Universities, Firm Location and Growth

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Abstract

We study how spatial spillovers from universities contribute to overall economic growth. Using data from China, we find that firms located closer to universities innovate more efficiently, newly established firms outperform incumbents in R&D, and firm locations exhibit strong persistence over time. Motivated by these empirical patterns, we build a quality-ladder model in which firms make decisions not only about their level of innovation effort but also about where to locate, subject to land availability constraints. Our quantitative analysis reveals that university spillovers contribute significantly to economic growth – reducing innovation productivity to the level of the farthest locations decreases growth from 3% to 2% – while limited land availability near universities hinders innovation. These findings reveal a previously overlooked inefficiency in firms' location choices, with important implications for innovation policy and regional development.

JEL Codes: O31, O41, R30

Key words: Knowledge Spillovers, Spatial Misallocation, Innovation Geography

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1 Introduction

Disseminating knowledge is widely regarded as a fundamental role of universities. Many empirical studies find that proximity to universities boosts firms' ability to develop new knowledge, significantly enhancing nearby firms' innovation activities (e.g., Jaffe 1989, Andrews 2017, Kantor & Whalley 2014, Hausman 2020). This is also evident in real-world examples such as Stanford, which has evolved into a major hub of innovation, attracting entrepreneurs and companies to the surrounding area known as "Silicon Valley." However, whereas knowledge spillovers have long been considered a crucial driver of aggregate economic growth in the macroeconomic literature (e.g., Romer 1990, Jones 1995, Lucas & Moll 2014), there is a lack of quantitative analysis examining the relationship between knowledge spillovers from universities and their impact on aggregate economic growth.

In this paper, we address this gap in the literature by developing a quantitative growth framework that incorporates creative destruction and a novel spatial dimension—specifically, proximity to universities, firm location choices, and land availability. Grounded in empirical evidence, our quantification highlights how the interplay between university proximity and land availability influences firm location decisions, potentially resulting in spatial misallocation and inefficient innovation investment.

To inform our theory, we begin by documenting descriptive facts about firms' innovation and their proximity to universities, using detailed Chinese data on manufacturing firms innovation, location, and geography. China serves as a relevant context due to its rapid increase in innovation—domestic invention applications surged over 15-fold from 2000 to 2015, with universities and research institutes contributing 30%—highlighting the significance of knowledge diffusion (Wei, Xie & Zhang 2017). It also features rich spatial variation, encompassing many regions and universities.

Our empirical analysis reveals three key patterns. First, within cities,[1] firms located closer to universities produce more patents per R&D worker, indicating higher innovation efficiency; however, patents per R&D expenditure remain relatively constant across distances. Second,

[1]We focus on within-city proximity to universities due to the localized nature of knowledge spillovers documented in the literature (Jaffe, Trajtenberg & Henderson 1993, Murata, Nakajima, Okamoto & Tamura 2014, Kerr & Kominers 2015, Berkes, Gaetani & Mestieri 2025).

new firms tend to innovate more efficiently than incumbents—particularly when situated farther from universities—suggesting they make more effective use of their workforce. Third, despite their innovation efficiency, new firms are less likely to locate near universities, and firm relocations are infrequent, underscoring the stickiness of initial location choices.

Building on these observations, we develop an endogenous growth model to quantify the effect of university knowledge spillovers on economic growth. The model is grounded in the classical quality-ladders framework (Aghion & Howitt 1992, Grossman & Helpman 1991), in which a fixed number of product lines are operated by incumbent firms. New entrants engage in innovation, and successful innovators improve product quality, thereby displacing the incumbent firm in the corresponding product line. To incorporate university knowledge spillovers, we assume that entrants can choose their proximity to universities, which influences their innovation efficiency due to varying exposure to academic knowledge. While all firms have an incentive to locate near universities to benefit from higher spillover effects, limited land availability constrains this behavior. Increased demand for proximity drives up land prices near universities, reducing firms profits and limiting clustering.

To isolate the model's novel mechanism about the interplay between land availability and university knowledge spillovers, we first analyze a simplified version in which the primary modification is adding land as an input for production. Entrants must purchase land to operate, and its availability depends on the rate of creative destruction. Comparing the competitive equilibrium to the social planners solution, we show that adding land increases the distance between private and socially optimal innovation, displaying an additional source of suboptimal innovation. We then extend the model to multiple regions, allowing for differential location choices and examining how firm proximity to universities shapes innovation and spatial misallocation.

We calibrate the model using our compiled Chinese firm and land data, combining external estimates with internally calibrated parameters via the simulated method of moments (SMM). We target several key moments include TFP growth, R&D intensity, patenting across distance bins, and land prices. Our estimates align well with those found in the literature, and the model captures the main documneted patterns, such as higher innovation efficiency near universities and greater R&D efficiency in new firms, matching both targeted and non-targeted data moments.

Our counterfactual exercises are still work in progress, but we aim to quantify the effects of knowledge spillovers and firm location choices, as well as explore the impact of land restrictions. We first analyze how reducing knowledge spillovers from universities would affect aggregate growth and welfare, and second, we assess the effects of relaxing land constraints on economic outcomes. Initial results suggest that diminished knowledge diffusion would significantly reduce growth and welfare while increasing land supply has a modest positive effect. We are also exploring additional policies, such as industrial land allocation and university funding, to further explore their impacts on spatial misallocation and regional disparities.

Literature. This paper relates to several strands of the literature. First, this paper connects with the macro literature on the role of education in driving economic growth. Romer (1990) models human capital as a crucial input for the research sector that generates new ideas and fosters technological progress. A substantial macro literature has since documented the positive cross-country relationship between higher education and future technology growth (e.g., Barro 1991, Benhabib & Spiegel 1994, Furman, Porter & Stern 2002, Valero & Reenen 2019). Universities are a vital component of the education system, playing a key role in cultivating talent and disseminating knowledge. While recent studies have highlighted how the supply of talent from universities contributes to economic growth (Akcigit, Pearce & Prato 2020, Ma 2024), there remains limited understanding of how knowledge spillovers from universities affect aggregate growth—an issue this paper seeks to address.

Our paper also contributes to a broad literature examining the impact of university spillovers, with a particular emphasis on identifying causal relationships. For instance, Andrews (2017) employs a finalist empirical strategy that leverages historical site selection decisions of U.S. universities to estimate causal effects. Similarly, Aghion, Bergeaud, Lequien & Melitz (2017) uses political shifts in education funding to assess the impact of colleges on innovation, and Hausman (2020) exploits the enactment of the Bayh-Dole Act as a natural experiment. Although these studies successfully exploit quasi-experimental variation to estimate the regional effects of universities, they largely focus on reduced-form relationships, leaving the aggregate implications for growth and policy insufficiently explored. This paper fills that gap by integrating empirical evidence with a general equilibrium spatial growth model to quantitatively evaluate the role of university spillovers in driving aggregate economic growth

and to assess policies that can amplify their impact.

Finally, our paper contributes to the quantitative literature on the geography of innovation and knowledge diffusion (e.g., Eaton & Kortum 2001, Alvarez, Buera & Lucas 2013, Arkolakis, Ramondo, Rodrıguez-Clare & Yeaple 2018, Desmet, Nagy & Rossi-Hansberg 2018, Buera & Oberfield 2020, Cai, Caliendo, Parro & Xiang 2022, Liu & Ma 2023), as surveyed by Lind & Ramondo (2019). While much of this work treats knowledge spillovers as exogenous or emphasizes their transmission through trade and migration networks, we take a different approach. Building on this literature, we develop a quantitative spatial growth model that highlights the role of universities in generating spatial spillovers depending on firms' proximity, and we examine how these spillovers influence both the spatial distribution of economic activity and the aggregate growth rate.

The rest of the paper is organized as follows. In Section 2, we describe our data and examine the empirical relationship between innovation and proximity to universities. Guided by these findings, we develop the Schumpeterian growth model incorporating land and firm location choices in Section 3. Section 4 presents our counterfactual exercises along with preliminary results. Finally, we conclude in Section 5.

2 Innovation and Distance to Universities

In this section, we document key empirical patterns linking firms' innovation activity to their proximity to universities. We examine how this relationship differs between new entrants and incumbent firms, and how it relates to their location decisions. These empirical facts serve as motivation for our theoretical model and provide discipline for our quantitative framework.

2.1 Data Sources

We begin by briefly describing the datasets of innovation, firm outcomes, and geographic information employed in our analysis.

Patent Data. We use Chinese patent application data assembled by the China National Intellectual Property Administration. It provides a comprehensive source of data that can be used to gain insights into the innovation activities of Chinese firms, covering detailed information on each patent, including the unique application number, application date, grant date, inventors, and International Patent Classification (IPC) code. We focus on all invention applications[2] that were applied for and eventually granted during the 1985–2021 period. To identify knowledge spillovers, we focus on patents filed solely by firms, excluding those resulting from collaborations between firms and universities.

Firm-level Data. For firm-level data, we integrate multiple sources. The primary dataset is Chinas Annual Survey of Manufacturing (ASM), an administrative dataset covering firm demographics and balance sheets. The ASM surveys 200,000 to 400,000 firms per year, representing over 90% of Chinas manufacturing output. We use data from 2000 to 2013, which includes firm names, value added, sales, employment, capital stock, 4-digit industry affiliation, and registration type for firms above a sales threshold.[3]

One limitation of the ASM data is the lack of R&D data,[4] particularly lacking detailed information on R&D personnel. To complement the ASM data, we use the Survey of R&D Firms from 2008 to 2014, which covers industrial firms engaged in R&D and includes roughly 300,000 firm-year observations. Through textual analysis, we match these firms to those in the ASM, achieving a linkage rate of over 95% of firm-year observations in the R&D survey. This dataset offers rich details on R&D activities, including workforce composition, educational background, funding sources, and expenditure components.

We link the patent data with firm-level data using firms' names, after cleaning and standardizing firm names. The specifics regarding the datasets and the process of consolidating firm names are outlined in Appendix A.1.

We enrich our dataset with geographic information by geocoding firm addresses using the

[2]China recognizes three types of patentsinvention, utility model, and design—with invention patents generally considered the most technology-intensive among them.

[3]From 2000 to 2007, the sales threshold was 5 million RMB (approximately $600,000), and the sample included all state-owned firms. After 2011, the threshold increased to 20 million RMB for all firms. Since the dataset covers all medium-sized and large firms, it provides a reliable measure of aggregate manufacturing sales by industry. Brandt, Van Biesebroeck & Zhang (2012) estimates that firms below this threshold accounted for only 9.9% of total industrial output in 2004.

[4]In the ASM, data on R&D expenditures are available only for the periods 2001–2002 and 2005–2007.

GaoDe Maps API, obtaining longitude and latitude coordinates for each firm-year observation. For the 2008–2014 R&D survey subsample, this process yields a match rate of 96%. We also collect geographic data on universities from their official websites and on research institutes (we exclude research institutes affiliated with firms, focusing instead on those associated with universities, the military, or government agencies) identified in the patent dataset. We apply the geographic coordinates to calculate each firms shortest distance to the nearest university or research institution.

Table **??** provides summary statistics for the key variables in our sample. On average, each R&D firm files approximately one patent per year, and the majority of R&D workers hold undergraduate or master's degrees. On average, firms are located 9 kilometers from the nearest university or research institution.

Land Data. Finally, to capture the interaction between land availability and proximity to universities in our quantitative analysis, we compile data on plot-level land transactions in China from 2000 to 2023.[5] Each transaction record includes the city, geographic coordinates, land price, land area, and designated land use (e.g., residential, commercial, or industrial). We use the geographic coordinates to calculate each lands shortest distance to the nearest university or research institution.

2.2 Facts: Proximity to Universities, Innovation, and Location

We use our compiled data to document various facts regarding how firms' innovation outcomes differ based on their proximity to universities. First, we explore how the intensity of innovation varies based on proximity to the nearest university and among different inputs. Next, we highlight the differences in this relationship between incumbent and new firms. Finally, we uncover differences in their location choices.

[5]The data are sourced from `https://www.landchina.com/`, a government platform that records and publishes land transaction information.

