Attracting Stars, Enhancing Ventures: Policy Induced Talent Inflows and Entrepreneurship Quality

Yifan Zheng Sifan Zhou Dongbo Shi Sen Chai *

Abstract: While human capital has long been recognized as a critical input to innovation and entrepreneurship, it remains unclear whether efforts by emerging economies to attract elite talent from developed economies and across domestic regions can generate meaningful benefits and, more importantly, under what local conditions such relocation translates into entrepreneurial upgrading. Exploiting the staggered introduction of local talent policies across Chinese cities as a quasi-natural experiment, we apply a difference-in-differences framework to rich administrative data. We find that these policies increase overseas and domestic inflow of star inventors by 16.7% and 23.0% respectively, and improve aggregate entrepreneurship quality by 9% without significantly affecting the startup formation rate. The realized number of high-growth startups increases by 14.7%, and the number of patent-active startups increases by 6.4%. Robust event-study analyses reveal that impacts grow steadily over time. Policy-induced talent inflows translate into better entrepreneurial outcomes when incoming talent can be matched to relevant opportunity spaces and absorbed by local domains of relative specialization. Their effectiveness also depends on local knowledge capabilities anchored in university-based research and strengthened through science–industry linkages.

Keywords: Entrepreneurship Quality; Migration; Talent Policies; Innovation.

*Zheng: School of Economics, Peking University (Email: yifanzheng.econ@gmail.com); Zhou: Faculty of Business in Scitech, School of Management, University of Science and Technology of China, Corresponding author (Email: zhousifan@gmail.com); Shi: The Digital Economy Lab, Beijing Institute of Mathematical Sciences and Applications; Shanghai Research Center for Innovation and Policy Evaluation, Shanghai Jiao Tong University (Email: shidongbo@bimsa.cn); Chai: Desautels Faculty of Management, McGill University (Email: sen.chai@mcgill.ca). Sifan Zhou acknowledges the support from the Youth Grant for Arts and Social Sciences of China's Ministry of Education (Grant No. 3YJC790208). Yifan Zheng acknowledges the support from the National Natural Science Foundation of China (Grant No.72473003). Dongbo Shi acknowledges the support from the National Natural Science Foundation of China (Grant No.72374140).

1 Introduction

The mobility of highly skilled individuals is shaped by economic, legal, and institutional environments that either facilitate or constrain movement across borders (Acosta & Marinoni, 2025; Agarwal et al., 2022; Kahn & MacGarvie, 2020; Koo & Eesley, 2025), including tax incentives (Akcigit et al., 2016; Kleven et al., 2013), legal frameworks (Marx et al., 2009; Starr et al., 2019), and other institutional structures (Armanios et al., 2017; Eesley, 2016; Tian & Xu, 2022). The relocation of elite talent generated by these environments has been shown to contribute to innovative (Borjas & Doran, 2012; Foley & Kerr, 2013; Ganguli, 2015; Kerr & Kerr, 2020; Kerr, 2020; Moser et al., 2014) and entrepreneurial (Chodavadia et al., 2025; Kerr & Kerr, 2020; Kerr & Kerr, 2016) gains in destination countries. However, this literature has mainly focused on cross-border brain drain from developing to developed economies, or on talent circulation within advanced economies. An open question, therefore, is whether emerging economies can actively attract elite talent from abroad as well as from other domestic locations and, more importantly, under what conditions such relocation translate into meaningful economic gains in entrepreneurial dynamism and quality.

Answering this research question is critical given the role of entrepreneurship in driving innovation, job creation, and long-term productivity growth (Decker et al., 2014; Kortum & Lerner, 2000; Schumpeter, 1942). Yet whether elite individuals are willing to relocate, and whether their relocation ultimately yields entrepreneurial gains, remains far from clear. Countries and regions that resort to talent-attraction policies are often precisely those that lack the luster to attract elite individuals in the first place. For instance, Grogger and Hanson (2015) find that foreign students from

less economically developed and less democratized countries are more likely to remain in the United States after completing their studies. Moreover, while human capital, such as experienced entrepreneurial talent (Azoulay et al., 2020; Lafontaine & Shaw, 2016), highly skilled technical workers and engineers (Almeida & Kogut, 1999; Saxenian, 1996), and academic scientists (Feldman, 2000; Zucker et al., 1998), is a strategic input in the emergence of technological clusters and hubs, prior research suggests that the value of such talent depends on complementary local conditions (Xia et al., 2025). Simply bringing elite talent into a location may not automatically generate local entrepreneurial or innovation gains.

To address whether talent policies attract elite individuals and how these inflows translate into entrepreneurial gains, we exploit a series of city-level talent policies in China, providing new evidence on the complementary conditions and institutional mechanisms linking skilled migration and entrepreneurship quality. Since the early 2000s, many Chinese cities have introduced tiered talent policies that offer preferential treatment, financial support, and institutional facilitation to highly skilled individuals, particularly scientists and engineers with demonstrable achievements. We supplement this policy data with Chinese business registration records, venture capital (VC) deals, initial public offerings (IPO), and patent data to create measures of local entrepreneurial activity as well as to track the mobility of star inventors from other cities and from overseas.

We employ a staggered difference-in-differences (DID) design. Our two-way fixed effects estimates show that implementing local talent policies leads to a 23% increase in domestic star inventor inflows and a 16.7% increase in overseas star inventor inflows. The startup formation rate is not significantly affected despite such surge in the local

pool of human capital. Yet aggregate entrepreneurship quality, a measure that captures startups' growth potential at inception following Andrews et al. (2022), increases by 9%. The realized number of high-growth startups rises by 14.7%, and the number of patent-active startups by 6.4%. Event study and modern staggered DID estimators yield a consistent pattern, with effects increasing over time. The entrepreneurial upgrading that we observe is also especially pronounced in human-capital-intensive industries and high-technology (high-tech) sectors.

These migratory and entrepreneurial effects are not uniformly distributed across high-tech industries or across cities. Rather, we show that the gains hinge on local industrial capabilities and knowledge infrastructure. The inflow of highly skilled talent improves entrepreneurship quality only when they can be matched to industries in which the city holds a relative specialization. Industries that are technologically related to these advantaged domains also receive talent inflows and experience increases in early-stage innovative activities, but these gains do not translate into improvements in aggregate entrepreneurship quality or realized high-growth entrepreneurship. A similar pattern emerges across cities. Benefits arise primarily in cities that host top-tier universities. While talent inflows stimulate university-based knowledge production more broadly, only translational knowledge linking universities to firms plays a decisive role in driving realized entrepreneurial success. Moreover, overseas star inventor inflows appear to contribute disproportionately to this science-to-market translation.

This paper contributes to the literature on global talent flow and entrepreneurship by examining how mobility shapes innovation and firm-level outcomes (Hernandez et al., 2025; Xia et al., 2025). While advanced economies have long benefited from inflows of highly educated STEM talent from emerging countries (Belderbos et

al., 2025; Uhlbach & Anckaert, 2025), many former talent-sending economies have recently sought to reposition themselves within the global brain circulation by attracting returnees and overseas-trained individuals into local innovation ecosystems (Shi et al., 2023). Focusing on city-level talent policies in China, we analyze how these initiatives influence domestic and international elite talent inflows and how such inflows affect startups' growth potential and innovative activity, shedding light on the microfoundations of economic and technological upgrading (Song et al., 2011). The paper also contributes to research on entrepreneurship quality by moving beyond startup formation to examine how access to highly skilled human capital shapes firms' growth trajectories, innovative capacity, and likelihood of becoming high-impact ventures. It addresses longstanding concerns about the limited scalability of most startups and the mixed effectiveness of broad-based entrepreneurship support (Akcigit et al., 2025; Decker et al., 2014; Lerner, 2009; Shane, 2009). Our study examines the impact of elite human capital on the growth and innovative potential of new firms, as well as the conditions under which such effects materialize, by exploiting local talent policies as an institutional lever.

2 Theoretical Considerations

2.1 Migration, Mobility and Entrepreneurial Quality

Scholars have widely adopted the human capital theoretical lens as a foundational input to entrepreneurship. Highly skilled technical workers and engineers, especially inventors holding patents, are key human capital input commonly associated with enhanced entrepreneurship, as their accumulated knowledge is an important asset for inventiveness (Almeida & Kogut, 1999; Balsmeier et al., 2025; Saxenian, 1996). Aca-

demic researchers, even those making basic scientific discoveries (Jensen & Thursby, 2001; Zucker et al., 1998), are also instrumental in generating commercially valuable inventions (Feldman, 2000; Hausman, 2022) that feed into industries through various translational schemes (Chai & Shih, 2016; Murray, 2004) and ultimately contribute to enhancing local entrepreneurship.

Given the importance of human capital in spurring entrepreneurship, productivity, and economic growth, firms, regions, and even countries have long sought to attract and retain talent. Many studies have elaborated conditions under which top talent is more likely to move and be poached by competitors, such as when employees collaborate with outsiders on R&D projects (Simeth & Mohammadi, 2022) and when the quality of their work and their level of complementarity with others are high (Palomeras & Melero, 2010). On the flip side, various institutional mechanisms are used to deter talent mobility. Non-compete agreements, which limit employees' post-employment job opportunities, can increase firms' costs of hiring and knowledge acquisition (Starr et al., 2019), depress startup growth (Marx, 2022), and deter talent inflows into regions where such agreements are enforced (Marx et al., 2009). Patent protection can generate similar effects. Early-career inventors are more likely to stay with their existing employer the more patents they receive (Melero et al., 2020), and firms' reputations for aggressive patent enforcement further discourage such mobility (Ganco et al., 2015).

In addition to regional mobility, the migration of talent across borders has also been extensively studied. This body of work has examined the cross-border relocation of top scientists and engineers and its beneficial impact on the scientific and technological advancement of destination countries. Much of the knowledge gap in American science in the last century was filled by immigrant scientists, as Soviet mathematician im-

migrants played a key role in boosting American mathematics (Borjas & Doran, 2012), while German Jewish immigrants did the same in chemistry (Moser et al., 2014). The ability of highly skilled immigrants to bridge cultural (Jang, 2017) and institutional boundaries also makes them critical intermediaries in cross-border knowledge transfer (Fry & Furman, 2025; Ganguli, 2015; Scellato et al., 2015). Moreover, immigrant talent account for a significant share of patenting and new business creation, particularly in high-tech sectors (Kerr & Kerr, 2022; Kerr, 2020; Kerr & Lincoln, 2010).

2.2 Migratory Policies

Many advanced economies, such as those in North America and Europe, have benefited from other waves of immigration as recipients of highly educated STEM students and talents (Belderbos et al., 2025; Martellini et al., 2024; Uhlbach & Anckaert, 2025). Since at least 2003, China has been the leading country of birth among foreign-born holders of science and engineering doctorates in the United States, accounting for 24% of this population in 2019, compared to 15% from India. China is also one of the largest source countries of recipients of U.S. science and engineering doctoral degrees on temporary visas, with relatively high expected stay rates, ranging from 82% to 88% (National Science Board, 2024). These migration trends have been facilitated by lower tax rates (Akcigit et al., 2016; Kleven et al., 2013) and visa regimes that do not restrict immigrants to paid employment (Agarwal et al., 2022; Kahn & MacGarvie, 2020).

These institutional levers have enhanced the attractiveness of developed economies to top talent, contributing to persistent brain drain from less advanced economies. Although studies suggest that brain drain can benefit origin countries through remittances and access to valuable foreign knowledge for inventors who re-

main (Agrawal et al., 2011; Batista et al., 2025), the adoption of talent policies represents a strategic response by these countries to reclaim talent to integrate them into their domestic innovation ecosystems (Shi et al., 2023) and reposition themselves within the global flow of human capital. However, little evidence exists as to whether these institutional levers for reverse migration are effective in attracting talent to return and spurring entrepreneurial quality. This paper seeks to address this gap by examining whether local talent policies crafted to select, attract, and support elite talent are effective both internationally from abroad and domestically from other regions and whether they translate into entrepreneurial gains.

In addition, while highly skilled human capital is a strategic input in the emergence of technological clusters and hubs, simply bringing elite talent into a location does not automatically generate local entrepreneurial or innovation gains. Prior research suggests that the value of such talent depends on complementary local conditions. Returnee contributions can be muted unless organizations possess bridging mechanisms that reconcile foreign and domestic logics (Xia et al., 2025). The success of highly selected scientific returnees hinge on whether they can obtain relevant research funding (Shi et al., 2023). Cross-regional talent inflows within a developed economy depends on skills alignment (Balsmeier et al., 2025). Consequently, this paper also seeks to better understand how, and the conditions under which, elite talent inflows influence the growth potential and innovative activities of local startups.

3 Empirical Setup

3.1 Institutional Context

Many emerging economies face a persistent challenge of talent outflow, as a significant number of their most skilled citizens pursue education and employment opportunities abroad. To win back talent, China launched a series of national programs. In 2008, the Thousand Talents Plan was introduced to attract overseas experts in science, technology, and entrepreneurship; it was followed in 2012 by the Ten-Thousand Talents Plan, which expanded support to domestic scientists, educators, and young innovators. Local governments also introduced city-level talent policies aimed at attracting and retaining highly skilled individuals domestically and internationally to support regional industrial upgrading and competitiveness. Unlike general entrepreneurship policies, such as subsidies to young and small businesses, or innovation programs that fund selected startups (Feldman & Kelley, 2003; Wang et al., 2017), these talent policies center on attracting and supporting qualified individuals.

