figure A2 to show how we define the rings. In this example, the two locations at C belong to university I. The three locations at D and E belong to university II. Point A stands for a non-university entity that has direct collaboration with university I. Point B stands for a non-university entity that has direct collaboration with university II. We treat all these locations as the centers of a set of concentric rings. Each concentric ring spans a distance of 500 meters. The concentric rings, hence, are the outer envelopes that trace the rings of the same distance away from the center locations.

Table 2 presents the summary statistics for the number of patents within different concentric rings in each year across cities. First, we notice that the magnitude of the patent counts in the closest ring dominates that of the outer rings. For all years, the number of patents decays sharply as the distance to universities increases. This suggests that the overall innovation activities around universities are more intense than other areas. Second, a positive trend exists for all rings over time with a sharper increase after 2000. For example, the average growth rate of patent counts in ring 1 was 21.5 percent from 1995 to 1999, but it increased to 54.6 percent from 2000 to 2007. We also found similar but more muted patterns for outer rings.

5. Results on New Patents

5.1. City-Level Analysis on Patent Growth

We first examine the impact of universities on citywide innovation activities. In Table 3, we report the results from estimating Equation (3.1) when we use the number of university teachers in 1990 as

[26] We include 10 rings which extend up to 5 km in our baseline specifications. We include 20 rings to cover a broader geographic scope for robustness checks.

the proxy for treatment intensity. The corresponding results when the number of university students in 1990 is used as treatment intensity are reported in Appendix Table A1.A. Column (1) of Table 3 suggests that cities with 1,000 more university teachers in 1990 experienced an additional increase of 341 university teachers after the university expansion. Columns (2) suggests that cities with larger university capacity in 1990 also experienced a larger increase in the total number of patents after the expansion.[27]

Next, we decompose the citywide total patent counts into the numbers of patents filed solely by inventors affiliated with universities, patents jointly filed by inventors affiliated with universities and inventors from industrial firms, and patents filed solely by industrial firms. Column (3) of Table 3 shows that cities with 1,000 more university teachers in 1990 experienced an additional increase of 33 university patents on average after the expansion. This suggests the expansion indeed boosted university innovation capacity, as represented by the number of university patents. Columns (4) and (5) show that cities with larger university capacity in 1990 also experienced a larger increase in collaborative patents and industry patents after the expansion. The impact on collaborative patents represents an important form of universities' contribution to the local economy by collaborating with other sectors.[28] The impact on industry patents implies potential spillovers from universities.

As discussed in the empirical framework, we can form a structural interpretation of the estimated coefficients in a Wald difference-in-differences setup, with additional assumptions. Specifically, dividing the reduced-form effect by the first-stage effect produces the Wald estimator of the impact of university's research capacity on industry patents. For example, in Table 3, the impact of university teachers on industry patents at the city level is 0.30 (101.75/341.02). Alternatively, the impact of university patents on industry patents at the city level is 3.05 (101.75/33.32). The magnitude of the effects is economically important: adding 100 more university patents to the average prefecture city increases the industry patents in the city by 305.[29]

To check on the parallel trend assumption and also to depict the dynamics of the treatment effects,

[27]Additional results are presented in Appendix Tables A1.B-A1.C to show robustness when we add city-level control variables, such as the non-agricultural population, the proportion of employment in the manufacturing industries, and the proportion of employment in the service industries.

[28]As illustrated in Hall et al. (2003), research projects with university involvement tend to be in areas involving new science. The social benefits from the collaborated patents can be large.

[29]We present the two-stage least squares estimation results in Appendix Tables A4.A and A4.B with corresponding statistical inference.

we estimate event study models as in Equations (3.5). Appendix Figures A3 and A4 present the estimation results. In Panel (a) of Appendix Figure A3, we show the dynamic effects of the university expansion on the numbers of university teachers and university patents using the number of university teachers in 1990 as the treatment intensity. Panel (b) shows the corresponding estimates using the number of university students in 1990 as the treatment intensity. Two patterns emerge. First, the university scale measured by the numbers of university teachers and patents do not present significant responses to variation in treatment intensity before the expansion when the number of university teachers in 1990 is used as the treatment intensity. However, there seems to be a small upward trend in university scale leading the expansion when the number of university students in 1990 is used as the treatment intensity. Second, the increases in the numbers of university teachers, university students, and university patents after 1999 are positively affected by the number of university teachers or students in 1990.

Appendix Figure A4 shows the dynamic effects of university expansion on collaborative patents and industry patents. In both panels, the dashed line presents the estimation results using the number of university teachers in 1990 as the treatment intensity, and the solid line presents the estimation results using the number of university students in 1990 as the treatment intensity. In both panels, there seems to exist an upward trend in outcome variables leading the treatment year of 1999. Starting from 2000, the numbers of both types of patents rose more dramatically, with more pronounced effects in later years.

The deviation in pre-trends across cities with varying treatment intensity raises concerns about potential estimation bias. We investigate and resolve this issue by the following. First, we detect the presence of a trend break by estimating the trend-break model in Equation (3.7), and we report the results in Table 4 using the number of university teachers in 1990 as the treatment intensity.[30] Across all columns in the table, we observe statistically significant evidence of trend breaks. The existence of a slope change in the variables of interest suggests the presence of a causal impact of the expansion on university scale and industry patenting activities (Almond et al. 2019).

Next, we strip away city-specific pre-expansion linear time trends following the de-trend approach in Bhuller et al. (2013), Monras (2019), and Garcia-López et al. (2020). We present the correspond-

[30]The results using the number of university students in 1990 as the treatment intensity is reported in Appendix Table A2.

ing results in Table 5. Compared with Table 3, the point estimates are very similar for the number of university teachers but reduced a bit for the numbers of different classifications of patents. For example, after adjusting for pre-trends, the estimates imply that cities with 1,000 more university teachers in 1990 experienced an additional increase of 83.89 industry patents on average. Again, the results suggest strong spillovers to local innovation activities from universities. In general, the results show strong robustness.

Furthermore, we re-estimate event study models to verify that the parallel trend assumption is satisfied after we strip away city-specific pre-trends. We report the results in Figures 3 and 4.[31] We do not observe significant pre-trends in the event study estimates for both figures. This suggests that the extent to which universities expanded at the city level was not predicted by any projected changes in local economic activities in deviation from city-specific time trends. We also find that the impact of university expansion on industry patents is increasing over time, suggesting dynamically increasing spillovers from universities to industry sectors. The increasing effects could be explained by the continually increasing scale of the higher education sector because the university expansion lasted for many years. It is also consistent with the idea that agglomeration spillovers tend to self-amplify once the initial shock takes place.

We conduct two additional sets of robustness checks to further corroborate our findings. First, we follow the parametric event study approach in Dobkin et al. (2018) and estimate the following specification:

$$\begin{aligned} IndustryInno_{c,t} = \mu \times Treatment_c \times \ell + \sum_{\ell=1}^{8} \beta_\ell \times Treatment_c \times \mathbf{1}\{t = 1999 + \ell\} \\ + \alpha_c + \gamma_t + \varepsilon_{c,t}, \end{aligned} \tag{5.1}$$

where ℓ indicates the year relative to 1999; μ captures the slope of the trend; β_ℓ captures year-specific treatment effect after controlling for city-specific time trend.[32] The rest variables are defined the same as before. We plot the corresponding estimates in Figure 5. The dashed lines capture the estimated linear trends. The gap between the crosses and red dashed line represents year-specific treatment

[31] The detailed estimation results that are used to draw Figures 3 and 4, and Appendix Figures A3 and A4 are reported in Appendix Tables A3.A and A3.B.

[32] We choose to include linear trends in the model because the non-parametric event study estimates in Figures A3 and A4 display patterns of a linear pre-trend.

effects using the number of university teachers in 1990 as the treatment measure. The gap between the circles and blue dashed line represents year-specific treatment effects using the number of university students in 1990 as the treatment measure. The evidence suggests a large effect of the expansion on industry patents. The patterns are consistent with the lower panel of Figure 4. This is not surprising as the parametric event study approach is analogous to the de-trend approach despite small technical variations (Goodman-Bacon 2018, 2021; Rambachan and Roth 2022).

Second, we obtain robust inference using the "honest approach" proposed in Rambachan and Roth (2022) after specifying how different post-treatment violations of parallel trends can be from the pre-treatment differences in trends. Hence, this approach allows us to address potential estimation bias arising from not only the presence of linear trends but also potential deviations from linearity. It also addresses further concerns that pre-trend tests implemented in the event study setup may fail to detect violations of parallel trends due to low statistical power or potential distortions arising from selection (Roth 2022). As in Rambachan and Roth (2022), we assume that the differential trends evolve smoothly over time (smoothness) and that the possible non-linearities in the post-treatment difference in trends are bounded by observed non-linearities in the pre-treatment difference in trends (relative magnitude bounds). To be consistent with Rambachan and Roth (2022), we use δ_t to indicate the difference in trends between the treated and control groups and specify the restriction as follows:

$$\Delta^{SDRM}(\bar{M}) = \left\{ \delta : \forall t \geqslant 0, |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leqslant \bar{M} \cdot \max_{s<0} |(\delta_{s+1} - \delta_s) - (\delta_s - \delta_{s-1})| \right\}, \quad (5.2)$$

where Δ is a set of possible differences in trends, and $\bar{M}$ governs the amount by which the slope of δ_t can change after the treatment period. If $\bar{M} = 0$, it requires the trend to be linear, which shares similar ideas as in Equations (3.7) and (5.1). If $\bar{M} > 0$, it means that we further allow a deviation from a linear trend in the post-treatment period, and the maximum deviation is bounded by $\bar{M} \geqslant 0$ times the equivalent maximum in the pre-treatment period.[33] We then construct robust confidence intervals of the treatment effect under the smoothness and relative magnitude bounds assumptions using the R package provided by Rambachan and Roth (2022).

We report the findings in Figure 6. The figure presents robust confidence sets for the estimated

[33] Applied researchers usually test the null hypothesis δ_{pre} = 0 to assess the existence of the pre-treatment non-parallel trends. See Section 2.2 in Rambachan and Roth (2022) for a more detailed discussion.

treatment effect averaged across post-treatment years, under the restrictions of $\Delta^{SDRM}(\bar{M})$. The left panel uses the number of university teachers in 1990 as the treatment intensity, and the right panel uses the number of university students in 1990 as the treatment intensity. The blue confidence intervals are obtained without making adjustments for pre-trends.[34] The red confidence sets depict the set of confidence intervals of the estimated coefficients if we allow for a deviation from a linear trend with the maximum deviation specified in Equation (5.2). We find that, even when we allow $\bar{M} = 0.25$, the estimated causal impact of university expansion on industry patents is still statistically different from zero. The breakdown value for a null effect is around $\bar{M} = 0.5$. Thus, even if we allow further deviations from the pre-expansion linear trend, as long as such deviations are not "too big", we are still able to claim the presence of a causal relationship.

5.2. Ring-level Analysis on Knowledge Spillovers

The key focus of this paper is to infer knowledge spillovers from the geographic nature of university spillovers. In this section, we present estimation results from ring-level analyses of the effects of the university expansion on industry patenting activities in close proximity to universities. Specifically, we extend the difference-in-differences framework by further examining whether the impact is larger in areas near universities relative to areas farther away. This within-city variation allows for estimating a triple-differences model, as in Equation (3.2).

Table 6 presents the estimation results when we use the number of university teachers in 1990 as the proxy for treatment intensity. The results using the number of university students in 1990 as the treatment proxy are reported in Appendix Table A5. We limit our analysis to areas within 5 km of universities in the baseline regressions. In Columns (1)-(3) of Table 6, we report results without removing the pre-expansion linear time trend. In Columns (4)-(6), we report results after removing pre-expansion linear time trend.[35] In Columns (1) and (4), we control for city fixed effects, year by ring fixed effects, in addition to treatment by ring dummy interactions. In Columns (2) and (5), we control for year by ring, year by city, and city by ring fixed effects. The latter specification is a standard generalized triple-differences model in which we treat the 4.5-5 km ring as the reference

[34] The point estimate is the average of year-specific estimates of the treatment effect in the post-treatment period.

[35] The necessity of addressing potential pre-trends is evident in Appendix Figure A5, which shows a small upward trend in the number of industry patents in the nearest ring (ring 1).

group.

The estimation results suggest that the university expansion significantly increases the number of industry patents in the closest concentric rings and the effects attenuate sharply with geographic distance. While the results are robust and consistent across all specifications, we focus on the results in Column (5), which is our preferred specification. The estimates suggest that cities with 1,000 more university teachers in 1990 experienced an additional increase of 76.5 industry patents in the 0-0.5 km ring relative to the 4.5-5 km ring after the university expansion. This effect reduces to 15.3 in the 0.5-1 km ring, which is smaller by a factor of 5. The effect further reduces as we move to the outer rings and becomes statistically insignificant after the 2 km radius.[36] In Column (6), we divide the coefficient estimates in Column (5) by the average number of patents in the corresponding ring during the pre-expansion period, which provides information on the percentage change of industry patents in each ring because of the university expansion. Again, the attenuation is quite dramatic in percentage terms. In the 0-0.5 km ring, industry patents increased by a factor of 3.12, while in 2-2.5 km ring, industry patents only increased by 43 percent. The attenuation is muted after 2-2.5 km ring.

In Figure 7, we plot the dynamic effects of the university expansion on industry patents in different concentric rings after we remove the pre-expansion linear time trend.[37] Panels (a) and (b) use the number of university teachers in 1990 and the number of university students in 1990 as the treatment intensity proxy, respectively. Again, the results show that the impact on the number of patents in the 0-0.5 km ring is the largest, followed by the second ring, third ring, and so on. As will be obvious in this paper, this attenuation pattern is what we consistently find in all specifications. More important, the sharp increasing trend in the 0-0.5 km ring suggests that the long-run benefit of locating near a university could be more amplified than the short-run effects. The figure also shows that the pre-trends are well controlled for, so the parallel trend assumption is not rejected in this case.

Next, we estimate a trend break model to detect the presence of a slope change in the number of industry patents at different distances (rings) as a result of the university expansion, as in Equation (3.8). The results are presented in Table 7 when we use the number of university teachers in 1990 as

[36] To mitigate the concern that many patents are of low quality, we conduct a robustness check in which we restrict our sample to patents with at least one citation. The results are qualitatively similar. We present the results in Appendix Tables A6.A and A6.B.

[37] Appendix Table A7.A and A7.B. present the corresponding regression results.

the treatment intensity.[38] Columns (1)-(10) look at each ring separately, and Column (11) pools all rings together and uses 4.5-5 km ring as the reference group. When studying each ring separately, we observe statistically significant evidence of trend breaks in all rings. Column (11) suggests that, comparing with the 4.5-5 km ring, the estimated slope change is statistically significant for the 0-0.5 km, 0.5-1 km, 1-1.5 km, and 1.5-2 km rings. More important, we find that the slope change is much larger in the closer rings. The results suggest that the trajectory of industry patenting activities experienced a trend break because of the expansion and that the causal impact of the expansion follows a dramatic attenuation pattern over space. This pattern supports our previous findings in Table 6.

As a robustness check, we present the estimation results from the parametric event study (Dobkin et al. 2018) in Figure 8. Panels (a) and (b) present results using the numbers of university teachers and students in 1990 as the proxy for treatment intensity, respectively. To save space, we only present the results for rings 1, 3, 6, and 9. The dashed lines in the figures represent the estimated linear trends in the number of industry patents (μ in Equation (5.1)). The gap between the crosses (circles) and the dashed lines capture the treatment effects of the expansion in deviation from a linear trend. Rings 1 and 6 are represented by crosses; Rings 3 and 9 are represented by circles. The figure shows that there is a significant effect of the university expansion on nearby industry patents in deviation from a linear time trend and that the effect is larger in closer rings to universities, a result we repetitively find in all specifications.

We also obtain robust inference for the ring-level analysis using the “honest approach” proposed in Rambachan and Roth (2022), as the second robustness check. The results are presented in Figure 9. The procedure is the same as what we described for the city-level analysis, except now we estimate and present the confidence intervals for each ring separately. The blue confidence intervals are obtained without making adjustments for pre-trends, and the red confidence intervals are obtained when we allow for a deviation from a linear trend with the maximum deviation specified in Equation (5.2). The general patterns are similar to the results in city-level analysis. That is, as long as deviations from a linear trend are not “too big", we continue to find statistically significant evidence of a causal impact of the university expansion on innovation activities. The values contained in the confidence intervals across rings also suggest a sharp attenuation of the impact.

[38]The results using the number of university students in 1990 as the treatment intensity is reported in Appendix Table A8.

In sum, we document consistent evidence across various specifications suggesting that spillovers from universities are very localized and dissipate sharply with geographic distance. We observe that the largest spillover effects take place within 2 km around the universities, and the impact on the 0-0.5 km ring is more than 30 times larger than that on the 1.5-2 km ring (Column (5) of Table 6). Similar spatial attenuation of agglomeration externalities is also documented in other studies focusing on different settings. For instance, Andersson et al. (2009) shows that between one-third and one-half of the total effect on productivity resulted from a university is within 5 km of the university. Rosenthal and Strange (2008) finds that the effect of urbanization economics on worker productivity is about half as large at distances over 8 km as it is at closer distances. Arzaghi and Henderson (2008) shows that the effect of localization economies on the birth of advertising agencies in Manhattan is mainly within 500 meters. Baum-Snow et al. (2021) finds that revenue and productivity spillovers that operate between firms are within 75 meter to 250 meter radius. As similarly argued in those studies, this important geographic decay of university spillovers suggests that knowledge spillovers play an important role in the effects of universities on local innovation (Arzaghi and Henderson 2008). It would be hard to reconcile such a sharp attenuation pattern with other explanations, such as improved local infrastructure or increased supply of high-skilled labor.[39]

Next, we conduct a set of extension and heterogeneity analyses. In the baseline ring-level analysis, we restrict our focus to areas within 5 km of universities. This restriction has two implications when interpreting the estimated coefficients. First, in the triple-differences specification, we use the 4.5-5 km ring as the reference area. Thus, the estimated coefficients capture the impact of the university expansion on the inner rings relative to the impact on the 4.5-5 km ring. Second, the area restriction ignores the possible impact of the university expansion outside the area. In Table 8 and Appendix Table A9, we extend the analysis to 10 km around universities, which usually covers a significant share of city areas with innovation activities. The quantitative results on spatial decay patterns are very similar. To better visually reveal the spatial decay pattern of university spillovers, Figures 10 and 11 present the spatial decay of university spillover benefits using the impact on the 0-0.5 km ring as the reference.[40] We can clearly see the strong spatial decay of the impact, especially within the first

[39]Our results do not exclude the possibility that other mechanisms are present in the neighborhoods of universities. We only claim that, without knowledge spillovers, the impact of university activities should not display a dramatic spatial decay pattern.

[40]The corresponding regression results are presented in Appendix Tables A10.A and A10.B.

2 km (4 rings) of universities. More important, the spillovers are small and stable beyond this scope, which suggests that we are not missing much by focusing on the 5 km areas around universities.

We further explore how knowledge spillovers from universities interact with other complementary factors, such as industrial and skill composition. In Table 9, we explore the heterogeneous effects of the university expansion across different regions.[41] It is well known that the Eastern coastal region of China is the most developed, followed by the Central region, and then the Western region. The industry structure across those regions is quite different. The Eastern region is the most successful in industrial transformation and upgrading, and it comprises high-tech manufacturing concentrations, such as telecommunications and software. The Western region is heavily concentrated with traditional manufacturing industries such as the steel industry. Therefore, spillovers from universities could be different across regions. The estimation results show that the impact of the university expansion is ubiquitous but most pronounced in the Eastern region.

In Table 10, we explore the heterogeneous effects of the university expansion across industries with different human capital intensity.[42] We define the human capital intensity of an industry in the following way. We assign each patent to a two-digit industry based on the reference table of International Patent Classification and National Industries Classification issued by the State Intellectual Property Office of China.[43] We obtain information on the share of workers with a college education and above from the ASIF dataset. Based on this information, we divide industries into high, medium, and low human capital intensity industries, depending on whether the industry-specific college employee ratio belongs to the top, middle, or bottom one-third of the distribution.[44] Finally, we separately count the number of patents linked to the high, medium, and low human capital intensity industries in each concentric ring. The estimation results in Table 10 suggest that the spatial attenuation of university spillovers is more pronounced for industries that are more reliant on high-skilled labor.

[41] Table 9 uses the number of university teachers in 1990 as the proxy for treatment intensity. The results using the number of university students in 1990 as the proxy are reported in Appendix Table A11.

[42] Table 10 uses the number of university teachers in 1990 as the proxy for treatment intensity. The results using the number of university students in 1990 as the proxy are reported in Appendix Table A12.

[43] The reference table can be found at http://www.sipo.gov.cn/gztz/1132609.htm. It is possible that a patent can be matched with more than one industries, in which case we count this patent in all the industries that it is linked to.

[44] High human capital industries include, for example, the chemical, electrical, and telecommunications industries; medium human capital industries include, for example, the food and beverage industries; and low human capital industries include, for example, the leather and wood industries.

6. Results on Patent Citations and New Products

6.1. Patent Citations

We now present direct evidence of knowledge flows from universities to nearby areas by examining the changes in patent citation links because of the university expansion.

In Table 11, we examine the effects of university expansion on patent citation links near universities. In Column (1), using the number of university teachers in 1990 as the treatment intensity measure, we examine the impact of university expansion on the number of times when industry patents in different rings cite university patents. We find that university patents are cited by more industry patents near universities after the university expansion. For example, after the university expansion, cities with 1,000 more university teachers in 1990 experienced an additional increase of 0.56 times when industry patents in the 0-0.5 km ring cite university patents, relative to that in the 4.5-5 km ring. The effect attenuates fast when we move away from the universities. The corresponding impact is 0.08 in the 0.5-1 km ring relative to the outermost ring, which is smaller than the effect in the 0-0.5 km ring by a factor of 7. The effect decays entirely after the 2 km radius, and the decay speed is as sharp as what we document for the effects on new patents. It is also consistent with the common perception that knowledge spillovers require close-range communications and interactions and, hence, decay fast spatially. In Column (3), we use the number of university students in 1990 as the proxy for treatment intensity, and we find very similar patterns.