2.2.1 Relationship between Firms' Innovation Outcomes and Proximity to the University

To document the correlations between innovation intensity and the distance to universities, we consider the following Poisson regression:

$$y_{it} = \exp\left(\beta_0 + \sum_{r=1}^{4} \beta_r bin_{r(i,t)} + \gamma \mathbf{X}_{it} + \delta_{c(i,t)} + \eta_t\right) + \epsilon_{it}. \quad (1)$$

We follow the literature (Silva & Tenreyro 2006, Cohn, Liu & Wardlaw 2022) to use a Poisson model, because patent applications are count data and often include zeros for many firms. Our primary outcome variable of interest, y_{it}, includes innovation output measured by the number of patent applications and innovation efficiency. We measure innovation efficiency in two ways: (1) by the number of patent applications per R&D worker; and (2) by the number of patent applications per R&D expenditure. For firms in each city and year, we divide firms into 5 equally sized bins, $r = 1, ..., 5$, based on the ranking of their distance to the *nearest* university or research institution, and we include the dummies of bins in the regression to explore how firms' innovation outcomes change with distance to the university. We treat the farthest firms as the baseline group and thus omit bin $r = 5$ in the regression. The control variables $\mathbf{X}_{it}$ include the education structure of the firm's R&D labor (the shares of undergraduates, masters, and PhDs), as well as firm deciles of firm sales and industry fixed effects to capture heterogeneity in innovation patterns across firm size and industries. $\delta_{c(i,t)}$ and η_t correspond to city and year fixed effects for firm i in time t.

Figure 1 illustrates how the number of patents varies with proximity to the nearest university. Firms located closer to universities tend to have higher patent counts compared to those farther away. However, this increased patent activity near universities may not necessarily indicate greater innovation efficiency, as it could also reflect higher input levels.

Thus, in Figure 2, we display the variation in innovation efficiency, measured by patents per R&D worker and expenses, across distance bins to the nearest university. Panel 2a shows the number of patents per R&D worker diminishes for firms located at a greater distance from the university. This suggests that, on average, workers in closer proximity to the university exhibit higher productivity compared to those further away, even after controlling for the

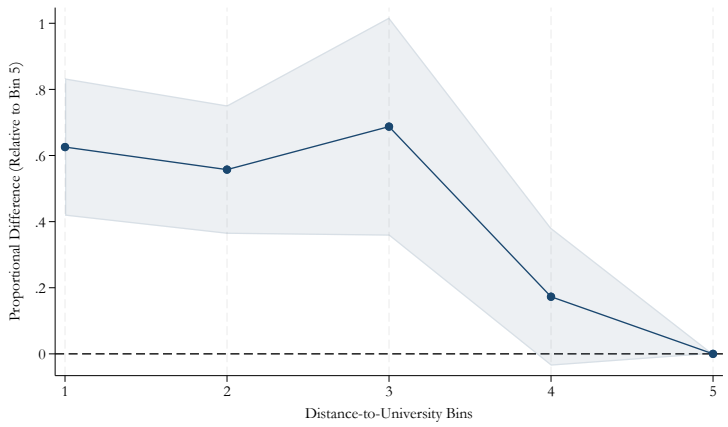


Figure 1: Number of Patent Applications

Notes: We perform the regression in equation (1), controlling for education composition of R&D workers, deciles of firm sales, industry fixed effects, city fixed effects, and year fixed effects. This graph plots proportional differences relative to firms in bin 5 (baseline group). The dotted line represents 95% confidence intervals, with robust standard errors.

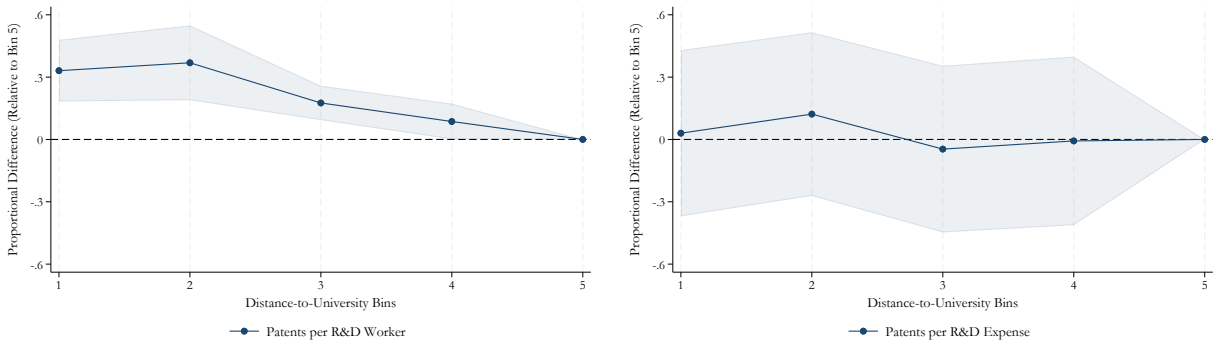
educational composition of R&D labor as we did in the regressions. However, when innovation outcomes are assessed based on patents per R&D expense, this relationship remains relatively stable across distances from the university, as shown by Figure 2b.

In Table 1, we present regression results using the continuous measure of distance rather than distance bins. Consistent with Figure 2, we find that patent applications per R&D worker decline with increasing distance from the university, while patents per R&D expenditure show no statistically significant relationship with distance. We also find that, conditional on distance to the university, higher skill levels among research personnel are generally associated with improved innovation outcomes, consistent with the findings in the literature Akcigit et al. (2020), Akcigit, Caicedo, Miguelez, Stantcheva & Sterzi (2025). Thus underscores the importance of accounting for the educational composition of R&D teams.

We summarize this finding as follows:

Fact 1. *Patents per R&D worker decline as distance to university increases, whereas patents per R&D expense show no clear trend with distance.*

This first finding indicates that research efficiency, when measured by the number of R&D workers, is higher near universities. However, this pattern does not hold when efficiency is measured in terms of R&D expenditures. In our model, we demonstrate that this outcome



(a) Number of Patents per R&D Worker (b) Number of Patents per R&D Expense

Figure 2: Distance to University and Innovation Outcomes

Notes: We perform the regression in equation (1), controlling for education composition of R&D workers, deciles of firm sales, industry fixed effects, city fixed effects, and year fixed effects. This graph plots proportional differences relative to firms in bin 5 (baseline group). The dotted line represents 95% confidence intervals, with robust standard errors.

can arise from an R&D production function that utilizes both labor and materials, along with knowledge spillovers from universities, and convex vacancy costs as commonly assumed in the literature (Acemoglu & Hawkins 2014).

2.2.2 New Firms versus Incumbents

We next examine if the age of firms affects the documented relationship between firm innovation intensity and proximity to universities, considering that new firms are typically more innovative and may also face difficulties in obtaining innovation resources. A firm is considered new if it is less than 9 years old, following the categorization used by Acemoglu, Akcigit, Alp, Bloom & Kerr (2018).

To understand how new firms perform differently relative to an incumbent firm, we extend the regression model (1) by interacting the distance bin with a dummy variable new_{it} indicating whether the firm is a new firm. We consider the following specification:

$$y_{it} = \exp\left(\beta_0 + \sum_{r=1}^{4} \beta_r \times bin_{r(i,t)} + \sum_{r=1}^{5} \theta_r^{new} \times bin_{r(i,t)} \times new_{it} + \gamma \mathbf{X}_{it} + \delta_{c(i,t)} + \eta_t\right) + \epsilon_{it}. \quad (2)$$

where the coefficient θ_r^{new} captures the difference in innovation performance between new firms and incumbents.

Table 1: Correlation Between Distance to Universities and Innovation Outcomes

	Number of Patent Applications			
	(1)	(2)	(3)	(4)
	All	Per Worker	Per R&D Cost	Per R&D Cost (excl. personnel)
Log(distance to university)	-0.041***	-0.068***	-0.011	-0.005
	(0.015)	(0.023)	(0.022)	(0.019)
% Undergrad in R&D	0.313*	0.411***	0.734***	0.892***
	(0.168)	(0.077)	(0.163)	(0.205)
% Master in R&D	3.949***	1.792***	0.425	1.231***
	(0.240)	(0.102)	(0.375)	(0.253)
% PhD in R&D	-0.444	1.442***	4.048***	0.338
	(0.478)	(0.182)	(1.513)	(0.620)
City & Year FE	Yes	Yes	Yes	Yes
Observations	164,285	164,285	164,285	161,915
Pseudo R-squared	0.430	0.054	0.042	0.046

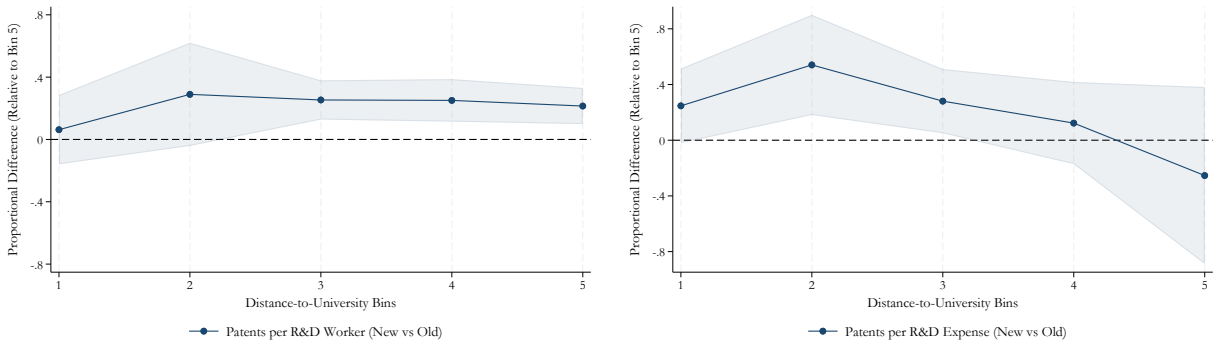
Note: We perform the regression in equation (1) but replace distance bins by the logarithm of distance to the university. We control for deciles of firm sales, industry fixed effects, city fixed effects, and year fixed effects. In Column (4), personnel costs are excluded from R&D expenditures when calculating the number of patent applications per unit of R&D cost. We report robust standard errors in parentheses. * 10% significance; ** 5% significance; *** 1% significance.

Figure 3 presents the estimated coefficients of θ_r^{new} from equation (2), using two alternative measures of innovation efficiency as dependent variables, along with their 95% confidence intervals. The results indicate that new firms generally exhibit more efficient R&D personnel than incumbents, particularly in regions farther from the university (see bins 35 in Figure 3a). Additionally, we observe differences between new firms and incumbents in terms of the number of patents generated per unit of R&D expenditure. These findings lead to the following key observation:

Fact 2. *New firms use R&D labor more efficiently than incumbents, especially when farther from universities.*

Given that newly established firms located farther from the university exhibit higher R&D labor efficiency than older firms, a natural question arises: are new firms more likely to locate near universities to better benefit from knowledge spillovers? To investigate this, we estimate a linear probability model to examine the likelihood of a firm choosing to locate close to a university:

$$new_{it} = \beta_0 + \sum_{r=1}^{4} \beta_r \times bin_{r(i,t)} + \gamma \mathbf{X}_{it} + \delta_{c(i,t)} + \eta_t + \epsilon_{it}. \tag{3}$$



(a) Number of Patents per R&D Worker (b) Number of Patents per R&D Expense

Figure 3: Distance to University and Innovation Outcomes, New Firms Relative to Incumbents

Notes: We perform the regression in equation (2), controlling for education composition of R&D workers, deciles of firm sales, industry fixed effects, city fixed effects, and year fixed effects. This graph plots proportional differences between incumbent and new firms within each bin. The dotted line represents 95% confidence intervals, with robust standard errors.

β_r denotes the comparative probability of new firms choosing to locate in bin r compared to the last bin ($r = 5$, baseline group). We continue to include firm-level controls, city-fixed effects, and time-fixed effects, as previously done.

The results shown in Figure 4 reveal that new firms are significantly less likely to establish themselves near a university compared to incumbent firms. Additionally, relocation after initial establishment is rare. In our sample, 92% of firms experience year-to-year changes in location of less than 0.001 kilometers. Only 3% of firms relocate more than 10 kilometers between two consecutive years.[6] Thus, we obtain the following fact. This leads to the last finding:

Fact 3. *New firms are less likely to be located near universities.*

[6]These small fluctuations are likely due to noise in the address data, as government regulations require the introduction of such noise in maps to protect confidentiality.