Early local talent policies in China focused on broad talent groups such as college graduates, easing inter-regional labor mobility mainly by loosening rigid household registration (*hukou*) constraints. Attempts to recruit elite talent were typically handled on a case-by-case basis with bespoke packages that were ad hoc, unpredictable, and lacked the systematic structure needed for broader implementation. In 2000, three cities (Dalian, Wenzhou, and Nanyang) pioneered the introduction of talent policies that categorized talent into distinct tiers and linked each to a corresponding set of benefits. These policies explicitly targeted highly skilled individuals, featuring transparent qualification criteria and detailed support packages, transforming talent sup-

port from symbolic or rhetorical gestures into a systematic, actionable, and scalable approach. Following the emergence of this model, many cities quickly followed suit, adapting and localizing similar tiered frameworks. Online Appendix Figure B1 shows that while 17 cities had adopted such systems by 2005, it increased to 59 by 2010 and to 129 by the end of our sample period in 2016, out of the total 189 cities in our sample.

Although each city's policies are independent and based on local conditions, they showed strong consistency in defining "elite talent" when adopting similar tiered structures. While elite talent primarily refers to individuals with outstanding achievements in scientific and technological fields, policy definitions sometimes also extend to individuals with notable accomplishments in managerial, artistic, or athletic domains. Local classification systems generally divide elite talent into three to five tiers. The top tier typically includes Nobel laureates and academicians of national academies of sciences or engineering. The intermediate tiers include recipients of national or provincial awards or formal recognition for contributions to natural science or technological invention, while the lower tiers include professionals with doctoral degrees obtained from universities placed within the global top 100 according to prominent international rankings such as QS or Times Higher Education. Support measures are often structured as comprehensive packages that include financial incentives and housing benefits, such as one-time settlement allowances, research startup grants, entrepreneurial support funds, annual salary subsidies, access to dedicated apartments or financial assistance for home purchases or rentals. These packages often also include additional setup facilitation, including streamlined procedures for household registration (*hukou*), preferential access to education for children, and support, such as healthcare privileges and assistance with employment for spouses. The value and

scope of these benefits generally decline across tiers, with higher-level talents receiving the most generous forms of support. Given that many of these talent policies aim to reverse brain drain and compete globally for skilled professionals, they often include provisions to attract individuals with overseas education or work experience.

Importantly, the staggered rollout of these policies across cities provides plausibly exogenous variation for identification. Although driven by a shared national directive to attract elite talent, the timing of adoption differed widely across localities due to idiosyncratic factors such as bureaucratic capacity and administrative readiness. These timing differences are unlikely to be directly tied to short-term shifts in local entrepreneurship, thus enabling a quasi-experimental research design that exploits variation in policy exposure across time and space.

3.2 Data and Sample

3.2.1 Policy Data

Since talent policies primarily targeted scientists and engineers, and both innovation and entrepreneurship activities are highly concentrated geographically, we restrict our sample to prefecture-level cities that filed at least 50 patents with the China National Intellectual Property Administration (CNIPA) in 2001, the starting year of our sample period. This restriction leaves us with 189 prefecture cities in our full sample out of a total of 332 in China. The sample covers 96.12% of patents and all four municipalities directly under the central government, all 31 provincial capitals, and all 41 cities that host highly ranked universities under the 985 or 211 Projects.[1]

[1] A "985 university" refers to one of the 39 institutions designated under China's 985 Project, a national initiative aimed at developing world-class universities through substantial government funding. A "211 university" refers to one of the 112 institutions selected under the 211 Project, which was launched to strengthen the overall research and education capacity of a broader set of key universities. All 39 universities in the 985 Project are part of those included in the 211 Project.

This sample restriction enhances the comparability between treated and control cities by ensuring a baseline level of innovative capacity across the board. Online Appendix Figure B2 displays the cities in our sample, with darker-shaded ones indicating those treated by 2016 and lighter-shaded ones representing controls. Most cities in our sample are located in eastern and central China, while excluded ones are mostly in the west. As a result, our sample covers the more economically developed and dynamic regions of the country, characterized by higher GDP per capita, greater patenting activity, and higher rates of startup formation (see Online Appendix Table B1). For these cities, we then conducted a systematic search for elite talent policies using official websites of municipal and provincial governments, including those of their Human Resources and Social Security Bureaus, PKULaw (Beida Fabao),[2] Wolters Kluwer Database on Human Resources Information,[3] newspapers and online media reports, as well as academic journal articles and theses from China National Knowledge Infrastructure (CNKI).[4]

For each prefecture-level city in our sample, we identify policy documents, if available, that satisfy the following criteria: (1) the policy must explicitly target elite talent, either by directly referencing terms such as "high-caliber" or "high-level," or through clear eligibility requirements that indicate a high qualification threshold; (2) the policy must include a tiered or classification system for talent;[5] and (3) the policy must specify benefits that are clearly tied to each talent tier or classification, with support packages

[2] https://www.pkulaw.com/

[3] The Wolters Kluwer Database was obtained from https://hr.wkinfo.com.cn/

[4] We identified a substantial number of master's theses focusing on local talent policies in specific cities. These studies provide detailed accounts of municipal policy development and serve as valuable references.

[5] Tiering refers to a hierarchical structure (e.g., Levels A, B, C, D), while classification refers to distinguishing between types of talent (e.g., innovation vs. entrepreneurship). For example, Beijing's High-Level Innovation and Entrepreneurship Talent Program and Shanghai's Leading Talent Program both include such distinctions, classifying individuals into groups such as basic research talent, applied research talent, humanities and social sciences experts, and managerial professionals.

tailored to match the qualifications or level of the recruited talent. These criteria help exclude vague policy guidelines that merely offer broad directions and are not immediately implementable, as well as general talent attraction initiatives targeting groups such as college graduates.

We use the implementation date of the policy documents to determine the timing of treatment.[6] If a city issued multiple qualifying policy documents, we use the implementation date of the earliest one. We restrict the sample period to end in 2016, as international talent mobility underwent a structural shift beginning in 2017 following the first Trump administration's adoption of more restrictive immigration policies and heightened scrutiny of Chinese scientists, including its "China Initiative" (Flynn et al., 2024; Jia et al., 2024; Xie et al., 2023). Cities that had not issued any qualifying policy by the end of 2016 serve as our control group. Our final dataset for the main analysis includes 3,024 observations at the city-year level, covering 189 cities over a 16-year period from 2001 to 2016.

3.2.2 Entrepreneurship and Talent Data

We obtain firm-level data on business entries in China since 1985 from the National Enterprise Credit Information Publicity System (NECIPS).[7] The data include firm name, legal status (active, dissolved, or merged), ownership type (e.g., individual proprietorship, privately owned firm, state- or collectively owned enterprise, foreign-

[6] If an implementation date is not explicitly specified, we use the policy release date as a proxy. When the implementation date includes only the year but not the month, we treat the policy as taking effect from January of that year. If the month is specified, we apply the following rule: if it falls between January and June, the treatment is considered to start in that same year; if it falls between July and December, we consider the treatment to start in the following year.

[7] All firms in China are required by the Company Law and the Partnership Law to register annually with the State Administration for Market Regulation (SAMR) to renew their business licenses and update any changes in business scope or ownership. SAMR releases these business registration records through NECIPS (http://gsxt.gdgs.gov.cn) to facilitate law enforcement and enable the public to search and verify firms' legal status. As a result of their administrative origin, these records cover the full population of business entries in China since 1985.

invested enterprise), industry classification, detailed business scope, amount of registered capital, incorporation date, address, and shareholder list. Our study focuses on privately owned firms founded from 2001 to 2016.

We match privately owned startups to VC deal data from the CVSource database,[8] IPO records from WIND,[9] and patent records from the CNIPA using firm names and geographic locations. These matched datasets allow us to construct city-year level measures of entrepreneurial performance. We also supplement our data with city-year level macroeconomic control variables, including GDP per capita by sector, employment by sector, and population density from the China City Statistical Yearbook.

To analyze talent flow, we use name-disambiguated inventor data from CNIPA[10] and the United States Patent and Trademark Office (USPTO).[11] The CNIPA data allow us to trace inventor mobility within China, while the USPTO data help identify inflows from overseas into specific Chinese cities. Following Marx et al. (2009), we define an inventor's move year as the midpoint between the first patent filing in a new city and the last filing in the prior city. Overseas star inventors are defined as those at or above the ninetieth percentile of cumulative patent output in the USPTO data (Moretti, 2021). Given the rapid expansion of patent filings and concerns about heterogeneous patent quality in the CNIPA system, patent counts may not reliably capture inventor quality. We therefore define domestic star inventors as those at or above the ninetieth percentile of average five-year citations per patent in the CNIPA data. Our results are robust to alternative percentile cutoffs (top 5 and top 15 percent) and to defining domestic stars based on quantity rankings.

[8] https://data.cvsource.com.cn
[9] https://www.wind.com.cn/
[10] Shi et al. 2025, "Disambiguation of Inventors in CNIPA Invention Patents."
[11] USPTO patent data was obtained from https://patentsview.org.

3.3 Measuring Entrepreneurial Quality

To measure city-year entrepreneurial quality, we first construct a startup-level measure of entrepreneurship quality and then aggregate it to the city-year level. Following prior work (Andrews et al., 2022; Guzman & Stern, 2020), we adopt a predictive analytics approach that links startups' performance—defined as receiving venture capital financing or undergoing an IPO within five years of registration—to early-stage choices observable at or near founding (see Online Appendix A for details). These founding choices reflect entrepreneurs' private information about the underlying idea, ambition, and growth potential, and therefore carry predictive power regarding the startup's future trajectory. Accordingly, the predicted probability of a high-growth event serves as a measure of startups' founding quality.

The primary city-year level measure is *aggregate entrepreneurship quality*, defined as the sum of predicted growth probabilities across all startups founded in a city-year cohort. It captures the expected number of growth events and can be interpreted as a quality-weighted startup formation rate. We also construct two outcome-based measures of realized performance: the *number of high-growth startups*, defined as firms that achieved VC funding or an IPO within five years of registration, and the *number of patent-active startups*, defined as firms that filed for patents within five years of registration, with at least one of these applications eventually granted. The latter variable captures the early-stage innovation capacity of startups, as reflected in their ability to generate patentable knowledge shortly after founding.

3.4 Summary Statistics

We organize the data at the city-year level and, in some specifications, at the city-industry-year level. Among the 189 cities in our sample, 60 never issued any local tiered talent policies that meet our criteria during the sample period and thus serve as the control group. We report summary statistics in Table 1 and the correlation matrix in Online Appendix Table B2. On average, each city sees 6,375 new startups per year, among which only 7.25 are predicted to achieve significant growth milestones within five years of founding, and 6.86 actually do so.[12] Additionally, 63 startups per city-year filed at least one patent application within five years of founding and eventually had it granted. These figures suggest that high-quality startups with strong growth potential and active engagement in innovative activity are rare. Such a low incidence is consistent with the findings of Andrews et al. (2022) for the United States, where there are 2,947.7 new entries per MSA-year and 1.86 are predicted to reach high-growth outcomes, corresponding to a rate of approximately 0.0006, quite close to that observed in our data (0.0007 in Table 1).

The inflow of star inventors varies by origin. In our city-year regression sample, the average inflow of domestic star inventors is 16.7 individuals (sd = 66.4). For overseas inventors, we document 23,599 total relocation cases into Chinese cities during our sample period of 2001–2016, with inflows increasing markedly over time, as illustrated in Online Appendix Figure B3. By last patenting location, the largest shares

[12] Because we require a five-year window to observe major growth events such as VC investment or IPO, and the version of CVSource data available to us ends in 2018, we lack complete outcome data for startups founded after 2013. As a result, the *number of high-growth startups* appears smaller in the years 2014–2016. In contrast, the *aggregate entrepreneurship quality* is a predicted measure and is not subject to such right-censoring. This discrepancy causes the mean *number of high-growth startups* to appear lower than that of *aggregate entrepreneurship quality* (a difference of 0.38). However, when we restrict the sample to the 2001–2013 period, during which both measures are unaffected by data censoring, their means are comparable: 3.81 for the *number of high-growth startups* and 3.66 for *aggregate entrepreneurship quality*.

Table 1: Summary Statistics

Variables	Mean	SD	Min	Max
Startup formation rate	6,374.54	14,589.12	71	277,167
Aggregate entrepreneurship quality	7.24	26.76	0.03	558.33
Number of high-growth startups	6.86	54.87	0	1,569
Number of patent-active startups	63.29	185.13	0	2,725
Domestic star inventor inflow	16.72	66.37	0	1,394
Overseas star inventor inflow	9.19	64.19	0	1,358
$Policy_{it}$	0.27	0.44	0	1
GDP per capita	33,290	29,274	2,269	467,749
Employment share (Manufacturing)	45.68	12.71	9.28	84.4
Employment share (Services)	50.95	11.62	9.91	83.51
GDP share (Manufacturing)	48.65	9.66	18.57	88.69
GDP share (Services)	38.05	8.73	9.24	80.23
Population density (people/km^2)	494.64	371.77	14.68	7,787.32

Notes: The number of observations is 3,024 at the city-year level (189 cities from 2001 to 2016).

originate from the United States (73.7%), Taiwan (9.9%), Canada (3.6%), Japan (2.9%), and Singapore (2.5%). Incoming overseas inventors are overwhelmingly concentrated at the upper end of the productivity distribution, with 95.3% of inflows accounted for by star inventors. At the city-year level, the average inflow of overseas star inventors is 9.2 individuals (sd = 64.2).

3.5 Identification Strategy

To examine the effects of the introduction of local tiered talent policies across cities and years on local entrepreneurial activity, we estimate the following two-way fixed effects (TWFE) model:

$$Y_{it} = \beta \cdot Policy_{it} + \gamma' X_{it} + \lambda_i + \mu_t + \sigma_{pt} + \epsilon_{it}. \tag{1}$$

The dependent variable Y_{it} is the logarithmic transformation of a measure of entrepreneurship quantity or quality for city i in year t. X_{it} includes city-year controls

such as GDP per capita, population density, and industrial structure. City fixed effects λ_i absorb time-invariant differences across cities, such as baseline variation in universities, capital markets, or labor pools, that may jointly affect entrepreneurship quality and policy adoption. Year fixed effects μ_t absorb shocks common to all cities, including macroeconomic conditions or nationwide VC and IPO restrictions (Huang & Tian, 2020). We further control for province-year fixed effects, σ_{pt}, to capture time-varying province-level shocks, such as regional development strategies and province-wide talent programs, thereby isolating variation across cities within the same province and year. Standard errors are clustered at the city level. The variable $Policy_{it}$ equals to one if city i has implemented a local talent policy in year t, and zero otherwise. Under the assumption of parallel trends, the coefficient β identifies the average treatment effect on the treated.