A possible argument against the identification of our triple-differences approach is that there may exist unobserved time-varying city- and location (distance)-specific factors that contribute to the increase in location-specific innovation activities after the university expansion. In this case, the increased number of patents that cite university patents in closer locations could result from the scale effect proportional to the increase in the number of total new patents driven by the unobservables. Such a hypothetical scenario is possible but very unlikely given the rare coincidence of multiple co-evolving factors—those factors must have the same timing as the university expansion and systematically impact innovation in a similar spatial pattern. Despite being remotely plausible, we conduct a falsification test to rule out such a possibility.

We examine the impact of university expansion on the spatial nature of the cases where nearby industry patents cite patents far away from universities. If the presence of the unobservables, coupled with the scale effect, forms the underlying mechanism, then we should observe that the impact on the number of cases where nearby patents cite patents far away from universities follows similar spatial decay patterns. Specifically, we examine whether patents outside the 5 km radius of universities are cited more by patents closer to universities after the university expansion. As shown in Columns (2) and (4) of Table 11, we do not find a clear spatial decay pattern of the impact. The evidence suggests that our results are not driven by unobserved time-varying city- and ring-specific factors that coincide with the university expansion and that follow a spatial attenuation pattern.

6.2. New Products

While patents are informative in measuring innovation, patenting only captures an intermediate step in converting new ideas into economic outputs. In this section, we examine the impact of the university expansion on creation of new products in nearby manufacturing firms by taking advantage of previously under-explored information on firm new products reported in the ASIF. We report the summary statistics of firm characteristics for our final regression sample in Appendix Table A13.

Table 12 reports the estimated impact of university expansion on the new product ratio of manufacturing firms in different rings when we use the number of university teachers in 1990 as the proxy for treatment intensity.[45] To capture dynamics, we report the estimated impact separately for the years after 2000, 2002, 2004, and 2006. That is, we report the average impact of university expansion from 2000 to 2007 in Column (1), the average impact of university expansion from 2002 to 2007 in Column (2), and so on. Two patterns emerge. First, for any given column, the impact of university expansion on nearby firms' new product ratio decays as the distance between firms and universities increases. The attenuation pattern is clear, but the speed of attenuation is not as fast as that for patents. Second, the impact gradually increases in later years. This increasing trend is evident when we compare the impact across different columns.

The results in Table 12 supplement our analyses on patents by showing that the university expansion also results in an increase in new commercial product sales at nearby firms, which, to some degree, reflects the economic value of innovations. This effect could be explained by a combination

[45] The results using the number of university students in 1990 as the treatment intensity are reported in Appendix Table A14.

of nearby existing firms innovating more and more innovative firms sorting into the neighborhood of universities. Table 12 does not intend to distinguish these two channels as they both indicate that there must be some advantages to be in the proximity of universities. The fast decay speed of the impact further suggests that knowledge spillover is a major underlying driving force. We also estimate a specification with firm fixed effects. The results are presented in Appendix Table A15. The coefficients are in general smaller than those in Table 12 but the attenuation pattern is still evident. The findings suggest that both the intensive margin and the extensive margin are in effect.

In Table 13, we examine the heterogeneous effects of university expansion on new product ratio using the number of university teachers in 1990 as the proxy for treatment intensity.[46] Columns (1)–(3) show the heterogeneous impact across industries with different levels of human capital intensity. The pattern that appears again is the attenuation of the impact over geographic distance. Moreover, we find that potential knowledge spillovers are larger in industries with higher human capital intensity, which is consistent with complementarity between human capital and knowledge spillovers. Columns (4)–(5) explore whether the impact varies for SOEs versus non-SOEs. Evidence suggests that the impact is more pronounced for non-SOE firms, which may be because non-SOEs are in general smaller in size and more productive than SOEs.[47] Thus, they are more active in the market and benefit more from learning and exchanging information.

7. Conclusion

Knowledge and innovation play a central role in advancing the technology frontier and promoting economic growth. Yet, despite being the center of knowledge creation and dissemination, the explicit role of universities in contributing to the innovation process is still understudied (Akcigit 2017). This paper exploits a unique quasi-experiment of university expansion in China to study the impact of university activities on local innovation. In particular, we utilize rich geocoded data on patent generations, patent citation links, and new products from firms to examine the geographic nature of the university impact and to identify the role of knowledge spillovers.

We find that the university expansion significantly increases universities' own innovation capacity,

[46] Appendix Table A16 reports the results using the number of university students in 1990 as the treatment intensity.

[47] This result is consistent to Acs et al. (1994). They use new product announcement data from the U.S. Small Business Administration and show that small firms are the recipients of nearby R&D spillovers.

which results in a dramatic boom of nearby firms' patenting activities. More important, the impact attenuates sharply with spatial distance. For example, the magnitude of the impact on nearby firm patenting activities reduces by about 80 percent from 0-0.5 km ring to 0.5-1 km ring around a university. There is another 65 percent decline of the impact when moving from 0.5-1 km ring to 1-1.5 km ring around the university. The result implies significant but very localized knowledge spillovers from universities. Further analysis suggests that the university expansion boosts nearby firms' new products and induces more industry patents to cite university patents. Those effects also follow similar spatial decay patterns. Taken together, these findings unanimously point to the importance of knowledge spillovers in fostering innovation in close proximity to education and research institutions. Thus, the evidence justifies the continually increasing support for research universities as a viable policy instrument for the government to promote long-term economic growth.

While our empirical analysis identifies and highlights the role of knowledge spillovers, future work would benefit from further explorations on the channels through which knowledge spillovers take place in a self-reinforcing way, as suggested by the dynamic evidence that we document in this paper. For instance, to take advantage of increased knowledge spillovers, nearby firms may hire more high-skilled labor and explore its complementarity with knowledge. Increased human capital increases the benefits of knowledge spillovers, which then leads to a self-reinforcing innovation process. Alternatively, increased knowledge spillovers could motivate firms to become more innovative and to enter the proximity of research-oriented universities to better draw on spillover benefits. Their entry and clustering could make it easier to use the knowledge from universities or to generate externalities within the clusters. These channels also reinforce the university spillovers. In a way, spillovers from universities can be viewed as both the "seed" and the "flower" of innovation (Harbison and Myers 1965). Altogether, the specific mechanisms explain the dynamic process through which high-tech clusters form in close proximity to higher education institutions.

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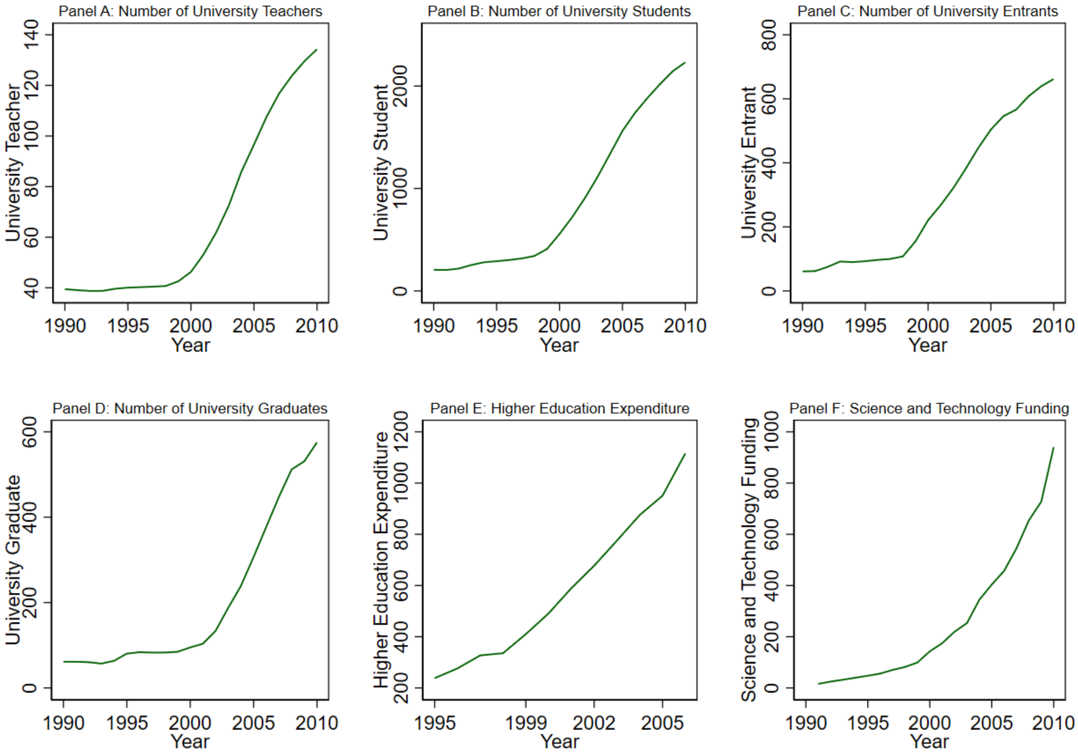


Figure 1: Various Aspects of the University Expansion

Notes: Numbers are counted in 10,000 from Panels A to D, and in 100,000,000 yuan in Panels E and F. Data for the numbers of university teachers, university students, university entrants, and university graduates are obtained from the Educational Statistics Yearbook of China. Data for higher education expenditure are from the Educational Finance Statistical Yearbook of China. Data for science and technology funding in the higher education sector are from the Compilation of Statistical Data on University Science and Technology Resource.

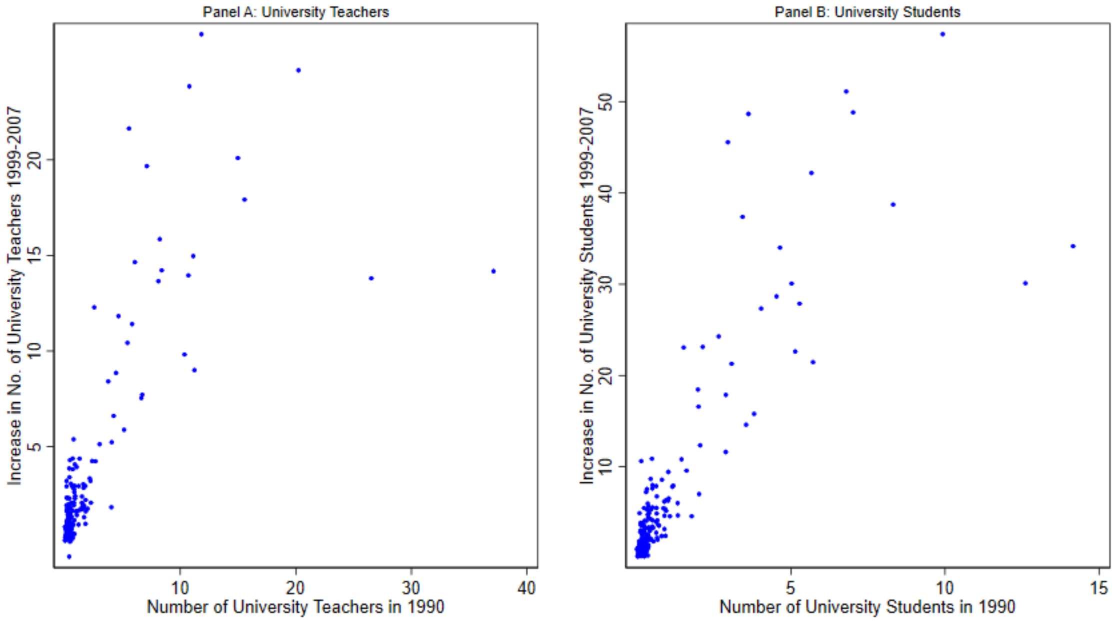
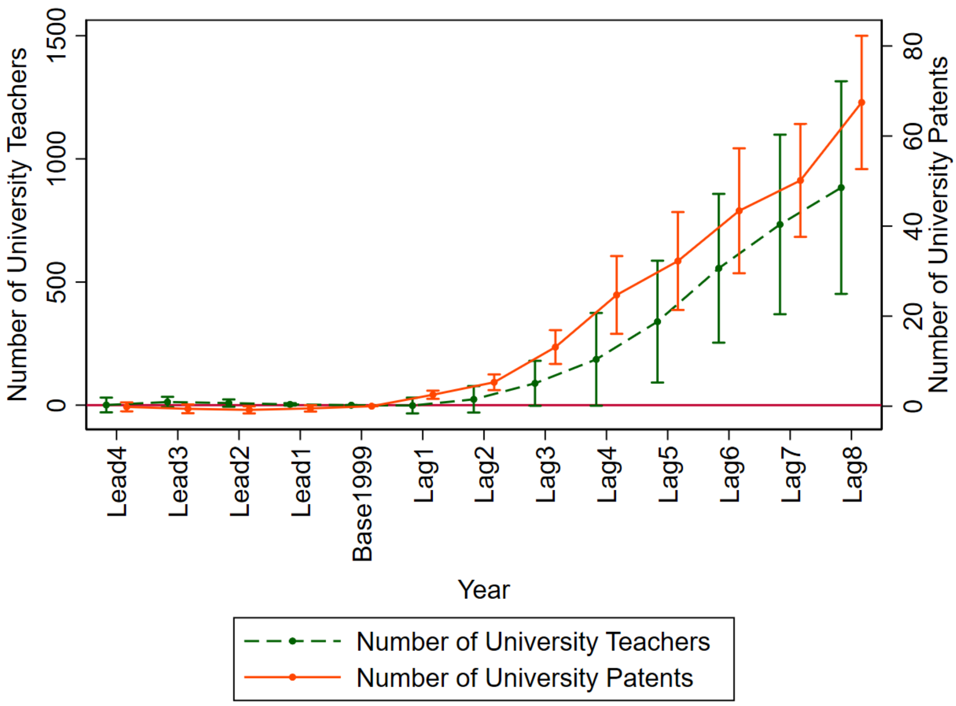
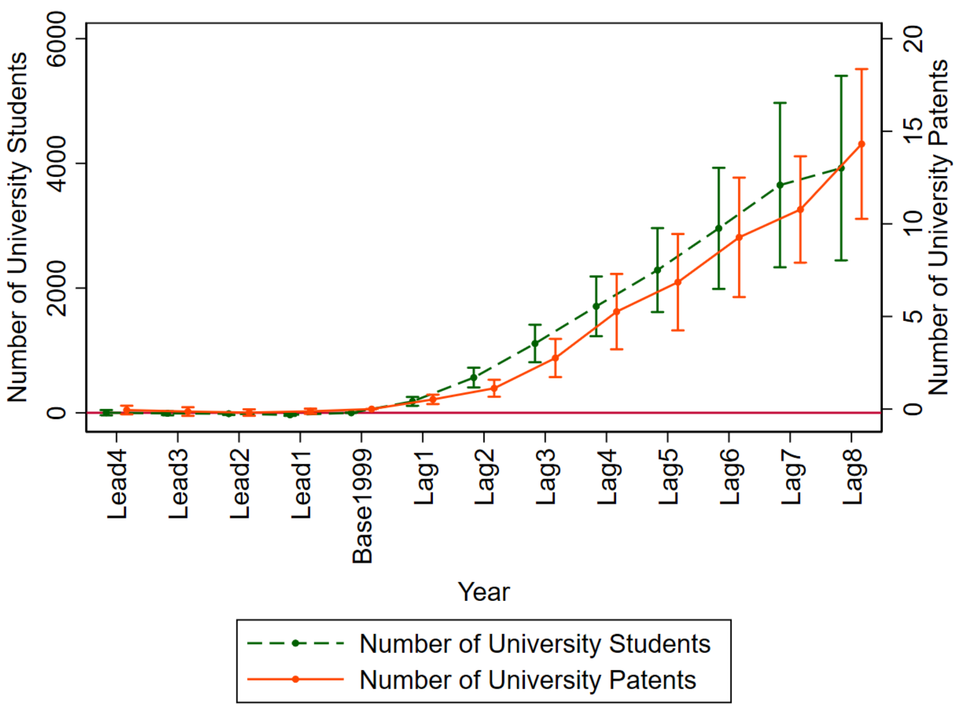


Figure 2: Growth in the University Scale between 1999 and 2007 in Relation to the University Scale in 1990

Notes: The number of university teachers is counted in 1,000. The number of university students is counted in 10,000. Data are obtained from the China City Statistical Yearbook.

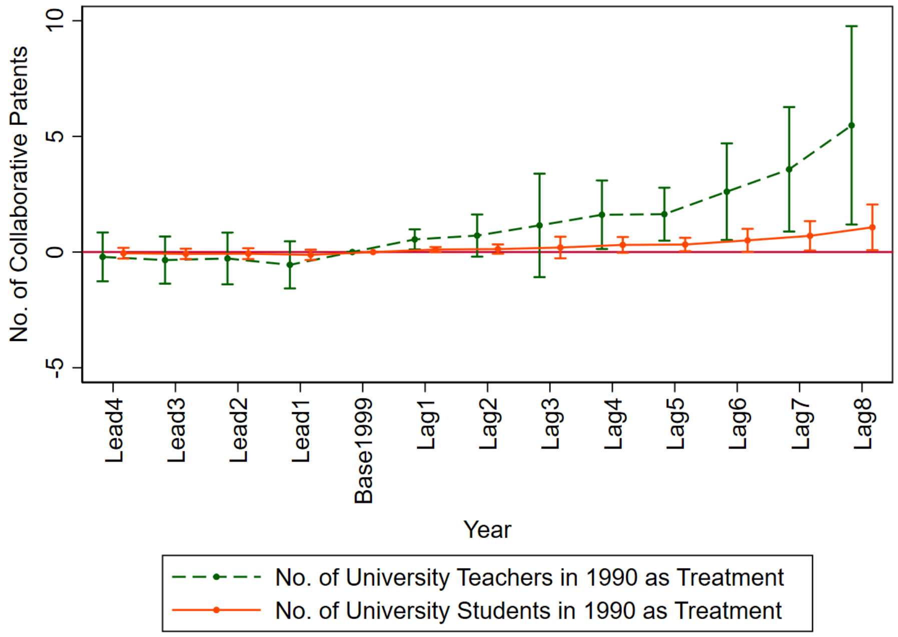


(a) No. of University Teachers in 1990 as Treatment

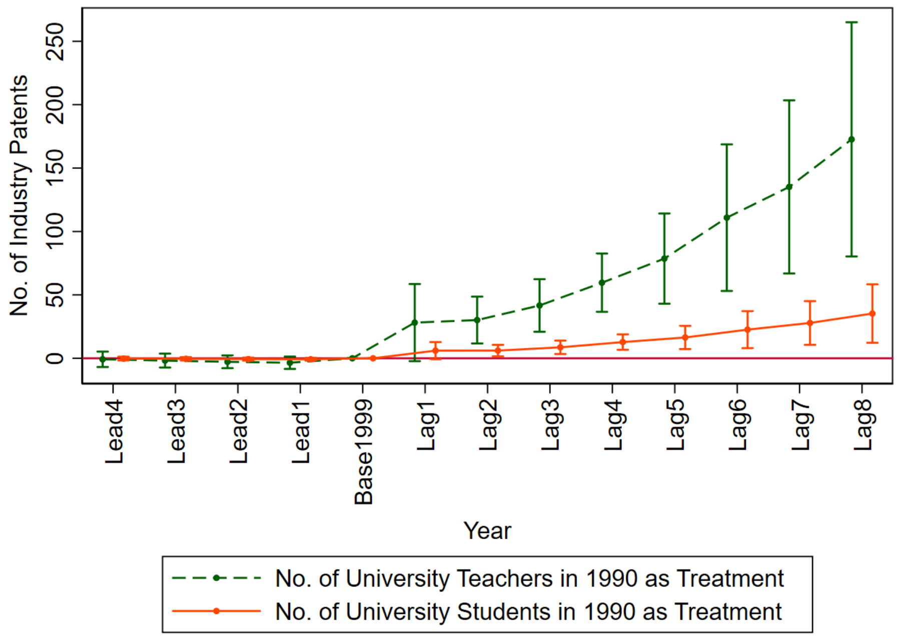


(b) No. of University Students in 1990 as Treatment

Figure 3: The Dynamic Effects of University Expansion on the Numbers of University Teachers, Students, and University Patents



(a) Collaborative Patents



(b) Industry Patents

Figure 4: The Dynamic Effects of University Expansion on the Numbers of Collaborative Patents and Industry Patents

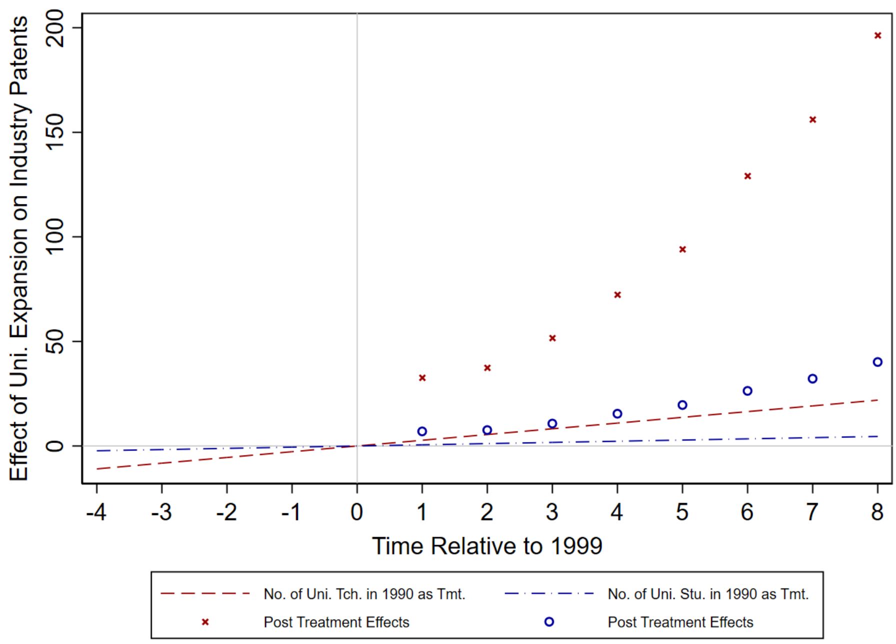


Figure 5: The Dynamic Effects of University Expansion on Industry Patents
— Parametric Event Study Approach in Dobkin et al. (2018)

Notes: This figure reports the results estimating Equation (5.1), which is a parametric event study approach introduced in Dobkin et al. (2018). The dashed line in the figure represents the estimated linear trend (the corresponding slope is μ in Equation (5.1)). The gap between the crosses (circles) and the dashed lines capture the estimated effects of the expansion.