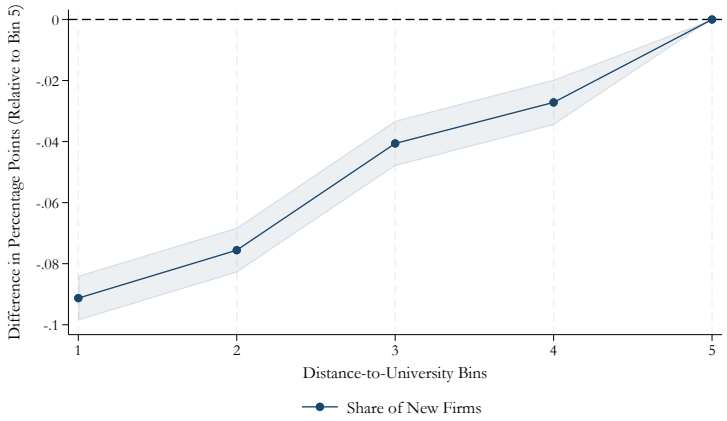


Figure 4: Probability of Entry of New Firms (relative to last bin)

Notes: The dotted line represents 95% confidence intervals, with robust standard errors.

The second and third findings point to a potential spatial misallocation of innovation. In our model, we account for land availability near the university, which may constrain innovative firms from locating nearby, thereby limiting their ability to fully benefit from university knowledge spillovers.

3 Model: Innovation, Land and Firms' Location

Innovation models have traditionally overlooked firm location choices. Yet our findings reveal that proximity to universities matters: firms near these institutions generate more innovations, while new entrants tend to locate farther away and miss out on this benefit. This creates a tradeoff where firms compete in the product space independently of their location decisions. In other words, when one firm displaces another through innovation, it does not inherit the displaced firm's advantageous location, potentially leading to a spatial misallocation of innovation.

Overview

We develop an endogenous growth model extending the canonical Schumpeterian framework to incorporate a land market and firms' location choices. Given the available locations, intermediate goods firms choose how much land to acquire for setting up operations upon entry. The land market is competitive, with land becoming available only after a firm

exits the product market due to creative destruction. Firms' innovation productivity is influenced by their distance from the university and also evolves stochastically over time as they age. The primary spatial friction arises from our restriction on firms relocating after they have entered the market, reflecting the highly persistent location choices documented in our empirical findings.

3.1 Simple Model: Linking Land to Creative Destruction

We first present a simplified model to highlight how the available land for innovation is endogenously linked to innovation. We introduce a land market where incumbent firms own land, requiring new entrants to purchase land to innovate and produce. Creative destruction has an additional pecuniary externality as it clears land for future innovators. Our main theoretical point is to show that the planner's solution entails relatively more creative destruction when land is included as an input and that inefficiency increases with the significance of land in production.

Final-good producers. Suppose there is a unique final consumption good produced in a competitive market where the final good producers assemble all the varieties and solve:

$$Y_t = \frac{1}{1-\beta} \int_0^1 q_{j,t}^{\beta} k_{j,t}^{1-\beta} dj. \tag{4}$$

where $q_{j,t}$ is the quality of variety j, and $k_{j,t}$ is the demand for variety j. Using the first-order condition (FOC), we can solve the demand function for variety j as:

$$p_{j,t} = q_{j,t}^{\beta} k_{j,t}^{-\beta}.$$

Producers of intermediate goods. Intermediate good producers require *land* and labor to produce each intermediate variety and operate under monopolistic competition. Land l is determined upon entry and is governed by elasticity $\theta \geq 0$, while labor u is measured in efficiency units and enters the production function linearly,

$$k_{j,t} = \bar{q}_t u l^{\theta},$$

where $\bar{q}_t \coloneqq \int_0^1 q_{j,t} dj$ denotes the aggregate productivity/quality in the economy.

We assume that labor markets are competitive with w_t denoting the wage rate for workers at time t. Taking land as given, the producer will choose labor u to maximize profits. For the producer of variety j, the profit maximization problem is:

$$\max_u \ \pi_{j,t} = p_{j,t} k_{j,t} - w_t u = q_{j,t}^{\beta} (\bar{q}_t u l^{\theta})^{1-\beta} - w_t u$$

We can solve the optimal labor demand,

$$u_{j,t}^* = \left[\frac{(1-\beta)\bar{q}_t}{w_t} \right]^{\frac{1}{\beta}} \frac{q_j}{\bar{q}_t} l^{\frac{(1-\beta)\theta}{\beta}}, \tag{5}$$

implying the corresponding quantity of intermediate goods produced and profits are,

$$k_{j,t} = \left[\frac{(1-\beta)\bar{q}_t}{w_t} \right]^{\frac{1-\beta}{\beta}} q_j l^{\frac{1-\beta}{\beta}\theta}; \ \pi_{j,t} = \frac{\beta}{1-\beta} w_t^{\frac{\beta-1}{\beta}} \left[(1-\beta)\bar{q}_t \right]^{\frac{1}{\beta}} \frac{q_j}{\bar{q}_t} l^{\alpha_l} = \pi_t q_j l^{\alpha_l}, \tag{6}$$

where $\pi_t = \frac{\beta}{1-\beta}(1-\beta)^{\frac{1}{\beta}} \left(\frac{w_t}{\bar{q}_t} \right)^{\frac{\beta-1}{\beta}}$ and $\alpha_l = \frac{\theta(1-\beta)}{\beta}$ denotes the exponent of the land for intermediate production, which we use to simplify the notation.

Aggregating labor across varieties yields,

$$u_t^* = \int u_{j,t}^* dj = \left(\frac{(1-\beta)\bar{q}_t}{w_t} \right)^{1/\beta} l_t^{\alpha_l}$$

and the final good output is,

$$Y_t = \frac{1}{1-\beta} \left(\frac{(1-\beta)\bar{q}_t}{w_t} \right)^{\frac{1-\beta}{\beta}} l_t^{\alpha_l} \bar{q}_t.$$

Entrant Innovation. Suppose, as in the simple Schumpeterian models, that only entrant firms innovate. Below in the quantitative model, we extend our results to consider the case where incumbents also innovate. Here, we focus on the start case where the entrants are the only innovators in the economy, while incumbents occupy the valuable land needed to enter the market.

Suppose a mass of entrants, M^e, that innovate randomly over the product space, $[0,1]$. After taking over a product, they collect the monopoly profits until the firm is creatively destroyed with arrival rate x. The value function of an entrant firm satisfies the usual Hamilton-Jacobi-Bellman (HJB) equation,

$$r_t V_t(q_j) - \dot{V}_t(q_j) = \pi_t l_t^{\alpha_l} q_j - x_t V_t(q_j). \tag{7}$$

Suppose the land market is competitive and entrants take the price of a unit of land κ as given. Entrants choose the amount of land l and the R&D resources R to solve,

$$\max_{l,R} \phi_t(R)\mathbb{E}[V_t(q_j(1+\lambda))] - R - \kappa_t l,$$

where $\phi_t(R)$ denotes the innovation production function that combines the R&D resources and labor and determines the arrival rate of innovations.

The FOCs are,

$$\begin{aligned}[l]: \ & \phi_t(R)\frac{\partial \mathbb{E}[V_t]}{\partial l} = \kappa_t, \\ [R]: \ & \frac{\partial \phi_t(R)}{\partial R}\mathbb{E}[V_t] = 1;\end{aligned}$$

Let l_t^* and R_t^* denote the solution to these equations. Note these quantities are not indexed by the varieties as innovation from entrant firms is undirected. Let ϕ_t^* denote the corresponding arrival rate of innovations.

Creative destruction equals the expected aggregate innovation by entrant firms,

$$x_t^* = \int_0^1 \phi_t^* dj = \phi_t^*. \tag{8}$$

Land Market. Let L denote the total amount of land in the economy. At a given point in time, t, not all land is available for entrants, as incumbents are using it for production. The available land is endogenously determined by creative destruction x.

The land market clearing condition equates the total demand for land to the land available,

$$l_t = x_t L, \tag{9}$$

where we normalize the mass of entrants to one.

Workers. We suppose the economy is populated by homogenous workers that maximize the expected value of the log utility of consuming the final good and discount the future at a rate ρ,

$$\max_{c_t} \int_0^\infty e^{-\rho t} \log(c_t).$$

Workers are endowed with a unit of time which they supply inelastically and earn wages w_t. The total supply of efficiency units of labor is H.

The usual Euler equation from the workers' utility-maximizing problem implies,

$$r_t = \rho + \frac{\dot{c}_t}{c_t}.$$

Labor Market. To close the model, we clear the labor markets. Aggregating the labor demand for production in equation (5) yields,

$$u_t^* = \int_0^1 u_{j,t}^* dj = \left(\frac{(1-\beta)\bar{q}_t}{w_t} \right)^{1/\beta} l_t^{\alpha_l}.$$

Since we simplified the problem and assume skilled workers are used only in the production of intermediate goods, the labor market clearing condition is,

$$u_t^* = H. \tag{10}$$

Equilibrium. The equilibrium is defined as a set of allocations $\{k_{j,t}^*, u_{j,t}^*, R_t^*, l_t^*, c_t^*\}$, prices $\{p_{j,t}, w_t, r_t, \kappa_t\}$ and the value function $V_t(q)$ such that

1. Final good producers choose $k_{j,t}^*$ to maximize profits taking prices $p_{j,t}$ as given.

2. Intermediate good producers choose effective units of labor $u_{j,t}^*$ to maximize profits of producing the intermediate variety taking wages w_t as given.

3. Entrant firms choose R&D resources R_t^* and land l_t^* to maximize the expected value of innovating taking κ_t as given.

4. The value function of incumbent firms satisfies the HJB equation (7).

5. Workers choose consumption c_t^* to maximize their utility.

6. Land market, labor market, and goods markets clear.

To further characterize the solution, we focus on the equilibrium on a balanced growth path (BGP).

Balanced Growth. Suppose aggregate quality grows at a constant rate $\frac{\dot{\bar{q}}_t}{\bar{q}_t} = g$. To illustrate the results, we assume a Cobb-Douglas innovation production function.[7]

$$\phi(R, h) = A\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r},$$

with $A > 0$ denoting the innovation productivity, $\alpha_r \in (0, 1)$.[8]

On a BGP land l^*, the labor allocation u_j^*, and the interest rate r^* are constant over time. Wages w_t^*, the price of land κ_t^*, consumption c_t^*, resources R_t^* and aggregate output Y_t^* grow at the same rate g.

The value function is stationary, $\dot{V}_t = 0$, and satisfies,

$$V(q) = \frac{\pi^*}{r^* + x^*} q l^{\alpha_l} =: v q l^{\alpha_l},$$

where the marginal profit $\pi^* = \beta(1-\beta)^{\frac{1-\beta}{\beta}} \left(\frac{\bar{q}_t^*}{w_t^*}\right)^{\frac{1-\beta}{\beta}}$ and the creative destruction rate x^* are constant.

[7] The same characterization is achieved if we assume that the innovation production function satisfies, ϕ_t and $\frac{\partial \phi_t}{\partial h}$ are constant and $\left(\frac{\partial \phi}{\partial R}\right)^{-1}$ grows at a constant rate g.

[8] Later in the full model, innovation productivity A varies across locations, capturing the effect of proximity to universities.

In Proposition 1, we show a sufficient condition for the existence of a unique BGP equilibrium and characterize the equilibrium creative destruction $x^* = \phi(R^*)$ on a BGP. All proofs are in Appendix B.1.

Proposition 1. *If $\alpha_r(1+\theta(1-\beta)) \leq 1$, the exists a unique BGP equilibrium where the equilibrium creative destruction x^* solves,*

$$x^{*(1-\alpha_r\theta(1-\beta))}\left(\frac{\rho + x^*(1+\lambda)}{\beta(1+\lambda)x^*}\right)^{\alpha_r} = A\left(\alpha_r H^{1-\beta}L^{\theta(1-\beta)}\right)^{\alpha_r}$$

Now, we turn to the planner's problem to analyze the efficiency tradeoff introduced by considering land as a necessary input for innovation and production.