Cities adopting talent policies earlier may differ from later or never-treated cities, potentially violating parallel trends. To assess the plausibility of exogenous policy timing, Online Appendix Table B3 examines whether pre-policy city characteristics predict the timing of policy adoption. The results show little systematic relationship between prior city conditions and policy timing (Chari et al., 2021). We further estimate an event study version of Equation (1) to assess parallel trends and examine dynamic treatment effects:

$$Y_{it} = \sum_{k=-5}^{6} \beta_k \cdot D_{k(it)} + \gamma' X_{it} + \lambda_i + \mu_t + \sigma_{pt} + \epsilon_{it} \tag{2}$$

where $D_{k(it)}$ equals one if for city i in year t is k years relative to policy implementation. We treat the period immediately preceding the implementation of the talent policy as the omitted category, so the coefficients β_k represent changes in entrepreneurship

quality k years before or after the policy relative to this reference period.

Recent development in the staggered difference-in-differences literature has showed that TWFE estimators as in Equation (1) may produce biased estimates when treatment effects vary across treated groups or over time (Goodman-Bacon, 2021). This concern is relevant in our setting, as later-adopting cities may implement more comprehensive policies and treatment effects may accumulate over time. To address this issue, we replicate our results using robust estimators introduced in de Chaisemartin and D'Haultfœuille (2020), Borusyak et al. (2024), Callaway and Sant'Anna (2021), and Cengiz et al. (2019).

4 Findings

4.1 Star Inventor Inflow and Entrepreneurial Upgrading

We first examine whether local talent policies attract highly skilled individuals using the two-way fixed effects specifications described in Equation (1). Table 2 columns (1) and (2) report that, following the implementation of talent policies, the inflow of domestic star inventors increases significantly by 23.0%, while that of overseas star inventors increases significantly by 16.7%, both significant at the 1% level. These findings provide direct evidence that local talent policies successfully attract highly productive inventors.

We next examine whether such talent inflows translate into improvements in local entrepreneurial outcomes. Column (3) of Table 2 shows that the *startup formation rate* is not significantly affected by the policy, and if anything, declines slightly by 1.1%. In contrast, column (4) shows that implementing local talent policies increases *aggregate entrepreneurship quality* by 9%, significant at the 1% level. Column (5) further shows

Table 2: Star Inventor Inflows and Entrepreneurial Outcomes

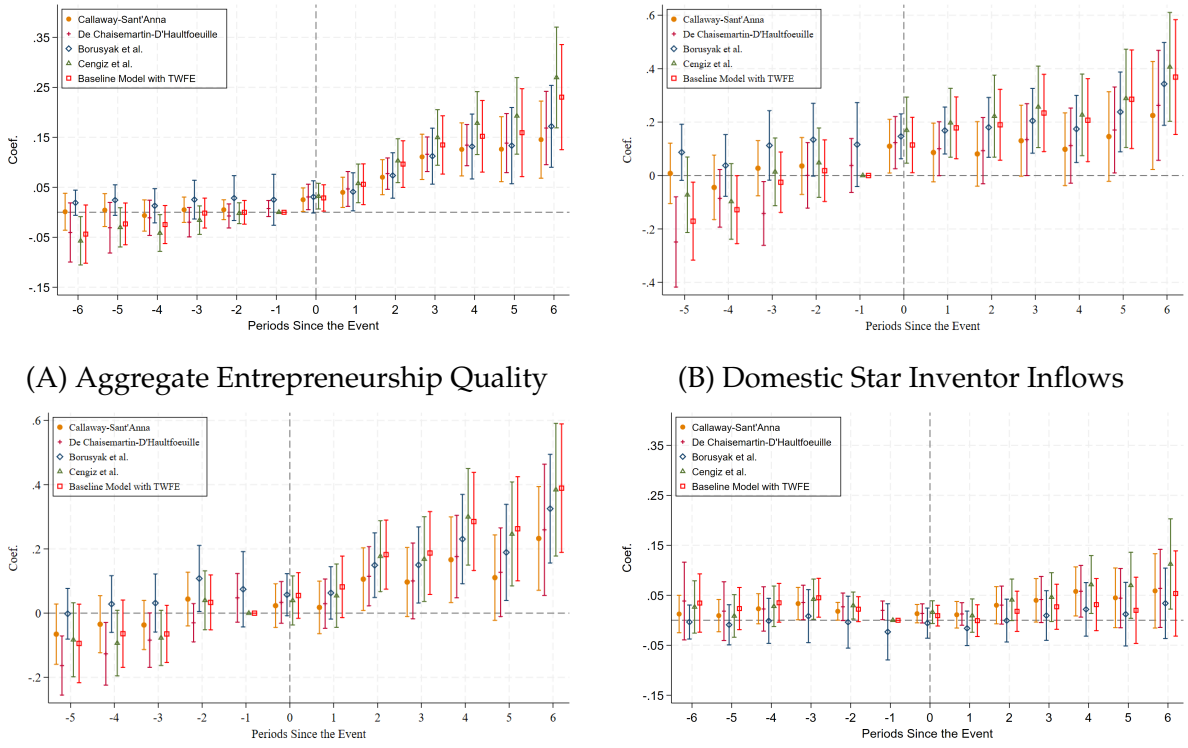
	Star inventor inflows		Entrepreneurial outcomes			
Dep. Var.	(1) Domestic	(2) Overseas	(3) Startup formation rate	(4) Aggregate EQ	(5) High-growth startups	(6) Patent-active startups
$Policy_{it}$	0.230***	0.167***	-0.011	0.090***	0.147***	0.064*
	(0.063)	(0.057)	(0.025)	(0.030)	(0.054)	(0.039)
Adjusted R^2	0.857	0.668	0.977	0.967	0.745	0.937
Observations	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. All dependent variables are transformed as $\log(1 + y)$. The sample size reflects the exclusion of singleton observations resulting from the inclusion of province-year fixed effects. EQ stands for Entrepreneurship Quality.

that the number of realized high-growth startups increased by 14.7%. Finally, column (6) indicates that local talent policies also increases the number of patent-active startups by 6.4% (significant at the 10% level).

The TWFE event-study estimates in Equation (2), shown as square markers in Figure 1, indicate that the pre-treatment coefficients are all close to zero, suggesting no discernible differential trends between treated and control cities conditional on controls and fixed effects. After policy implementation, *aggregate entrepreneurship quality* rises by 5.6% in the first year and continues to grow steadily, reaching 23% six years later (Panel A). Given that a city has, on average, about seven startups expected to achieve substantial growth, this implies roughly 1.6 additional high-growth startups, an economically meaningful effect in light of the disproportionate role such firms play in employment, innovation, and local economic development. Star inventor inflows from domestic (Panel B) and overseas (Panel C), as well as the number of high-growths startups and patent-active startups (Online Appendix Figure B4) follow a similar pattern, whereas startup formation rate remains largely unchanged (Panel D). Alternative

estimators robust to treatment-effect heterogeneity (Borusyak et al., 2024; Callaway & Sant'Anna, 2021; Cengiz et al., 2019; de Chaisemartin & D'Haultfœuille, 2020), also shown in Figure 1, likewise support the parallel-trends assumption and reveal the same pattern of steadily increasing treatment effects over time.



(A) Aggregate Entrepreneurship Quality

(B) Domestic Star Inventor Inflows

(C) Overseas Star Inventor Inflows

(D) Startup Formation Rate

Figure 1: Event-Study Estimates: Parallel Trends and Dynamic Effects

Notes: This figure overlays event-study plots constructed using five different estimators: (1) Callaway and Sant'Anna (2021); (2) de Chaisemartin and D'Haultfœuille (2020); (3) Borusyak et al. (2024); (4) Cengiz et al. (2019), a stacked difference-in-differences estimator; and (5) a dynamic version of our baseline model with TWFE as specified in Equation (2). The dependent variable is $log(1 + y)$ transformed. The bars represent a 90% confidence interval. Standard errors are clustered at the city-level.

We conduct a series of robustness analyses that address concerns related to variable definition, sample definition, model specification, and omitted variable bias. First, in Online Appendix Table B4, we show that the migratory effects of the policies are robust to alternative definitions of star inventors. Second, our baseline sample includes cities with at least 50 granted patents filed in 2001 to ensure comparability between treated

and control cities. Online Appendix Table B5 shows that the results remain robust when we raise the cutoff to at least 100 patents. Third, given concerns that log-plus-one transformations may be arbitrary (Bellemare & Wichman, 2020), we re-estimate Table 2 using the inverse hyperbolic sine (IHS) transformation. The results remain consistent in both magnitude and statistical significance (Online Appendix Table B6).

One remaining concern is that unobserved city–year shocks, such as impending economic booms or the introduction of general pro-entrepreneurship policies, may simultaneously enhance a city's ability to attract talent and foster entrepreneurship. To address this concern, we strengthen identification using a three-way difference-in-differences (DDD) design. We restructure the data into a city–year–industry panel and assign inventors to industries based on their technological specialization. Specifically, each inventor is assigned a primary IPC technology class based on their most frequent patent field, which is then mapped to the industry in which it is most heavily concentrated. We interact $Policy_{it}$ with industry-level measures of human-capital intensity, including average wages (column (2) of Online Appendix Table B7), the share of college-educated workers (column (3)), and an indicator for high-tech industries (column (4)). The regressions include city–industry, industry–year, and province–year fixed effects, so identification comes from differential changes across industries within the same city-year. Across all specifications, the interaction terms are positive and statistically significant, indicating systematically stronger policy effects in more human-capital-intensive industries including high-tech sectors (Balsmeier et al., 2025). This pattern helps rule out city-wide confounding shocks and points to a talent-related channel.

To further assess whether talent inflows constitute an important mechanism link-

ing talent policies to entrepreneurial upgrading, Table 3 incorporates measures of domestic and overseas star inventor inflows into the entrepreneurship regressions. Both inflows are positively associated with improvements in entrepreneurial quality outcomes, while the coefficients on $Policy_{it}$ decline in magnitude and decrease in statistical significance. This attenuation suggests that part of the policy effect operates through the attraction of high-quality talent.

Table 3: The Role of Talent Inflows in Explaining Policy Effects on Entrepreneurship

Dep. Var.	(1) Startup formation rate	(2) Aggregate EQ	(3) High-growth startups	(4) Patent-active startups
Policy$_{it}$	-0.005	0.056**	0.088*	0.048
	(0.025)	(0.026)	(0.049)	(0.038)
Domestic Star Inflow	-0.034***	0.100***	0.170***	0.030
	(0.012)	(0.013)	(0.024)	(0.019)
Overseas Star Inflow	0.013	0.070***	0.118***	0.055**
	(0.015)	(0.016)	(0.043)	(0.026)
Adjusted R^2	0.977	0.971	0.758	0.937
Observations	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. Dependent variables are transformed as $\log(1+y)$. The sample size reflects the exclusion of singleton observations resulting from the inclusion of province-year fixed effects. EQ stands for Entrepreneurship Quality.

In summary, these findings establish that local talent policies attract highly skilled talent not only from other cities within China but also from overseas. Although these talent inflows do not significantly increase the overall rate of new business formation, they are associated with substantial entrepreneurial upgrading especially in human-capital-intensive industries and high-tech sectors. Yet these aggregate effects are unlikely to arise uniformly across all high-tech activities. After all, policy-driven attempts to build the next "Silicon Valley" have often fallen short, suggesting that upgrading into high-tech sectors rarely succeeds from scratch. This naturally raises two

important questions. First, through what mechanisms are policy-induced talent inflows converted into entrepreneurial upgrading? Second, under what conditions are such effects strongest? If the productive impact of incoming talent requires specific industrial and knowledge conditions, then policy-induced gains should depend on whether such talent can be matched to locally specialized opportunity spaces and supported by knowledge infrastructures that facilitate the translation of ideas into viable ventures. We turn to address these questions next.

4.2 How Talent Inflow Translates into Entrepreneurial Quality

Although local talent policies improve entrepreneurial quality especially in high-tech sectors, such aggregate estimates do not by themselves reveal how policy-induced talent inflows are translated into better entrepreneurial outcomes. We argue that this translation is not automatic and depends on whether incoming talent can be matched to relevant opportunity spaces and absorbed by local domains of relative specialization, as well as recombined through existing knowledge and organizational linkages. These considerations imply that the effects of talent policy would vary systematically across industries and local contexts. In this subsection, we examine two distinct but complementary forms of local capability that condition the effectiveness of talent inflows: industrial capabilities rooted in existing technological specialization, and knowledge capabilities anchored in university-based research and science–industry linkages.

4.2.1 Industrial Complementarities and Technological Relatedness

To examine whether policy-induced talent inflows are absorbed through complementarities with local industrial capabilities, we partition each city-industry pair within high-tech sectors into three mutually exclusive categories. The first category consists of industries in which the city has a revealed comparative advantage (RCA), measured based on the city's patent specialization across industries (Boschma et al., 2015; Leten et al., 2016). Specifically, an industry is classified as advantaged in city i if

$$RCA_{ik} = \frac{X_{ik}/\sum_k X_{ik}}{\sum_i X_{ik}/\sum_i \sum_k X_{ik}} > 1,$$

where X_{ik} denotes the concordance-weighted[13] number of patents for city i in industry k. Importantly, RCA does not mean that the industry is necessarily dominant within the city in absolute terms; rather, it indicates that the city is relatively more specialized in that industry than other cities are. RCA is constructed using pre-sample-period patents, making it time-invariant and plausibly exogenous to subsequent policy adoption. The second category consists of industries in which the city does not exhibit RCA but that are technologically related to the city's RCA industries through knowledge linkages. Specifically, related industries are identified using the patent citation network as the top five citing or cited industries of each RCA industry. The third group consists of unrelated industries that are neither RCA nor technologically connected to RCA industries.