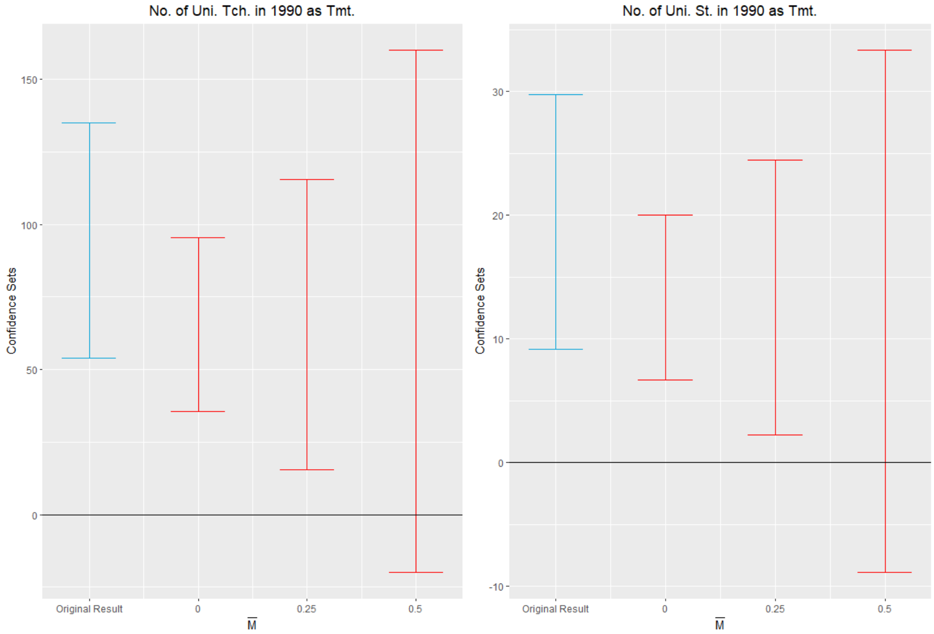
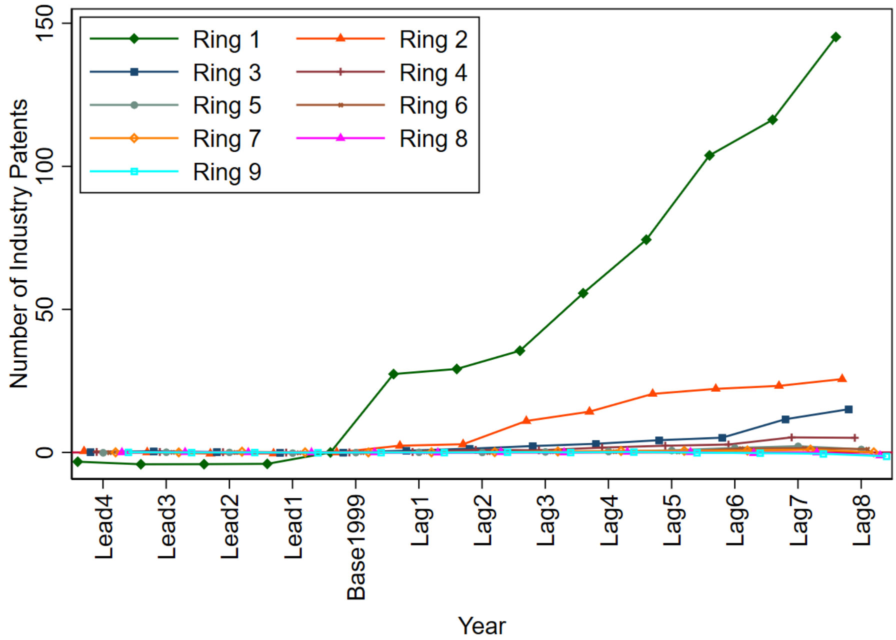
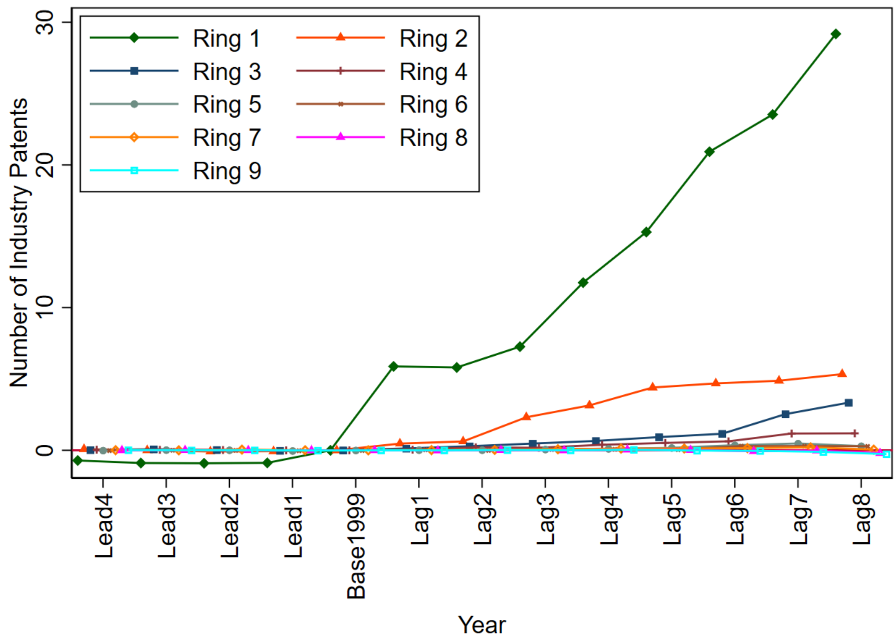


Figure 6: “Honest" Approach — Confidence Sets for the Effects of University Expansion on Industry Patents

Notes: This figure reports robust confidence sets for the average treatment effect across all post-treatment periods. It is produced using the R package provided by Rambachan and Roth (2022). The number of university teachers in 1990 is used as the treatment intensity in the left panel, and the number of university students in 1990 is used as the treatment intensity in the right panel. The blue confidence intervals are obtained without making adjustments for pre-trends. The red confidence sets depict the set of confidence intervals of the estimated coefficients if we allow for a deviation from a linear trend as specified in Equation (5.2).

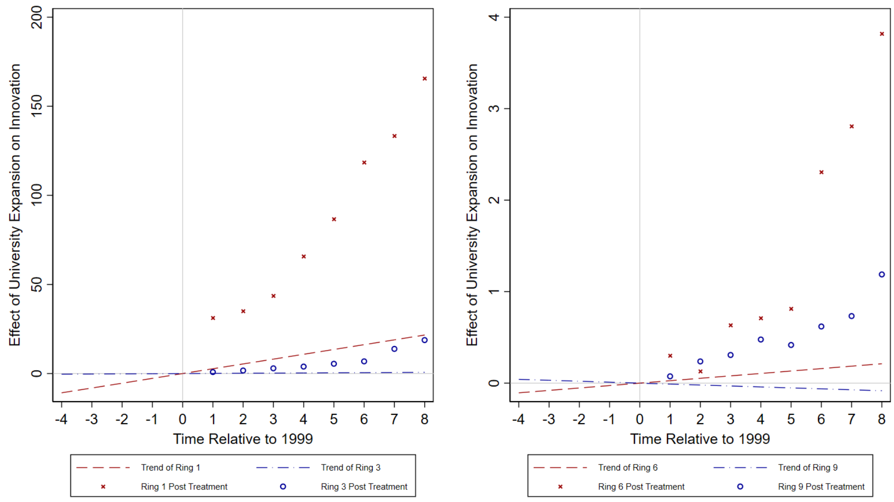


(a) No. of University Teachers in 1990 as Treatment

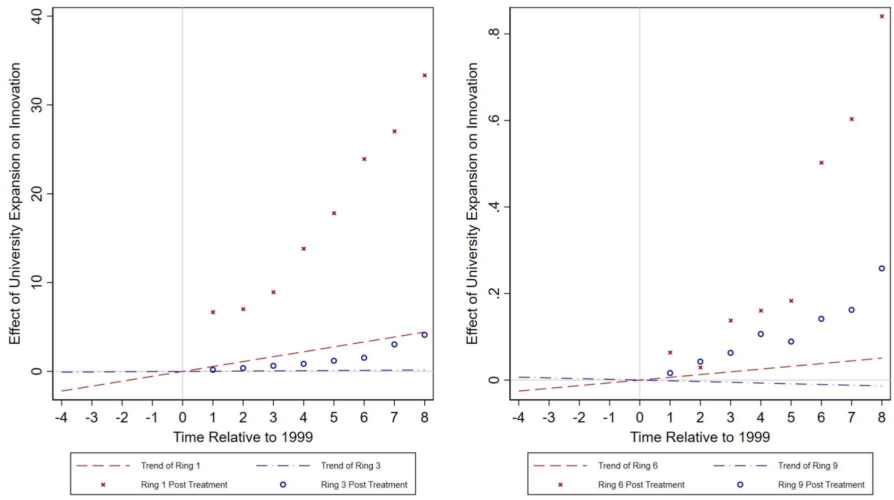


(b) No. of University Students in 1990 as Treatment

Figure 7: The Dynamic Effects of University Expansion on the Number of Industry Patents at the Ring Level — Pre-expansion Time Trend Removed



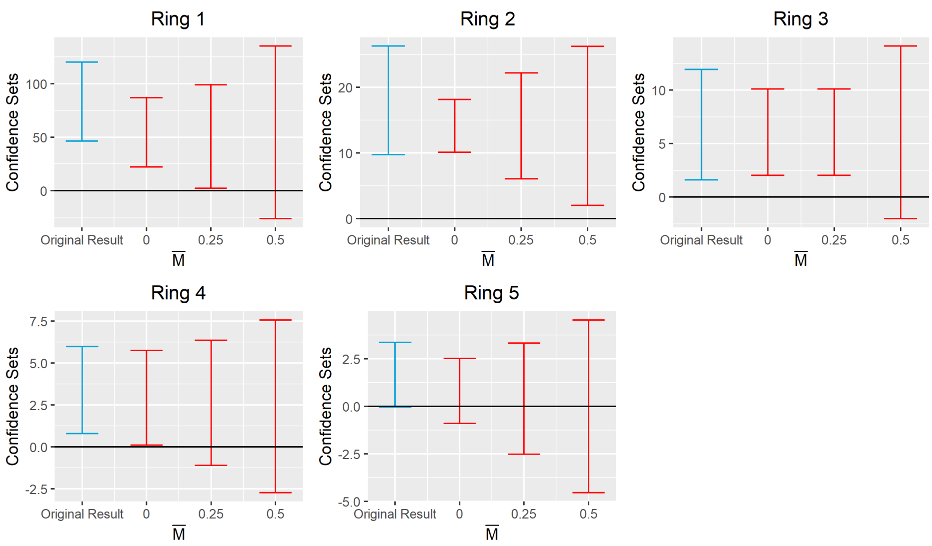
(a) No. of University Teachers in 1990 as Treatment



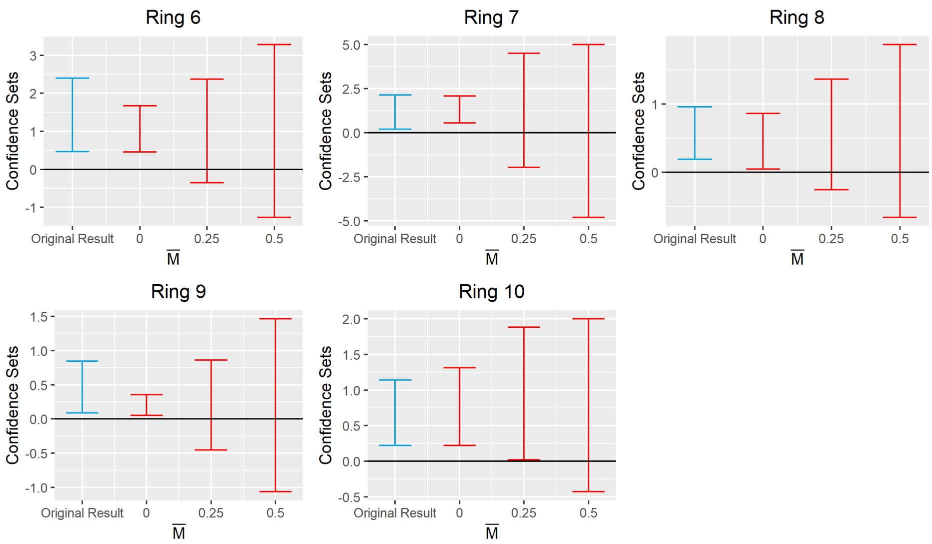
(b) No. of University Students in 1990 as Treatment

Figure 8: The Dynamic Effects of University Expansion on Industry Patents at the Ring Level — Parametric Event Study Approach in Dobkin et al. (2018)

Notes: The specification used for each ring is specified in Equation (5.1), where ℓ is the year relative to 1999. We only present the results for rings 1, 3, 6, and 9 to save space. The dashed lines in the figures represent the estimated linear trends (the corresponding slope is μ in Equation (5.1)). The gap between the crosses (circles) and the dashed lines capture the estimated effects of the expansion. Rings 1 and 6 are represented by crosses; Rings 3 and 9 are represented by circles.



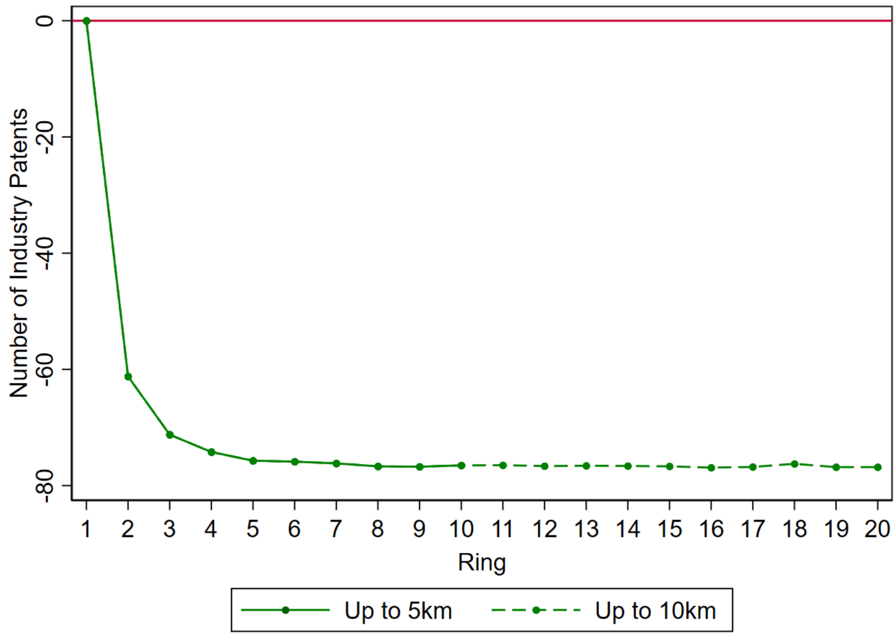
(a) Ring 1 - Ring 5



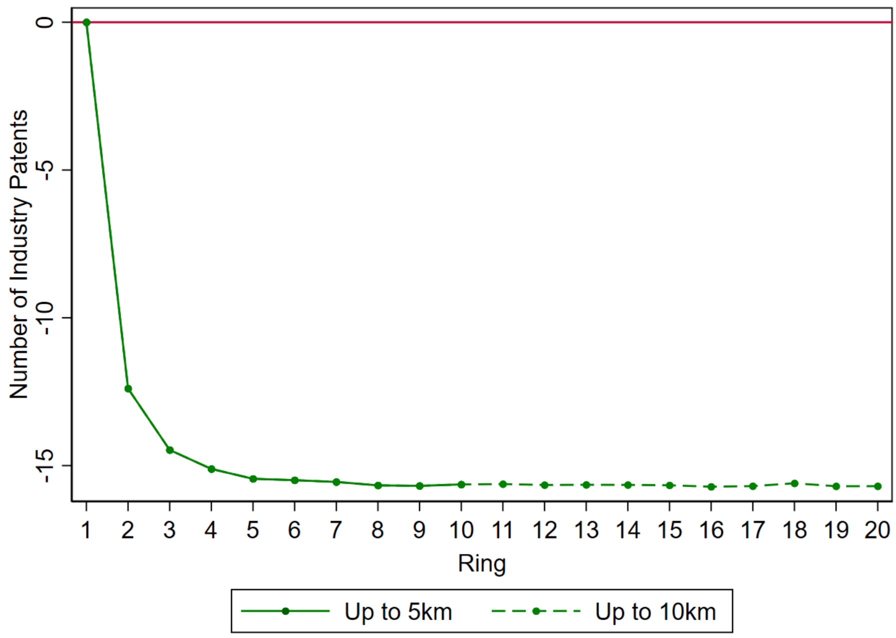
(b) Ring 6 - Ring 10

Figure 9: “Honest" Approach — Confidence Sets for the Effect of University Expansion on Patents in Ring 1-10

Notes: This figure reports robust confidence sets for the average treatment effect across all post-treatment periods for each ring. It is produced using the R package provided by Rambachan and Roth (2022). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The blue confidence intervals are obtained without making adjustments for pre-trends. The red confidence sets depict the set of confidence intervals of the estimated coefficients if we allow for a deviation from a linear trend as specified in Equation (5.2).



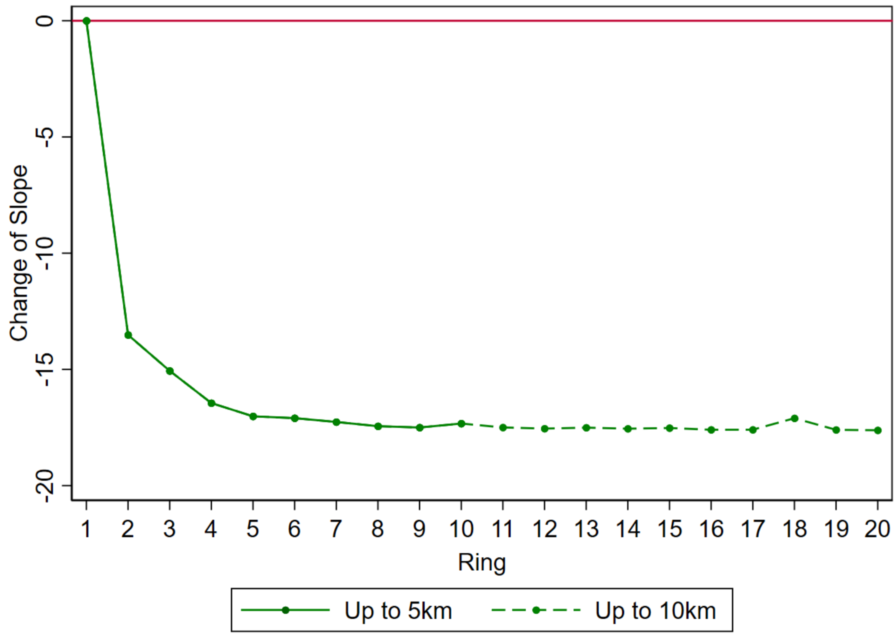
(a) No. of University Teachers in 1990 as Treatment



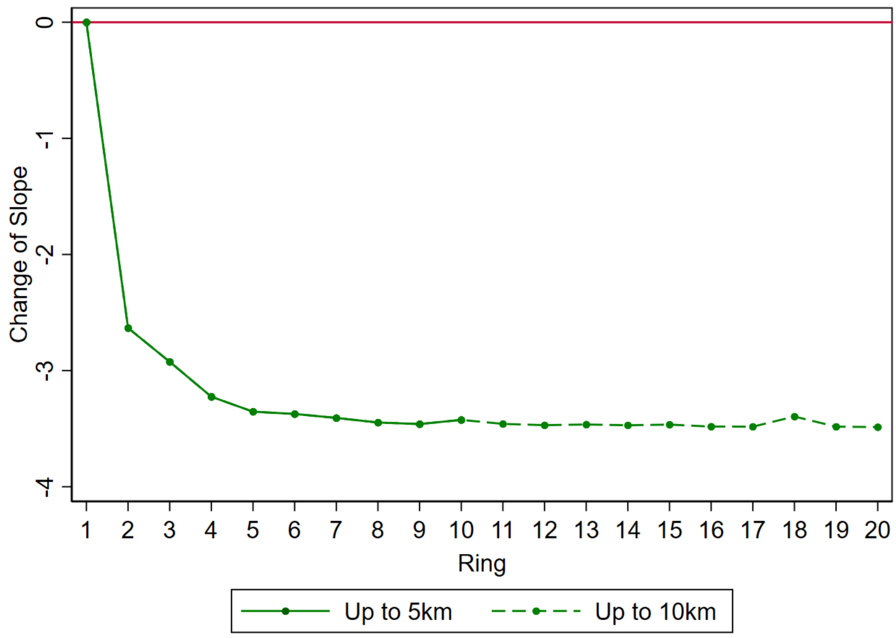
(b) No. of University Students in 1990 as Treatment

Figure 10: Spatial Decay of University Spillovers — Relative to the Effect on Ring 1

Notes: This figure depicts the effect of the university expansion on different rings using the de-trend method, relative to the effect on ring 1 (0-0.5 km ring). The number of university teachers (students) in 1990 is used as the measure of treatment intensity in the top (bottom) panel. Both variables are counted in 1,000.



(a) No. of University Teachers in 1990 as Treatment



(b) No. of University Students in 1990 as Treatment

Figure 11: Spatial Decay of University Spillovers — Relative to the Effect on Ring 1 (Trend Break Model)

Notes: This figure depicts the effect of the university expansion on different rings using the trend break model, relative to the effect on ring 1 (0-0.5 km ring). The number of university teachers (students) in 1990 is used as the measure of treatment intensity in the top (bottom) panel. Both variables are counted in 1,000.