Planner's Problem

Consider a social planner that maximizes the utility of workers taking as given the resource and technological constraints in the economy,

$$\begin{aligned}
&\max_{l_t,u_{jt},R_t} \int_0^\infty e^{-\rho t}\log C_t dt \\
&\quad s.t.\ Y_t = C_t + R_t\ ,\quad Y_t = \frac{1}{1-\beta}\int q_j^\beta \bar{q}_t^{1-\beta} u_{jt}^{1-\beta} l_t^{(1-\beta)\theta} dj \\
&\quad \int u_{jt}dj = H\ ,\quad \frac{\dot{\bar{q}}_t}{\bar{q}_t} = \phi(R_t)\lambda\ ,\quad l_t = \phi(R_t)L.
\end{aligned}$$

We can simplify the Planners' problem to,

$$\begin{aligned}
&\max_{l,u_j,R} \int_0^\infty e^{-\rho t}\log\left(C_0 e^{gt}\right)dt \equiv \max_{l,u_j,R}\frac{\phi(R)\lambda}{\rho} + \log C_0 \\
&\quad s.t.\ C_0 = Y_0 - R\ ,\quad Y_0 = \frac{1}{1-\beta}\int q_j^\beta \bar{q}_0^{1-\beta} u_j^{1-\beta} l^{(1-\beta)\theta} dj \\
&\quad \int u_j dj = H\ ,\quad l = \phi(R,h)L,
\end{aligned}$$

and solve it using the usual Lagrangian approach,

$$\mathcal{L} = \frac{\phi(R)\lambda}{\rho} + \log C_0 + \mu_h\left(H - \int u_j dj\right) + \mu_l(\phi(R)L - l)$$

The optimality conditions are,

$$
\begin{aligned}
[u_j]: \quad & \frac{1}{C_0} q_j^{\beta} \bar{q}^{1-\beta} u_j^{-\beta} l^{(1-\beta)\theta} = \mu_h \\
[R]: \quad & \alpha_r \phi \left(\frac{\lambda}{\rho} + \mu_l L \right) = \frac{R}{C_0} \\
[l]: \quad & \frac{1}{C_0} \theta \int q_j^{\beta} \bar{q}^{(1-\beta)} u_j^{1-\beta} l^{(1-\beta)\theta} dj = \mu_l l
\end{aligned}
$$

We can combine these equations and use the resource constraints to solve for the optimal R&D resources R^s used by the social planner and the corresponding creative destruction, $x^s = \phi(R^s)$. In Proposition 2, we show sufficient conditions for the existence of the planner's solution and characterize the optimal creative destruction.

Proposition 2. *If $\alpha_r(1+\theta(1-\beta)) \leq 1$, there exists a unique solution to the planner's problem with creative destruction x^s solves,*

$$
(x^s)^{1-\alpha_r\theta(1-\beta)} \left(\frac{(1-\beta)(\rho + \alpha_r \lambda x^s)}{\theta(1-\beta)\rho + \lambda x^s} \right)^{\alpha_r} = A \left(\alpha_r H^{1-\beta} L^{(1-\beta)\theta} \right)^{\alpha_r}
$$

By comparing Propositions 1 and 2, we assess how land affects innovation efficiency. As in standard Schumpeterian models, the planners innovation rate is not always higher than the markets, particularly when innovation spillovers and monopolistic markups are small. In such cases, the 'business-stealing' effect (Aghion & Howitt 1992), where entrants displace incumbents, may dominate, leading to overinvestment. However, empirical estimates often suggest that positive innovation spillovers outweigh destructive effects, implying underinvestment in innovation.

A key result from the simplified model is that adding land strengthens positive spillovers, as creative destruction determines land availability and is a complementary input for intermediate goods. This deepens inefficiencies since entrants must acquire land, but its supply depends on firm turnover rather than optimal allocation. Moreover, we also show that the inefficiency of creative destruction increases with the importance of land in production, captured by parameter θ. We formalize this in Proposition 3.

Proposition 3. *If $\alpha_r(1+\theta(1-\beta)) \leq 1$ and $x^s > x^*$, $\frac{x^s}{x^*}$ is increasing in θ.*

Having examined how adding land amplifies innovation inefficiencies, we extend the model to a quantitative version to measure the magnitude of this effect using Chinese microdata. In the next section, we expand the simple model in several key directions, targeting empirical moments to discipline the calibration.

3.2 Quantitative Model

In this section, we explain how we expand the simple model into a quantitative model by incorporating multiple regions and distances to universities. This targets our empirical observations on the importance of firm location for innovation, including innovation by both incumbents and entrants, with labor as an additional input, as well as the life cycle of firms innovation capacity. To avoid redundancy, we focus solely on the aspects of the model that differ from the simple version.

Suppose there are N regions, each divided into D discrete bins according to the distance of universities, $d = 1, 2, ...D$. Each region-bin hosts a measure of firms that produce a variety, which will be endogenously determined by entry and creative destruction, as described below. We suppose there is free trade of varieties between regions.

The problem for final and intermediate goods producers remains largely the same. The only additional assumption is that labor markets operate at the regional level, so wages for intermediate producers are also indexed by the region n where they produce.

Innovation by incumbent firms. Contrary to the simple model, we consider incumbent producers also innovate on their products. They hire R&D labor to improve the quality of their current intermediate goods. To reflect the lifecycle pattern in innovation capacities, we posit that incumbent firms in region n and distance d, start with innovation efficiency $A_{n,d}$. However, over time, they can transition to a lower innovation efficiency ($\zeta A_{n,d}$) with $\zeta \leq 1$, with probability ψ. We refer to firms with innovation efficiency $A_{n,d}$ as *high-innovation-capacity* firms and firms with innovation efficiency $\zeta A_{n,d}$ as *low-innovation-capacity* firms. As usual in the Schumpeterian models, if innovation is successful, the quality of the product increases by step size $\lambda \bar{q}_t$, depending on the economy's aggregate quality $\bar{q}_t$.

Incumbent firms are replaced by others at the creative destruction rate x. This rate is

determined endogenously in equilibrium and influences not only the innovation rate in the typical manner highlighted in innovation literature but also the availability of land for new entrant firms.

An incumbent firm chooses the amount of R&D labor h and the R&D resources R to maximize the discounted value of the expected lifetime profits. We can express the value function of a high-innovation-capacity firm with quality q_j as:

$$\begin{aligned} rV^H_{n,d,t}(q_j,l) - \dot{V}^H_{n,d,t}(q_j,l) = \max_{\{R,h\}} \; & \pi_{n,t} q_j l^{\frac{(1-\beta)\theta}{\beta}} + \phi_{n,d}(h,R)\left[V^H_{n,d,t}(q_j+\lambda\bar{q}_t,l) - V^H_{n,d,t}(q_j,l)\right] \\ & - (w_{n,t}h + \xi\bar{q}_t h^\gamma + R) + \psi\left[V^L_{n,d,t}(q_j,l) - V^H_{n,d,t}(q_j,l)\right] - xV^H_{n,d,t}(q_j,l), \end{aligned}$$

where $\phi_{n,d}(h,R)$ is the probability of successful innovation, and $\xi\bar{q}_t h^\gamma$ with $\xi \geq 0$, $\gamma > 1$ is a convex cost of hiring R&D wokers.

For our quantitative exercises we suppose that the innovation production function is Cobb-Douglas combining the productivity-scaled R&D resources and the R&D labor, $\phi_{n,d}(h,R) = A_{n,d}\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h^{\alpha_h}$.

The FOCs imply the marginal value of innovation inputs must be equal to the marginal costs,

$$\begin{aligned} [h]: \;& \alpha_h A_{n,d}\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h^{\alpha_h - 1}\left[V^H_{n,d,t}(q_j+\lambda\bar{q}_t,l) - V^H_{n,d,t}(q_j,l)\right] = w_{n,t} + \xi\gamma\bar{q}_t h^{\gamma-1} \\ [R]: \;& \alpha_r A_{n,d}\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r - 1} h^{\alpha_h}\left[V^H_{n,d,t}(q_j+\lambda\bar{q}_t,l) - V^H_{n,d,t}(q_j,l)\right] = \bar{q}_t \end{aligned}$$

We can solve the optimal R&D resource and labor $R^{H*}_{n,d,t}$ and $h^{H*}_{n,d,t}$ and denote the optimal innovation rate as $\phi^{H*}_{n,d,t} = A_{n,d}\left(\frac{R^{H*}_{n,d,t}}{\bar{q}_t}\right)^{\alpha_r}\left(h^{H*}_{n,d,t}\right)^{\alpha_h}$.

Similarly, the value function of a low-innovation-capacity firm with quality q_j is:

$$\begin{aligned} rV^L_{n,d,t}(q_j,l) - \dot{V}^L_{n,d,t}(q_j,l) = \max_{\{R,h\}} \; & \pi_{n,t} q_j l^{\frac{(1-\beta)\theta}{\beta}} + \zeta\phi_{n,d}(h,R)\left[V^L_{n,d,t}(q_j+\lambda\bar{q}_t,l) - V^L_{n,d,t}(q_j,l)\right] \\ & - (w_{n,t}h + \xi\bar{q}_t h^\gamma + R) - xV^L_{n,d,t}(q_j,l). \end{aligned}$$

Note the main difference with respect to high-innovation capacity firms is the decreased

innovation productivity, $\zeta \leq 1$. The FOCs once again equate the innovation marginal benefits and costs:

$$[h]: \ \alpha_h \zeta A_{n,d} \left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h^{\alpha_h - 1} \left[V^L_{n,d,t}(q_j + \lambda \bar{q}_t, l) - V^L_{n,d,t}(q_j, l)\right] = w_{n,t} + \xi \gamma \bar{q}_t h^{\gamma - 1}$$

$$[R]: \ \alpha_r \zeta A_{n,d} \left(\frac{R}{\bar{q}_t}\right)^{\alpha_r - 1} h^{\alpha_h} \left[V^L_{n,d,t}(q_j + \lambda \bar{q}_t, l) - V^L_{n,d,t}(q_j, l)\right] = \bar{q}_t$$

Let $R^{L*}_{n,d,t}$ and $h^{L*}_{n,d,t}$ denote the optimal R&D resources and labor, and $\phi^{L*}_{n,d,t} = \zeta A_{n,d} \left(\frac{R^{L*}_{n,d,t}}{\bar{q}_t}\right)^{\alpha_r} \left(h^{L*}_{n,d,t}\right)^{\alpha_h}$ the optimal innovation rate.

Innovation by entrants. In each region n and bin d, becoming an entrant incurs fixed entry costs, $\eta^e_{n,d} \bar{q}_t$, in units of final goods, representing registration and setup costs. The entrants not only choose the innovation rate but also the amount of land l they will allocate to production. A successful innovation will lead to randomly replacing an existing variety with an increment of quality $\lambda \bar{q}_t$. Firms initially enter the market as high-capacity innovation firms, but their innovation capabilities may decrease over time.

We assume that the land market is also competitive, so entrants take the price of land $\kappa_{n,d,t}$ in the region n and bin d in year t as given and solve,

$$V^e_{n,d,t} = \max_{\{R,h,l\}} \phi_{n,d}(h_d, R) \left[\mathbb{E}V^H_{n,d,t}(q_j + \lambda \bar{q}_t, l) - \kappa_{n,d,t} l\right] - (w_{n,t} h_d + \xi \bar{q}_t h_d^{\gamma} + R).$$

Entrants equate the marginal benefits and costs of entering the market by employing R&D resources and workers and acquiring land that solves,

$$[h]: \ \alpha_h A_{n,d} \left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h_d^{\alpha_h - 1} \left[\mathbb{E}V^H_{n,d,t}(q_j + \lambda \bar{q}_t, l) - \kappa_{n,d,t} l\right] = w_{n,t} + \xi \gamma \bar{q}_t h_d^{\gamma - 1},$$

$$[R]: \ \alpha_r A_{n,d} \left(\frac{R}{\bar{q}_t}\right)^{\alpha_r - 1} h_d^{\alpha_h} \left[\mathbb{E}V^H_{n,d,t}(q_j + \lambda \bar{q}_t, l) - \kappa_{n,d,t} l\right] = \bar{q}_t,$$

$$[l]: \ \frac{\partial \mathbb{E}V_{n,d,t}(q_j + \lambda \bar{q}_t, l)}{\partial l} = \kappa_{n,d,t}.$$

In the equilibrium, free-entry conditions require:

$$V^e_{n,d,t} \leq \eta^e_{n,d} \bar{q}_t. \tag{11}$$

The equality holds if the number of potential entrants $M^e_{n,d,t}$ is strictly positive.