Table 4 shows that policy-induced domestic and overseas star inventor inflows

[13]We construct a probabilistic concordance to map IPC subclasses to two-digit industries. Specifically, each IPC subclass is assigned a vector of weights across industries based on its empirical distribution of patent activity, with weights summing to one. This approach allows a single technology class to contribute fractionally to multiple industries, capturing the multi-industry nature of many technological fields.

Table 4: Complementarities with Industrial Specialization—within High-Tech Industries

	Star Inventor inflows		Entrepreneurial outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Domestic	Overseas	Aggregate EQ	Startup formation rate	High-growth startups	Patent-active startups
$Policy_{it} \times RCA_j$	0.102***	0.038***	0.030***	-0.051	0.034***	0.114***
	(0.024)	(0.012)	(0.010)	(0.033)	(0.011)	(0.024)
$Policy_{it} \times NonRCA_j \times Related_j$	0.104***	0.053***	0.020	0.041	-0.005	0.113***
	(0.032)	(0.018)	(0.012)	(0.037)	(0.010)	(0.035)
$Policy_{it} \times NonRCA_j \times Unrelated_j$	0.002	-0.006	-0.007	-0.024	-0.009*	-0.017
	(0.014)	(0.009)	(0.006)	(0.029)	(0.005)	(0.016)
Adjusted R^2	0.721	0.782	0.772	0.894	0.486	0.708
Observations	60,480	60,480	60,480	60,480	60,480	60,480

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample is restricted to high-tech industries. For results across all industries, see Online Appendix Table B8. All specifications include city fixed effects, province × year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. Dependent variables are transformed as $\log(1+y)$. The sample size reflects the exclusion of singleton observations resulting from the inclusion of province-year fixed effects. EQ stands for Entrepreneurship Quality.

are concentrated not only in advantaged industries of the destination city, but also in non-advantaged industries that are technologically connected to those advantaged domains, while technologically unrelated industries receive no such gains. A similar pattern emerges in early-stage innovation activities: the number of patent-active startups increases by comparable magnitudes in both advantaged and technologically related industries. However, this pattern does not extend to downstream entrepreneurial outcomes. Improvements in aggregate entrepreneurial quality and the number of high-growth startups are observed only in industries in which the city exhibits revealed comparative advantage. In contrast, although technologically related industries receive similar inflows of talent and experience increases in innovative activity, these gains do not translate into improvements in aggregate entrepreneurial quality or realized high-growth entrepreneurship.

This divergence between innovation and entrepreneurial upgrading highlights an

important boundary condition of talent-driven development. While talent inflows can broaden innovative activity into adjacent technological domains, the generation of high-quality entrepreneurship requires deeper capability complementarities that are present only in locally specialized industries. In this sense, related industries benefit from knowledge spillovers at the innovation stage but lack the capability depth necessary to support downstream venture growth.

4.2.2 Knowledge Complementarities and Science-to-Market Translation

The effectiveness of talent inflows on entrepreneurial quality also depends on knowledge capabilities anchored in university-based research and strengthened through science–industry linkages. Table 5 shows that talent policies enhance a city's attractiveness to star inventors and improve entrepreneurship quality only when the city hosts highly ranked universities.

Not all university-based research contributes equally to economic outcomes. Prior research has highlighted the gap between academic research and its translation into technologies that become viable products—the so-called "valley of death" between science and commercialization (Bikard, 2018; Etzkowitz & Leydesdorff, 2000; Etzkowitz et al., 2000). Translational schemes where university researchers collaborate with industry have been shown to alleviate the problem (Chai & Shih, 2016). Building on this insight, we next examine how talent inflows contribute to different forms of university knowledge production, and whether translational knowledge linking universities to firms plays a distinctive role in driving entrepreneurial success.

In Table 6, we use city-year-level patents assigned to universities as a measure for university-based research, and distinguish those co-assigned to firms as a proxy

Table 5: Complementarity with University Knowledge Base

	Star Inventor inflows		Entrepreneurial outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Domestic	Overseas	Aggregate EQ	Startup formation	High-growth startups	Patent-active startups
$Policy_{it}\times$ (985 cities)	0.671***	0.545**	0.437***	-0.050	1.155***	0.139*
	(0.124)	(0.217)	(0.075)	(0.053)	(0.125)	(0.072)
$Policy_{it}\times$ (211 cities)	0.779***	0.245	0.285***	-0.141	0.480***	-0.007
	(0.121)	(0.187)	(0.062)	(0.102)	(0.154)	(0.113)
$Policy_{it}\times$ (Other cities)	0.094	0.097	0.012	0.011	-0.053	0.061
	(0.066)	(0.068)	(0.030)	(0.028)	(0.050)	(0.046)
Observations	2,880	2,880	2,880	2,880	2,880	2,880
R^2	0.886	0.842	0.975	0.981	0.813	0.948

Notes: Robust standard errors clustered at the city-level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The dependent variable is $log(1 + y)$ transformed. In all specifications, control variables include the natural logarithm of GDP per capita, population density, indicators of local industrial structure, city fixed effects, and year fixed effects by province. The "985 cities" dummy indicates cities that have one or more of the 39 universities designated under the 985 Project, China's national initiative aimed at supporting top-tier universities with significant government funding to become world-class institutions. The "211 cities" dummy indicates cities that host one or more of the 73 universities not included in the 985 Project but supported by the 211 Project, another national initiative aimed at strengthening the overall higher education and research capabilities of a broader group of key universities. Cities that host both 985 and 211 universities are classified as 985 cities. EQ stands for Entrepreneurship Quality.

for translational knowledge linking universities to firms. Such co-assigned patents may reflect direct university-industry collaboration, commercialization of academic research, or faculty entrepreneurial activity. By contrast, university-only patents are more likely to capture basic research outputs with limited immediate commercial application. Roughly 6.13% of university patents fall into the co-assigned category[14]. Columns (1) and (2) show that talent policy raises both types of patents by similar magnitudes: 27.3% for co-assigned patents and 29.1% for university-only patents, significant at the 1% level. Columns (3) and (4) show that part of this policy effect operates through star inventor inflows. Domestic star inventor inflows significantly increase both co-assigned and university-only patents by 27% and 25%, respectively, suggesting that domestic talent broadly contributes to local knowledge production.

[14]Between 2001 and 2016, universities in China applied for 978,675 patents that were subsequently granted. Among them, 59,947 patents were co-assigned with firms.

By contrast, overseas star inventor inflows increase only co-assigned university-firm patents, indicating that overseas talent plays an important role in generating translational knowledge that bridges science and industry.

Table 6: Policy, Talent Inflow, and Knowledge Translation

	University Patents				Entrepreneurial Outcomes	
Dep. Var.	(1) Coassigned w/ firm	(2) Without firm	(3) Coassigned w/ firm	(4) Without firm	(5) Aggregate EQ	(6) High-growth startups
$Policy_{it}$	0.273***	0.291***	0.189***	0.226**	0.061**	0.106**
	(0.078)	(0.100)	(0.069)	(0.098)	(0.027)	(0.050)
Star Inventors Inflow:						
Domestic			0.269***	0.249***		
			(0.032)	(0.042)		
Overseas			0.131***	0.046		
			(0.038)	(0.054)		
University Patents:						
Coassigned					0.081***	0.172***
					(0.014)	(0.025)
Without firm					0.024***	-0.023
					(0.009)	(0.021)
Adjusted R^2	0.824	0.912	0.837	0.915	0.969	0.756
Observations	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city-level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. Dependent variables and star inventor inflows are transformed as $\log(1+y)$. EQ stands for Entrepreneurship Quality.

These two types of university knowledge affect local entrepreneurship in sharply different magnitudes. Column (5) shows that a 10% increase in university-firm co-patents raises entrepreneurship quality at founding (*aggregate entrepreneurship quality*) by 0.81%, more than three times the effect of university-only patents. This divergence becomes even more pronounced when considering realized entrepreneurial success. Column (6) indicates that a 10% increase in university-firm co-assigned patents raises the *number of high-growth startups* by 1.72%, significant at the 1% level, whereas university-only patents exhibit no significant effect.[15]

[15]This divergence is not driven by quality differences between the two types of patents. On average, co-assigned patents with firms receive 0.916 forward citations within three years of grant, while

Taken together, these results suggest that talent inflows stimulate university knowledge production broadly, but only translational knowledge linking universities to firms plays a decisive role in driving realized entrepreneurial success. In particular, star inventors from overseas appear to contribute disproportionately to this science-to-market translation process.

4.2.3 Alternative explanations and equilibrium concerns

Elite talent typically earn higher income, and their inflow into a city could in principle generate new demand for local products and services, thereby contributing to the success of local startups. To test this demand spillover channel, we restructure the original city-year panel into a city-year-industry panel covering 18 one-digit industries and re-estimate the baseline specification for each industry. In Online Appendix Table B10, we show that in service industries such as Culture, Sports, and Entertainment (column (1)) and Wholesale and Retail (column (2)), the estimated coefficients are small and only marginally significant, and in Accommodation and Catering (column (3)) they are statistically insignificant. This suggests that income effects, such as spending on retail, food, or leisure, from higher-earning talent inflows play at most a modest role. Interestingly, Construction (column (4)) and Real Estate (column (5)) do experience significant improvements in entrepreneurship quality. This pattern is consistent with derived demand from businesses and households: housing is a major component of household expenditure, and many talent policies provide one-time cash transfers explicitly labeled as "housing subsidies." Thus, inflows of higher-income workers likely stimulated local real estate markets more than everyday consumption. Among

university-only patents receive 0.893—a statistically insignificant difference. Regression results based on citation-weighted patent counts (Online Appendix Table B9) show a similar pattern.

these 18 one-digit industries, the strongest effects arise in knowledge-intensive sectors where aggregate entrepreneurship quality increases by 9.2% in ICT (column (6)) and by 12.4% in R&D Services (column (7)) following talent policy implementation. Leasing and Business Services (column (8)) also experience an 8.5% increase in entrepreneurship quality, likely reflecting derived demand generated by the growing ICT and R&D firms for more office space and professional services. For the remaining industries, $Policy_{it}$ shows no significant impact on entrepreneurship quality. These results point away from demand-side consumption spillovers and instead reinforce the interpretation that the policies work primarily by strengthening local human capital capacity and fostering knowledge-intensive entrepreneurial activity.

Another key alternative explanation for our findings is the classic *beggar-thy-neighbor* concern that often arises in place-based policies (Wilson, 2009). Under decentralized policymaking, one city's gain may come partly or entirely at the expense of other cities. If high-level talent policies merely reallocate talent and entrepreneurial activity away from untreated cities, standard difference-in-differences estimates may overstate the policy's effect: the treated group would improve while the untreated group would decline, causing the treated–control contrast to mechanically exaggerate the policy impact. In the extreme, local gains could be fully offset by losses elsewhere, implying little or no aggregate efficiency gain.

We provide two pieces of evidence suggesting that our results are not driven by such displacement. First, Online Appendix Figure B5 presents stacked difference-in-differences plots that trace entrepreneurial quality around the time of policy implementation for treated cities and their corresponding never-treated controls. Because treatment is staggered, we align treated cities by event time and average across treat-

ment cohorts; for each cohort, the never-treated cities are reused as the comparison group. Two patterns stand out. Before treatment, treated and control cities exhibit relatively stable and broadly parallel trends. After treatment, entrepreneurial quality rises sharply in treated cities, but does not fall in the control group. If anything, the control group also continues to improve gradually. Thus, the estimated treatment effect does not appear to be driven by a deterioration in untreated cities.

Second, Online Appendix Table B11 reports regression-based evidence that directly examines whether neighboring cities' talent policies depress local outcomes. Following the logic of Wilson (2009), we augment our baseline specification with measures of neighboring cities' policy exposure in addition to the focal city's own policy status. If local talent policies operate primarily through beggar-thy-neighbor competition, policy adoption in nearby cities would be expected to reduce local outcomes, yielding negative coefficients on neighboring cities' policy exposure. Instead, we find no evidence of such negative spillovers. The coefficients on neighboring cities' policy exposure are generally small and statistically insignificant, and in the case of domestic star inventor inflows, the estimated coefficient is positive and statistically significant. This pattern suggests that nearby policy adoption does not draw talent away from focal cities; if anything, it is consistent with regional crowding-in of domestic talent. Moreover, the coefficient on the focal city's own policy remains stable in magnitude and significance, indicating that the estimated local gains are not driven by offsetting losses in nearby locations

Jointly, these findings suggest that the estimated effect of a focal city's own policy is unlikely to arise from depressing entrepreneurial quality in other cities, and that the effects of local talent policies are therefore unlikely to be purely zero-sum. Two reasons

may help explain why. First, even when policies shift domestic talent across cities, such reallocation need not be inefficient if talent is drawn toward locations where it can be most productive. Agglomeration economies and stronger complementarities in talent-dense clusters may raise the overall productivity of innovation (Moretti, 2021). Our earlier results, showing stronger effects in cities' domains of revealed comparative advantage, are consistent with this interpretation. Second, these policies do not simply reshuffle domestic talent; they also attract overseas talent. Our evidence on foreign star inventor inflows suggests that local talent policies can expand the effective talent pool available to Chinese cities, making the resulting entrepreneurial upgrading more plausibly positive-sum rather than merely redistributive.