Table 1: City-Level Summary Statistics

Year	(1) Cities	(2) University Teachers	(3) University Students	(4) Total Patents	(5) University Patents	(6) Collaborative Patents	(7) Industry Patents
1995	184	2066.14	14544.88	44.11	2.56	0.30	41.26
1996	184	2092.56	15274.52	49.84	2.86	0.40	46.58
1997	184	2106.44	15928.52	53.55	2.80	0.54	50.21
1998	184	2092.70	16781.35	59.97	3.80	0.56	55.60
1999	184	2111.27	18066.50	71.42	4.97	1.13	65.32
2000	184	2199.40	21705.90	114.96	8.28	1.74	104.93
2001	184	2376.25	28130.00	139.22	12.48	2.23	124.51
2002	184	2648.45	37005.33	197.61	22.43	2.93	172.24
2003	184	3084.78	46802.86	274.86	38.29	4.01	232.56
2004	184	3653.77	58002.03	308.14	49.88	4.65	253.61
2005	184	4310.27	69309.45	404.68	68.80	6.32	329.57
2006	184	4896.28	81839.51	528.77	85.07	8.46	435.23
2007	184	5403.83	88653.08	644.54	105.72	10.63	528.19

Notes: Column (1) reports the number of cities in each year. Columns (2)–(7) report the mean of the respective city-level variable. University patents are the patents filed solely by inventors affiliated with higher-education institutions. Collaborative patents are the patents jointly filed by inventors affiliated with universities and inventors from the private sector. Industry patents are the patents filed solely by inventors from the private sector.

Table 2: The Average Number of Patents at the Ring Level

Year	(1) Ring 1	(2) Ring 2	(3) Ring 3	(4) Ring 4	(5) Ring 5	(6) Ring 6	(7) Ring 7	(8) Ring 8	(9) Ring 9	(10) Ring 10
1995	18.20	6.33	3.40	2.32	1.35	0.80	0.62	0.58	0.46	0.33
1996	20.77	6.64	3.66	2.34	1.64	1.24	0.70	0.66	0.39	0.40
1997	23.45	6.61	3.93	2.23	1.80	1.22	0.85	0.49	0.48	0.46
1998	26.47	7.81	4.25	2.57	2.10	1.44	0.97	0.70	0.43	0.48
1999	33.86	8.82	4.62	2.90	2.42	1.52	1.05	0.77	0.58	0.52
2000	65.55	12.48	6.60	3.89	2.73	1.92	1.37	0.82	0.83	0.77
2001	79.36	14.72	7.93	5.11	3.02	1.97	1.78	1.36	0.88	0.88
2002	107.49	28.36	10.57	6.20	4.92	3.30	2.64	1.71	1.30	1.24
2003	150.23	39.66	13.91	8.51	6.22	4.23	3.51	2.57	2.21	1.61
2004	167.61	44.65	16.84	10.53	6.42	4.56	3.99	3.30	2.39	2.27
2005	211.91	48.41	22.48	13.95	10.19	7.98	6.15	4.27	3.01	3.91
2006	267.29	53.45	32.04	21.36	14.08	11.53	8.41	6.78	4.24	6.33
2007	316.14	65.49	39.30	25.49	17.35	15.03	11.33	8.41	6.40	9.64

Notes: This table reports the average numbers of patents in different concentric rings in each year across cities. Ring i refers to the concentric ring area between the buffer zones $(i-1)$ and i, and the boundaries of consecutive buffer zones are 500 meters apart.

Table 3: Impact of University Expansion on University Scale and Innovation — City-level Regression

Dependent Variable: No. of	(1) University Teachers	(2) Total Patents	(3) University Patents	(4) Collabo-rative Patents	(5) Industry Patents
Treatment × After	341.02***	138.74***	33.32***	3.67***	101.75***
	(3.23)	(5.20)	(7.57)	(3.95)	(4.52)
Observations	2384	2392	2392	2392	2392
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	3006.14	222.44	31.38	3.38	187.68
Adj. R^2	0.913	0.585	0.647	0.676	0.539

Notes: This table reports the estimates of the effects of university expansion on the numbers of university teachers and different classifications of patents. The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The number of university teachers is considered as a proxy for university scale. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact of University Expansion on University Scale and Innovation
— City-level Analysis of Trend Break Model

Dependent Variable: No. of	(1) University Teachers	(2) Total Patents	(3) University Patents	(4) Collabo-rative Patents	(5) Industry Patents
Treatment × Trend	155.40***	32.55***	10.09***	0.647**	21.81***
×After 2000	(4.64)	(5.59)	(9.15)	(2.47)	(4.23)
Observations	2384	2392	2392	2392	2392
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	3006.14	222.44	31.38	3.38	187.68
Adj. R^2	0.949	0.679	0.873	0.783	0.602

Notes: This table reports the estimates of the slope change in the numbers of university teachers and different classifications patents as a result of the university expansion, using the specification in Equation (3.7). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of University Expansion on University Scale and Innovation
— City-level Regression with Pre-expansion Linear Trend Removed

Dependent Variable: No. of	(1) University Teachers	(2) Total Patents	(3) University Patents	(4) Collabo-rative Patents	(5) Industry Patents
Treatment × After	346.06***	116.61***	30.27***	2.44***	83.89***
	(3.28)	(4.37)	(6.88)	(2.63)	(3.73)
Observations	2384	2392	2392	2392	2392
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	831.91	138.63	24.12	1.24	113.27
Adj. R^2	0.710	0.475	0.589	0.492	0.426

Notes: This table reports the estimates of the effects of university expansion on the numbers of university teachers and different classifications of patents. The city-specific pre-expansion linear trend is removed for the dependent variable in the specifications. The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The number of university teachers is considered as a proxy for university scale. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of University Expansion on Industry Innovation — Ring-level Regressions

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment ×	90.41***	89.70***	3.65	76.93***	76.52***	3.12
After × 0.5km	(4.46)	(4.44)		(3.80)	(3.79)	
Treatment ×	19.03***	18.33***	2.53	15.72***	15.31***	2.11
After × 1km	(4.28)	(4.27)		(3.54)	(3.57)	
Treatment ×	6.98**	6.28**	1.58	5.70**	5.29**	1.33
After × 1.5km	(2.55)	(2.42)		(2.08)	(2.04)	
Treatment ×	3.48***	2.78**	1.13	2.71**	2.30*	0.93
After × 2km	(2.60)	(2.33)		(2.03)	(1.93)	
Treatment ×	1.76**	1.06	0.57	1.21	0.81	0.43
After × 2.5km	(1.98)	(1.40)		(1.36)	(1.07)	
Treatment ×	1.49***	0.79*	0.64	1.05*	0.65	0.52
After × 3km	(2.71)	(1.90)		(1.91)	(1.55)	
Treatment ×	1.15**	0.44	0.53	0.75	0.34	0.41
After × 3.5km	(2.13)	(1.04)		(1.39)	(0.80)	
Treatment ×	0.60***	-0.11	-0.17	0.24	-0.16	-0.26
After × 4km	(2.75)	(-0.65)		(1.12)	(-1.01)	
Treatment ×	0.49**	-0.22	-0.46	0.18	-0.23	-0.48
After × 4.5km	(2.14)	(-1.31)		(0.79)	(-1.38)	
Treatment ×	0.70***	-	-	0.41*	-	-
After × 5km	(3.12)	-		(1.81)	-	
Observations	23920	23920	-	23920	23920	-
Treatment × Ring Dummies	Yes	No	-	Yes	No	-
City FE	Yes	No	-	Yes	No	-
Year × Ring FE	Yes	Yes	-	Yes	Yes	-
Year × City FE	No	Yes	-	No	Yes	-
City × Ring FE	No	Yes	-	No	Yes	-
Dependent Variable Mean	18.21	18.21	-	10.91	10.91	-
Adj. R^2	0.387	0.570	-	0.255	0.482	-

Notes: This table reports the estimated effects of university expansion on industry patents at different distances (rings). The city-ring-specific pre-expansion time trend is removed for the dependent variable in Columns (4)-(5). Columns (3) and (6) are obtained by dividing the coefficients in Columns (2) and (5) by the average number of patents in the corresponding ring during the pre-expansion periods, respectively. The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Impact of University Expansion on Industry Innovation — Ring-level Regressions of Trend Break Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Ring 1	Ring 2	Ring 3	Ring 4	Ring 5	Ring 6	Ring 7	Ring 8	Ring 9	Ring 10	Ring 1 - 10
Treatment × Trend	17.65^{***}										17.33^{***}
×After× 0.5km	(3.54)										(3.47)
Treatment × Trend		4.137^{***}									3.815^{***}
×After× 1km		(4.66)									(4.56)
Treatment × Trend			2.588^{**}								2.267^{*}
×After× 1.5km			(2.02)								(1.85)
Treatment × Trend				1.202^{***}							0.881^{**}
×After× 2km				(2.74)							(2.29)
Treatment × Trend					0.633^{*}						0.311
×After× 2.5km					(1.90)						(1.10)
Treatment × Trend						0.554^{**}					0.233
×After× 3km						(2.60)					(1.41)
Treatment × Trend							0.388^{**}				0.0670
×After× 3.5km							(2.23)				(0.50)
Treatment × Trend								0.208^{**}			-0.114
×After× 4km								(2.49)			(-1.41)
Treatment × Trend									0.150^{*}		-0.171^{*}
×After× 4.5km									(1.80)		(-1.96)
Treatment × Trend										0.321^{***}	
×After× 5km										(3.07)	
Observations	2392	2392	2392	2392	2392	2392	2392	2392	2392	2392	23920
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year × Ring FE	No	No	No	No	No	No	No	No	No	No	Yes
Year × City FE	No	No	No	No	No	No	No	No	No	No	Yes
City × Ring FE	No	No	No	No	No	No	No	No	No	No	Yes
Dependent Variable Mean	114.50	26.42	13.04	8.26	5.71	4.37	3.34	2.49	1.82	2.22	18.21
Adj. R^2	0.606	0.672	0.561	0.621	0.450	0.455	0.450	0.379	0.430	0.213	0.627

Notes: This table reports the estimates of the slope change in the number of industry patents at different distances (rings) as a result of the university expansion, using the specification in Equation (3.8). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The trend-break model is used in all specifications. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Robustness Check — Ring-level Regressions up to 10 km

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents			
	(1)	(2)	(3)	(4)
Treatment ×	90.41***	90.29***	77.06***	77.07***
After × 0.5km	(4.46)	(4.46)	(3.80)	(3.81)
Treatment ×	19.03***	18.92***	15.85***	15.86***
After × 1km	(4.28)	(4.30)	(3.57)	(3.60)
Treatment ×	6.98**	6.87**	5.83**	5.84**
After × 1.5km	(2.55)	(2.55)	(2.13)	(2.17)
Treatment ×	3.48***	3.37***	2.84**	2.85**
After × 2km	(2.60)	(2.61)	(2.12)	(2.21)
Treatment ×	1.76**	1.65*	1.35	1.36
After × 2.5km	(1.98)	(1.96)	(1.51)	(1.61)
Treatment ×	1.49***	1.38***	1.18**	1.20**
After × 3km	(2.71)	(2.74)	(2.15)	(2.37)
Treatment ×	1.15**	1.03**	0.88	0.89*
After × 3.5km	(2.13)	(2.07)	(1.63)	(1.78)
Treatment ×	0.60***	0.49***	0.37*	0.39**
After × 4km	(2.75)	(2.87)	(1.73)	(2.29)
Treatment ×	0.49**	0.38**	0.31	0.32*
After × 4.5km	(2.14)	(2.14)	(1.37)	(1.84)
Treatment ×	0.70***	0.59***	0.54**	0.55***
After × 5km	(3.12)	(3.07)	(2.39)	(2.86)
Treatment ×	0.44***	0.33***	0.28**	0.30***
After × 5.5km	(3.25)	(3.40)	(2.09)	(3.05)
Treatment ×	0.29**	0.18*	0.14	0.15
After × 6km	(2.06)	(1.75)	(0.97)	(1.45)
Treatment ×	0.34***	0.23***	0.20**	0.21***
After × 6.5km	(3.46)	(3.94)	(2.04)	(3.63)
Treatment ×	0.31**	0.20	0.17	0.18
After × 7km	(2.32)	(1.59)	(1.27)	(1.45)
Treatment ×	0.24*	0.13	0.10	0.11
After × 7.5km	(1.68)	(0.89)	(0.68)	(0.75)
Treatment ×	0.02	-0.09*	-0.12**	-0.11**
After × 8km	(0.40)	(-1.69)	(-2.30)	(-2.04)
Treatment ×	0.14***	0.03	0.01	0.02
After × 8.5km	(2.89)	(0.43)	(0.15)	(0.31)
Treatment ×	0.68	0.57	0.53	0.55
After × 9km	(1.59)	(1.28)	(1.26)	(1.24)
Treatment ×	0.11**	-0.00	-0.03	-0.01
After × 9.5km	(2.29)	(-0.04)	(-0.54)	(-0.23)
Treatment ×	0.11**	-	-0.01	-
After × 10km	(2.11)	-	(-0.23)	-
Observations	47840	47840	47840	47840
Treatment × Ring Dummies	Yes	No	Yes	No
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	No	Yes	No	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Dependent Variable Mean	9.62	9.62	5.86	5.86
Adj. R^2	0.375	0.563	0.243	0.475

Notes: This table reports the estimated effects of university expansion on industry patents at different distances (rings) for up to 10 km. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (3) and (4). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Heterogeneity Analysis — Eastern, Central, and Western Regions

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Eastern	Central	Western	Eastern	Central	Western
Treatment ×	114.89***	31.21***	26.51***	98.54***	25.05***	21.32***
After × 0.5km	(8.20)	(7.42)	(5.92)	(7.03)	(5.96)	(4.76)
Treatment ×	23.53***	5.74***	6.38***	20.10***	3.61**	4.39***
After × 1km	(4.21)	(3.56)	(5.19)	(3.60)	(2.24)	(3.57)
Treatment ×	7.92**	2.19***	2.46***	7.00*	1.05***	1.36**
After × 1.5km	(2.09)	(7.28)	(3.80)	(1.85)	(3.49)	(2.10)
Treatment ×	3.09*	1.88***	2.15*	2.61	1.37***	1.79
After × 2km	(1.77)	(8.17)	(2.02)	(1.50)	(5.94)	(1.68)
Treatment ×	1.18	0.84***	0.50***	0.96	0.47***	0.23*
After × 2.5km	(1.07)	(7.77)	(4.10)	(0.88)	(4.37)	(1.87)
Treatment ×	0.91	0.36***	0.71***	0.77	0.17**	0.56***
After × 3km	(1.51)	(5.25)	(6.17)	(1.29)	(2.58)	(4.84)
Treatment ×	0.43	0.42***	0.51*	0.33	0.31***	0.37
After × 3.5km	(0.71)	(5.59)	(1.83)	(0.55)	(4.09)	(1.33)
Treatment ×	-0.24	0.18**	0.27	-0.30	0.18**	0.09
After × 4km	(-1.05)	(2.63)	(1.52)	(-1.29)	(2.65)	(0.53)
Treatment ×	-0.32	0.02	0.08	-0.33	0.02	0.03
After × 4.5km	(-1.26)	(0.27)	(0.96)	(-1.29)	(0.19)	(0.33)
Treatment ×	-	-	-	-	-	-
After × 5km	-	-	-	-	-	-
Observations	10920	8320	4550	10920	8320	4550
Year × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	30.55	6.41	10.69	20.41	3.071	6.089
Adj. R^2	0.589	0.694	0.674	0.493	0.531	0.557

Notes: This table reports the estimated effects of university expansion on industry patents across different regions in China. The Eastern, Central and Western regions are divided according to the 7th "Five-Year Plan for the National Economic and Social Development" of China. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (4)-(6). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Heterogeneity Analysis — Industries with High, Medium, and Low Human Capital Intensity

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Medium	Low	High	Medium	Low
Treatment ×	68.58***	14.61***	3.81***	58.27***	11.65***	2.85***
After × 0.5km	(3.72)	(5.51)	(4.73)	(3.16)	(4.39)	(3.54)
Treatment ×	14.14***	3.30***	1.01***	11.86***	2.51**	0.76***
After × 1km	(4.24)	(3.03)	(3.83)	(3.55)	(2.30)	(2.88)
Treatment ×	4.62**	1.11**	0.50*	3.91*	0.76*	0.40
After × 1.5km	(2.19)	(2.54)	(1.96)	(1.86)	(1.74)	(1.57)
Treatment ×	1.61**	0.77*	0.26***	1.24*	0.61	0.22***
After × 2km	(2.30)	(1.68)	(3.44)	(1.77)	(1.33)	(2.97)
Treatment ×	0.44	0.21	0.13*	0.24	0.10	0.09
After × 2.5km	(0.99)	(1.01)	(1.82)	(0.54)	(0.49)	(1.34)
Treatment ×	0.46	0.17	0.10	0.34	0.13	0.08
After × 3km	(1.29)	(1.28)	(1.49)	(0.94)	(0.97)	(1.16)
Treatment ×	0.09	0.08	0.10*	0.02	0.05	0.10*
After × 3.5km	(0.28)	(0.78)	(1.85)	(0.05)	(0.47)	(1.72)
Treatment ×	-0.32	0.06	0.03*	-0.37*	0.04	0.02
After × 4km	(-1.46)	(0.46)	(1.84)	(-1.73)	(0.34)	(1.42)
Treatment ×	-0.34	-0.05	0.05	-0.35	-0.05	0.05
After × 4.5km	(-1.48)	(-0.64)	(1.24)	(-1.54)	(-0.70)	(1.28)
Treatment ×	-	-	-	-	-	-
After × 5km	-	-	-	-	-	-
Observations	23660	23660	23660	23660	23660	23660
Year × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	14.13	3.709	1.191	8.580	2.056	0.643
Adj. R^2	0.470	0.732	0.693	0.402	0.614	0.544

Notes: This table reports the estimated effects of university expansion on industry patents across industries with different human capital intensity. We define high human capital intensity industry as the industries that rank among the top one-third in the college employee ratio, medium as the middle one-third, and low as the rest. The industry college employee ratio is calculated as the percentage of workers with a college education and above using the 2004 ASIF. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (4)-(6). The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effects of University Expansion on Patent Citations — Ring-level Regressions

	No. of Teachers in 1990 as Treatment		No. of Students in 1990 as Treatment	
	(1)	(2)	(3)	(4)
Dependent Variable: No. of	Citations to University Patents	Citations to Patents beyond 5km	Citations to University Patents	Citations to Patents beyond 5km
Treatment ×	5.59e-01***	7.29e-02	1.14e-01**	1.52e-02
After × 0.5km	(3.24)	(1.15)	(2.59)	(0.98)
Treatment ×	8.23e-02**	4.81e-03	1.85e-02**	1.03e-03
After × 1km	(2.51)	(0.34)	(2.49)	(0.30)
Treatment ×	1.86e-02*	2.72e-02*	4.49e-03**	5.38e-03
After × 1.5km	(1.99)	(1.91)	(2.20)	(1.55)
Treatment ×	3.04e-02***	-1.41e-03	6.65e-03***	2.52e-04
After × 2km	(4.96)	(-0.10)	(4.13)	(0.08)
Treatment ×	7.07e-03	8.19e-03	1.87e-03	2.13e-03
After × 2.5km	(1.23)	(0.96)	(1.44)	(1.07)
Treatment ×	7.71e-03	1.64e-02	1.82e-03	3.88e-03*
After × 3km	(1.45)	(1.65)	(1.59)	(1.71)
Treatment ×	8.03e-03*	2.43e-02***	1.86e-03*	5.19e-03**
After × 3.5km	(1.81)	(3.14)	(1.71)	(2.57)
Treatment ×	-1.58e-03	7.77e-03	-2.62e-04	1.81e-03
After × 4km	(-0.40)	(1.16)	(-0.27)	(1.19)
Treatment ×	3.86e-03	8.22e-03	9.78e-04	1.70e-03
After × 4.5km	(1.07)	(1.28)	(1.11)	(1.08)
Treatment ×	-	-	-	-
After × 5km	-	-	-	-
Observations	4500	4500	4500	4500
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.32	0.46	0.32	0.46
Adj. R^2	0.668	0.522	0.653	0.522

Notes: This table reports the estimates of the effects of university expansion on patent citations at different distances (rings). The dependent variable for Columns (1) and (3) is the ring-specific number of times when industry patents cite university patents. The dependent variable for Columns (2) and (4) is the ring-specific number of times when industry patents cite patents beyond 5 km distance from universities. The number of university teachers (students) in 1990 is used as the measure of treatment intensity in the left (right) panel. Both variables are counted in 1,000. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Effects of University Expansion on New Product Ratio — Ring-level Regressions

Dependent Variable	New Product Ratio			
	(1)	(2)	(3)	(4)
After Dummy	2000	2002	2004	2006
Treatment ×	4.16e-03**	4.84e-03**	6.35e-03**	6.68e-03**
After × 0.5km	(2.17)	(2.15)	(2.19)	(2.17)
Treatment ×	2.74e-03**	3.32e-03**	4.26e-03***	4.58e-03**
After × 1km	(2.57)	(2.59)	(2.68)	(2.46)
Treatment ×	1.76e-03***	2.07e-03***	2.74e-03***	2.89e-03***
After × 1.5km	(4.98)	(5.17)	(4.87)	(4.60)
Treatment ×	1.28e-03***	1.47e-03***	1.75e-03***	1.77e-03***
After × 2km	(4.91)	(4.80)	(5.14)	(4.78)
Treatment ×	1.66e-03***	2.03e-03***	1.73e-03***	1.63e-03***
After × 2.5km	(3.65)	(3.90)	(3.62)	(3.20)
Treatment ×	1.07e-03***	1.31e-03***	1.63e-03***	1.68e-03***
After × 3km	(4.51)	(5.10)	(4.69)	(4.59)
Treatment ×	6.20e-04***	7.28e-04**	1.04e-03***	1.21e-03***
After × 3.5km	(2.74)	(2.54)	(3.12)	(3.39)
Treatment ×	6.66e-04***	7.85e-04***	1.24e-03***	1.56e-03***
After × 4km	(2.78)	(2.99)	(3.97)	(4.31)
Treatment ×	6.06e-04	6.96e-04	9.91e-04	1.14e-03**
After × 4.5km	(1.19)	(1.24)	(1.61)	(2.01)
Treatment ×	5.54e-04**	6.84e-04**	1.11e-03***	1.38e-03***
After × 5km	(2.17)	(2.13)	(2.84)	(3.38)
Observations	1196263	996185	759980	589233
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.034	0.035	0.037	0.037
Adj. R^2	0.091	0.097	0.107	0.106