Workers. Each region is populated by homogenous workers that maximize the expected value of the log utility of consuming the final good and discount the future at a rate ρ,

$$\max_{c_t} \int_0^\infty e^{-\rho t} \log(c_t).$$

They are endowed with a unit of time which they supply inelastically and earn wages $w_{n,t}$. Each region n has a total supply of efficiency units of labor H_n. We abstract from labor migration aspects and assume that labor is fixed in each region.

Labor market clearing. Denote the measures of actively operating firms with high innovation efficiency and low innovation efficiency as $M^H_{n,d,t}$ and $M^L_{n,d,t}$, respectively. The labor market clears in each region n,

$$\int_{j \in n} h^*_t(q_j) dj + \sum_d M^H_{n,d,t} h^{H*}_{n,d,t} + \sum_d M^L_{n,d,t} h^{L*}_{n,d,t} + \sum_d M^e_{n,d} h^{e*}_{n,d,t} = H_n, \quad \forall n$$

Land market clearing. For each region n and distance d, we suppose there is a total supply of land $L_{n,d}$ owned by exogenous land owners who spend all their income on final goods. The available land depends on the mass of companies creatively destroyed each period x, so the land market clearing is,

$$M^e_{n,d} \phi^{e*}_{n,d} l^{e*}_{n,d,t} = x L_{n,d}, \quad \forall n, d.$$

Balanced Growth Path

We focus on characterizing the equilibrium on a balanced growth path (BGP), where the aggregate productivity, $\bar{q}_t$, grows at a constant rate $g := \frac{\dot{\bar{q}}_t}{\bar{q}_t}$. From the final goods producer

output in equation (4), this implies the overall economy grows at the same rate g.

From the intermediate good producers problem, wages $w_{n,t}$ must grow at the same rate of the economy, implying that marginal profits $\pi_{n,t} = \pi_n$.

On a BGP the R&D resources $R^{\tau}_{n,d,t}$ of both types of incumbent firms, $\tau \in \{H, L\}$, grow at the same rate as aggregate productivity, while R&D labor $h^{\tau}_{n,d,t}$ is constant. This implies that the innovation arrival rate is also constant with balanced growth, $\phi^{\tau}_{n,d,t} = A_{n,d}\left(\frac{R^{\tau}_{n,d,t}}{\bar{q}_t}\right)^{\alpha_r}\left(h^{\tau}_{n,d,t}\right)^{\alpha_h}$.

We conjecture that the value functions on BGP satisfy, $V^{\tau}_{n,d,t}(q_j, l) = (v_{n,d}q_j + \bar{v}^{\tau}_{n,d}\bar{q}_t)l^{\frac{(1-\beta)\theta}{\beta}}$, where $v_{n,d}$ and $\bar{v}_{n,d}$ are scalars. By replacing the value functions, we get the following system of equations,

$$v_{n,d} = \frac{\pi_n}{r+x}, \quad \bar{v}^{L}_{n,d} = \frac{(1-\alpha_h-\alpha_r)\phi^{L*}_{n,d}v_{n,d}\lambda}{r-g+x}, \quad \bar{v}^{H}_{n,d} = \frac{(1-\alpha_h-\alpha_r)\phi^{H*}_{n,d}v_{n,d}\lambda + \psi\bar{v}^{L}_{n,d}}{r-g+x+\psi}.$$

We omit the dependence of $\phi^{H*}_{n,d,t}$ and $\phi^{L*}_{n,d,t}$ on l, because l is constant on the balanced growth path.

For entrant firms, we can plug the formula of value functions into the FOCs:

$$\begin{aligned}
[h]: \ & \alpha_h A_{n,d}\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h_d^{\alpha_h-1}\left[\bar{q}_t\left(v_{n,d}(1+\lambda)+\bar{v}^{H}_{n,d}\right)l^{\frac{(1-\beta)\theta}{\beta}} - \kappa_{n,d,t}l\right] = w_{n,t} + \xi\gamma\bar{q}_t h_d^{\gamma-1} \\
[R]: \ & \alpha_r A_{n,d}\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r-1} h_d^{\alpha_h}\left[\bar{q}_t\left(v_{n,d}(1+\lambda)+\bar{v}^{H}_{n,d}\right)l^{\frac{(1-\beta)\theta}{\beta}} - \kappa_{n,d,t}l\right] = \bar{q}_t \\
[l]: \ & \frac{(1-\beta)\theta}{\beta}\bar{q}_t\left(v_{n,d}(1+\lambda)+\bar{v}^{H}_{n,d}\right)l^{\frac{(1-\beta)\theta}{\beta}-1} = \kappa_{n,d,t}
\end{aligned}$$

We can solve the optimal level of $R^{e*}_{n,d,t}$, $h^{e*}_{n,d,t}$, and $l^{e*}_{n,d,t}$ for new entrants, as well as the corresponding innovation intensity $\phi^{e*}_{n,d} = A_{n,d}\left(\frac{R^{e*}_{n,d,t}}{\bar{q}_t}\right)^{\alpha_r}\left(h^{e*}_{n,d,t}\right)^{\alpha_h}$ on the balanced growth path.

Note that land prices $\kappa_{n,d,t}$ grow at rate g, so the land demand is constant on a BGP.

Now replacing the labor demand $h^*(q_j)$ on the labor market clearing condition, we get that

for every region n,

$$\left[\frac{(1-\beta)\bar{q}_t}{w_{n,t}}\right]^{\frac{1}{\beta}} \sum_d \frac{\bar{q}_{n,d,t}}{\bar{q}_t} (l^{e*}_{n,d})^{\frac{(1-\beta)\theta}{\beta}} (M^H_{n,d} + M^L_{n,d}) + \sum_d M^H_{n,d} h^{H*}_{n,d} + \sum_d M^L_{n,d} h^{L*}_{n,d} + \sum_d M^e_{n,d} h^{e*}_{n,d} = H_n,$$

where $\bar{q}_{n,d,t}$ is the average quality of firms in region n at distance d and time t. Note that the mass of incumbent and entrant firms is also constant with balanced growth and that the average quality of firms in each region and distance must grow at the same rate as the economy.

Finally, the usual Euler equation from the workers' problem implies $r = \rho + g$.

Change of $\bar{q}_{n,d,t}$ The growth rate of average quality of firms in region n at distance d is given by:

$$\begin{aligned}\frac{\dot{\bar{q}}_{n,d,t}}{\bar{q}_{n,d,t}} &= \frac{\lambda \bar{q}_t M^H_{n,d} \phi^{H*}_{n,d} + \lambda \bar{q}_t M^L_{n,d} \phi^{L*}_{n,d} + M^e_{n,d} \phi^{e*}_{n,d} (\bar{q}_t + \lambda \bar{q}_t) - x(M^H_{n,d} + M^L_{n,d}) \bar{q}_{n,d,t}}{(M^H_{n,d} + M^L_{n,d}) \bar{q}_{n,d,t}} \\ &= \frac{\lambda M^H_{n,d} \phi^{H*}_{n,d} + \lambda M^L_{n,d} \phi^{L*}_{n,d} + M^e_{n,d} \phi^{e*}_{n,d} (1+\lambda)}{(M^H_{n,d} + M^L_{n,d})} \times \frac{\bar{q}_t}{\bar{q}_{n,d,t}} - x\end{aligned}$$

Since $\frac{\dot{\bar{q}}_{n,d,t}}{\bar{q}_{n,d,t}} = g$ on a BGP, we can solve the relative quality of each region-bin to the national total $\frac{\bar{q}_t}{\bar{q}_{n,d,t}}$.

The share of high-capacity firms in each region n at distance d equals to $\frac{(1-x-\psi) M^H_{n,d} + \phi^{e*}_{n,d} M^e_{n,d}}{(1-x) \cdot (M^H_{n,d} + M^L_{n,d}) + \phi^{e*}_{n,d} M^e_{n,d}}$

Growth rate and creative destruction. Finally, we can derive expressions for the growth rate,

$$g = \sum_{n,d} \left[M^H_{n,d} \phi^{H*}_{n,d} + M^L_{n,d} \phi^{L*}_{n,d} + M^e_{n,d} \phi^{e*}_{n,d} \right] \lambda, \tag{12}$$

and the creative destruction rate,

$$x = \sum_{n,d} M^e_{n,d} \phi^{e*}_{n,d}.$$

3.3 Calibration (Work in Progress)

We now calibrate our model to the data moments computed from the Chinese innovation and firm-level data used in our empirical analysis.

Externally Calibrated Parameters

We first set some parameters directly according to the data and the literature, as shown in Panel A of Table 2. We consider $N = 123$ regions (areas with consistent boundaries over time),[9] and each region is divided into $D = 5$ discrete bins corresponding to the ranked distance of each firm to the nearest university, $d = 1, 2, ..., 5$.

The elasticity of final goods with respect to quality, β, can be inferred from the markup of firms, which in the model corresponds to $\beta/(1-\beta)$. According to Brandt, Van Biesebroeck, Wang & Zhang (2017), the markup is 0.23 on average across the Chinese manufacturing sector in 2001-2007. This implies a $\beta = 0.19$. The importance of land in production, θ can be inferred from the land share of production costs. The relative ratio of land to labor costs is 0.14 according to Tombe & Zhu (2019). This ratio is θ in the model, implying $\theta = 0.14$. For the convexity parameter γ in the cost of hiring, we follow Acemoglu & Hawkins (2014) and assume it is a quadratic function $\gamma = 2$. We set the number of employment in each city H_n according to the total observed employment in each city, with the minimum level of employment normalized to 1. We set the number of potential entrants $M^e_{n,d}$ to be proportional to region-bin-level observed employment, with the total amount of potential entrants normalized to 1.

Internally Calibrated Parameters

We jointly estimate the remaining eight sets of parameters $\{\lambda, \zeta, \psi, \alpha_r, \alpha_h, \xi, A_{n,d}, L_{n,d}\}$ using the simulated method of moments (SMM), targeting eight sets of moments from our Chinese firm-level and land data: aggregate TFP growth; the average R&D intensity for young (aged 2–5) year and old (aged 6–10) firms relative to new entrants; the regression coefficient of

[9] We aggregate cities into areas with consistent boundaries over the 1980–2015 period, according to IMPUS International. We only keep regions with positive patent numbers in each bin.

firm sales growth with respect to R&D/sales ratio; the share of labor in the total R&D costs; the relative number of patents per worker across distance bins 1–5 vs 6–10; annual patent numbers in region-bins;[10] and the land price in each region-bin.[11]

To inform our choice of moments for the determination of parameters, we trace the dependence of certain parameters to specific moments. For instance, innovation productivity in each region-bin, denoted as $A_{n,d}$, has a direct impact on the number of patents in that region-bin, while the amount of land supply, $L_{n,d}$, influences the local land price. Given the total patent count, the innovation step size, λ, determines the overall TFP growth. In terms of firms' innovation life cycle, the transition probability (ψ) and the penalty for becoming a low-type firm (ζ) can be derived from changes in firms' innovation intensity over time. The convexity parameters of innovation returns, α_r and α_h, can be inferred from the relative benefits of innovation (compared to costs) and the share of labor costs within total innovation expenses. Lastly, a higher value for the parameter ξ indicates greater marginal hiring costs for innovation workers, which results in larger disparities in the marginal benefits of innovation between bins located closer or farther from universities.

Calibration Results

Panel B of Table 2 reports the calibrated parameters. The parameter values are reasonable compared with the literature. For instance, our findings show that, in each period, high-capacity firms have a 10% probability of transitioning to a low-capacity firm. The combined elasticities of successful innovation with respect to innovation costs (including both labor and material costs) are $\alpha_r + \alpha_h = 0.36$, which is close to the 0.5 typically cited in the literature (see Acemoglu et al. (2018) for a review). Additionally, we observe that $A_{n,d}$ tends to be higher for bins located closer to the university, suggesting greater innovation efficiency among firms situated nearer to it.