5 Discussion

This paper provides causal evidence of how an increased supply of talent both from overseas and domestically can improve entrepreneurship quality in a developing economy. Exploiting the gradual introduction of local talent policies across Chinese cities as a natural experiment, we apply a staggered difference-in-differences framework using rich administrative data. The results show that, although these policies were not explicitly designed to improve general entrepreneurial activity, they significantly enhance the quality of newly established local ventures by strengthening the local talent pool, as reflected in both predictive indicators and realized outcomes. However, we find that simply attracting talent to a location does not automatically yield entrepreneurial or innovation gains nor are the benefits uniform across sectors. Rather, it depends on the degree of knowledge complementarity between the incoming talent and the destination location's technological strengths. In particular, our results show

that policy-induced talent inflows translate into better entrepreneurial outcomes when incoming talent can be matched to relevant opportunity spaces and absorbed by local domains of relative specialization, as well as recombined through existing knowledge and organizational linkages that facilitate science-to-market translation.

Our null finding on entrepreneurial *quantity* and positive finding on entrepreneurial *quality* is also notable. In other words, talent inflows do not significantly increase the overall rate of new business formation, but are associated with substantial entrepreneurial upgrading especially in human-capital-intensive industries and high-tech sectors. This pattern can be explained by two factors. First, unlike broad pro-entrepreneurship policies or targeted innovation programs that primarily provide financial subsidies, business support services and/or administrative relief to stimulate entry, talent policies attract elite individuals who are more likely to raise startup quality and enhance entrepreneurial success. Our findings on the noticeable shift toward high-tech industries in local entrepreneurial activity and the limited demand-side spillovers are consistent with this interpretation that talent policies operate primarily through a supply-side upgrading of entrepreneurial quality. Second, the elite talent that is attracted and ultimately relocates appears to be positively matched, with individuals sorting into locations where their skills can be used most productively. Our evidence of stronger effects in cities' domains of revealed comparative advantage, based on measures of industrial complementarities and technological relatedness, supports this interpretation.

In sum, this paper addresses a relatively understudied gap in understanding the relationship between skilled migration and entrepreneurship quality, particularly the mobility of individuals with demonstrated achievements across international borders

and within countries. Although our findings allowed us to causally establish the relationship between migratory trends and entrepreneurial quality by leveraging an institutional policy lever that spurs the mobility of highly skilled individuals, it has several limitations, which point to opportunities for future research. We were unable to track whether the talent inflows also brought financial resources with them, either through their own investment or through their network of potential investors (Vaaler, 2011; Yavuz & Bahadir, 2022). We also did not dive into details of each city's rewards policy, such as how much subsidy was provided and in what format. Finally, we did not track the individual roles of incoming highly skilled talent—such as academics, startup founders, or inventor employees—and their relative contributions to local entrepreneurship quality. Future research exploring these dimensions could provide additional valuable insights.

5.1 Contributions to Literature

This paper contributes to several strands of literature. We extend the literature on global talent migration and its implications for economic growth. Our findings add to recent works on immigration (Acosta & Marinoni, 2025; Agarwal et al., 2022) by showing that talent policies attract star inventors both domestically and internationally, and shape the destination city's entrepreneurial and innovation ecosystem. Much of the existing literature focuses on national-level immigration policies that regulate inflows, such as H-1B visas (Kerr & Kerr, 2022; Kerr & Lincoln, 2010; Tareque et al., 2024) and employment-based permanent residency in the United States (Kahn & MacGarvie, 2020). In contrast, we study a setting where local-level targeted policies within a country traditionally characterized by talent outflows actively incentivize talent in-

flows, providing novel evidence on reverse migration and its impact on entrepreneurship and innovation. In the same vein, we contribute to the literature on determinants of talent mobility. The geographic mobility of highly skilled individuals can be influenced by economic incentives (Akcigit et al., 2016; Moretti & Wilson, 2017), contract law (Marx et al., 2009; Starr et al., 2019), institutional intermediaries (Armanios et al., 2017; Tian & Xu, 2022) and other growth-oriented policies (Eesley, 2016). Our findings show how elite human capital respond to city-level talent policies when deciding where to relocate.

We also add to the literature on entrepreneurial quality and its determinants. Although entrepreneurship is widely recognized as a driver of economic growth, most startups fail to scale (Decker et al., 2014). Recent work by Balsmeier et al. (2025) causally establishes the positive relationship between human capital and entrepreneurship quality in a market-driven migration setting in the United States. Beyond replicating their finding that local entrepreneurial activity shifts from low-tech to high-tech industries, we go further by showing that, even within high-tech sectors, entrepreneurial gains depend on the complementarity between the incoming talent's knowledge and the destination city's domains of relative advantage. Policy-induced talent inflows thus deepen cities' existing specialization. At the same time and more interestingly, these gains also extend selectively to technologically adjacent industries, although such broadening is primarily reflected in early-stage innovation and does not translate into further downstream growth outcomes. In addition, entrepreneurial gains are contingent on complementary knowledge capabilities anchored in university-based research and reinforced through science–industry linkages.

5.2 Managerial and Policy Implications

Our findings suggest that managers seeking to enhance entrepreneurial quality should prioritize effective talent strategies and leverage talent policies when available, as these policies help attract highly skilled individuals including those trained abroad. Thoughtful integration of such globally experienced talent into local organizational routines and innovation practices can further amplify their contributions to entrepreneurial quality and innovation (Xia et al., 2025). At the same time, the results carry important implications for entrepreneurs' location choices: while talent policies can be advantageous, their benefits are highly uneven, concentrating in specific cities and industries where complementary knowledge and specialization already exist. Entrepreneurs therefore may benefit most from locating in cities with strong universities and established talent pools, and should be mindful that these policies mainly support growth in particular areas rather than broadly across all locations or sectors.

These results also carry important policy implications. In contexts where talent is mobile and unevenly distributed, local governments can play a critical role in shaping entrepreneurial outcomes by targeting highly skilled individuals and strengthening the local innovation ecosystem. The effectiveness of such policies appears to hinge on the local environment's industrial and knowledge capacity, and may be amplified by mechanisms that facilitate the translation of innovation into business success and bridge science to market.

More broadly, in an increasingly knowledge-intensive global economy, where many countries face rapidly aging populations, competition for mobile, highly skilled entrepreneurs and innovators is mounting (Kerr & Kerr, 2022). Recent pullbacks from and added restrictions to U.S. immigration programs, including the F-1 international

student visa and the H-1B work visa, create an opportune moment for other countries, particularly traditional source countries of talent, to reverse some of the migratory trends of previous decades through targeted talent policies. Our results underscore the strategic value of such policies in fostering innovation and entrepreneurship in this international context.

6 Conclusion

In conclusion, this paper demonstrates that elite talent inflows induced by policy can substantially raise the quality of entrepreneurial activity. By attracting highly accomplished individuals who sort into industries and locations where their skills are most productively matched, these policies promote high-growth and innovation-oriented entrepreneurship. Overall, the results suggest that place-based talent strategies can be an effective lever for strengthening entrepreneurial ecosystems and long-run economic dynamism when local industrial and knowledge complementarities are present.

References

Acosta, C., & Marinoni, A. (2025). Uncertainty and immigrant entrepreneurship: Evidence from brexit. *Organization Science*, *36*(3), 1072–1087.

Agarwal, R., Ganco, M., & Raffiee, J. (2022). Immigrant entrepreneurship: The effect of early career immigration constraints on new venture formation. *Organization Science*, *33*(4), 1372–1395.

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. (2011). Brain drain or brain bank? the impact of skilled emigration on poor-country innovation. *Journal of Urban Economics*, *69*(1), 43–55.

Akcigit, U., Alp, H., Pearce, J., & Prato, M. (2025). *Transformative and subsistence entrepreneurs: Origins and impacts on economic growth* (Working Paper No. 33766). National Bureau of Economic Research.

Akcigit, U., Baslandze, S., & Stantcheva, S. (2016). Taxation and the international mobility of inventors. *American Economic Review*, *106*(10), 2930–2981.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Andrews, R. J., Fazio, C., Guzman, J., Liu, Y., & Stern, S. (2022). The startup cartography project: Measuring and mapping entrepreneurial ecosystems. *Research Policy*, *51*(9), 104581.

Armanios, D. E., Eesley, C. E., Li, J., & Eisenhardt, K. M. (2017). How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources. *Strategic Management Journal*, *38*(7), 1373–1390.

Azoulay, P., Jones, B. F., Kim, J. D., & Miranda, J. (2020). Age and high-growth entrepreneurship. *American Economic Review: Insights*, *2*(1), 65–82.

Balsmeier, B., Fleming, L., Marx, M., & Shin, S. R. (2025). Startups, unicorns, and the local influx of inventors. *The Review of Economics and Statistics*, 1–44.

Batista, C., Han, D., Haushofer, J., Khanna, G., McKenzie, D., Mobarak, A. M., Theoharides, C., & Yang, D. (2025). Brain drain or brain gain? effects of high-skilled international emigration on origin countries. *Science*, *388*(6749), eadr8861.

Belderbos, R., Leten, B., Nguyen, N. H., & Vancauteren, M. (2025). Multinational firms and the quest for global talent: Employing (skilled) foreign workers at home and abroad. *Journal of International Business Studies*, *56*(2), 151–173.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61.

Bikard, M. (2018). Made in academia: The effect of institutional origin on inventors' attention to science. *Organization Science*, *29*(5), 818–836.

Borjas, G. J., & Doran, K. B. (2012). The collapse of the soviet union and the productivity of american mathematicians. *The Quarterly Journal of Economics*, *127*(3), 1143–1203.

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *The Review of Economic Studies*, *91*(6), 3253–3285.

Boschma, R., Balland, P.-A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in us metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), 223–250.

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs*. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Chai, S., & Shih, W. (2016). Bridging science and technology through academic–industry partnerships. *Research Policy*, *45*(1), 148–158.

Chari, A., Liu, E. M., Wang, S.-Y., & Wang, Y. (2021). Property rights, land misallocation, and agricultural efficiency in china. *The Review of Economic Studies*, *88*(4), 1831–1862.

Chodavadia, S., Kerr, S. P., Kerr, W., & Maiden, L. (2025). *Immigrant entrepreneurship: New estimates and a research agenda*. Edward Elgar Publishing.

de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), 2964–2996.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, *28*(3), 3–24.

Eesley, C. (2016). Institutional barriers to growth: Entrepreneurship, human capital and institutional change. *Organization Science*, *27*(5), 1290–1306.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and "mode 2" to a triple helix of university–industry–government relations. *Research policy*, *29*(2), 109–123.

Etzkowitz, H., Webster, A., Gebhardt, C., & Terra, B. R. C. (2000). The future of the university and the university of the future: Evolution of ivory tower to entrepreneurial paradigm. *Research policy*, *29*(2), 313–330.

Feldman, M. P. (2000). Where science comes to life: University bioscience, commercial spin-offs, and regional economic development. *Journal of Comparative Policy Analysis: Research and Practice*, *2*(3), 345–361.

Feldman, M. P., & Kelley, M. R. (2003). Leveraging research and development: Assessing the impact of the us advanced technology program. *Small Business Economics*, *20*(2), 153–165.

Flynn, R., Glennon, B., Murciano-Goroff, R., & Xiao, J. (2024). *Building a wall around science: The effect of us-china tensions on international scientific research* (tech. rep.). National Bureau of Economic Research.

Foley, C. F., & Kerr, W. R. (2013). Ethnic innovation and us multinational firm activity. *Management Science*, *59*(7), 1529–1544.

Fry, C., & Furman, J. L. (2025). Migration and global network formation: Evidence from female scientists in developing countries. *Organization Science*, *36*(3), 1047–1071.

Ganco, M., Ziedonis, R. H., & Agarwal, R. (2015). More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. *Strategic Management Journal*, *36*(5), 659–685.

Ganguli, I. (2015). Immigration and ideas: What did russian scientists "bring" to the united states? *Journal of Labor Economics*, *33*(S1), S257–S288.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.

Grogger, J., & Hanson, G. H. (2015). Attracting talent: Location choices of foreign-born phds in the united states. *Journal of Labor Economics*, *33*(S1), S5–S38.

Guzman, J., & Stern, S. (2020). The state of american entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 us states, 1988–2014. *American Economic Journal: Economic Policy*, *12*(4), 212–243.

Hausman, N. (2022). University innovation and local economic growth. *The Review of Economics and Statistics*, *104*(4), 718–735.

Hernandez, E., Choudhury, P., Kulchina, E., Wang, D., Shaver, J. M., Zellmer-Bruhn, M., & Khanna, T. (2025). Why should organizational scholars study migration? *Organization Science*, *36*(3), 1021–1046.

Huang, Z., & Tian, X. (2020). China's venture capital market. *The Handbook of China's Financial System*, 383–418.

Jang, S. (2017). Cultural brokerage and creative performance in multicultural teams. *Organization Science*, *28*(6), 993–1009.

Jensen, R., & Thursby, M. (2001). Proofs and prototypes for sale: The licensing of university inventions. *American Economic Review*, *91*(1), 240–259.

Jia, R., Roberts, M. E., Wang, Y., & Yang, E. (2024). The impact of us–china tensions on us science: Evidence from the nih investigations. *Proceedings of the National Academy of Sciences*, *121*(19), e2301436121.

Kahn, S., & MacGarvie, M. (2020). The impact of permanent residency delays for stem phds: Who leaves and why. *Research Policy*, *49*(9), 103879.