Notes: This table reports the estimated effects of university expansion on firms' new product ratio using the number of university teachers in 1990 as the proxy for treatment intensity. The dependent variable is firm-level new product ratio. Columns (1)–(4) report the triple-differences estimates. The after dummy equals 1 if year is 2000 or after, 2002 or after, 2004 or after, or 2006 or after in Columns (1), (2), (3), and (4), respectively. The after dummy equals 0 if year is before 2000 for all four columns. Observations in the years in which the after dummy is not defined are dropped. The reference group is the firms outside 10 km of universities. Control variables include firm age, fixed assets, SOE status, and employment size. The number of university teachers in 1990 is counted in 1,000. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Heterogeneity Analysis — Industries with High, Medium, and Low Human Capital Intensity and SOE versus Non-SOE

Dependent Variable	New Product Ratio				
	(1)	(2)	(3)	(4)	(5)
	High	Medium	Low	SOE	Non-SOE
Treatment ×	4.70e-03**	2.77e-03**	1.41e-03	8.92e-04	4.31e-03**
After × 0.5km	(2.20)	(2.43)	(1.13)	(1.15)	(1.99)
Treatment ×	3.88e-03**	1.41e-03**	1.08e-03**	9.88e-04*	2.99e-03***
After × 1km	(2.51)	(2.10)	(2.53)	(1.92)	(2.62)
Treatment ×	2.79e-03***	1.29e-03***	1.48e-04	7.21e-04***	1.91e-03***
After × 1.5km	(4.20)	(5.00)	(0.80)	(2.89)	(4.91)
Treatment ×	1.52e-03**	8.51e-04***	7.62e-04***	5.37e-04*	1.44e-03***
After × 2km	(2.43)	(3.29)	(3.79)	(1.70)	(6.24)
Treatment ×	2.99e-03**	5.98e-04**	6.66e-04***	1.36e-03***	1.74e-03***
After × 2.5km	(2.17)	(2.30)	(3.16)	(4.99)	(3.52)
Treatment ×	1.54e-03***	8.52e-04**	2.58e-04	8.97e-04**	1.21e-03***
After × 3km	(3.73)	(2.03)	(1.29)	(2.08)	(5.76)
Treatment ×	7.64e-04*	4.43e-04	2.49e-04	3.63e-05	8.57e-04***
After × 3.5km	(1.78)	(1.14)	(0.80)	(0.08)	(3.41)
Treatment ×	7.00e-04	6.94e-05	6.37e-04**	-1.96e-04	9.36e-04***
After × 4km	(0.67)	(0.24)	(2.02)	(-0.41)	(3.16)
Treatment ×	8.83e-04*	-2.00e-04	9.10e-04***	-6.10e-04*	9.00e-04*
After × 4.5km	(1.67)	(-0.34)	(3.78)	(-1.78)	(1.89)
Treatment ×	-2.63e-04	5.37e-04	7.76e-04***	1.67e-04	8.22e-04***
After × 5km	(-0.46)	(0.93)	(3.12)	(0.33)	(3.42)
Observations	394427	385023	456632	136171	1060023
Year × Ring FE	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.059	0.025	0.020	0.046	0.033
Adj. R^2	0.119	0.057	0.049	0.111	0.096

Notes: Columns (1)–(3) report the estimated effects of university expansion on firms' new product ratio across industries with different human capital intensity. We define high human capital intensity industry as the industries that rank among the top one-third in the college employee ratio, medium as the middle one-third, and low as the rest. The industry college employee ratio is calculated as the percentage of workers with a college education and above using the 2004 ASIF. Columns (4) and (5) report the estimates of the effects of university expansion on firms' new product ratio for SOEs and non-SOEs separately. The number of university teachers in 1990 is counted in 1,000, and it is used as the treatment intensity. Control variables include firm age, fixed assets, SOE status, and employment size. The reference group consists of the firms outside 10 km of universities. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix: Figures and Tables

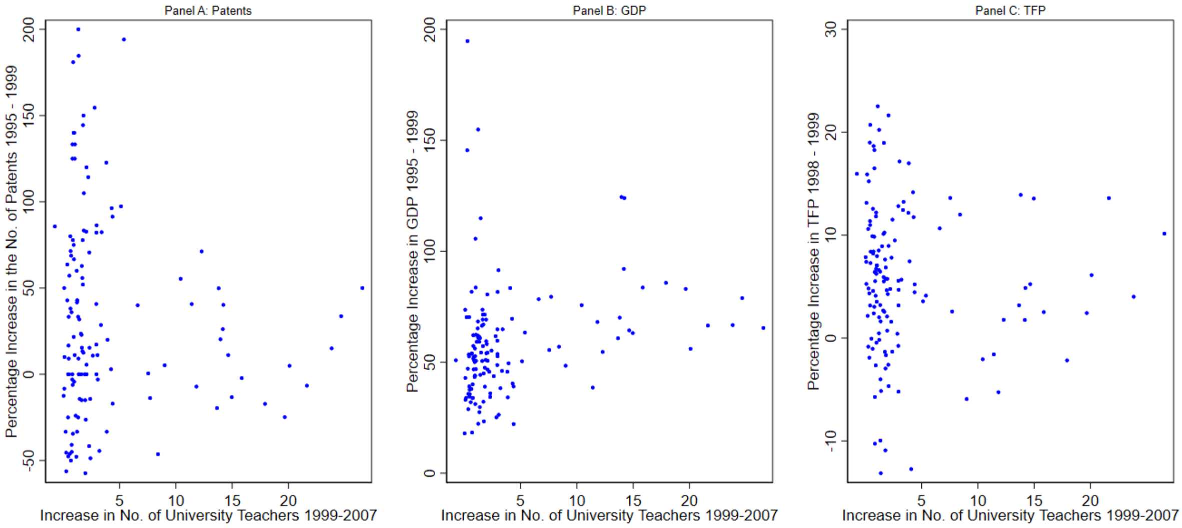


Figure A1: The Extent of University Expansion and Pre-expansion Growth of Patents, GDP and TFP

Notes: Panel A shows the scatter plot of pre-expansion growth of patents against the extent of university expansion at the city level. Panel B shows the scatter plot of pre-expansion growth of GDP against the extent of university expansion at the city level. Panel C shows the scatter plot of pre-expansion growth of average firm TFP against the extent of university expansion at the city level. The correlation coefficients are -0.10, 0.24 and -0.05 respectively. The number of university teachers is counted in 1,000.

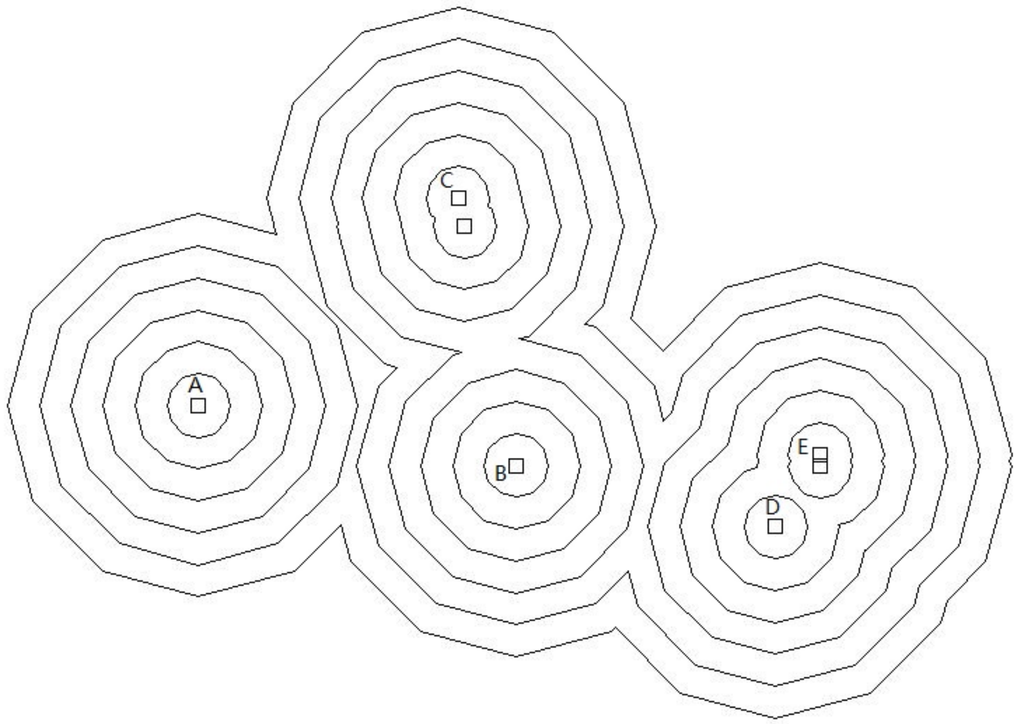
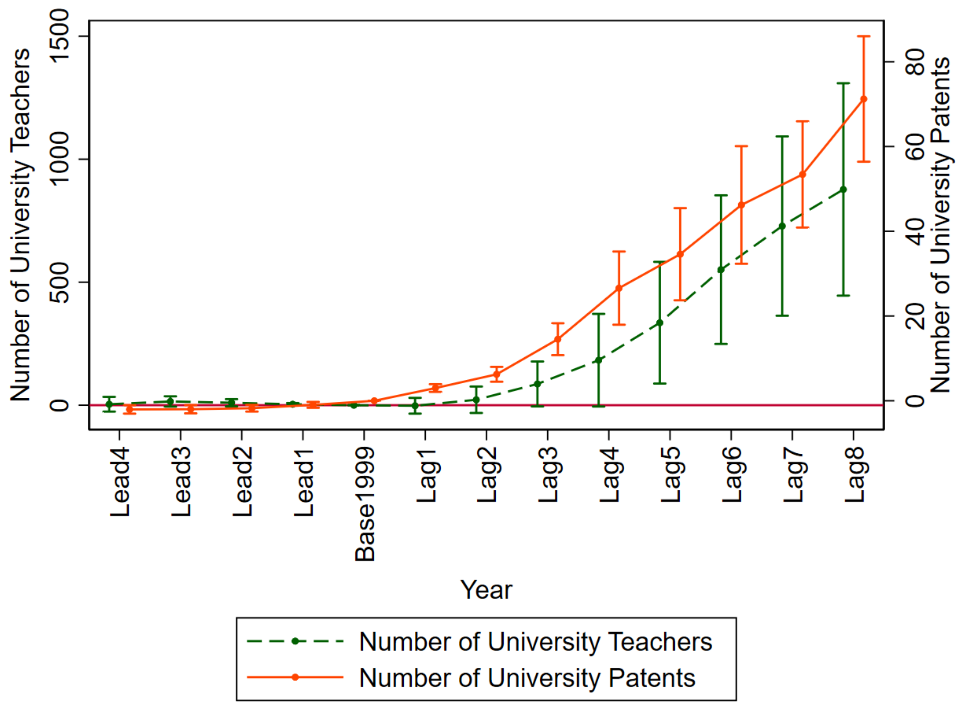
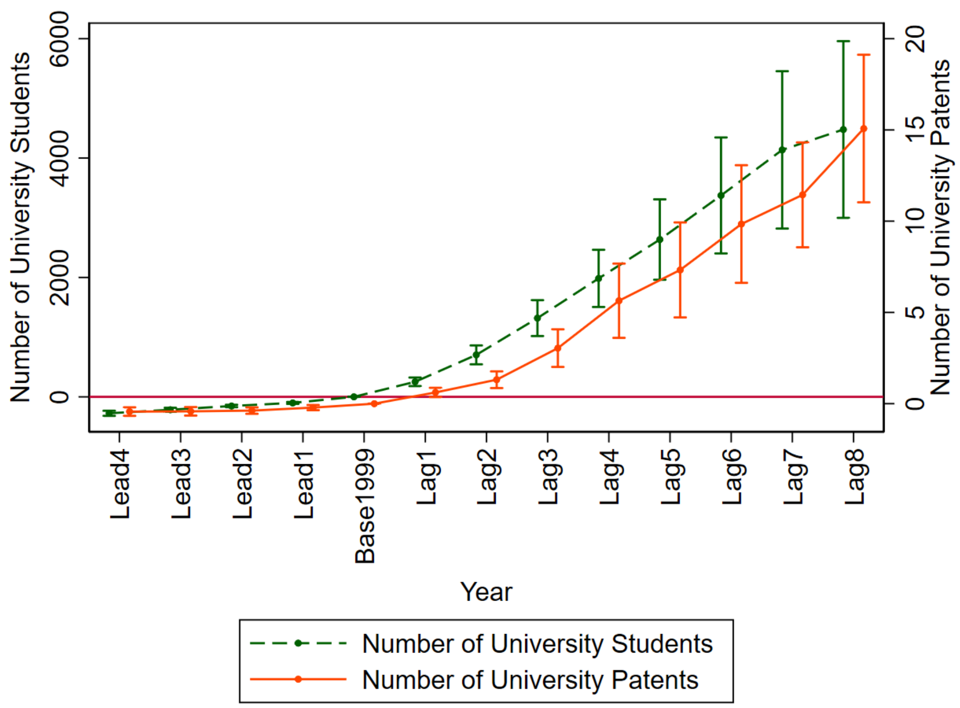


Figure A2: Illustrative Graph for the Construction of Concentric Rings

Notes: The centers of the rings comprise the locations of universities and entities that have direct collaborations with universities. The two locations at C belong to university I. The three locations at D and E belong to university II. One university can have multiple locations in the dataset because the address filed in a patent application points to the exact building of the patent applicant. Point A stands for a non-university entity that has direct collaboration with university I. Point B stands for a non-university entity that has direct collaboration with university II.

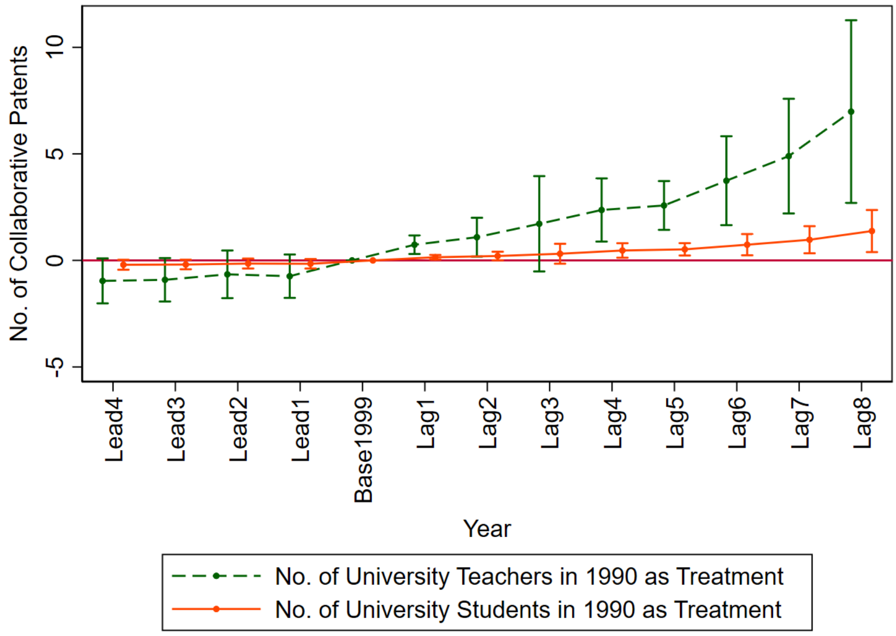


(a) No. of University Teachers in 1990 as Treatment

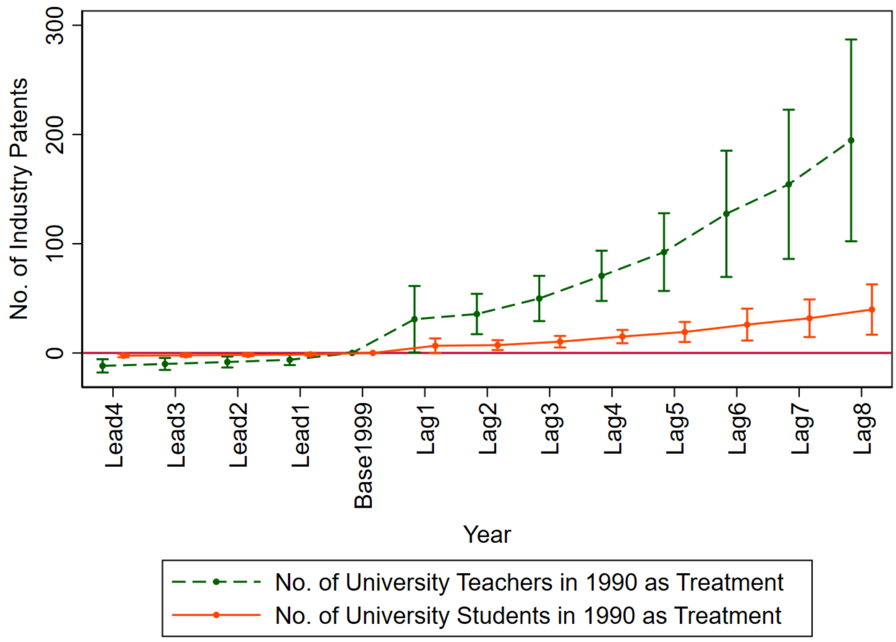


(b) No. of University Students in 1990 as Treatment

Figure A3: The Dynamic Effects of University Expansion on the Numbers of University Teachers, Students, and University Patents – Pre-expansion Time Trend Not Removed

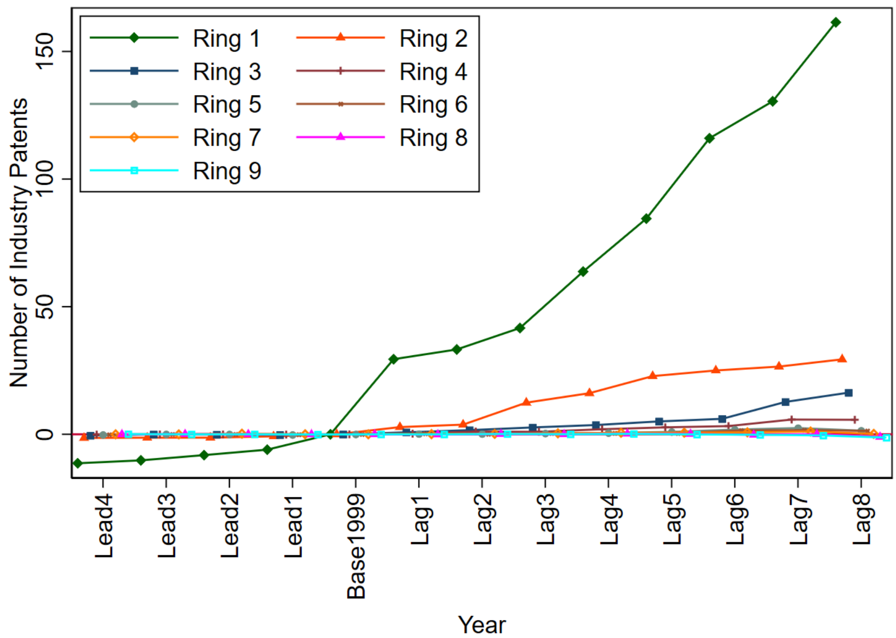


(a) Collaborative Patents

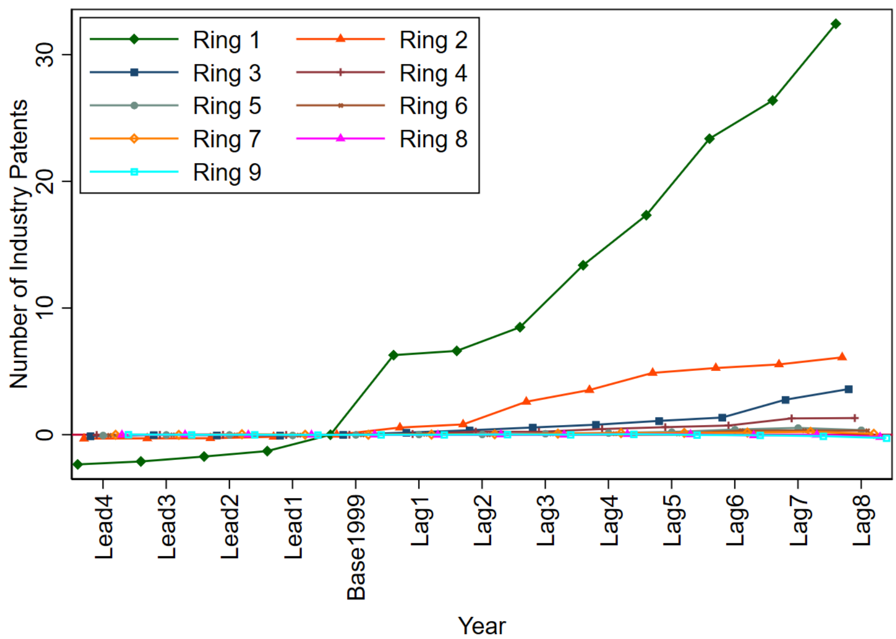


(b) Industry Patents

Figure A4: The Dynamic Effects of University Expansion on the Numbers of Collaborative Patents and Industry Patents – Pre-expansion Time Trend Not Removed



(a) No. of University Teachers in 1990 as Treatment



(b) No. of University Students in 1990 as Treatment

Figure A5: The Dynamic Effects of University Expansion on the Number of Industry Patents at the Ring Level — Pre-expansion Time Trend Not Removed