[10] In our model, the total number of patents plays a key role in determining the speed of creative destruction. Since we normalize the total measure of product lines to one in the model, we also normalize the data on the annual number of patents so that the rate of creative destruction aligns with 0.10, which is consistent with the observed firm exit rates in our data.

[11] Using the land transaction data for each city, we first calculate the elasticity of land price per unit of area with respect to distance from the university. Next, for each city, using this elasticity and the average distance of each bin to the university, derived from our firm data, we compute the land price for each bin relative to the bin closest to the university. Finally, we match the average land price in each city to the data (adjusted for time effects).

Table 2: Parameter Values

Parameters	Definition	Value	Source/Targeted Moment
	Panel A: Externally Calibrated Parameters		
N	Number of regions	123	Data
d	Number of bins	10	Data
β	Elasticity of final goods with respect to quality	0.19	Data
θ	Relative share of land costs to labor costs	0.14	Data
γ	Convexity parameter in hiring costs	2	Acemoglu & Hawkins (2014)
H_n	City-level employment	44.3 (78.4)	Data
$M^e_{n,d}$	Number of potential entrants	1.6e-3 (2.9e-3)	Data
	Panel B: Internally Calibrated Parameters		
λ	Innovation step size	0.20	Joint estimation
ζ	Decrease in innovation possibility	0.43	
ψ	Transition rate from high to low type	0.48	
α_r	Elasticity of successful innovation regarding R&D expenditure	0.19	
α_h	Elasticity of successful innovation regarding R&D worker	0.17	
ξ	Constant in search costs for worker	0.19	
$A_{n,d}$	Innovation productivity	0.02 (0.02)	
$L_{n,d}$	Amount of land area	0.69 (1.06)	

The calibrated model also aligns well with some non-targeted moments. For example, our main findings show that patents per R&D worker decline as the distance to the university increases, whereas patents per R&D expense show no clear trend with distance. Additionally, new firms exhibit higher efficiency in utilizing R&D labor compared to incumbents. Figure 6 displays the model-generated trends of patents per worker and patents per R&D investment, along with comparisons between incumbents and new firms, which are consistent with our basic facts.

Table 3: Data Moments and Targeted Moments

Moment	Data	Model
Aggregate TFP growth	0.03	0.03
Relative ratio of average R&D intensity (age 2-5 rel. to 1)	0.61	0.61
Relative ratio of average R&D intensity (age 6-10 rel. to 1)	0.53	0.54
Coefficient of firm sales growth on R&D/sales ratio	2.00	2.05
Share of labor in total R&D costs	0.35	0.35
Relative ratio of num of patents per worker (bin 1-2 v.s. 3-10)	1.32	1.32
Relative patent numbers across region-bins	2.1e-4 (8.0e-4)	2.0e-4 (7.7e-4)
Land price in each region-bin	1.09 (0.45)	1.09 (0.45)

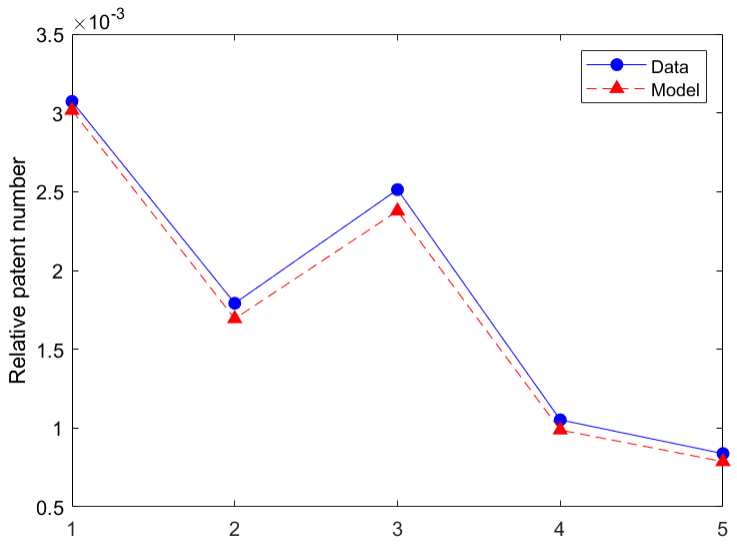
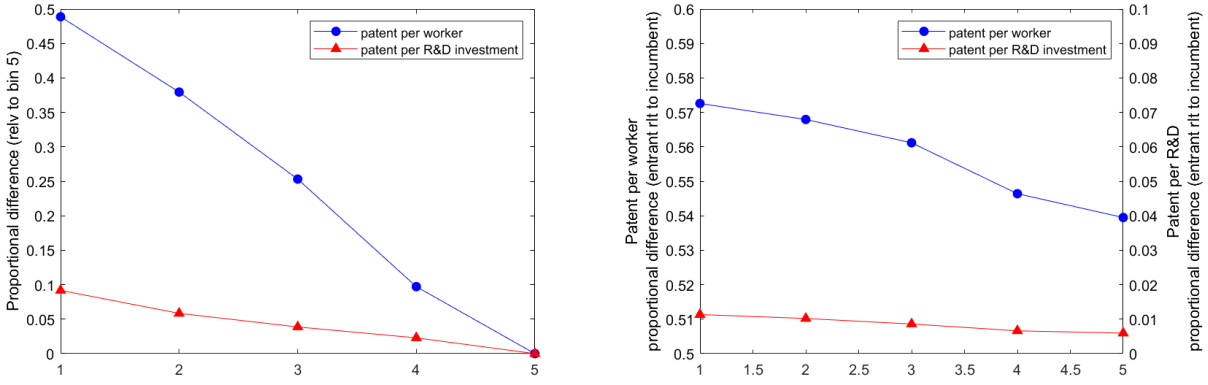


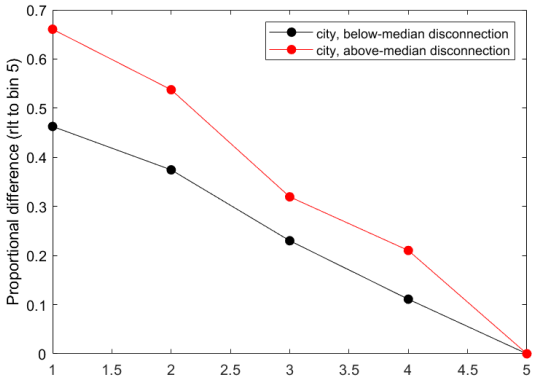
Figure 5: Distance to University and Relative Patents Numbers: Data and Model



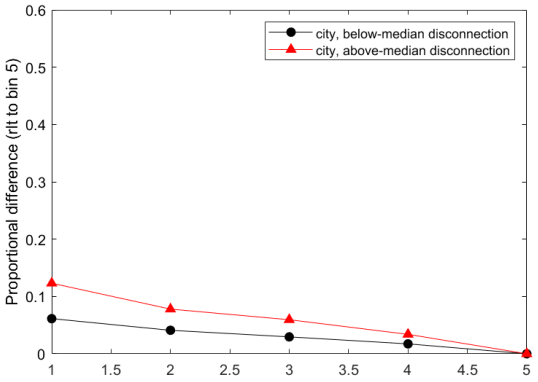
(a) Distance to University and Innovation Outcomes

(b) Distance to University and Innovation Outcomes, New Firms Relative to Incumbents

Figure 6: Distance to University and Innovation Outcomes



(a) Number of Patents per R&D Worker



(b) Number of Patents per R&D Expense

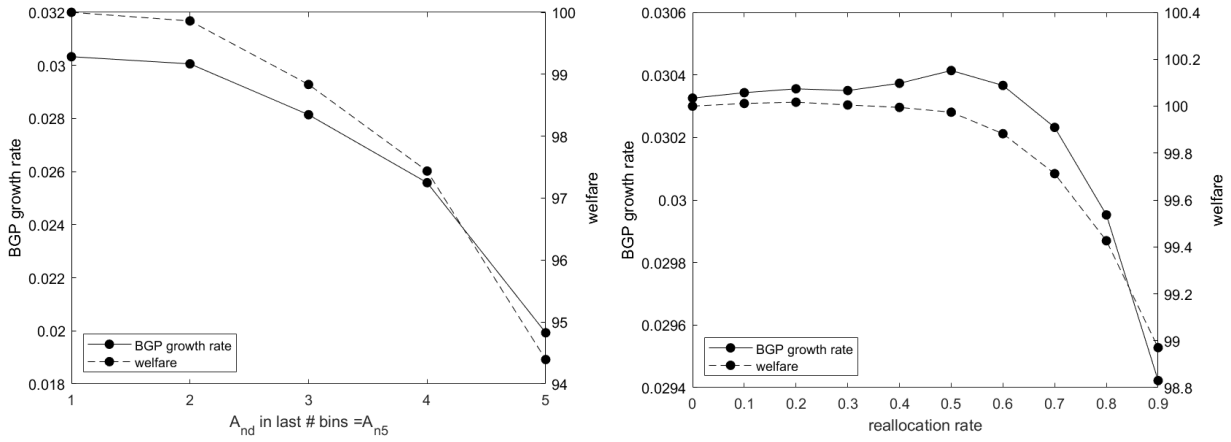
Figure 7: Distance to University and Innovation Outcomes

4 Counterfactual Exercises

Knowledge spillovers from universities and land constraints play important roles in the economy. Therefore, we conduct two counterfactual exercises. First, we examine how reduced knowledge spillovers affect aggregate growth and welfare. Second, we analyze the impact of relaxing land constraints.

To illustrate the impact of reduced knowledge spillovers, we gradually set the A_{nd} in the last # bins equal to A_{n5} in each city n. Panel (a) in Figure 9 indicates that if knowledge diffusion from universities in each bin of each city decreases to the level observed in the last bin, the BGP growth rate will drop from 3% to 2% and the welfare will decrease by 5.5%.

Panel (b) in Figure 9 depicts the impact of land reallocation. We gradually reallocate 10%, 20%, , 90% of the land in bin d to bin $d-1$, and when the reallocation rate equals 0.9, it means almost all the land has been reallocated to the first bin. The results show that initially, with more land reallocation, the bins closer to the university experience a slight increase in both BGP growth rate and welfare. However, as more firms enter the first bin, the increase in R&D leads to reduced consumption, which decreases welfare.



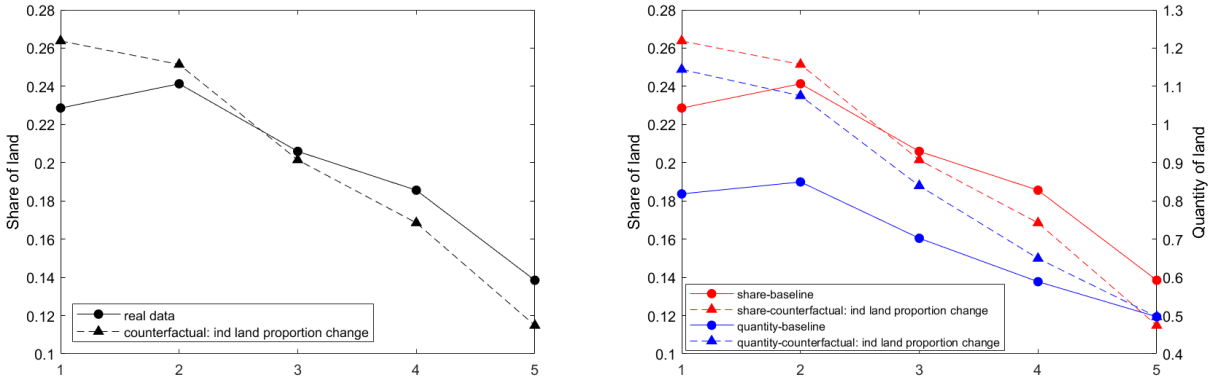
(a) Reduced Knowledge Diffusion (b) Reallocation of land

Figure 8: Counterfactual Exercise

Additional Counterfactual Policies: Work in Progress

1. Policies

    - Industrial land policy: what happens if we change the proportion of land allocated to firms? Fixed amount of land, but could change the proportion across bins



(a) Proportion change with constant total land supply

(b) Proportion change with land supply increment

Figure 9: Industrial Land Policy

(a) The BGP growth rate increases from 3.03% to 3.04%, and the welfare increases by 0.03%

(b) The BGP growth rate increases from 3.03% to 3.04%, and the welfare increases by 0.15%

    - University funding from the government: What is the best funding model among cities? How does it affect inequality and concentration? What benefits can we see in terms of welfare and growth?