Kerr, S. P., & Kerr, W. (2020a). Immigrant entrepreneurship in america: Evidence from the survey of business owners 2007 & 2012. *Research Policy*, *49*(3), 103918.
Kerr, S. P., & Kerr, W. R. (2016). Immigrants play a disproportionate role in american entrepreneurship. *Harvard Business Review*, *3*.
Kerr, S. P., & Kerr, W. R. (2020b). Immigration policy levers for us innovation and startups.
Kerr, S. P., & Kerr, W. R. (2022). Immigration policy levers for us innovation and startups. *Innovation and Public Policy*, 85.
Kerr, W. R. (2020). *The gift of global talent: How migration shapes business, economy & society*. Stanford University Press.
Kerr, W. R., & Lincoln, W. F. (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics*, *28*(3), 473–508.
Kleven, H. J., Landais, C., & Saez, E. (2013). Taxation and international migration of superstars: Evidence from the european football market. *American Economic Review*, *103*(5), 1892–1924.
Koo, W. W.-Y., & Eesley, C. E. (2025). Take me home, country roads: Return migration and platform-enabled entrepreneurship. *Organization Science*, *36*(3), 1202–1220.
Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital. *The RAND Journal of Economics*, *31*(4), 674–692.
Lafontaine, F., & Shaw, K. (2016). Serial entrepreneurship: Learning by doing? *Journal of Labor Economics*, *34*(S2), S217–S254.
Lerner, J. (2009). *Boulevard of broken dreams: Why public efforts to boost entrepreneurship and venture capital have failed–and what to do about it*. Princeton University Press.
Leten, B., Belderbos, R., & Van Looy, B. (2016). Entry and technological performance in new technology domains: Technological opportunities, technology competition and technological relatedness. *Journal of Management Studies*, *53*(8), 1257–1291.
Martellini, P., Schoellman, T., & Sockin, J. (2024). The global distribution of college graduate quality. *Journal of Political Economy*, *132*(2), 434–483.
Marx, M. (2022). Employee non-compete agreements, gender, and entrepreneurship. *Organization Science*, *33*(5), 1756–1772.
Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the michigan non-compete experiment. *Management Science*, *55*(6), 875–889.
Melero, E., Palomeras, N., & Wehrheim, D. (2020). The effect of patent protection on inventor mobility. *Management Science*, *66*(12), 5485–5504.
Moretti, E. (2021a). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, *111*(10), 3328–3375.
Moretti, E. (2021b). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, *111*(10), 3328–3375.
Moretti, E., & Wilson, D. J. (2017). The effect of state taxes on the geographical location of top earners: Evidence from star scientists. *American Economic Review*, *107*(7), 1858–1903.
Moser, P., Voena, A., & Waldinger, F. (2014). German jewish émigrés and us invention. *American Economic Review*, *104*(10), 3222–3255.
Murray, F. (2004). The role of academic inventors in entrepreneurial firms: Sharing the laboratory life. *Research policy*, *33*(4), 643–659.
National Science Board. (2024). *Science and engineering indicators 2024* (tech. rep.). National Science Foundation.

Palomeras, N., & Melero, E. (2010). Markets for inventors: Learning-by-hiring as a driver of mobility. *Management Science*, *56*(5), 881–895.

Saxenian, A. (1996). *Regional advantage: Culture and competition in silicon valley and route 128*. Harvard University Press.

Scellato, G., Franzoni, C., & Stephan, P. (2015). Migrant scientists and international networks. *Research Policy*, *44*(1), 108–120.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics*, *33*, 141–149.

Shi, D., Liu, W., & Wang, Y. (2023). Has china's young thousand talents program been successful in recruiting and nurturing top-caliber scientists? *Science*, *379*(6627), 62–65.

Simeth, M., & Mohammadi, A. (2022). Losing talent by partnering up? the impact of r&d collaboration on employee mobility. *Research Policy*, *51*(7), 104551.

Song, Z., Storesletten, K., & Zilibotti, F. (2011). Growing like china. *American Economic Review*, *101*(1), 196–233.

Starr, E., Frake, J., & Agarwal, R. (2019). Mobility constraint externalities. *Organization Science*, *30*(5), 961–980.

Tareque, I. S., Guzman, J., & Wang, D. (2024). High-skilled immigration enhances regional entrepreneurship. *Proceedings of the National Academy of Sciences*, *121*(37), e2402001121.

Tian, X., & Xu, J. (2022). Do place-based policies promote local innovation and entrepreneurship? *Review of Finance*, *26*(3), 595–635.

Uhlbach, W.-H., & Anckaert, P.-E. (2025). Migration and innovation: How foreign r&d hires shape firm-level exploration in their host country. *Organization Science*, *36*(3), 1110–1130.

Vaaler, P. M. (2011). Immigrant remittances and the venture investment environment of developing countries. *Journal of International Business Studies*, *42*(9), 1121–1149.

Wang, Y., Li, J., & Furman, J. L. (2017). Firm performance and state innovation funding: Evidence from china's innofund program. *Research Policy*, *46*(6), 1142–1161.

Wilson, D. J. (2009). Beggar thy neighbor? the in-state, out-of-state, and aggregate effects of r&d tax credits. *The Review of Economics and Statistics*, *91*(2), 431–436.

Xia, J., Yao, F. K., Li, J., Liu, C., Wang, F., Ding, W. W., & Zhang, H. (2025a). Bridging the divide: How dual-background leaders unlock returnee innovation in politically connected chinese firms. *Journal of Management Studies*.

Xia, J., Yao, F. K., Li, J., Liu, C., Wang, F., Ding, W. W., & Zhang, H. (2025b). Bridging the divide: How dual-background leaders unlock returnee innovation in politically connected chinese firms. *Journal of Management Studies*.

Xie, Y., Lin, X., Li, J., He, Q., & Huang, J. (2023). Caught in the crossfire: Fears of chinese–american scientists. *Proceedings of the National Academy of Sciences*, *120*.

Yavuz, R. I., & Bahadir, B. (2022). Remittances, ethnic diversity, and entrepreneurship in developing countries. *Small Business Economics*, *58*(4), 1931–1952.

Zucker, L. G., Darby, M. R., & Brewer, M. B. (1998). Intellectual human capital and the birth of us biotechnology enterprises. *American Economic Review*, *88*(1).

Online Appendices

A Construction of the Entrepreneurship Quality Measure

To measure city-year level entrepreneurial quality, we first construct a startup-level indicator of entrepreneurship quality and then aggregate it to the city-year level. Following Andrews et al. (2022), we adopt a predictive analytics approach that links the ultimate performance of startups to early-stage choices made by entrepreneurs—choices that are observable at or near the time of founding. These decisions reflect the entrepreneur's private information about their underlying idea, their ambition, and the idea's growth potential. As such, they carry predictive power regarding the startup's future trajectory.

Specifically, using data on all privately registered business ventures between 2001 and 2013, we estimate the probability $\theta_{i,c,t}$ that entrepreneur i, who founded a firm in city c and year t, achieves a growth milestone within five years of founding, using a logistic specification based on observable characteristics at the time of founding. We restrict the sample to firms founded after 2001 because China's capital markets were underdeveloped in earlier decades.[1] We limit the training data to firms founded no later than 2013 to ensure that five-year post-founding outcomes can be fully observed, as our CVSource data cover deals only up to 2018.

$$\theta_{i,c,t} = Prob\left(g_{i,c,t} \mid H_{i,c,t}\right) \tag{A1}$$

The growth outcome, $g_{i,c,t}$, is defined as a binary indicator that equals one if startup firm i registered in city c and year t attracts at least one round of VC investment or undergoes an IPO within five years of its initial registration with the State Administration for Market Regulation (SAMR). Among the 12,332,665 firms in our training sample, 9,653 firms (0.078%) meet this criterion. This share of high-growth startups is comparable to, though slightly higher than, the corresponding figure for the United States (0.071%), as reported by Guzman and Stern (2020).

The startup characteristics at founding, $H_{i,c,t}$, include six sets of predictors: (1) the length of the firm's name, which may reflect the formality or perceived credibility of the venture; (2) the enterprise category, for which we construct dummy variables for limited liability companies (LLCs) and shareholding companies (SHCs) among privately owned firms, using individually owned private firms as the reference category;[2] (3) the natural logarithm of registered capital, which reflects the amount shareholders (pledge to) contribute upon incorporation and serves as a ceiling on liability to creditors and a signal of credibility in partnership selection and loan applications; (4) two non-mutually exclusive dummy variables related to shareholder composition—one

[1] Although business registration data are available from 1985 onward, China's stock and VC markets were still underdeveloped in the 1990s and virtually nonexistent in the 1980s. China's two main stock exchanges, the Shanghai and Shenzhen Stock Exchanges, were reestablished in 1990, with early listings dominated by state-owned enterprises. Venture capital activity was minimal: only 22 VC deals were recorded in 1995, compared to 466 in 2005 and 9,806 in 2015.

[2] Privately owned firms can be registered as private firms (individually owned), limited liability companies (LLCs), or shareholding companies (SHCs). An LLC refers to a firm in which shareholders are liable only up to the amount of their capital contributions; it cannot offer shares to the public and is limited to a maximum of 50 shareholders in China. An SHC can offer shares to the public. In the training data, 22.1% of firms are LLCs, and only 0.3% are SHCs. Among high-growth firms, however, 29.6% are LLCs, and 8.8% are SHCs.

indicating the presence of at least one university shareholder, and the other indicating at least one public research institute shareholder (e.g., the Chinese Academy of Sciences); (5) three dummy variables capturing intellectual property ownership, indicating whether the firm applied for at least one of each type of invention, utility model, or design patent[3] with CNIPA within the first year of founding; and (6) the firm's one-digit industry classification. To avoid mechanically attributing startups' quality to their city of origin, we explicitly exclude from $H_{i,c,t}$ any variable that is constant across all startups within a given city-year cohort and that varies only at the city-year level.

In Table A1, we present the estimation results from the prediction model. Shorter firm names, larger registered capital, being a shareholding corporation, having filed an invention patent within one year of founding, and having a university as a shareholder are all positively and significantly associated with the likelihood of achieving high-growth milestones. To evaluate the model's predictive power, we perform a tenfold cross-validation comparing the estimated entrepreneurial quality with actual growth outcomes—i.e., whether a startup subsequently receives VC funding or achieves an IPO. The results, shown in Figure A1, indicate that the model performs well in predicting growth outcomes in the held-out folds of the cross-validation: 86% to 90% of all high-growth firms fall within the top 10% of the distribution of estimated entrepreneurial quality, and 74% to 79% fall within the top 5%.

The estimated probability $\hat{\theta}_{i,c,t}$ of achieving a growth outcome, based on startup characteristics at founding, serves as a predictive measure of the entrepreneurship quality of startup i. Using this firm-level measure as a foundation, we construct several city-year level variables to evaluate local entrepreneurship quality. The first variable is the *aggregate entrepreneurship quality* of startups founded in a given city-year, calculated by summing $\hat{\theta}_{i,c,t}$ across all startups in that cohort. This measure captures both the quantity and quality of entrepreneurial activity and reflects the expected number of growth events based on founding characteristics. It can be interpreted as a quality-weighted startup formation rate. The second variable is the *average entrepreneurship quality*, defined as the ratio of aggregate entrepreneurship quality to the number of startups in the city-year cohort.

In addition to these predictive measures, we construct two outcome-based variables to characterize realized entrepreneurial performance. One is the *number of high-growth startups*, measured by the number of firms in a given city-year that reached growth milestones, such as VC funding or an IPO within five years of founding. The other is the *number of patent-active startups*, defined as the number of startups that filed for patents within five years of founding and successfully obtained at least one granted patent. This variable captures the early-stage innovation capacity of startups, as reflected in their ability to generate patentable knowledge shortly after founding.

To illustrate the spatial distribution of entrepreneurial activity and its quality, Table A2 reports the top 50 cities by predicted *aggregate entrepreneurship quality* over the period 2001 to 2016. In addition to megacities such as Shenzhen and Shanghai, the list is dominated by provincial capitals and cities in southeastern China—all of which are included in our sample.

[3]Invention patents in China resemble utility patents in the United States and cover novel technical solutions or improvements to products or processes. Utility model patents apply to novel structural or functional designs of products. Design patents protect the external appearance of products, including their shape, pattern, and color.

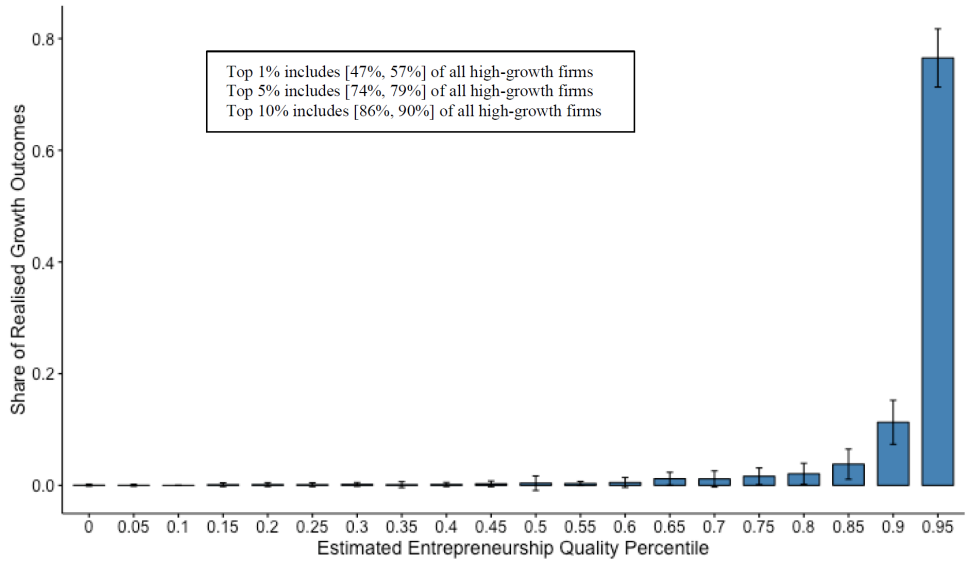


Figure A1: Cross Validation of the Quality Estimation Model

Notes: The figure plots results of an out-of-sample 10-fold cross validation procedure performed on all privately owned firms registered between 2001 and 2013. Ten-fold cross-validation is a frequently used technique to evaluate predictive models, where we randomly partition the original sample into 10 equal size subsamples and use one subsample as the test data and the other 9 as training data. We repeat this validation procedure 10 times.