Table A1.A: Impact of University Expansion on University Scale and and Innovation

	Pre-expansion Time Trend Not Removed					Pre-expansion Time Trend Removed				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: No. of	University Students	Total Patents	University Patents	Collabo-rative Patents	Industry Patents	University Students	Total Patents	University Patents	Collabo-rative Patents	Industry Patents
Treatment × After	2509.57***	28.83***	7.08***	0.73***	21.02***	2059.45***	24.31***	6.46***	0.48**	17.37***
	(7.25)	(4.20)	(6.53)	(3.20)	(3.70)	(5.95)	(3.54)	(5.96)	(2.11)	(3.06)
Observations	2352	2352	2352	2352	2352	2352	2352	2352	2352	2352
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	No	No	No	No	No	No	No	No	No	No
Dependent Variable Mean	39387.99	222.44	31.38	3.38	187.68	20274.18	136.63	23.86	1.13	111.64
Adj. R^2	0.829	0.575	0.638	0.652	0.530	0.657	0.466	0.579	0.469	0.419

Notes: This table reports the estimated effects of university expansion on the numbers of university students and different classifications of patents. The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The number of university students is considered as a proxy for university scale. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.B: Impact of University Expansion on University Scale and and Innovation — Robustness

	Pre-expansion Time Trend Not Removed					Pre-expansion Time Trend Removed				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: No. of	University Teachers	Total Patents	University Patents	Collabo-rative Patents	Industry Patents	University Teachers	Total Patents	University Patents	Collabo-rative Patents	Industry Patents
Treatment × After	220.99**	113.88***	28.83***	3.31***	81.75***	232.85**	93.35***	25.86***	2.11**	65.38***
	(2.28)	(4.22)	(7.68)	(3.66)	(3.44)	(2.40)	(3.46)	(6.90)	(2.34)	(2.75)
Observations	2330	2338	2338	2338	2338	2330	2338	2338	2338	2338
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	3032.32	225.23	31.93	3.43	189.87	802.97	141.56	25.38	1.66	114.52
Adj. R^2	0.930	0.604	0.674	0.686	0.556	0.759	0.497	0.620	0.500	0.443

Notes: This table reports the estimated effects of university expansion on the numbers of university teachers and different classifications of patents. The number of university teachers in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The number of university teachers is considered as a proxy for university scale. Control variables include the non-agricultural population, the proportion of employment in the manufacturing industries, and the proportion of employment in the service industries. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.C: Impact of University Expansion on University Scale and and Innovation — Robustness

	Pre-expansion Time Trend Not Removed					Pre-expansion Time Trend Removed				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: No. of	University Students	Total Patents	University Patents	Collabo-rative Patents	Industry Patents	University Students	Total Patents	University Patents	Collabo-rative Patents	Industry Patents
Treatment × After	1991.77***	23.06***	6.05***	0.64***	16.37***	1602.58***	18.87***	5.44***	0.39*	13.04**
	(5.73)	(3.44)	(6.35)	(2.97)	(2.86)	(4.73)	(2.81)	(5.72)	(1.82)	(2.28)
Observations	2338	2338	2338	2338	2338	2338	2338	2338	2338	2338
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	39659.82	225.23	31.93	3.43	189.87	19914.02	140.17	25.17	1.58	113.42
Adj. R^2	0.860	0.595	0.663	0.664	0.548	0.714	0.488	0.609	0.478	0.437

Notes: This table reports the estimated effects of university expansion on the numbers of university students and different classifications of patents. The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The number of university students is considered as a proxy for university scale. Control variables include the non-agricultural population, the proportion of employment in the manufacturing industries, and the proportion of employment in the service industries. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Impact of University Expansion on University Scale and Innovation — City-level Analysis of Trend Break Model

Dependent Variable: No. of	(1) University Students	(2) Total Patents	(3) University Patents	(4) Collabo-rative Patents	(5) Industry Patents
Treatment × Trend	609.1***	6.690***	2.153***	0.126**	4.411***
×After 2000	(5.28)	(4.33)	(8.01)	(2.20)	(3.41)
Observations	2392	2392	2392	2392	2392
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	3006.14	222.44	31.38	3.38	187.68
Adj. R^2	0.924	0.660	0.854	0.742	0.586

Notes: This table reports the estimates of the slope change in the numbers of university students and different classifications patents as a result of the university expansion, using the specification in Equation (3.7). The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.A: The Dynamic Effects of University Expansion on the Number of Teachers and Innovation

	Pre-expansion Time Trend Not Removed					Pre-expansion Time Trend Removed				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: No. of	University Teachers	Total Patents	University Patents	Collabo-rative Patents	Industry Patents	University Teachers	Total Patents	University Patents	Collabo-rative Patents	Industry Patents
Treatment × 1995	3.97	-14.83***	-2.04***	-0.97*	-11.83***	1.01	-1.17	-0.16	-0.21	-0.81
	(0.26)	(-3.73)	(-4.03)	(-1.80)	(-3.84)	(0.07)	(-0.30)	(-0.31)	(-0.39)	(-0.26)
Treatment × 1996	14.90	-12.98***	-1.99***	-0.91*	-10.08***	12.68	-2.74	-0.58	-0.35	-1.81
	(1.41)	(-3.49)	(-4.03)	(-1.77)	(-3.61)	(1.20)	(-0.74)	(-1.17)	(-0.67)	(-0.65)
Treatment × 1997	10.22	-10.71***	-1.75***	-0.66	-8.30***	8.74	-3.89	-0.81**	-0.28	-2.79
	(1.37)	(-3.14)	(-4.35)	(-1.16)	(-3.25)	(1.17)	(-1.14)	(-2.02)	(-0.49)	(-1.09)
Treatment × 1998	4.04	-7.99**	-0.96***	-0.74	-6.28**	3.30	-4.57	-0.49	-0.55	-3.53
	(1.63)	(-2.42)	(-2.71)	(-1.44)	(-2.54)	(1.33)	(-1.39)	(-1.39)	(-1.07)	(-1.43)
Treatment × 2000	-2.19	34.70**	3.02***	0.74***	30.95**	-1.45	31.29**	2.54***	0.55**	28.20*
	(-0.13)	(2.21)	(6.58)	(3.34)	(2.00)	(-0.09)	(1.99)	(5.55)	(2.49)	(1.83)
Treatment × 2001	21.81	43.06***	6.27***	1.09**	35.71***	23.29	36.24***	5.32***	0.71	30.20***
	(0.80)	(4.19)	(7.08)	(2.36)	(3.81)	(0.86)	(3.53)	(6.01)	(1.55)	(3.22)
Treatment × 2002	85.72*	66.17***	14.57***	1.72	49.88***	87.94*	55.92***	13.15***	1.15	41.61***
	(1.86)	(5.26)	(7.66)	(1.52)	(4.74)	(1.90)	(4.45)	(6.92)	(1.02)	(3.96)
Treatment × 2003	181.77*	99.63***	26.63***	2.37***	70.63***	184.72*	85.98***	24.75***	1.61**	59.61***
	(1.91)	(6.80)	(6.08)	(3.15)	(6.05)	(1.94)	(5.87)	(5.65)	(2.15)	(5.11)
Treatment × 2004	333.73***	129.62***	34.66***	2.58***	92.37***	337.43***	112.54***	32.31***	1.64***	78.60***
	(2.67)	(5.76)	(6.28)	(4.46)	(5.11)	(2.70)	(5.00)	(5.86)	(2.83)	(4.35)
Treatment × 2005	549.53***	177.42***	46.31***	3.74***	127.36***	553.96***	156.93***	43.49***	2.61**	110.83***
	(3.59)	(5.16)	(6.58)	(3.54)	(4.34)	(3.62)	(4.57)	(6.18)	(2.47)	(3.77)
Treatment × 2006	726.80***	212.83***	53.51***	4.90***	154.42***	731.97***	188.93***	50.22***	3.58***	135.14***
	(3.93)	(5.38)	(8.41)	(3.59)	(4.45)	(3.96)	(4.78)	(7.89)	(2.62)	(3.90)
Treatment × 2007	875.96***	273.44***	71.41***	7.00***	195.04***	881.87***	246.13***	67.64***	5.49**	173.00***
	(4.00)	(5.06)	(9.52)	(3.22)	(4.16)	(4.03)	(4.55)	(9.02)	(2.52)	(3.69)
Observations	2344	2352	2352	2352	2352	2344	2352	2352	2352	2352
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	3016.79	223.97	31.74	3.41	188.82	832.77	139.57	24.41	1.26	113.91
Adj. R^2	0.954	0.682	0.885	0.794	0.604	0.847	0.580	0.856	0.624	0.491

Notes: This table reports the estimates of the dynamic effects of university expansion on the number of university teachers and and different classifications of patents. The estimates are used to plot Figure 3, Figure 4, Appendix Figure A3, and Appendix Figure A4. The number of university teachers in 1990 is used as the treatment intensity measure, and it is counted in 1,000. The base year is 1999. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.B: The Dynamic Effects of University Expansion on the Number of Students and Innovation

	Pre-expansion Time Trend Not Removed					Pre-expansion Time Trend Removed				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable: No. of	University Students	Total Patents	University Patents	Collabo- rative Patents	Industry Patents	University Students	Total Patents	University Patents	Collabo- rative Patents	Industry Patents
Treatment × 1995	-275.17***	-3.11***	-0.43***	-0.21*	-2.47***	1.64	-0.32	-0.05	-0.05	-0.22
	(-12.72)	(-3.23)	(-3.67)	(-1.73)	(-3.28)	(0.08)	(-0.33)	(-0.43)	(-0.43)	(-0.29)
Treatment × 1996	-215.85***	-2.74***	-0.42***	-0.19*	-2.12***	-8.25	-0.65	-0.13	-0.08	-0.43
	(-13.21)	(-3.11)	(-3.56)	(-1.71)	(-3.18)	(-0.50)	(-0.73)	(-1.13)	(-0.69)	(-0.65)
Treatment × 1997	-152.82***	-2.30***	-0.38***	-0.15	-1.77***	-14.41	-0.90	-0.19**	-0.07	-0.64
	(-15.09)	(-2.95)	(-4.29)	(-1.25)	(-2.97)	(-1.42)	(-1.16)	(-2.13)	(-0.60)	(-1.08)
Treatment × 1998	-101.87***	-1.72**	-0.21***	-0.16	-1.35**	-32.67***	-1.02	-0.12	-0.12	-0.79
	(-12.52)	(-2.37)	(-2.98)	(-1.40)	(-2.44)	(-4.02)	(-1.41)	(-1.65)	(-1.06)	(-1.42)
Treatment × 2000	251.56***	7.36**	0.62***	0.15***	6.60*	182.36***	6.67*	0.52***	0.11**	6.04*
	(6.94)	(2.10)	(4.81)	(2.75)	(1.93)	(5.03)	(1.90)	(4.07)	(2.03)	(1.76)
Treatment × 2001	702.15***	8.74***	1.32***	0.21**	7.22***	563.75***	7.35***	1.13***	0.13	6.09***
	(8.77)	(3.41)	(5.68)	(2.03)	(3.15)	(7.04)	(2.87)	(4.86)	(1.27)	(2.66)
Treatment × 2002	1316.18***	13.69***	3.05***	0.31	10.33***	1108.57***	11.60***	2.76***	0.20	8.64***
	(8.66)	(4.18)	(5.84)	(1.32)	(3.84)	(7.29)	(3.54)	(5.29)	(0.83)	(3.22)
Treatment × 2003	1981.72***	21.16***	5.65***	0.46***	15.04***	1704.92***	18.37***	5.27***	0.31*	12.79***
	(8.16)	(5.40)	(5.48)	(2.69)	(4.88)	(7.02)	(4.69)	(5.11)	(1.80)	(4.15)
Treatment × 2004	2618.09***	27.08***	7.35***	0.52***	19.21***	2272.09***	23.59***	6.87***	0.33**	16.40***
	(7.76)	(4.60)	(5.57)	(3.53)	(4.13)	(6.74)	(4.01)	(5.21)	(2.22)	(3.52)
Treatment × 2005	3363.46***	36.56***	9.87***	0.74***	25.95***	2948.25***	32.38***	9.29***	0.51**	22.58***
	(6.85)	(4.09)	(6.04)	(2.92)	(3.50)	(6.00)	(3.62)	(5.69)	(2.00)	(3.05)
Treatment × 2006	4123.38***	44.23***	11.47***	0.97***	31.79***	3638.98***	39.35***	10.80***	0.70**	27.85***
	(6.19)	(4.32)	(7.88)	(3.00)	(3.63)	(5.46)	(3.84)	(7.42)	(2.17)	(3.18)
Treatment × 2007	4465.99***	56.34***	15.12***	1.38***	39.84***	3912.38***	50.77***	14.35***	1.07**	35.34***
	(5.96)	(4.03)	(7.38)	(2.75)	(3.40)	(5.22)	(3.63)	(7.01)	(2.14)	(3.02)
Observations	2352	2352	2352	2352	2352	2352	2352	2352	2352	2352
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	39448.11	223.97	31.74	3.41	188.82	20221.56	137.52	24.14	1.14	112.24
Adj. R^2	0.926	0.662	0.865	0.750	0.587	0.830	0.558	0.834	0.571	0.474

Notes: This table reports the estimates of the dynamic effects of university expansion on the number of university students and different classifications of patents. The estimates are used to plot Figure 3, Figure 4, Appendix Figure A3, and Appendix Figure A4. The number of university students in 1990 is used as the treatment intensity measure, and it is counted in 1,000. The base year is 1999. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4.A: 2SLS Estimates — Effects of University Innovation Capacity on Local Innovation Activities (Pre-expansion Time Trend Not Removed)

	(1)	(2)	(3)	(4)
	Panel A: No. of University Teachers in 1990 Interacted with Post-expansion Dummy as the IV			
	No. of University Teachers as First-Stage Dependent Variable		No. of University Patents as First-Stage Dependent Variable	
Dependent Variable: No. of	Collaborative Patents	Industry Patents	Collaborative Patents	Industry Patents
University Innovation Capacity	10.754*	298.337**	110.039***	3053.193***
	(1.81)	(1.99)	(4.40)	(6.53)
Observations	2384	2384	2392	2392
First-stage F-statistics	9.616	9.616	52.902	52.902
Dependent Variable Mean	3.389	188.201	3.378	187.677
Adj. R^2	0.106	0.255	0.829	0.639
	Panel B: No. of University Students in 1990 Interacted with Post-expansion Dummy as the IV			
	No. of University Students as First-Stage Dependent Variable		No. of University Patents as First-Stage Dependent Variable	
Dependent Variable: No. of	Collaborative Patents	Industry Patents	Collaborative Patents	Industry Patents
University Innovation Capacity	0.292**	8.375**	103.5***	2969.6***
	(2.28)	(2.51)	(4.55)	(6.63)
Observations	2392	2392	2392	2392
First-stage F-statistics	48.453	48.453	39.380	39.380
Dependent Variable Mean	3.378	187.677	3.378	187.677
Adj. R^2	0.523	0.463	0.835	0.640
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table reports the 2SLS estimates of the effects of university innovation capacity on innovation activities at the city level, using the number of university teachers or students in 1990 interacted with the after dummy as the instrument. All the First-Stage Dependent Variables are counted in 1,000. The F-statistics is calculated based on Montiel Olea and Pflueger (2013), which is robust to heteroskedasticity, autocorrelation, and clustering. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4.B: 2SLS Estimates — Effects of University Innovation Capacity on Local Innovation Activities (Pre-expansion Time Trend Removed)

	(1)	(2)	(3)	(4)
	Panel A: No. of University Teachers in 1990 Interacted with Post-expansion Dummy as the IV			
	No. of University Teachers as First-Stage Dependent Variable		No. of University Patents as First-Stage Dependent Variable	
Dependent Variable: No. of	Collaborative Patents	Industry Patents	Collaborative Patents	Industry Patents
University Innovation Capacity	7.062	242.401*	80.706***	2771.068***
	(1.49)	(1.85)	(2.94)	(5.29)
Observations	2384	2384	2392	2392
First-stage F-statistics	9.903	9.903	43.663	43.663
Dependent Variable Mean	1.246	113.626	1.242	113.270
Adj. R^2	0.005	0.181	0.711	0.539
	Panel B: No. of University Students in 1990 Interacted with Post-expansion Dummy as the IV			
	No. of University Students as First-Stage Dependent Variable		No. of University Patents as First-Stage Dependent Variable	
Dependent Variable: No. of	Collaborative Patents	Industry Patents	Collaborative Patents	Industry Patents
University Innovation Capacity	0.234	8.435**	74.679***	2690.238***
	(1.59)	(2.07)	(2.76)	(5.19)
Observations	2392	2392	2392	2392
First-stage F-statistics	32.631	32.631	32.787	32.787
Dependent Variable Mean	1.127	111.641	1.127	111.641
Adj. R^2	0.283	0.316	0.715	0.544
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table reports the 2SLS estimates of the effects of university innovation capacity on innovation activities at the city level, using the number of university teachers or students in 1990 interacted with the after dummy as the instrument. All the First-Stage Dependent Variables are counted in 1,000. The F-statistics is calculated based on Montiel Olea and Pflueger (2013), which is robust to heteroskedasticity, autocorrelation, and clustering. The city-specific pre-expansion time trend is removed for the dependent variable in all specifications. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of University Expansion on Industry Innovation — Ring-level Regressions

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment ×	18.43***	18.28***	0.74	15.72***	15.64***	0.64
After × 0.5km	(3.61)	(3.60)		(3.08)	(3.08)	
Treatment ×	4.02***	3.87***	0.53	3.33***	3.24***	0.45
After × 1km	(3.91)	(3.89)		(3.24)	(3.26)	
Treatment ×	1.53***	1.38**	0.35	1.25**	1.17**	0.29
After × 1.5km	(2.71)	(2.58)		(2.21)	(2.18)	
Treatment ×	0.78***	0.63***	0.25	0.61**	0.52**	0.21
After × 2km	(2.93)	(2.65)		(2.28)	(2.21)	
Treatment ×	0.40**	0.25	0.13	0.28	0.19	0.10
After × 2.5km	(2.24)	(1.64)		(1.53)	(1.26)	
Treatment ×	0.33***	0.18**	0.14	0.23**	0.14*	0.12
After × 3km	(2.89)	(2.05)		(2.00)	(1.67)	
Treatment ×	0.26**	0.11	0.13	0.17	0.08	0.10
After × 3.5km	(2.42)	(1.24)		(1.57)	(0.99)	
Treatment ×	0.13***	-0.02	-0.03	0.05	-0.03	-0.05
After × 4km	(2.97)	(-0.48)		(1.16)	(-0.83)	
Treatment ×	0.11**	-0.05	-0.10	0.04	-0.05	-0.10
After × 4.5km	(2.15)	(-1.19)		(0.72)	(-1.25)	
Treatment ×	0.15***	-	-	0.08	-	-
After × 5km	(3.00)	-		(1.64)	-	
Observations	23920	23920	-	23920	23920	-
Treatment × Ring dummies	Yes	No	-	Yes	No	-
City FE	Yes	No	-	Yes	No	-
Year × Ring FE	Yes	Yes	-	Yes	Yes	-
Year × City FE	No	Yes	-	No	Yes	-
City × Ring FE	No	Yes	-	No	Yes	-
Dependent Variable Mean	18.21	18.21	-	10.59	10.59	-
Adjusted R^2	0.351	0.560	-	0.228	0.479	-

Notes: This table reports the estimates of the effects of university expansion on industry patents at different distances (rings). The city-ring-specific pre-expansion time trend is removed for the dependent variable in columns (4)-(5). Column (3) and (6) are obtained by dividing the coefficients in column (2) and (5) by the average number of patents in the corresponding ring during the pre-expansion periods. The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.A: Impact of University Expansion on Innovation — Ring Regressions (Robustness)

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents that are Cited at least Once			
	(1)	(2)	(3)	(4)
Treatment ×	22.79***	19.69**	16.80*	16.38**
After × 0.5km	(2.67)	(2.59)	(1.97)	(2.15)
Treatment ×	4.92***	4.43***	4.12***	3.72***
After × 1km	(5.74)	(5.26)	(4.81)	(4.42)
Treatment ×	1.51**	1.56**	1.74**	1.36**
After × 1.5km	(2.10)	(2.56)	(2.41)	(2.24)
Treatment ×	0.66	0.80**	1.07**	0.69*
After × 2km	(1.24)	(2.06)	(2.02)	(1.79)
Treatment ×	0.05	0.26	0.59*	0.22
After × 2.5km	(0.16)	(1.32)	(1.75)	(1.11)
Treatment ×	-0.04	0.17	0.51*	0.13
After × 3km	(-0.14)	(1.34)	(1.94)	(1.04)
Treatment ×	-0.18	0.05	0.40*	0.03
After × 3.5km	(-0.80)	(0.46)	(1.73)	(0.27)
Treatment ×	-0.29	-0.05	0.30	-0.07
After × 4km	(-1.50)	(-0.61)	(1.58)	(-0.80)
Treatment ×	-0.34*	-0.10	0.26	-0.11
After × 4.5km	(-1.83)	(-1.31)	(1.44)	(-1.43)
Treatment ×	-0.25	-	0.37**	-
After × 5km	(-1.40)	-	(2.07)	-
Observations	8600	8600	8600	8600
Treatment × Ring Dummies	Yes	No	Yes	No
City FE	Yes	No	Yes	No
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	No	Yes	No	Yes
City × Ring FE	No	Yes	No	Yes
Dependent Variable Mean	7.45	7.45	5.14	5.14
Adj. R^2	0.246	0.473	0.158	0.410

Notes: This table reports the estimates of the effects of university expansion on industry patents with at least one citation at different distances (rings). The city-ring-specific pre-expansion time trend is removed for the dependent variable in columns (3)-(4). The number of university teachers in 1990 is used as the measure of treatment intensity, and it is counted in 1,000. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.B: Impact of University Expansion on Innovation — Ring Regressions (Robustness)