2. Spatial misallocation

    - Extend the model to include migration frictions that can explain differences in the supply of labor across regions. What is the optimal supply of labor if no frictions are present and taking productivity of cities and bins as given?

5 Conclusion

Universities play a crucial role in diffusing knowledge and fostering innovation. In this paper, we show that firms located near universities innovate more efficiently, new firms outperform incumbents in R&D, and firm locations remain stable over time. Proximity to knowledge hubs enhances innovation efficiency by stimulating the diffusion of knowledge, leading to higher productivity in firms closer to universities. Our model also accounts for the dynamic reallocation of land for innovation, where less innovative incumbents occupy valuable land that is only freed up upon their exit, but new entrants do not inherit these prime locations, contributing to spatial misallocation.

Through our quantitative model, we highlight the importance of both the innovation efficiency premium associated with proximity to universities and the land allocation process in shaping economic outcomes. Calibration using Chinese firms and land data reveals that these factors significantly influence economic growth and welfare, emphasizing the inefficiencies caused by spatial misallocation. Additionally, our findings suggest that policies aimed at improving land allocation and knowledge diffusion could enhance innovation and reduce regional disparities. Our work underscores the importance of considering firm location choices in innovation policy and the design of regional development strategies.

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Appendix to "Universities, Firm Location and Growth"

A Additional Empirical Results

A.1 Standardizing Firm Names

In this paper, we merge patent data, registration data, and firm financial data using firm names. To ensure accurate name matching, we implement a name matching method that involves standardizing firms' names, which is similar to the method employed in **?**. The specific steps for standardization are as follows:[12]

- Step 1: We standardize the firm's name by making the following adjustments: (1) we replace "gu fen you xian gong zi" and "you xian ze ren gong si" with "you xian gong si" in the firm's name; (2) we replace "chang you xian gong si" and "chang qi ye" with "chang" in the firm's name; and (3) we remove terms such as "dai qing li," "ge zhuan qi," "si ying zhuan he huo," and similar terms from the firm's name.
- Step 2: We convert all uppercase letters to lowercase and transform full-width characters into half-width characters.
- Step 3: We remove various special symbols from the data, such as "*", "¿", etc.

A.2 Evidence on Implications

We follow Harari (2020) to measure the shape of cities using the disconnection index. The index is commonly in the urban planning literature and defined as the average Euclidean distance, in kilometers, between any two points within a polygon, as illustrated in Figure A.1. For a given footprint area, higher values of the disconnection index are associated with larger distances between points in the city and a less compact shape. Harari (2020) find that

[12]We thank Dr. Xin Wang from Tsinghua for generously providing us with standardization codes.

firms located in non-compact cities tend to cluster in few employment subcenters, which indicates larger land constraints for these non-compact cities.

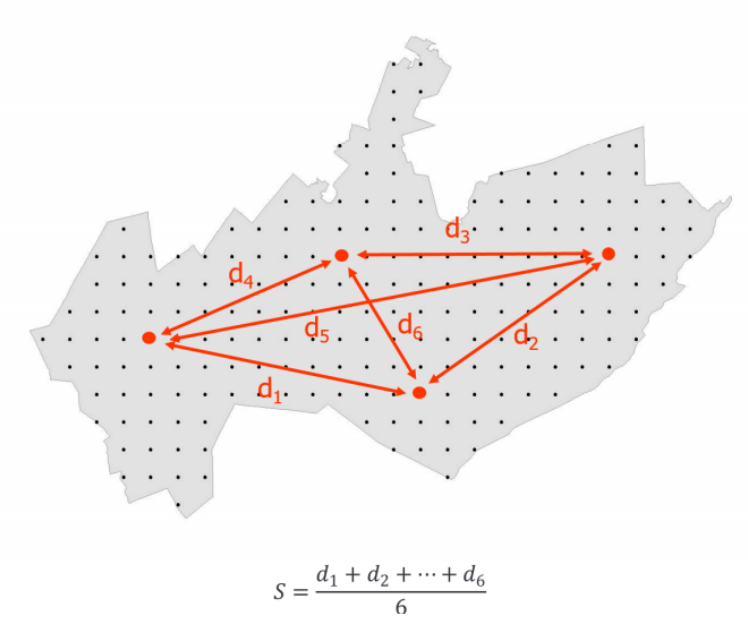


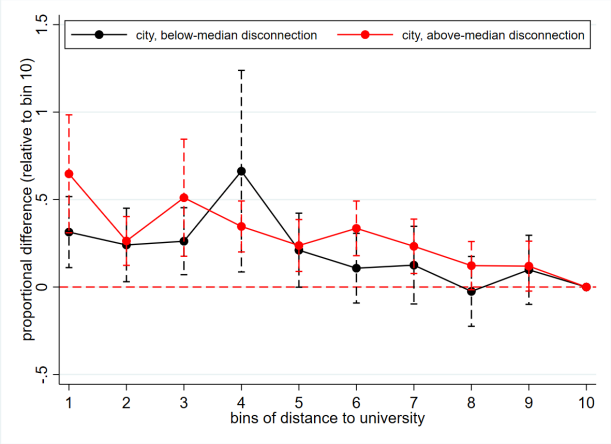
Figure A.1: An Example of Disconnection Index, from Angel, Civco, and Parent (2009)

We compute this index for all Chinese cities with available data. In particular, given that land area may matter for computing the index (bigger cities tend to have larger average distances between two points), we compute the normalized index, which is invariant to the area of the polygon.[13] We then perform regression (1) separately for firms in cities with above-median disconnection index among all cities and for firms in cities with below-median disconnection index.

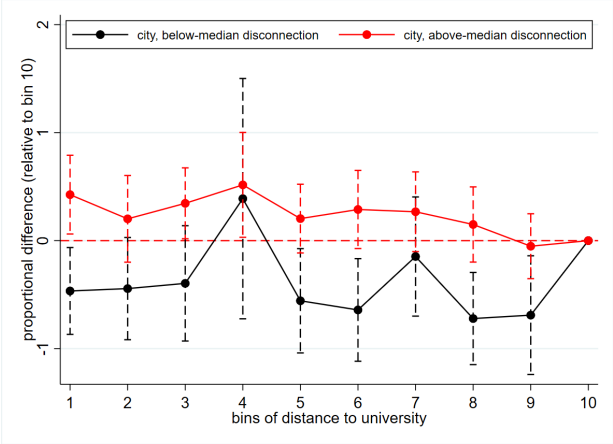
Figures A.2a and A.2b show the results. Consistent with the model predictions, we find that in cities with larger land constraints, the decline in innovations per R&D worker or R&D expense tends to be stronger.

A.3 Additional Tables and Figures

[13]The normalized index is computed by dividing the index by the radius of a circle with an area equal to that of the polygon.



(a) Number of Patents per R&D Worker



(b) Number of Patents per R&D Expense

Figure A.2: Distance to University and Innovation Outcomes

Notes: The dotted line represents 95% confidence intervals, with robust standard errors.

Table A.1: Summary Statistics

Variables	Obs	Mean	Std Dev
Innovation Outcomes			
Patent applications	293,976	0.87	22.04
Patents per R&D worker	293,976	0.014	0.320
Patents per R&D cost	293,972	0.00017	0.00493
Patents per R&D cost (excl. personnel)	293,972	0.00036	0.01285
R&D Personnel Composition			
Share of undergraduates	186,933	0.568	0.281
Share of masters	186,933	0.086	0.128
Share of PhDs	186,933	0.025	0.069
Firm Characteristics			
Log(firm sales)	270,350	11.79	1.46
Distance to closest university (km)	282,874	8.97	13.58

B Theory

B.1 Proofs

Market Equilibrium

Proposition. *If $\alpha_r(1+\theta(1-\beta)) \leq 1$, the exists a unique BGP equilibrium where the equilibrium creative destruction x^* solves,*

$$x^{*(1-\alpha_r\theta(1-\beta))}\left(\frac{\rho + x^*(1+\lambda)}{\beta(1+\lambda)x^*}\right)^{\alpha_r} = A\left(\alpha_r H^{1-\beta}L^{\theta(1-\beta)}\right)^{\alpha_r}$$

Proof. Suppose entrants only use R&D resources,

$$\max_{l,R} A\left(\frac{R}{\bar{q}}\right)^{\alpha_r} v\bar{q}(1+\lambda)l^{\alpha_l} - R - \kappa l,$$

The FOCs are,

$$[l]: \ \alpha_l\phi v\bar{q}(1+\lambda)l^{\alpha_l} = \kappa l$$
$$[R]: \ \alpha_r\phi v\bar{q}(1+\lambda)l^{\alpha_l} = R.$$

From the second condition,

$$\phi = A\left(\alpha_r\phi v(1+\lambda)l^{\alpha_l}\right)^{\alpha_r}.$$

Recall,

$$v = \frac{\pi}{r+x} = \frac{\pi}{\rho+g+x} = \frac{\pi}{\rho+\phi(1+\lambda)},$$

with $\pi = \beta(1-\beta)^{\frac{1-\beta}{\beta}}\left(\frac{w}{\bar{q}}\right)^{\frac{\beta-1}{\beta}}$. From the intermediate good production, the demand for labor is,

$$u = \left(\frac{(1-\beta)\bar{q}}{w}\right)^{1/\beta} l^{\alpha_l}$$

We can solve for $\frac{w}{\bar{q}}$ using the labor market condition,

$$u = \left(\frac{(1-\beta)\bar{q}}{w}\right)^{1/\beta} l^{\alpha_l} = H \implies \frac{w}{\bar{q}} = (1-\beta) l^{\alpha_l \beta} H^{-\beta}$$

Replacing in the marginal value equation,

$$v = \frac{\pi}{\rho + \phi(1+\lambda)} = \frac{\beta H^{1-\beta} l^{-\alpha_l(1-\beta)}}{\rho + \phi(1+\lambda)}$$

Replacing in the FOC for R,

$$\phi = A\left(\alpha_r(1+\lambda)\beta H^{1-\beta} l^{\alpha_l \beta} \frac{\phi}{\rho + \phi(1+\lambda)}\right)^{\alpha_r}$$

Using the land market clearing condition, $l = \phi L$,

$$\phi = A\left(\alpha_r(1+\lambda)\beta H^{1-\beta} (\phi L)^{\alpha_l \beta} \frac{\phi}{\rho + \phi(1+\lambda)}\right)^{\alpha_r}$$

Rearranging,

$$\phi^{1-\alpha_r(1+\theta(1-\beta))} \left(\rho + \phi(1+\lambda)\right)^{\alpha_r} = A\left(\alpha_r(1+\lambda)\beta H^{1-\beta} L^{\theta(1-\beta)}\right)^{\alpha_r}$$

Since $x^* = \phi$, we obtain the equation of the proposition. This equation has a unique solution as the RHS is equal to zero when $x^* = 0$, and is increasing in x when $\alpha_r(1+\theta(1-\beta)) \leq 1$, while the LHS is constant in x^* and positive.