Table A1: Predictive Model on the Training Dataset (2001-2013)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.		VC or IPO		VC	IPO
Invention		2.577***	1.766***	1.840***	1.397***
		[13.16]	[5.847]	[6.297]	[4.043]
		(0.050)	(0.045)	(0.048)	(0.094)
Utility model		0.743***	0.637***	0.375***	1.410***
		[2.102]	[1.891]	[1.455]	[4.096]
		(0.056)	(0.051)	(0.057)	(0.097)
Design		0.910***	0.955***	0.964***	0.901***
		[2.484]	[2.599]	[2.622]	[2.462]
		(0.059)	(0.059)	(0.066)	(0.099)
University shareholder		1.205***	0.679***	0.843***	-0.493
		[3.337]	[1.972]	[2.323]	[0.611]
		(0.130)	(0.128)	(0.129)	(0.400)
Public research institute		0.516***	0.167	0.207	-0.017
shareholder		[1.675]	[1.182]	[1.230]	[0.983]
		(0.141)	(0.138)	(0.148)	(0.267)
Length of name	-0.018***	-0.013*	-0.059***	-0.062***	-0.038***
	[0.982]	[0.987]	[0.943]	[0.940]	[0.983]
	(0.005)	(0.005)	(0.006)	(0.006)	(0.013)
LLC	0.006	-0.073**	-0.120***	-0.025	-0.606***
	[1.006]	[0.930]	[0.887]	[0.975]	[0.546]
	(0.023)	(0.024)	(0.024)	(0.026)	(0.059)
SHC	2.493***	2.274***	2.052***	1.859***	2.085***
	[12.10]	[9.718]	[7.783]	[6.417]	[8.045]
	(0.042)	(0.044)	(0.046)	(0.053)	(0.076)
Log registered capital	0.478***	0.432***	0.494***	0.459***	0.648***
	[1.613]	[1.540]	[1.639]	[1.582]	[1.912]
	(0.005)	(0.005)	(0.006)	(0.006)	(0.012)
Industry fixed effects	No	No	Yes	Yes	Yes
Pseudo R^2	0.100	0.143	0.219	0.207	0.250
Observations	12,332,665	12,332,665	12,257,931	12,257,931	12,257,931

Notes: The analysis model uses logistic regressions. The dependent variables are dummies indicating whether a firm has attracted at least one round of VC investment or experienced an IPO event within five years from its initial registration. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Odds-ratio coefficients are in square brackets. Pseudo R2 is McFadden Pseudo R^2. Other variable definitions are as follows. (1) Invention (dummy): 1 indicates that a firm applies for at least one invention patent to CNIPA within the first year of its registration; 0 otherwise; (2) Utility model (dummy): 1 indicates that a firm applies for at least one utility model patent to the CNIPA within the first year of its registration; 0 otherwise; (3) Design (dummy): 1 indicates that a firm applies for at least one design patent to the CNIPA within the first year of its registration; 0 otherwise; (4) University shareholder (dummy): 1 indicates that a firm has at least one shareholder that is a university; 0 otherwise; (5) Public research institute shareholder (dummy): 1 indicates that a firm has at least one shareholder that is a public research institute; 0 otherwise; (6) Length of name: number of characters of a firm's name; (7) LLC (dummy): 1 indicates that a firm is registered as a limited liability corporation; 0 otherwise; (8) SHC (dummy): 1 indicates that a firm is registered as a shareholding corporation; 0 otherwise; (9) Log registered capital: natural logarithm of the value for registered capital in 1,000 RMB.

Table A2: Top 50 Cities in *Aggregate Entrepreneurship Quality* (2001–2016)

Rank	City	Aggregate entrepreneurship quality	Startup formation rate
1	Beijing	2,357.5	1,074,764
2	Shanghai	1,902.0	1,504,102
3	Shenzhen	1,546.4	1,231,281
4	Guangzhou	927.2	574,952
5	Hangzhou	786.6	433,020
6	Chengdu	717.3	504,288
7	Tianjin	634.9	396,854
8	Nanjing	533.7	456,228
9	Suzhou	489.9	336,439
10	Wuhan	466.0	339,430
11	Chongqing	418.1	489,551
12	Zhengzhou	391.3	336,649
13	Changsha	382.8	202,248
14	Xi'an	354.5	260,817
15	Wuxi	345.1	210,476
16	Xiamen	338.5	208,627
17	Hefei	284.8	229,632
18	Shijiazhuang	277.9	267,826
19	Qingdao	271.4	309,440
20	Jinan	268.0	203,336
21	Kunming	248.7	228,646
22	Fuzhou	245.8	182,303
23	Ningbo	244.9	246,051
24	Shenyang	188.2	201,489
25	Dongguan	186.4	281,685
26	Nanning	180.5	178,253
27	Taiyuan	169.1	141,489
28	Dalian	165.8	189,556
29	Nantong	163.9	154,419
30	Guiyang	162.3	140,221
31	Changzhou	158.6	121,581
32	Harbin	154.5	148,974
33	Changchun	141.4	154,603
34	Zhuhai	133.4	82,927
35	Nanchang	133.0	128,355
36	Quanzhou	132.8	143,572
37	Xuzhou	121.4	136,814
38	Foshan	119.9	192,483
39	Haikou	117.6	102,112
40	Yancheng	117.5	118,228
41	Weifang	114.3	135,573
42	Wenzhou	107.3	162,400
43	Urumqi	101.9	109,244
44	Yantai	100.3	132,984
45	Jiaxing	99.0	96,394
46	Jinhua	96.4	144,415
47	Lanzhou	95.9	105,336
48	Taizhou	89.1	78,691
49	Yangzhou	86.7	84,929
50	Zhenjiang	82.4	69,335

B Robustness Checks and Additional Analyses

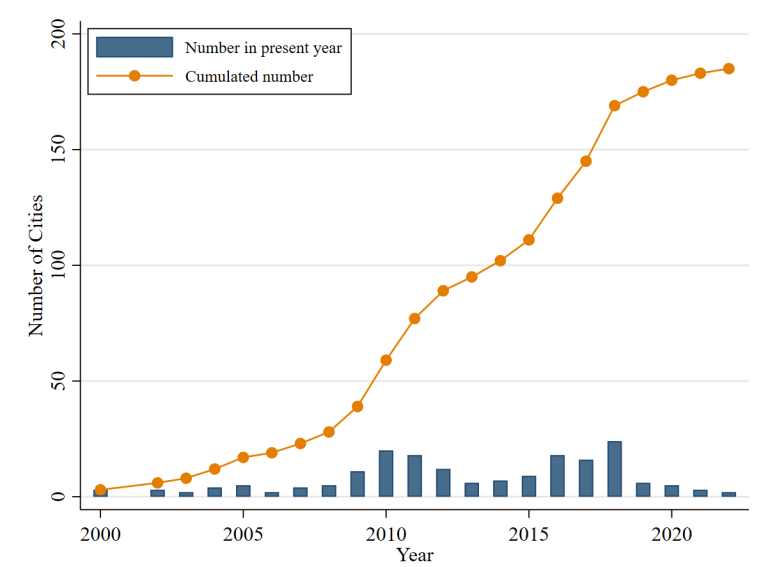


Figure B1: Policy Adoption over Time

Notes: This figure shows policy adoption over time among the 189 prefectural cities in the sample from 2000 to 2022.

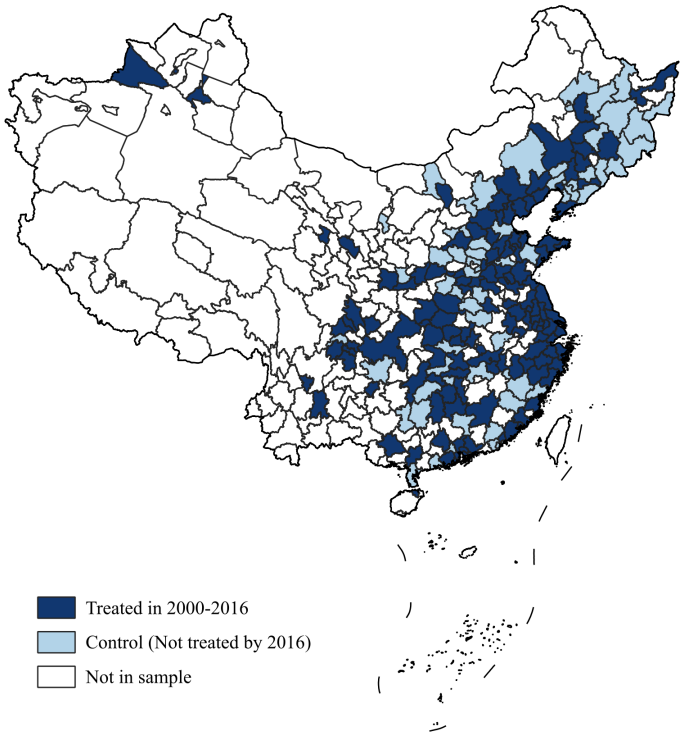


Figure B2: Local Talent Policy in China

Notes: Each delineated area in the map indicates a prefecture-level administrative unit.

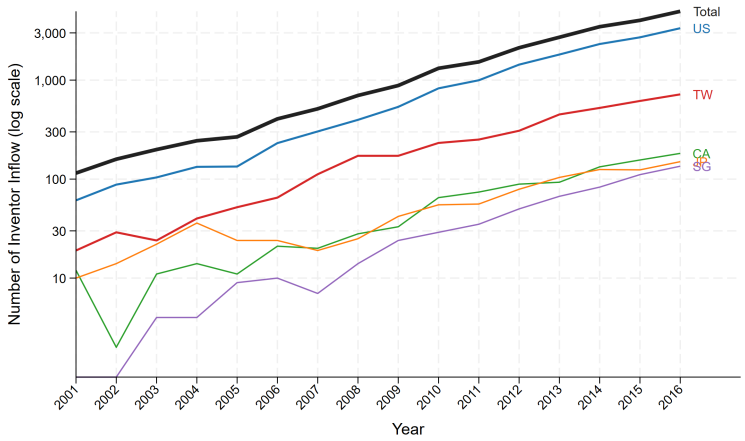
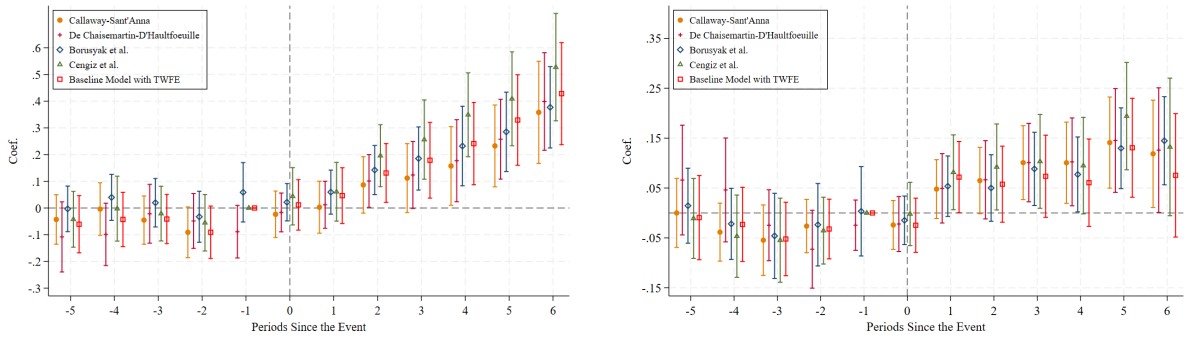


Figure B3: USPTO Inventor Inflows into China by Origin

Notes: This figure plots the annual number of USPTO inventor inflows into China by prior patenting location. The solid black line shows total foreign inventor inflows, while colored lines indicate inflows from selected major source locations. The y-axis is presented on a logarithmic scale.



(A) Number of High-Growth Startups (B) Number of Patent-Active Startups

Figure B4: Event-Study Estimates: Parallel Trends and Dynamic Effects

Notes: This figure overlays event-study plots constructed using five different estimators: (1) Callaway and Sant'Anna (2021); (2) de Chaisemartin and D'Haultfœuille (2020); (3) Borusyak et al. (2024); (4) Cengiz et al. (2019), a stacked difference-in-differences estimator; and (5) a dynamic version of our baseline model with TWFE as specified in Equation (2). The dependent variable is $log(1 + y)$ transformed. The bars represent a 90% confidence interval. Standard errors are clustered at the city-level.

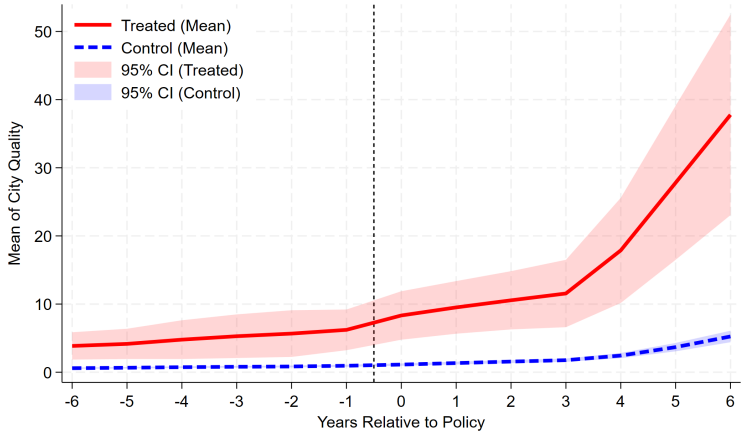


Figure B5: Treated vs. Control Means of Aggregate Entrepreneurship Quality by Event Time

Notes: This figure plots the average aggregate entrepreneurship quality for treated and never-treated cities relative to the year of policy implementation. Treated cities are aligned by event time and averaged across cohorts under a stacked DID design, with never-treated cities serving as the comparison group. Shaded areas indicate 95% confidence intervals.