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents that are Cited at least Once			
	(1)	(2)	(3)	(4)
Treatment ×	4.49**	3.87**	3.31	3.22*
After × 0.5km	(2.25)	(2.17)	(1.65)	(1.80)
Treatment ×	1.04***	0.93***	0.87***	0.78***
After × 1km	(4.54)	(4.17)	(3.80)	(3.51)
Treatment ×	0.35**	0.35**	0.38**	0.30**
After × 1.5km	(2.32)	(2.62)	(2.58)	(2.28)
Treatment ×	0.16	0.18**	0.24**	0.16*
After × 2km	(1.50)	(2.27)	(2.26)	(1.98)
Treatment ×	0.02	0.06	0.13*	0.05
After × 2.5km	(0.33)	(1.40)	(1.86)	(1.17)
Treatment ×	0.00	0.04	0.11**	0.03
After × 3km	(0.02)	(1.34)	(2.04)	(1.04)
Treatment ×	-0.03	0.01	0.09*	0.01
After × 3.5km	(-0.64)	(0.56)	(1.85)	(0.39)
Treatment ×	-0.05	-0.01	0.07	-0.01
After × 4km	(-1.30)	(-0.53)	(1.56)	(-0.70)
Treatment ×	-0.07	-0.02	0.06	-0.02
After × 4.5km	(-1.62)	(-1.22)	(1.39)	(-1.33)
Treatment ×	-0.05	-	0.08**	-
After × 5km	(-1.22)	-	(2.05)	-
Observations	8600	8600	8600	8600
Treatment × Ring Dummies	Yes	No	Yes	No
City FE	Yes	No	Yes	No
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	No	Yes	No	Yes
City × Ring FE	No	Yes	No	Yes
Dependent Variable Mean	7.45	7.45	5.13	5.13
Adj. R^2	0.216	0.460	0.138	0.405

Notes: This table reports the estimates of the effects of university expansion on industry patents with at least one citation at different distances (rings). The city-ring-specific pre-expansion time trend is removed for the dependent variable in columns (3)-(4). The number of university students in 1990 is used as the measure of treatment intensity, and it is counted in 1,000. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7.A: The Dynamic Effects of University Expansion on Industry Innovation — Ring Regressions (No. of University Teachers in 1990 as Treatment)

Dependent Variable:	Number of Patents								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ring i	Ring 1	Ring 2	Ring 3	Ring 4	Ring 5	Ring 6	Ring 7	Ring 8	Ring 9
Treatment × 1995	-3.96	0.32	0.13	0.16	-0.05	-0.04	0.04	0.01	0.08
× Ring i	(-1.28)	(0.54)	(0.60)	(1.47)	(-0.61)	(-0.27)	(0.49)	(0.08)	(0.71)
Treatment × 1996	-4.67	-0.02	0.40*	0.17*	0.14	0.08	0.01	0.08	0.01
× Ring i	(-1.63)	(-0.05)	(1.95)	(1.69)	(0.96)	(0.78)	(0.17)	(0.94)	(0.09)
Treatment × 1997	-4.46*	-0.44	0.17	0.08	0.08	0.06	0.26	0.03	0.02
× Ring i	(-1.88)	(-1.04)	(1.04)	(1.08)	(0.89)	(0.64)	(1.64)	(0.53)	(0.43)
Treatment × 1998	-4.17*	-0.37	-0.08	-0.05	-0.18***	-0.08	0.03	-0.03	-0.07
× Ring i	(-1.81)	(-0.84)	(-0.61)	(-0.41)	(-2.79)	(-0.97)	(0.55)	(-0.55)	(-1.57)
Treatment × 2000	27.58*	2.39***	0.62***	0.16	0.10	0.22***	0.05	-0.08*	-0.01
× Ring i	(1.72)	(3.40)	(4.08)	(1.12)	(1.21)	(3.44)	(1.27)	(-1.74)	(-0.28)
Treatment × 2001	29.54***	2.92***	1.32***	0.92	0.05	0.00	0.12	0.07	0.13
× Ring i	(2.89)	(2.65)	(4.67)	(1.45)	(0.26)	(0.09)	(1.48)	(1.03)	(0.69)
Treatment × 2002	36.10***	11.09***	2.24***	0.77**	0.23	0.32***	0.34	-0.02	0.03
× Ring i	(3.40)	(3.45)	(2.77)	(2.00)	(1.22)	(5.01)	(1.06)	(-0.19)	(0.34)
Treatment × 2003	56.37***	14.37***	3.02***	1.70**	0.39	0.34*	0.53**	0.18	0.16
× Ring i	(4.86)	(2.66)	(2.86)	(2.25)	(0.94)	(1.85)	(2.25)	(0.97)	(1.11)
Treatment × 2004	75.26***	20.61**	4.28***	2.35**	0.74	0.24	0.55**	0.08	-0.07
× Ring i	(4.10)	(2.58)	(3.35)	(2.49)	(1.52)	(0.99)	(2.01)	(0.62)	(-0.45)
Treatment × 2005	104.91***	22.39***	5.15*	2.78*	1.59	1.39**	0.68	-0.26	-0.20
× Ring i	(3.67)	(3.22)	(1.94)	(1.78)	(1.20)	(2.30)	(1.00)	(-0.62)	(-0.50)
Treatment × 2006	117.54***	23.46***	11.62**	5.27**	2.17	1.48**	1.00	-0.05	-0.47
× Ring i	(3.86)	(4.23)	(2.14)	(2.24)	(1.46)	(2.10)	(1.31)	(-0.10)	(-0.92)
Treatment × 2007	146.65***	25.87***	15.10*	5.12*	1.11	1.17	0.05	-1.10*	-1.32**
× Ring i	(3.65)	(4.59)	(1.75)	(1.91)	(0.61)	(0.85)	(0.05)	(-1.77)	(-2.58)
Dependent Variable Mean	10.59	Observations	23920	Adj. R^2	0.548	Fixed Effects	Yes		

Notes: This table reports the estimates of the dynamic effects of university expansion on industry patents at different distances (rings). The estimates are used to plot Panel (a) of Figure 7. Year × Ring, Year × City, and City × Ring fixed effects are included in all regressions. The city-ring-specific pre-expansion time trend is removed for the dependent variable in all specifications. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7.B: The Dynamic Effects of University Expansion on Industry Innovation — Ring Regressions
(No. of University Students in 1990 as Treatment)

Dependent Variable:	Number of Patents								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ring i	Ring 1	Ring 2	Ring 3	Ring 4	Ring 5	Ring 6	Ring 7	Ring 8	Ring 9
Treatment × 1995	-0.72	0.08	0.02	0.04*	-0.01	-0.01	0.01	-0.00	0.01
× Ring i	(-1.03)	(0.63)	(0.51)	(1.78)	(-0.68)	(-0.41)	(0.41)	(-0.14)	(0.61)
Treatment × 1996	-0.89	0.00	0.08*	0.03	0.02	0.01	0.00	0.01	0.00
× Ring i	(-1.35)	(0.04)	(1.71)	(1.52)	(0.78)	(0.65)	(0.02)	(0.64)	(0.01)
Treatment × 1997	-0.91*	-0.08	0.03	0.02	0.01	0.01	0.05	0.00	0.00
× Ring i	(-1.66)	(-0.89)	(0.87)	(1.00)	(0.69)	(0.49)	(1.43)	(0.21)	(0.37)
Treatment × 1998	-0.88*	-0.06	-0.02	-0.00	-0.04**	-0.02	0.00	-0.01	-0.01
× Ring i	(-1.72)	(-0.64)	(-0.74)	(-0.20)	(-2.12)	(-1.08)	(0.43)	(-0.66)	(-1.37)
Treatment × 2000	5.88*	0.47***	0.13***	0.04*	0.02	0.05***	0.01	-0.02	-0.00
× Ring i	(1.66)	(2.82)	(3.52)	(1.65)	(1.02)	(3.06)	(1.35)	(-1.40)	(-0.00)
Treatment × 2001	5.81**	0.62***	0.28***	0.21	0.02	0.00	0.03*	0.01	0.02
× Ring i	(2.45)	(2.65)	(4.41)	(1.60)	(0.42)	(0.14)	(1.73)	(0.74)	(0.54)
Treatment × 2002	7.27***	2.32***	0.47**	0.18**	0.06*	0.07***	0.08	-0.01	0.00
× Ring i	(2.90)	(3.09)	(2.59)	(2.34)	(1.69)	(4.39)	(1.17)	(-0.35)	(0.16)
Treatment × 2003	11.75***	3.15***	0.66***	0.39***	0.11	0.08**	0.12**	0.04	0.04
× Ring i	(3.97)	(2.77)	(2.90)	(2.73)	(1.37)	(2.23)	(2.56)	(1.08)	(1.31)
Treatment × 2004	15.30***	4.40**	0.93***	0.52***	0.17*	0.06	0.12**	0.02	-0.02
× Ring i	(3.38)	(2.56)	(3.52)	(2.71)	(1.75)	(1.09)	(2.22)	(0.53)	(-0.61)
Treatment × 2005	20.93***	4.69***	1.16**	0.63**	0.36	0.30**	0.15	-0.06	-0.04
× Ring i	(3.02)	(2.96)	(2.13)	(1.99)	(1.26)	(2.26)	(1.04)	(-0.70)	(-0.42)
Treatment × 2006	23.54***	4.88***	2.53**	1.18**	0.48	0.30*	0.21	-0.02	-0.11
× Ring i	(3.17)	(3.62)	(2.25)	(2.42)	(1.49)	(1.82)	(1.23)	(-0.19)	(-1.00)
Treatment × 2007	29.19***	5.34***	3.34*	1.19**	0.30	0.29	0.05	-0.20	-0.26**
× Ring i	(3.02)	(3.75)	(1.83)	(2.29)	(0.81)	(1.01)	(0.22)	(-1.39)	(-2.20)
Dependent Variable Mean	10.59	Observations	23920	Adj. R^2	0.526	Fixed Effects	Yes		

Notes: This table reports the estimates of the dynamic effects of university expansion on industry patents at different distances (rings). The estimates are used to plot Panel (b) of Figure 7. Year × Ring, Year × City, and City × Ring fixed effects are included in all regressions. The city-ring-specific pre-expansion time trend is removed for the dependent variable in all specifications. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Impact of University Expansion on Industry Innovation — Ring-level Regressions of Trend Break Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Ring 1	Ring 2	Ring 3	Ring 4	Ring 5	Ring 6	Ring 7	Ring 8	Ring 9	Ring 10	Ring 1 - 10
Treatment $\times$ Trend	3.494***										3.425***
$\times$After$\times$ 0.5km	(2.98)										(2.93)
Treatment $\times$ Trend		0.861***									0.791***
$\times$After$\times$ 1km		(3.91)									(3.81)
Treatment $\times$ Trend			0.570**								0.500*
$\times$After$\times$ 1.5km			(2.14)								(1.96)
Treatment $\times$ Trend				0.269***							0.200***
$\times$After$\times$ 2km				(3.10)							(2.62)
Treatment $\times$ Trend					0.140**						0.0710
$\times$After$\times$ 2.5km					(2.02)						(1.18)
Treatment $\times$ Trend						0.120***					0.0512
$\times$After$\times$ 3km						(2.67)					(1.43)
Treatment $\times$ Trend							0.0862**				0.0169
$\times$After$\times$ 3.5km							(2.41)				(0.59)
Treatment $\times$ Trend								0.0468***			-0.0225
$\times$After$\times$ 4km								(2.70)			(-1.18)
Treatment $\times$ Trend									0.0334*		-0.0358*
$\times$After$\times$ 4.5km									(1.88)		(-1.76)
Treatment $\times$ Trend										0.0693***	
$\times$After$\times$ 5km										(2.95)	
Observations	2392	2392	2392	2392	2392	2392	2392	2392	2392	2392	23920
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year $\times$ Ring FE	No	No	No	No	No	No	No	No	No	No	Yes
Year $\times$ City FE	No	No	No	No	No	No	No	No	No	No	Yes
City $\times$ Ring FE	No	No	No	No	No	No	No	No	No	No	Yes
Dependent Variable Mean	114.50	26.42	13.04	8.26	5.71	4.37	3.34	2.49	1.82	2.22	18.21
Adj. R^2	0.584	0.660	0.565	0.632	0.457	0.456	0.455	0.383	0.433	0.212	0.607

Notes: This table reports the estimates of the slope change in the number of industry patents at different distances (rings) as a result of the university expansion, using the specification in Equation (3.8). The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. The trend-break model is used in all specifications. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Robustness Check — Ring-level Regressions up to 10 km

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents			
	(1)	(2)	(3)	(4)
Treatment ×	18.43***	18.41***	15.75***	15.76***
After × 0.5km	(3.61)	(3.62)	(3.09)	(3.09)
Treatment ×	4.02***	4.00***	3.36***	3.36***
After × 1km	(3.91)	(3.92)	(3.27)	(3.30)
Treatment ×	1.53***	1.51***	1.28**	1.28**
After × 1.5km	(2.71)	(2.72)	(2.26)	(2.32)
Treatment ×	0.78***	0.76***	0.64**	0.64**
After × 2km	(2.93)	(2.96)	(2.40)	(2.52)
Treatment ×	0.40**	0.38**	0.31*	0.31*
After × 2.5km	(2.24)	(2.23)	(1.71)	(1.84)
Treatment ×	0.33***	0.30***	0.26**	0.26**
After × 3km	(2.89)	(2.96)	(2.27)	(2.55)
Treatment ×	0.26**	0.23**	0.20*	0.20**
After × 3.5km	(2.42)	(2.39)	(1.86)	(2.08)
Treatment ×	0.13***	0.11***	0.08*	0.09**
After × 4km	(2.97)	(3.20)	(1.84)	(2.57)
Treatment ×	0.11**	0.08**	0.07	0.07*
After × 4.5km	(2.15)	(2.17)	(1.34)	(1.88)
Treatment ×	0.15***	0.13***	0.11**	0.12***
After × 5km	(3.00)	(2.94)	(2.25)	(2.74)
Treatment ×	0.10***	0.07***	0.06*	0.07***
After × 5.5km	(3.15)	(3.26)	(1.95)	(2.93)
Treatment ×	0.06**	0.04*	0.03	0.03
After × 6km	(2.12)	(1.84)	(0.95)	(1.55)
Treatment ×	0.07***	0.05***	0.04	0.04***
After × 6.5km	(2.97)	(3.15)	(1.61)	(2.91)
Treatment ×	0.07**	0.04	0.03	0.04
After × 7km	(2.40)	(1.64)	(1.22)	(1.49)
Treatment ×	0.05*	0.03	0.02	0.03
After × 7.5km	(1.78)	(0.95)	(0.67)	(0.80)
Treatment ×	0.01	-0.02	-0.03**	-0.02**
After × 8km	(0.53)	(-1.65)	(-2.56)	(-2.03)
Treatment ×	0.03**	0.00	-0.00	0.00
After × 8.5km	(2.33)	(0.15)	(-0.44)	(0.03)
Treatment ×	0.12	0.10	0.09	0.09
After × 9km	(1.37)	(1.08)	(1.00)	(1.04)
Treatment ×	0.02**	-0.00	-0.01	-0.00
After × 9.5km	(2.22)	(-0.06)	(-0.76)	(-0.23)
Treatment ×	0.02*	-	-0.01	-
After × 10km	(1.91)	-	(-0.44)	-
Observations	47840	47840	47840	47840
Treatment × Ring Dummies	Yes	No	Yes	No
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	No	Yes	No	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Dependent Variable Mean	9.62	9.62	5.70	5.70
Adj. R^2	0.338	0.552	0.215	0.473

Notes: This table reports the estimates of the effects of university expansion on industry patents at different distances (rings) for up to 10 km. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (3) and (4). The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10.A: Spatial Decay of University Spillovers (Relative to the Effect on Ring 1)

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents			
	(1)	(2)	(3)	(4)
Treatment ×	-	-	-	-
After × 0.5km	-	-	-	-
Treatment ×	-71.37***	-71.37***	-61.21***	-61.21***
After × 1km	(-3.82)	(-3.82)	(-3.28)	(-3.28)
Treatment ×	-83.43***	-83.43***	-71.23***	-71.23***
After × 1.5km	(-4.18)	(-4.18)	(-3.57)	(-3.57)
Treatment ×	-86.92***	-86.92***	-74.22***	-74.22***
After × 2km	(-4.30)	(-4.30)	(-3.67)	(-3.67)
Treatment ×	-88.64***	-88.64***	-75.71***	-75.71***
After × 2.5km	(-4.39)	(-4.39)	(-3.75)	(-3.75)
Treatment ×	-88.91***	-88.91***	-75.87***	-75.87***
After × 3km	(-4.41)	(-4.41)	(-3.76)	(-3.76)
Treatment ×	-89.26***	-89.26***	-76.18***	-76.18***
After × 3.5km	(-4.40)	(-4.40)	(-3.75)	(-3.75)
Treatment ×	-89.81***	-89.81***	-76.68***	-76.68***
After × 4km	(-4.44)	(-4.44)	(-3.79)	(-3.79)
Treatment ×	-89.92***	-89.92***	-76.75***	-76.75***
After × 4.5km	(-4.46)	(-4.46)	(-3.80)	(-3.80)
Treatment ×	-89.70***	-89.70***	-76.52***	-76.52***
After × 5km	(-4.44)	(-4.44)	(-3.79)	(-3.79)
Treatment ×	-	-89.96***	-	-76.77***
After × 5.5km	-	(-4.45)	-	(-3.80)
Treatment ×	-	-90.12***	-	-76.92***
After × 6km	-	(-4.46)	-	(-3.80)
Treatment ×	-	-90.06***	-	-76.86***
After × 6.5km	-	(-4.46)	-	(-3.81)
Treatment ×	-	-90.09***	-	-76.89***
After × 7km	-	(-4.44)	-	(-3.79)
Treatment ×	-	-90.16***	-	-76.96***
After × 7.5km	-	(-4.44)	-	(-3.79)
Treatment ×	-	-90.38***	-	-77.18***
After × 8km	-	(-4.46)	-	(-3.81)
Treatment ×	-	-90.27***	-	-77.05***
After × 8.5km	-	(-4.46)	-	(-3.81)
Treatment ×	-	-89.73***	-	-76.52***
After × 9km	-	(-4.49)	-	(-3.83)
Treatment ×	-	-90.30***	-	-77.08***
After × 9.5km	-	(-4.46)	-	(-3.80)
Observations	23920	47840	23920	47840
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Dependent Variable Mean	18.21	9.62	10.91	5.86
Adj. R^2	0.570	0.563	0.482	0.475

Notes: This table reports the estimates of the effects of university expansion on industry patents at different distances (rings) for up to 5 km or 10 km. The reference group is ring 1. The estimates are used to plot Figure 10. The number of university teachers in 1990 is counted in 1,000. and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10.B: Spatial Decay of University Spillovers (Relative to the Effect on Ring 1)

	Pre-expansion Time Trend Not Removed		Pre-expansion Time Trend Removed	
Dependent Variable	Number of Patents			
	(1)	(2)	(3)	(4)
Treatment ×	-	-	-	-
After × 0.5km	-	-	-	-
Treatment ×	-14.41***	-14.41***	-12.39***	-12.39***
After × 1km	(-3.19)	(-3.19)	(-2.74)	(-2.74)
Treatment ×	-16.90***	-16.90***	-14.47***	-14.47***
After × 1.5km	(-3.43)	(-3.43)	(-2.94)	(-2.93)
Treatment ×	-17.65***	-17.65***	-15.11***	-15.11***
After × 2km	(-3.50)	(-3.50)	(-3.00)	(-3.00)
Treatment ×	-18.03***	-18.03***	-15.45***	-15.45***
After × 2.5km	(-3.56)	(-3.56)	(-3.05)	(-3.05)
Treatment ×	-18.10***	-18.10***	-15.49***	-15.49***
After × 3km	(-3.58)	(-3.58)	(-3.06)	(-3.06)
Treatment ×	-18.17***	-18.17***	-15.55***	-15.55***
After × 3.5km	(-3.57)	(-3.57)	(-3.06)	(-3.06)
Treatment ×	-18.30***	-18.30***	-15.67***	-15.67***
After × 4km	(-3.60)	(-3.60)	(-3.08)	(-3.08)
Treatment ×	-18.33***	-18.33***	-15.68***	-15.68***
After × 4.5km	(-3.61)	(-3.61)	(-3.09)	(-3.09)
Treatment ×	-18.28***	-18.28***	-15.64***	-15.64***
After × 5km	(-3.60)	(-3.60)	(-3.08)	(-3.08)
Treatment ×	-	-18.34***	-	-15.69***
After × 5.5km	-	(-3.61)	-	(-3.09)
Treatment ×	-	-18.37***	-	-15.72***
After × 6km	-	(-3.61)	-	(-3.09)
Treatment ×	-	-18.36***	-	-15.71***
After × 6.5km	-	(-3.62)	-	(-3.09)
Treatment ×	-	-18.36***	-	-15.72***
After × 7km	-	(-3.60)	-	(-3.08)
Treatment ×	-	-18.38***	-	-15.73***
After × 7.5km	-	(-3.60)	-	(-3.08)
Treatment ×	-	-18.43***	-	-15.78***
After × 8km	-	(-3.62)	-	(-3.10)
Treatment ×	-	-18.41***	-	-15.76***
After × 8.5km	-	(-3.62)	-	(-3.10)
Treatment ×	-	-18.31***	-	-15.66***
After × 9km	-	(-3.64)	-	(-3.11)
Treatment ×	-	-18.41***	-	-15.76***
After × 9.5km	-	(-3.61)	-	(-3.09)
Observations	23920	47840	23920	47840
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Dependent Variable Mean	18.21	9.62	10.59	5.70
Adj. R^2	0.560	0.552	0.479	0.473

Notes: This table reports the estimates of the effects of university expansion on industry patents at different distances (rings) for up to 5 km or 10 km. The reference group is ring 1. The estimates are used to plot Figure 10. The number of university students in 1990 is counted in 1,000. and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Heterogeneity Analysis — Eastern, Central, and Western Regions