□

Planner's problem

Proposition. *If $\alpha_r(1+\theta(1-\beta)) \leq 1$, there exists a unique solution to the planner's problem with creative destruction x^s solves,*

$$(x^s)^{1-\alpha_r\theta(1-\beta)} \left(\frac{(1-\beta)\left(\rho + \alpha_r \lambda x^s\right)}{\theta(1-\beta)\rho + \lambda x^s}\right)^{\alpha_r} = A\left(\alpha_r H^{1-\beta} L^{(1-\beta)\theta}\right)^{\alpha_r}$$

Proof. The simplified the Planners' problem is,

$$\begin{aligned}
&\max_{l,u_j,R} \frac{\phi(R)\lambda}{\rho} + \log C_0 \\
&\quad s.t.\ C_0 = Y_0 - R\ ,\quad Y_0 = \frac{1}{1-\beta}\int q_j^{\beta}\bar{q}_0^{1-\beta}u_j^{1-\beta}l^{(1-\beta)\theta}dj \\
&\quad \int u_j dj = H\ ,\quad l = \phi(R)L,
\end{aligned}$$

The optimality conditions are,

$$\begin{aligned}
[R]:&\ \ \alpha_r\phi\left(\frac{\lambda}{\rho} + \mu_l L\right) = \frac{R}{C_0} \\
[l]:&\ \ \frac{1}{C_0}\theta q_j^{\beta}\bar{q}^{(1-\beta)}u_j^{1-\beta}l^{(1-\beta)\theta}dj = \mu_l l \\
[u_j]:&\ \ \frac{1}{C_0}q_j^{\beta}\bar{q}^{1-\beta}u_j^{1-\beta}l^{(1-\beta)\theta} = \mu_h u_j
\end{aligned}$$

Integrating the last condition we get,

$$Y_0 = \frac{1}{1-\beta}u^{1-\beta}\bar{q}_0 l^{(1-\beta)\theta}.$$

From the land FOC and the market clearing condition, $l = \phi L$,

$$\mu_l L = \frac{\theta(1-\beta)Y_0}{\phi C_0}.$$

Replacing in R FOC,

$$R = \alpha_r\phi\left(\frac{\lambda}{\rho}C_0 + \frac{\theta(1-\beta)Y_0}{\phi}\right)$$

Using the resource constraint, $C = Y_0 - R$ and solving for R,

$$R = \frac{\alpha_r\left(\frac{\lambda\phi}{\rho} + \theta(1-\beta)\right)}{\left(1 + \frac{\alpha_r\phi\lambda}{\rho}\right)}Y_0$$

Replacing Y_0 and using the labor market clearing condition $u = H$,

$$R = \frac{\alpha_r \left(\lambda\phi + \rho\theta(1-\beta)\right)}{\left(\rho + \alpha_r\phi\lambda\right)} \frac{1}{1-\beta} H^{1-\beta} \bar{q}_0 \left(\phi L\right)^{(1-\beta)\theta}$$

Replacing the innovation production function,

$$\phi = A\left(\frac{R}{\bar{q}_0}\right)^{\alpha_r} = A\left[\frac{\alpha_r \left(\lambda\phi + \rho\theta(1-\beta)\right)}{\left(\rho + \alpha_r\phi\lambda\right)} \frac{1}{1-\beta} H^{1-\beta} \left(\phi L\right)^{(1-\beta)\theta}\right]^{\alpha_r}$$

Reorganizing some terms,

$$\phi^{1-\alpha_r\theta(1-\beta)} \left(\frac{\rho + \alpha_r\lambda\phi}{\theta(1-\beta)\rho + \lambda\phi}\right)^{\alpha_r} (1-\beta)^{\alpha_r} = A\left(\alpha_r H^{1-\beta} L^{(1-\beta)\theta}\right)^{\alpha_r}$$

Since $x^s = \phi$, we obtain the equation of the proposition. This equation has a unique solution as the RHS is equal to zero when $x^s = 0$, and is increasing in x when $\alpha_r(1 + \theta(1-\beta)) \leq 1$, while the LHS is constant in x^s and positive. □

Optimal Creative Destruction

Proposition. *If $\alpha_r(1 + \theta(1-\beta)) \leq 1$ and $x^s > x^* > 0$, $\frac{x^s}{x^*}$ is increasing in θ.*

Proof. From Proposition 1 and 2 we can compute the ratio $\frac{x^s}{x^*}$,

$$\frac{x^s}{x^*} = \left(\frac{(\theta(1-\beta)\rho + \lambda x^s)(\rho + x^*(1+\lambda))}{(1-\beta)\left(\rho + \alpha_r\lambda x^s\right)\beta(1+\lambda)x^*}\right)^{\frac{\alpha_r}{1-\alpha_r\theta(1-\beta)}} := G(\theta)^{\frac{\alpha_r}{1-\alpha_r\theta(1-\beta)}}$$

Taking the derivative with respect to θ,

$$\frac{\partial \frac{x^s}{x^*}}{\partial\theta} = G(\theta)^{\left(\frac{\alpha_r}{1-\alpha_r\theta(1-\beta)} - 1\right)} \ln G(\theta) \frac{\alpha_r\alpha_r(1-\beta)}{(1-\alpha_r\theta(1-\beta))^2}.$$

Since $x^s > x^*$, then, $G(\theta) > 1$ as $\frac{\alpha_r}{1-\alpha_r\theta(1-\beta)} > 0$. So $\ln G(\theta) > 0$. Together this implies $\frac{\partial \frac{x^s}{x^*}}{\partial\theta} > 0$.

□

B.2 Extensions Simple Model

B.2.1 Adding labor to Innovation Production

Entrant Innovation. Suppose, the same simple Schumpeterian models are described above, but entrants also choose R&D the labor h to solve,

$$\max_{l,R,h} \phi_t(R,h)\mathbb{E}[V_t(q_j(1+\lambda))] - w_t h - R - \kappa_t l,$$

where $\phi_t(R,h)$ denotes the innovation production function that combines the R&D resources and labor and determines the arrival rate of innovations.

The FOCs are,

$$\begin{aligned}
[l]: \ & \phi_t(R,h)\frac{\partial \mathbb{E}[V_t]}{\partial l} = \kappa_t, \\
[R]: \ & \frac{\partial \phi_t(R,h)}{\partial R}\mathbb{E}[V_t] = 1; \\
[h]: \ & \frac{\partial \phi_t(R,h)}{\partial h}\mathbb{E}[V_t] = w_t.
\end{aligned} \tag{B.13}$$

Let l_t^*, R_t^*, and h_t^* denote the solution to these equations. Note these quantities are not indexed by the varieties as innovation from entrant firms is undirected. Let ϕ_t^* denote the corresponding arrival rate of innovations.

Creative destruction equals the expected aggregate innovation by entrant firms,

$$x_t = \int_0^1 \phi_t^* dj = \phi_t^*. \tag{B.14}$$

Equilibrium. The equilibrium is defined as a set of allocations $\{k_{j,t}^*, u_{j,t}^*, h_t^*, R_t^*, l_t^*, c_t^*\}$, prices $\{p_{j,t}, w_t, r_t, \kappa_t\}$ and the value function $V_t(q)$ such that

1. Final good producers choose $k_{j,t}^*$ to maximize profits taking prices $p_{j,t}$ as given.
2. Intermediate good producers choose effective units of labor $u_{j,t}^*$ to maximize profits of producing the intermediate variety taking wages w_t as given.

3. Entrant firms choose R&D labor h_t^*, R&D resources R_t^* and land l_t^* to maximize the expected value of innovating taking as given w_t and κ_t.

4. The value function of incumbent firms satisfies the HJB equation (7).

5. Workers choose consumption c_t^* to maximize their utility.

6. Land market, labor market, and goods markets clear.

To further characterize the solution, we focus on the equilibrium on a balanced growth path (BGP).

Balanced Growth. Suppose aggregate quality grows at a constant rate $\frac{\dot{\bar{q}}_t}{\bar{q}_t} = g$. To illustrate the results, we assume a Cobb-Douglas innovation production function.[14]

$$\phi(R,h) = A\left(\frac{R}{\bar{q}_t}\right)^{\alpha_r} h^{\alpha_h},$$

with $A > 0$ denoting the innovation productivity, $\alpha_h, \alpha_r \in (0,1)$ and $\alpha_h + \alpha_r < 1$. Later in the full model, innovation productivity A varies across locations, capturing the effect of proximity to universities. For now, let's characterize the stationary equilibrium in this simplified model to study how adding endogenous land supply affects the equilibrium and optimal innovation decisions.

On a BGP land l^*, labor allocations u_j^* and h^*, and the interest rate r^* are constant over time. Wages w_t^*, the price of land κ_t^*, consumption c_t^*, resources R_t^* and aggregate output Y_t^* grow at the same rate g.

The value function is stationary, $\dot{V}_t = 0$, and satisfies,

$$V(q) = \frac{\pi^*}{r^* + x^*} q l^{\alpha_l} =: v q l^{\alpha_l},$$

where the marginal profit $\pi^* = \beta(1-\beta)^{\frac{1-\beta}{\beta}} \left(\frac{\bar{q}_t^*}{w_t^*}\right)^{\frac{1-\beta}{\beta}}$ and the creative destruction rate x^* are constant.

[14] The same characterization is achieved if we assume that the innovation production function satisfies, ϕ_t and $\frac{\partial \phi_t}{\partial h}$ are constant and $\left(\frac{\partial \phi}{\partial R}\right)^{-1}$ grows at a constant rate g.

In Proposition 4, we show a sufficient condition for the existence of a unique BGP equilibrium and characterize the equilibrium creative destruction $x^* = \phi(h^*, R^*)$ on a BGP.

Proposition 4. *If $\alpha_r + \alpha_h + \alpha_l \leq 1$, the exists a unique BGP equilibrium where the equilibrium creative destruction x^* solves,*

$$\left(\mathcal{I}_0 + \mathcal{I}_1 \frac{x^*}{\rho + x^*(1+\lambda)}\right) x^{* \frac{(1+\alpha_l)(1-\alpha_r-\alpha_h)}{\beta}} \left(\rho + x^*(1+\lambda)\right)^{\frac{\alpha_r+\alpha_h}{\beta}} = \mathcal{I}_2,$$

where $\mathcal{I}_0 = (1-\beta)^{1/\beta}$, $\mathcal{I}_1 = \alpha_h \beta (1-\beta)^{\frac{1-\beta}{\beta}}$ *and* $\mathcal{I}_2 = H\left(A \alpha_r^{\alpha_r} \alpha_h^{\alpha_h} \left(\beta(1-\beta)^{\frac{1-\beta}{\beta}}\right)^{(\alpha_r+\alpha_h)} L^{\alpha_l(\alpha_r+\alpha_h-\beta)}\right)^{1/\beta}$.

Consider a social planner that maximizes the utility of workers taking as given the resource and technological constraints in the economy,

$$\begin{aligned}
&\max_{h_t, u_{jt}, R_t, l_t} \int_0^\infty e^{-\rho t} \log C_t dt \\
&\quad s.t.\ Y_t = C_t + R_t \ , \quad Y_t = \frac{1}{1-\beta} \int q_j^\beta \bar{q}_t^{1-\beta} u_{jt}^{1-\beta} l_t^{(1-\beta)\theta} dj \\
&\quad h_t + \int u_{jt} dj = H \ , \quad \frac{\dot{\bar{q}}_t}{\bar{q}_t} = \phi(R_t, h_t)\lambda \ , \quad l_t = \phi(R_t, h_t) L.
\end{aligned}$$

We can simplify the Planners' problem to,

$$\begin{aligned}
&\max_{l, h, u_j, R} \int_0^\infty e^{-\rho t} \log\left(C_0 e^{gt}\right) dt \equiv \max_{l, h, u_j, R} \frac{\phi(R,h)\lambda}{\rho} + \log C_0 \\
&\quad s.t.\ C_0 = Y_0 - R \ , \quad Y_0 = \frac{1}{1-\beta} \int q_j^\beta \bar{q}_0^{1-\beta} u_j^{1-\beta} l^{(1-\beta)\theta} dj \\
&\quad h + \int u_j dj = H \ , \quad l = \phi(R,h) L,
\end{aligned}$$

and solve it using the usual Lagrangian approach,

$$\mathcal{L} = \frac{\phi(R,h)\lambda}{\rho} + \log C_0 + \mu_h \left(H - h - \int u_j dj\right) + \mu_l (\phi(R,h)L - l)$$

The optimality conditions are,

$$
\begin{aligned}
[h]: &\quad \alpha_h \phi \left(\frac{\lambda}{\rho} + \mu_l L \right) = \mu_h h \\
[u_j]: &\quad \frac{1}{C_0} q_j^{\beta} \bar{q}^{1-\beta} u_j^{-\beta} l^{(1-\beta)\theta} = \mu_h \\
[R]: &\quad \alpha_r \phi \left(\frac{\lambda}{\rho} + \mu_l L \right) = \frac{R}{C_0} \\
[l]: &\quad \frac{1}{C_0} \theta \int q_j^{\beta} \bar{q}^{(1-\beta)} u_j^{1-\beta} l^{(1-\beta)\theta} dj = \mu_l l
\end{aligned}
$$

Combining these equations and using the resource and technological constraints,

$$
\alpha_h \phi \left(\frac{\lambda}{\rho} C_0 + \frac{(1-\beta)\theta Y_0}{\phi} \right) = \frac{(1-\beta) Y_0 h}{u}
$$