Table B1: In-Sample and Out-of-Sample City Attributes

Variables	In-sample Mean (std.)	Out-of-sample Mean (std.)	Diff.	t-value
GDP per capita	11,563.80	6,417.35	5,146.45	3.27***
	(13,212.00)	(6,715.30)		
Patent application	385.15	26.76	358.39	3.78***
	(837.27)	(12.66)		
Startup formation rate	1,942.63	240.35	1,702.28	3.97***
	(3780.25)	(138.85)		
Employment share (Manufacturing)	42.77	38.36	4.41	2.48***
	(11.81)	(16.19)		
Employment share (Services)	52.48	54.76	-2.27	-1.33
	(10.96)	(16.13)		
GDP share (Manufacturing)	44.91	40.83	4.09	2.75***
	(9.74)	(13.71)		
GDP share (Services)	37.18	34.62	2.57	2.59**
	(7.63)	(6.68)		
Population density (people/km^2)	488.18	446.94	41.25	0.39
	(425.45)	(1295.84)		

Notes: China consisted of 332 prefecture-level administrative units in 2001, which include 265 prefecture-level cities, 32 regions, 30 autonomous prefectures, and 5 leagues. The in-sample cities include all 189 prefecture-level units with at least 50 patents that year, consisting of 187 prefecture-level cities and 2 autonomous prefectures. The out-of-sample cities include the remaining 78 prefecture-level cities. Summary statistics are calculated using data from the China City Statistical Yearbook and the statistical yearbooks of these two specific autonomous prefectures.

Table B2: Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Startup formation rate												
2. Aggregate entrepreneurship quality	0.91***											
3. Number of high-growth startups	0.71***	0.81***										
4. Number of patent-active startups	0.93***	0.90***	0.73***									
5. Domestic star inventor inflow	0.78***	0.83***	0.83***	0.81***								
6. Overseas star inventor inflow	0.75***	0.77***	0.87***	0.73***	0.83***							
7. $Policy_{it}$	0.32***	0.27***	0.14***	0.34***	0.24***	0.15***						
8. GDP per capita	0.53***	0.45***	0.29***	0.58***	0.47***	0.32***	0.49***					
9. Employment share (Manufacturing)	0.09***	0.03	-0.05**	0.13***	0.01	-0.03*	0.21***	0.42***				
10. Employment share (Services)	-0.01	0.03	0.08***	-0.07***	0.05***	0.07***	-0.13***	-0.34***	-0.80***			
11. GDP share (Manufacturing)	-0.13***	-0.16***	-0.15***	-0.10***	-0.16***	-0.15***	0.04**	0.22***	0.58***	-0.45***		
12. GDP share (Services)	0.49***	0.44***	0.33***	0.45***	0.45***	0.35***	0.23***	0.35***	-0.07***	0.11***	-0.57***	
13. Population density	0.42***	0.31***	0.25***	0.39***	0.31***	0.32***	0.14***	0.23***	0.19***	-0.02	0.10***	0.17***

Notes: The number of observations is 3,024 at the city-year level (189 cities from 2001 to 2016). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Domestic star inventor inflow refers to the inflow of top 10% domestic inventors (CNIPA data); overseas star inventor inflow refers to the inflow of top 10% inventors with overseas patenting experience (USPTO data).

Table B3: Determinants of Policy Timing

	(1)	(2)
	Treated	Treated
GDP per capita	0.000	0.000
	(0.000)	(0.000)
GDP share (Manufacturing)	-0.205	-0.098
	(0.264)	(0.103)
GDP share (Services)	0.323	-0.080
	(0.342)	(0.137)
Employment share (Manufacturing)	-0.011	-0.030
	(0.126)	(0.073)
Employment share (Services)	-0.032	-0.028
	(0.136)	(0.070)
Population density	0.001	-0.001
	(0.002)	(0.001)
Expenditure on S&T per capita	0.023	0.012
	(0.016)	(0.014)
Telecommunications development	0.002	0.003
	(0.003)	(0.002)
College density	28.853	23.260
	(22.182)	(21.597)
Tier-one Cities		0.015
		(8.226)
Tier-two Cities		0.888
		(2.824)
Tier-Three Cities		-1.946
		(2.629)
Cities with 985 or 211		1.849
		(2.450)
City FE	Y	
Year FE	Y	Y
Year FE by Province	Y	Y
R-squared	0.337	0.246
Adjusted R^2	0.137	0.116
Observations	1,966	1,970

Notes: The city-year sample is limited to the periods including the policy implementation year and the years prior, and the dependent variable is an indicator for the policy year. This exercise examines whether characteristics at the city level predict the timing of policy implementation.

Table B4: Robustness Checks—Alternative Definitions of Star Inventors

	Domestic star inventors					Foreign star inventors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Rank by Citations		Rank by Patents			Rank by Patents	
Dep. Var.	Top 15%	Top 5%	Top 15%	Top 10%	Top 5%	Top 15%	Top 5%
$Policy_{it}$	0.222***	0.234***	0.085**	0.090**	0.123***	0.168***	0.160***
	(0.059)	(0.064)	(0.037)	(0.038)	(0.043)	(0.058)	(0.055)
Adjusted R^2	0.877	0.764	0.944	0.940	0.928	0.816	0.789
Observations	2,880	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In all specifications, control variables include the natural logarithm of GDP per capita, population density, indicators of local industrial structure, city fixed effects, and province-by-year fixed effects. We identify domestic star inventors using CNIPA patent data and foreign star inventors using USPTO patent data. Columns (1)–(2) define domestic star inventors by their average forward citations per patent (5-year window); columns (3)–(7) define star inventors by their cumulative patent counts. Inventors in the top 10% of the USPTO productivity distribution account for 95.3% of inflows into China; those in the top 15% account for 98.7%, and those in the top 5% account for 84.9%. All dependent variables are transformed as $\log(1+y)$.

Table B5: Robustness Checks—Alternative Sample Selection

	Star inventor inflows		Entrepreneurial outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Domestic	Overseas	Startup formation rate	Aggregate EQ	High-growth startups	Patent-active startups
$Policy_{it}$	0.236***	0.223**	-0.013	0.095**	0.140*	0.078*
	(0.067)	(0.086)	(0.031)	(0.041)	(0.080)	(0.044)
Adjusted R^2	0.891	0.816	0.977	0.972	0.778	0.943
Observations	1,728	1,728	1,728	1,728	1,728	1,728

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. All dependent variables are transformed as $\log(1+y)$. The sample is restricted to cities that filed at least 100 patents with CNIPA in 2001. EQ stands for Entrepreneurship Quality.

Table B6: Robustness Checks—Inverse Hyperbolic Sine Transformation

	Star inventor inflows		Entrepreneurial outcomes			
Dep. Var.	(1) Domestic	(2) Overseas	(3) Startup formation rate	(4) Aggregate EQ	(5) High-growth startups	(6) Patent-active startups
$Policy_{it}$	0.241***	0.195***	-0.011	0.089***	0.170***	0.035
	(0.072)	(0.069)	(0.025)	(0.031)	(0.064)	(0.042)
Adjusted R^2	0.848	0.796	0.977	0.974	0.737	0.926
Observations	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include city fixed effects, province × year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. All dependent variables are transformed using the inverse hyperbolic sine function, $\text{asinh}(y) = \log\left(y + \sqrt{y^2+1}\right)$, which is well-defined at zero and approximates $\log(y)$ for large y while accommodating zero observations.

Table B7: Robustness Checks—Industry Reliance on Human Capital

	(1)	(2)	(3)	(4)
Dep. Var.	Aggregate entrepreneurship quality			
$Policy_{it}$	0.005**	-0.011***	-0.014***	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)
$Policy_{it}$ × Average salary		0.010***		
		(0.003)		
$Policy_{it}$ × Higher-education share			0.118***	
			(0.027)	
$Policy_{it}$ × High-tech industry				0.025***
				(0.006)
Adjusted R^2	0.780	0.781	0.782	0.781
Observations	275,184	275,184	275,184	275,184

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions are estimated using a city–year–industry panel covering 91 two-digit industries. All specifications include control variables for the natural logarithm of GDP per capita, population density, and local industrial structure, as well as city-by-industry, industry-by-year, and province-by-year fixed effects. Industry-level average salary is measured using 2003 data from CEIC (www.ceicdata.com) and expressed in units of 10,000 RMB. The industry-level share of workers with a college degree or higher is based on data from the Fifth Population Census of China (2000) (international.ipums.org). The high-tech industry indicator is defined based on the Intellectual Property Intensive Industries Statistical Classification (2019) (https://www.gov.cn/gongbao/content/2019/content_5419213.htm). High-tech industries include ICT manufacturing, ICT services, advanced equipment manufacturing, new materials manufacturing, pharmaceuticals and medical industries, environmental protection industries, and research, design, and technical services.

Table B8: Complementarities with Local Industrial Specialization—across All Industries

	Star Inventor inflows		Entrepreneurial outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Domestic	Overseas	Aggregate EQ	Startup formation rate	High-growth startups	Patent-active startups
$Policy_{it} \times RCA_j$	0.026***	0.010***	0.010***	-0.020	0.007**	0.043***
	(0.006)	(0.003)	(0.003)	(0.024)	(0.003)	(0.009)
$Policy_{it} \times NonRCA_j \times Related_j$	0.105***	0.054***	0.022*	0.048	-0.002	0.124***
	(0.031)	(0.018)	(0.013)	(0.035)	(0.011)	(0.035)
$Policy_{it} \times NonRCA_j \times Unrelated_j$	-0.002	-0.003	-0.001	-0.041**	-0.001	-0.006
	(0.004)	(0.002)	(0.002)	(0.019)	(0.002)	(0.007)
Adjusted R^2	0.688	0.757	0.781	0.906	0.461	0.676
Observations	290,304	290,304	290,304	290,304	290,304	290,304

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure, including the shares of the service and manufacturing sectors in both GDP and employment. Dependent variables and star inventor inflows are transformed as $\log(1 + y)$. The sample size reflects the exclusion of singleton observations resulting from the inclusion of province-year fixed effects. EQ stands for Entrepreneurship Quality.

Table B9: Policy, Talent Inflow, and Knowledge Translation: Citation-Weighted Patent Measures

	University Patents				**Entrepreneurial Outcomes**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Coassigned w/ firm	Without firm	Coassigned w/ firm	Without firm	Aggregate EQ	High-growth startups
$Policy_{it}$	0.278***	0.353***	0.169**	0.258**	0.059**	0.095*
	(0.095)	(0.106)	(0.082)	(0.099)	(0.026)	(0.049)
Star Inventors Inflow:						
Domestic			0.363***	0.357***		
			(0.043)	(0.046)		
Overseas			0.151***	0.076		
			(0.046)	(0.054)		
University Patents:						
Coassigned					0.065***	0.149***
					(0.011)	(0.021)
Without firm					0.038***	0.030*
					(0.007)	(0.017)
Adjusted R^2	0.748	0.892	0.770	0.899	0.970	0.759
Observations	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. University patent measures are weighted by forward citations received within three years of grant. All specifications include city fixed effects, province $\times$ year fixed effects, and city-level macroeconomic controls, including the natural logarithm of GDP per capita, population density, and indicators of local industrial structure. Dependent variables and star inventor inflows are transformed as $\log(1 + y)$. EQ stands for Entrepreneurship Quality.

Table B10: Industry Heterogeneity and the Limited Role of Demand-Side Spillovers

Aggregate entrepreneurship quality as Dep. Var.						
	Transp., Storage, Postal	Accom. & Catering	ICT	Agriculture	Manufacturing	Health & Social Work
	(1)	(2)	(3)	(4)	(5)	(6)
$Policy_{it}$	0.008†	0.001	0.092***	0.001	0.021	0.004
	(0.005)	(0.003)	(0.032)	(0.007)	(0.017)	(0.005)
Adj. R^2	0.729	0.475	0.888	0.759	0.903	0.423
Obs.	2,880	2,880	2,880	2,880	2,880	2,880
	Residential Services	Construction	Real Estate	Wholesale & Retail	Education	Culture, Sports, Entertainment
	(7)	(8)	(9)	(10)	(11)	(12)
$Policy_{it}$	-0.006	0.017***	0.009**	0.032†	-0.002	0.035†
	(0.009)	(0.006)	(0.004)	(0.022)	(0.004)	(0.022)
Adj. R^2	0.398	0.676	0.792	0.858	0.325	0.678
Obs.	2,880	2,880	2,880	2,880	2,880	2,880
	Water, Env., Public Facilities	Electricity, Heat, Gas, Water	Scientific Research	Leasing & Business	Mining	Finance
	(13)	(14)	(15)	(16)	(17)	(18)
$Policy_{it}$	0.000	0.000	0.124***	0.085***	-0.002†	-0.002
	(0.002)	(0.003)	(0.044)	(0.028)	(0.001)	(0.017)
Adj. R^2	0.569	0.578	0.904	0.835	0.221	0.478
Obs.	2,880	2,880	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. † denotes marginal significance with a p-value smaller than 0.15. In all specifications, control variables include the natural logarithm of GDP per capita, population density, indicators of local industrial structure, city fixed effects, and province-by-year fixed effects.

Table B11: Geographic Neighbor Policy Effects

	(1)	(2)	(3)	(4)
Dep. Var.	Domestic star inventor inflow	Foreign star inventor inflow	Aggregate entrepreneurship quality	Startup formation rate
$Policy_{it}$	0.271***	0.179**	0.093***	-0.014
	(0.062)	(0.058)	(0.028)	(0.026)
$NeighborPolicy_{it}$	0.340**	0.102	0.019	-0.028
	(0.124)	(0.110)	(0.065)	(0.055)
Adjusted R^2	0.858	0.804	0.967	0.977
Number of Observations	2,880	2,880	2,880	2,880

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All specifications include controls for the natural logarithm of GDP per capita, population density, and local industrial structure, as well as city fixed effects and province-by-year fixed effects. $NeighborPolicy_{it}$ is defined as the average policy exposure among the five geographically closest neighboring cities.