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Eastern	Central	Western	Eastern	Central	Western
Treatment ×	25.44***	6.38***	5.01***	21.91***	5.14***	4.03***
After × 0.5km	(5.57)	(7.13)	(6.01)	(4.80)	(5.74)	(4.83)
Treatment ×	5.42***	1.20***	1.20***	4.66***	0.77**	0.83***
After × 1km	(4.78)	(3.43)	(5.12)	(4.12)	(2.20)	(3.54)
Treatment ×	1.91**	0.45***	0.46***	1.70**	0.21***	0.26**
After × 1.5km	(2.51)	(7.68)	(3.77)	(2.23)	(3.68)	(2.10)
Treatment ×	0.76**	0.39***	0.40*	0.65*	0.28***	0.33
After × 2km	(2.11)	(8.60)	(2.01)	(1.80)	(6.29)	(1.67)
Treatment ×	0.31	0.17***	0.09***	0.26	0.09***	0.04*
After × 2.5km	(1.30)	(7.89)	(4.33)	(1.08)	(4.33)	(2.03)
Treatment ×	0.22*	0.07***	0.13***	0.19	0.03**	0.10***
After × 3km	(1.69)	(4.63)	(6.07)	(1.45)	(2.19)	(4.77)
Treatment ×	0.11	0.08***	0.10*	0.09	0.06***	0.07
After × 3.5km	(0.84)	(5.13)	(1.84)	(0.69)	(3.69)	(1.35)
Treatment ×	-0.05	0.03**	0.05	-0.06	0.03**	0.02
After × 4km	(-0.88)	(2.42)	(1.50)	(-1.09)	(2.42)	(0.53)
Treatment ×	-0.07	0.00	0.02	-0.08	0.00	0.01
After × 4.5km	(-1.17)	(0.21)	(1.00)	(-1.19)	(0.15)	(0.38)
Treatment ×	-	-	-	-	-	-
After × 5km	-	-	-	-	-	-
Observations	10920	8320	4550	10920	8320	4550
Year × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	30.55	6.41	10.69	19.53	2.97	6.09
Adj. R^2	0.582	0.697	0.675	0.491	0.533	0.557

Notes: This table reports the estimated effects of university expansion on industry patents across different regions in China. The Eastern, Central and Western regions are divided according to the 7th "Five-Year Plan for the National Economic and Social Development" of China. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (4)-(6). The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Heterogeneity Analysis — Industries with High, Medium, and Low Human Capital Intensity

	Pre-expansion Time Trend Not Removed			Pre-expansion Time Trend Removed		
Dependent Variable	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Medium	Low	High	Medium	Low
Treatment ×	13.78***	3.03***	0.81***	11.72***	2.44***	0.62***
After × 0.5km	(3.11)	(4.39)	(4.36)	(2.64)	(3.53)	(3.33)
Treatment ×	2.95***	0.71***	0.22***	2.48***	0.55**	0.16***
After × 1km	(3.70)	(3.13)	(3.67)	(3.11)	(2.40)	(2.78)
Treatment ×	1.01**	0.25***	0.11**	0.86*	0.17*	0.09
After × 1.5km	(2.30)	(2.83)	(2.05)	(1.94)	(1.94)	(1.65)
Treatment ×	0.36**	0.18*	0.06***	0.28**	0.14	0.05***
After × 2km	(2.59)	(1.87)	(3.82)	(2.02)	(1.50)	(3.31)
Treatment ×	0.10	0.05	0.03**	0.06	0.03	0.02
After × 2.5km	(1.13)	(1.24)	(2.02)	(0.65)	(0.67)	(1.51)
Treatment ×	0.10	0.04	0.02*	0.07	0.03	0.02
After × 3km	(1.24)	(1.58)	(1.82)	(0.89)	(1.20)	(1.49)
Treatment ×	0.03	0.02	0.02*	0.01	0.01	0.02*
After × 3.5km	(0.35)	(0.94)	(1.92)	(0.14)	(0.58)	(1.76)
Treatment ×	-0.07	0.02	0.01*	-0.08	0.01	0.00
After × 4km	(-1.31)	(0.56)	(1.69)	(-1.55)	(0.43)	(1.25)
Treatment ×	-0.07	-0.01	0.01	-0.08	-0.01	0.01
After × 4.5km	(-1.40)	(-0.55)	(1.18)	(-1.45)	(-0.61)	(1.21)
Treatment ×	-	-	-	-	-	-
After × 5km	-	-	-	-	-	-
Observations	23660	23660	23660	23660	23660	23660
Year × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	14.13	3.71	1.19	8.37	2.00	0.65
Adj. R^2	0.462	0.721	0.689	0.401	0.612	0.555

Notes: This table reports the estimated effects of university expansion on industry patents across industries with different human capital intensity. We define high human capital intensity industry as the industries that rank among the top one-third in the college employee ratio, medium as the middle one-third, and low as the rest. The industry college employee ratio is calculated as the percentage of workers with a college education and above using the 2004 ASIF. The city-ring-specific pre-expansion time trend is removed for the dependent variables in Columns (4)-(6). The number of university students in 1990 is counted in 1,000, and it is used as the measure of treatment intensity. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Summary Statistics of Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	No. of Firms	New Product	Output	Fixed Assets	SOE	Firm Age	Employment
1998	125954	3934.99	33653.85	45043.08	0.29	14.55	348.68
1999	126528	4515.49	36260.19	49413.91	0.26	14.71	362.18
2000	125204	5411.33	37641.48	57134.02	0.22	14.34	336.75
2001	134677	6311.51	37539.98	60340.50	0.18	12.73	313.96
2002	146290	7186.15	37347.27	65840.98	0.15	12.06	301.97
2003	159423	8216.19	33295.39	76591.23	0.11	10.91	287.69
2004	231811	–	31756.00	72843.79	0.08	8.64	232.73
2005	224051	9814.97	36728.77	91410.37	0.06	8.78	249.65
2006	247992	11814.78	37504.38	101072.40	0.05	8.64	237.28
2007	276058	12518.99	37743.88	110539.40	0.03	8.38	229.20

Notes: Column (1) reports the number of firms in each year. Columns (2)-(7) report the means of new product value, output, fixed assets, SOE status, firm age and employment at the firm level. New product, output, and fixed assets are counted in 1,000 yuan in the year 1998 value. Information on new product value in 2004 is not available.

Table A14: Effects of University Expansion on New Product Ratio — Ring-level Regressions

Dependent Variable	New Product Ratio			
	(1)	(2)	(3)	(4)
After Dummy	2000	2002	2004	2006
Treatment ×	8.47e-04	9.85e-04	1.30e-03	1.36e-03
After × 0.5km	(1.58)	(1.57)	(1.60)	(1.58)
Treatment ×	5.77e-04*	6.99e-04*	9.03e-04**	9.59e-04*
After × 1km	(1.95)	(1.96)	(2.03)	(1.87)
Treatment ×	3.96e-04***	4.67e-04***	6.16e-04***	6.44e-04***
After × 1.5km	(3.14)	(3.21)	(3.13)	(2.97)
Treatment ×	2.91e-04***	3.35e-04***	4.12e-04***	4.10e-04***
After × 2km	(2.89)	(2.87)	(3.27)	(2.89)
Treatment ×	3.60e-04**	4.41e-04**	4.13e-04***	3.92e-04***
After × 2.5km	(2.44)	(2.56)	(3.33)	(3.16)
Treatment ×	2.54e-04***	3.10e-04***	3.97e-04***	4.06e-04***
After × 3km	(3.18)	(3.41)	(3.99)	(3.79)
Treatment ×	1.56e-04**	1.88e-04**	2.63e-04***	3.02e-04***
After × 3.5km	(2.34)	(2.47)	(2.90)	(2.91)
Treatment ×	1.60e-04*	1.92e-04*	2.99e-04**	3.62e-04**
After × 4km	(1.74)	(1.89)	(2.35)	(2.42)
Treatment ×	1.77e-04**	2.01e-04**	2.69e-04***	2.96e-04***
After × 4.5km	(2.50)	(2.48)	(2.67)	(2.97)
Treatment ×	1.45e-04*	1.77e-04*	2.74e-04**	3.35e-04**
After × 5km	(1.95)	(1.94)	(2.16)	(2.57)
Observations	1196263	996185	759980	589233
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.034	0.035	0.035	0.037
Adj. R^2	0.091	0.097	0.107	0.105

Notes: This table reports the estimated effects of university expansion on firms' new product ratio using the number of university students in 1990 as the proxy for treatment intensity. Dependent variable is firm-level new product ratio. Columns (1)–(4) report the triple-differences estimates. The after dummy equals 1 if year is 2000 or after, 2002 or after, 2004 or after, or 2006 or after in Columns (1), (2), (3), and (4), respectively. The after dummy equals 0 for years before 2000 for all four columns. Observations in the years in which the after dummy is not defined are dropped. The reference group is the firms outside 10 km of universities. Control variables include firm age, fixed assets, SOE status, and employment size. Data on new product in 2004 is not available. The number of university students in 1990 is counted in 1,000. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Effects of University Expansion on New Product Ratio — Ring-level Regressions with Firm Fixed Effects

Dependent Variable	New Product Ratio			
	(1)	(2)	(3)	(4)
After Dummy	2000	2002	2004	2006
Treatment ×	8.08e-04**	9.10e-04*	1.82e-03***	2.20e-03**
After × 0.5km	(1.98)	(1.81)	(3.14)	(2.32)
Treatment ×	4.45e-04**	7.42e-04***	1.43e-03***	1.79e-03***
After × 1km	(2.38)	(3.25)	(6.46)	(2.66)
Treatment ×	6.44e-04***	9.24e-04***	1.12e-03***	1.15e-03**
After × 1.5km	(3.60)	(3.63)	(2.97)	(2.36)
Treatment ×	6.24e-04***	5.92e-04**	8.38e-04***	7.43e-04**
After × 2km	(3.01)	(2.17)	(3.28)	(2.46)
Treatment ×	5.63e-04***	7.71e-04**	1.41e-03***	1.04e-03**
After × 2.5km	(2.94)	(2.39)	(3.10)	(2.11)
Treatment ×	2.11e-04	2.26e-04	4.53e-04	3.28e-04
After × 3km	(1.13)	(1.22)	(1.40)	(0.77)
Treatment ×	3.45e-04*	4.05e-04*	3.12e-04	5.03e-04
After × 3.5km	(1.93)	(1.90)	(0.68)	(0.96)
Treatment ×	1.12e-04	3.08e-04	3.79e-04	-6.87e-05
After × 4km	(-0.57)	(-1.24)	(-1.07)	(-0.15)
Treatment ×	2.45e-04	5.87e-04	1.07e-03	1.05e-03
After × 4.5km	(-0.52)	(-0.90)	(-1.26)	(-1.18)
Treatment ×	2.99e-04*	2.53e-04	1.50e-04	3.57e-04
After × 5km	(1.71)	(0.87)	(0.34)	(0.54)
Observations	1099149	895751	668829	498355
Year × Ring FE	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.035	0.036	0.038	0.037
Adj. R^2	0.541	0.541	0.572	0.589

Notes: This table reports the estimated effects of university expansion on firms' new product ratio using the number of university teachers in 1990 as the proxy for treatment intensity, with firm fixed effects. The dependent variable is firm-level new product ratio. Columns (1)–(4) report the triple-differences estimates. The after dummy equals 1 if year is 2000 or after, 2002 or after, 2004 or after, or 2006 or after in Columns (1), (2), (3), and (4), respectively. The after dummy equals 0 if year is before 2000 for all four columns. Observations in the years in which the after dummy is not defined are dropped. The reference group is the firms outside 10 km of universities. Control variables include firm age, fixed assets, SOE status, and employment size. The number of university teachers in 1990 is counted in 1,000 t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Heterogeneity Analysis - Industries with High, Medium, and Low Human Capital Intensity and SOE versus Non-SOE

Dependent Variable	New Product Ratio				
	(1)	(2)	(3)	(4)	(5)
	High	Medium	Low	SOE	Non-SOE
Treatment ×	9.49e-04	5.79e-04*	2.62e-04	1.49e-04	8.61e-04
After × 0.5km	(1.59)	(1.75)	(0.87)	(0.66)	(1.52)
Treatment ×	8.13e-04*	2.93e-04	2.32e-04*	2.03e-04	6.31e-04**
After × 1km	(1.92)	(1.58)	(1.95)	(1.37)	(2.01)
Treatment ×	6.16e-04***	2.93e-04***	3.76e-05	1.65e-04**	4.25e-04***
After × 1.5km	(2.91)	(3.37)	(0.73)	(2.22)	(3.04)
Treatment ×	3.30e-04*	1.93e-04**	1.66e-04***	1.12e-04	3.32e-04***
After × 2km	(1.74)	(2.39)	(2.70)	(1.24)	(3.22)
Treatment ×	6.04e-04*	1.41e-04**	1.61e-04***	3.14e-04***	3.75e-04**
After × 2.5km	(1.68)	(2.03)	(3.53)	(3.60)	(2.34)
Treatment ×	3.53e-04**	2.10e-04**	5.70e-05	2.25e-04**	2.86e-04***
After × 3km	(2.43)	(2.29)	(1.03)	(2.32)	(3.35)
Treatment ×	1.73e-04	1.09e-04	7.19e-05	2.55e-05	2.09e-04**
After × 3.5km	(1.23)	(1.16)	(1.14)	(0.23)	(2.49)
Treatment ×	1.27e-04	3.26e-05	1.62e-04***	-4.30e-05	2.19e-04*
After × 4km	(0.47)	(0.47)	(3.07)	(-0.35)	(1.88)
Treatment ×	2.35e-04**	-1.66e-05	2.13e-04***	-1.40e-04	2.43e-04***
After × 4.5km	(2.52)	(-0.13)	(3.86)	(-1.54)	(4.61)
Treatment ×	-4.94e-05	1.50e-04	1.73e-04**	5.77e-05	1.98e-04**
Observations	394427	385023	456632	136171	1060023
Year × Ring FE	Yes	Yes	Yes	Yes	Yes
Year × City FE	Yes	Yes	Yes	Yes	Yes
City × Ring FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Dependent Variable Mean	0.059	0.025	0.020	0.046	0.033
Adj. R^2	0.119	0.057	0.049	0.111	0.096

Notes: Columns (1)–(3) report the estimated effects of university expansion on firms' new product ratio across industries with different human capital intensity. We define high human capital intensity industry as the industries that rank among the top one-third in the college employee ratio, medium as the middle one-third, and low as the rest. The industry college employee ratio is calculated as the percentage of workers with a college education and above using the 2004 ASIF. Columns (4) and (5) report the estimates of the effects of university expansion on firms' new product ratio for SOEs and non-SOEs separately. The number of university students in 1990 is counted in 1,000, and it is used as the treatment intensity. Control variables include firm age, fixed assets, SOE status, and employment size. The reference group consists of the firms outside 10 km of universities. t statistics based on clustered standard errors at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix: Conceptual Framework

The impact of universities on local innovation can be mediated through a collection of channels, such as an increased supply of human capital, knowledge spillovers, or a direct demand effect (Valero and Van Reenen 2019). Most channels, such as the human capital channel and demand effect, operate at a broad geographic scale. For example, the human capital channel usually operates at the city level because workers are mobile within a city. The geographic scope of knowledge spillovers, however, is often limited. We highlight below the specific channels through which the impact of universities is especially pronounced at close geographic distances (within 2-3 km in general).

First, areas with better access to universities benefit from improved chances of collaborating with universities to convert university-based knowledge to commercial products. The development of the Founder Group in Zhongguancun (ZGC) Science Park is a typical example. The Founder Group, established by Peking University in 1986, is now a major Chinese technology conglomerate. The company's take-off benefited tremendously from Professor Xuan Wang at Peking University, who is known as the "Father of Chinese Character Laser Typesetting." His laser typesetting system allowed the Founder Group to earn its first pot of gold in the early 1990s. Between 2000 and 2007, the Founder Group published 232 invention patents, with 86 percent in collaboration with Peking University.

Second, universities may disproportionately benefit firms in close proximity through knowledge transfers. Areas close to universities enjoy convenient access to fundamental background knowledge and frontier technologies produced by university-based experts and professionals. Those factors are key drivers of innovation. Theory-based fundamental knowledge is the essential cornerstone of applicable innovations. Frontier technologies—grown out from the development of the fundamentals—lead to new commercializable product varieties as in Romer (1990) or upgrading of existing products through Schumpeterian creative destruction (Aghion and Howitt 1992; Grossman and Helpman 1991). The tacit part of knowledge and technologies requires lengthy face-to-face communications to disseminate. Locating close to universities allows nearby inventors to attend university workshops, seminars, and conferences and offers abundant opportunities for face-to-face interactions.

Third, proximity to universities allows firms to establish and foster strong professional and informational networks. Technology advancement is fast-evolving and subject to uncertain dynamics.

Maintaining formal and informal operational links with universities and other research institutions to receive ceaseless updates on new information allows innovative firms to be at the front of technology development. A salient example is Baidu, Inc. Upon returning from Silicon Valley, the founder and CEO of Baidu, Yanhong Li, chose ZGC Science Park to develop his Chinese search engine empire. As he revealed in an interview, the location advantage of ZGC allows the company to maintain strong ties with experts at nearby universities, including Peking University from which he graduated (Zhao 2018). This idea is closely related to the networking benefits in the advertising industry as emphasized in Arzaghi and Henderson (2008).

In sum, firms in close proximity to universities benefit from improved collaboration opportunities, knowledge transfers, and information networks. However, we note a fundamental distinction between direct collaborations and the latter two channels. Collaboration benefits do not constitute spillovers because universities would internalize the benefits. We refer to the latter two channels as knowledge spillovers, which is the main focus of this paper. We also explore the collaboration channel quantitatively by treating innovative firms in direct collaboration with universities differently in our empirical analysis.

Next, we outline a simple conceptual framework to formalize the identification of knowledge spillovers by drawing on the localized nature of knowledge spillovers documented in the literature. Note again that we focus on variations within close geographic distances (within 2-3 km in general) to identify the fast spatial decay of knowledge spillovers. In this framework, the number of new ideas, NI, is assumed to be a function of the existing knowledge stock, A, and the number of researchers, R, who spend time producing them:

$$NI = f(A, R). \tag{1}$$

Conceptually, we specify the production function for each firm, i, but i is suppressed for simplicity. The number of new products, NP, is assumed to be a function of new ideas, NI, and the necessary facility, equipment, and personnel, X, to convert the new ideas into new products:

$$NP = g(NI, X). \tag{2}$$

We further assume that the knowledge stock, A, is affected by a nearby university's scale or its innovation capacity, U, through the channel of knowledge spillovers as well as the distance to the university, D, which captures the sharp spatial attenuation of knowledge spillovers:

$$A = a(U,D). \tag{3}$$

If nearby universities experience an increase in innovation capacity and generate more knowledge for sharing, the knowledge stock for nearby firms will increase. If a firm is closer to universities spatially, the firm has better access to university knowledge and receives a larger impact when the universities experience a knowledge boom. Therefore, we have $\frac{\partial a}{\partial U} > 0$, $\frac{\partial a}{\partial D} < 0$, and $\frac{\partial^2 a}{\partial U \partial D} < 0$.

Knowledge spillover is not the only channel through which universities affect local innovation. For instance, the number of researchers, R, could also be a function of local universities' scale, U:

$$R = r(U). \tag{4}$$

On a broad geographic scale, the number of researchers could also be a function of the geographic distance to the university. For instance, better university access may increase the probability that local young people attend a university, become researchers, and seek work in the same city (Card 1995). However, in this paper, we restrict our attention to narrow geographic scopes of 2-3 km, within which the number of available researchers to firms are unlikely to be subject to spatial attenuation.[1] Hence, we assume away the role of distance in driving the number of available researchers in nearby firms.[2]

Based on the conceptual setup, it is easy to see that an increase in local university scale impacts the creation of new ideas and new products through either knowledge spillovers or the labor market channel. However, a further difference of the university impact along the spatial dimension helps tease out the labor market mechanism and highlight the role of knowledge spillovers. To see this clearly, we assume linearity for all functional forms and write the determinants of new ideas at "close" and

[1]The argument is consistent with the general consensus in the literature that it is easier to "move" labor than to "move" ideas (Rosenthal and Strange 2001; Ganguli et al. 2020). The chances of meetings and conversations that enable idea exchanges are significantly reduced even at modest distances (Arzaghi and Henderson 2008). Yet, labor market benefits are realized at a large geographic scope—usually within the same commuting zones (Combes and Gobillon 2015).

[2]Essentially, the labor market channel should not operate in such localized geographic scales. However, the assumption does not preclude that, in equilibrium, firms closer to universities benefit more from knowledge spillovers and disproportionately hire more university graduates as researchers. This hiring is, in fact, likely if knowledge stock and the number of researchers are complementary.

"far" distances as follows:

$$NI_{D(close)} = A_{D(close)} + R_{D(close)} = \alpha_{D(close)}U + \beta U, \tag{5}$$

and

$$NI_{D(far)} = A_{D(far)} + R_{D(far)} = \alpha_{D(far)}U + \beta U, \tag{6}$$

where $NI_{D(close)}$ stands for the creations of new ideas at firms located sufficiently close to a university and $NI_{D(far)}$ stands for new ideas at firms located relatively far from the university. They are determined by the knowledge stock and the number of researchers at respective locations, indexed by $A_{D(close)}$, $A_{D(far)}$, $R_{D(close)}$, and $R_{D(far)}$. $\alpha_{D(close)}$, $\alpha_{D(far)}$, and β are the corresponding parameters that link $A_{D(close)}$, $A_{D(far)}$, $R_{D(close)}$, and $R_{D(far)}$ to U.

Since the number of available researchers to firms are not subject to spatial attenuation, as discussed earlier, we have $R_{D(close)} = R_{D(far)} = \beta U$. A comparison of the impact of universities for locations that are close and far from universities gives us the following.

$$NI_{D(close)} - NI_{D(far)} = A_{D(close)} - A_{D(far)} = \left[\alpha_{D(close)} - \alpha_{D(far)}\right] U. \tag{7}$$

Therefore, any differences in the impact of universities across various close-range spatial distances can be attributed to the difference in A—the varying degrees of knowledge spillovers in promoting nearby firms' innovation activities. We adopt a triple-differences model to highlight this variation in our empirical analysis.

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