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Scientist Mobility and Innovative Entrepreneurship

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Abstract

High-level scientific talent serves as a key driver of knowledge creation and the commercialization of technology. However, there remains a lack of systematic empirical evidence on how the cross-regional mobility of high-level scientific talent influences local innovative entrepreneurship. This paper uses the initial inflow of highly cited scientists into a city as an exogenous shock to construct a quasi-natural experiment design. By matching data on Chinese business registrations with patent data, we examine the impact of highly cited scientist mobility on local innovative entrepreneurship and its underlying mechanisms. The study finds that the inflow of highly cited scientists significantly promotes innovation and entrepreneurship in the receiving regions. Mechanism analysis indicates that the mobility of highly cited scientists primarily exerts its effects through channels such as facilitating the diffusion of cutting-edge knowledge, driving the clustering of innovative talent, and enhancing the attraction of innovation capital. Heterogeneity analysis reveals that the promotional effect on innovation and entrepreneurship is more pronounced when there is a higher degree of alignment between the scientists' research fields and the local technological structure, when the scientists themselves possess greater academic influence, and when the receiving region has more robust innovation infrastructure. Further analysis indicates that the inter-city mobility of highly cited scientists does not significantly weaken the level of innovation-driven entrepreneurship in the regions from which they originate. This paper reveals the key mechanisms through which the mobility of high-level scientific talent promotes innovation-driven entrepreneurship, providing new micro-level evidence for understanding the relationship between high-level talent mobility and regional innovation development.

1. Introduction

Against the backdrop of intensifying global innovation competition, knowledge-based innovation is increasingly becoming a new source of regional economic growth. Innovation-driven entrepreneurship, as a vital form of knowledge commercialization, is emerging as a key foundation for regional innovation-driven growth (Block et al., 2017; Malerba & McKelvey, 2020). In recent years, entrepreneurial activity in China has grown rapidly, significantly driving the country's economic growth. However, from the perspective of innovation-driven entrepreneurship, there remains an issue of "rapid quantitative expansion but insufficient qualitative leadership." According to StartupBlink's "2025 Global Startup Ecosystem Index" report, China's startup ecosystem growth rate reached 45.9% in 2025, with 10,548 active startups; yet, its overall ranking stood at only 13th globally, trailing the United States and the United Kingdom, and even falling behind Australia. The reason for this is that while China performs exceptionally well in terms of "quantity," it remains relatively weak in the dimensions of "quality" and "business environment." Consequently, how China can foster more innovation-driven entrepreneurship based on new knowledge and technologies in a highly competitive environment has become a critical issue that urgently needs to be addressed.

High-level scientific talent has long been regarded as a vital foundation for knowledge transfer and technological innovation (Lucas, 1988; Romer, 1990; Dobrev et al., 2023). In China, the cultivation and

allocation of high-level scientific talent have also consistently been prioritized; policies such as the "Changjiang Scholars Program," the "National Science Fund for Distinguished Young Scholars," and the "National Special Support Program for High-Level Talents" provide support for the research activities and career development of such talent (Jing et al., 2023). Research indicates that the cross-regional mobility of high-level talent not only alters the allocation of local human capital but also reshapes the regional innovation landscape through channels such as knowledge diffusion, organizational learning, and collaborative innovation (Breschi et al., 2020; Wigger, 2022; Uhlbach et al., 2022; Xu et al., 2023; Behera et al., 2024; Giorgi et al., 2025; Qin et al., 2026). For example, Agarwal et al. (2007) noted that the mobility of knowledge creators facilitates the entry of knowledge—which has not been fully utilized by existing organizations—into the market through entrepreneurship, thereby transforming knowledge spillovers into economic value. The theory of knowledge-spillover entrepreneurship proposed by Acs et al. (2013) also indicates that entrepreneurship is a crucial pathway for the commercialization of scientific and technical knowledge, and that the entrepreneurial activities of knowledge producers can drive regional innovation and development. The aforementioned studies provide an important foundation for understanding the innovation effects of talent mobility, but there remains room for further exploration regarding how the mobility of high-level scientific talent influences innovative entrepreneurship. On the one hand, existing research on talent mobility primarily focuses on the mobility effects of inventors, researchers, and highly skilled workers (Rahko, 2017; Aksnes et al., 2013; Baruffaldi & Landoni, 2012; Agrawal et al., 2006; Kerr et al., 2016; Xu et al., 2023), and lack in-depth analysis of the role played by high-level scientists as a distinct category of knowledge agents. High-level scientists are embedded in extensive academic collaboration networks and possess stronger capabilities for resource linkage and knowledge transfer (Rahko, 2017; Zhang & Lucey, 2019; Cao et al., 2026), and their cross-regional mobility exerts deeper impacts on the receiving regions. On the other hand, existing research on innovative entrepreneurship has focused more on external institutional environments and regional support conditions (Darnihamedani et al., 2018; Prenzel et al., 2024; Chen & Zhou, 2023), with insufficient attention paid to how agents of knowledge creation drive the formation of innovation-driven entrepreneurship. Innovation-driven entrepreneurship is, by its very nature, an entrepreneurial activity highly dependent on the supply of knowledge (Baumol, 2010; Malerba & McKelvey, 2020). High-level scientists serve as key agents in driving knowledge creation and transformation; however, the impact of their mobility on innovation-driven entrepreneurship and the underlying mechanisms have not yet been fully elucidated.

To address gaps in existing research, this study uses Elsevier's "Highly Cited Chinese Scholars" list from 2014 to 2024 to identify instances of high-level scientists moving between cities. By linking data on Chinese business registrations with patent data, we construct a panel dataset on innovative entrepreneurship at the city-by-year level. The findings indicate that the inflow of highly cited scientists significantly promotes the development of local innovative entrepreneurship. This conclusion holds up under a series of robustness tests, including the Goodman-Bacon decomposition, a robust DID that accounts for heterogeneous treatment effects, placebo tests, propensity score-matched difference-in-differences, and replacement of the dependent variable. Mechanism analysis indicates that the inflow of highly cited scientists primarily drives local innovation and entrepreneurship through the diffusion of

cutting-edge knowledge, the aggregation of innovative talent, and the attraction of innovation capital. Heterogeneity analysis reveals that the stronger the match between a scientist's research field and the local technological structure, the stronger the promotional effect; the inflow of scientists with varying levels of influence all contributes to enhancing innovation and entrepreneurship, but the intensity of this effect varies depending on the dimension of influence; and the more developed the innovation infrastructure in the destination city, the more significant the promotional effect of scientist mobility. Further analysis indicates that the inter-city mobility of highly cited scientists does not come at the expense of innovation and entrepreneurship in the origin cities.

The marginal contributions of this paper are primarily reflected in the following three aspects. First, this study expands the scope of research on high-level talent mobility in terms of both research subjects and data sources. Existing studies primarily rely on census or survey data to characterize talent mobility patterns (Liu & Shen, 2017; Cao et al., 2018; Fang et al., 2020). However, such data struggle to accurately identify the mobility of high-level scientific talent or distinguish between general skilled workers and high-level scientists. This study utilizes Elsevier's "China Highly Cited Scholars" directory to continuously track changes in scientists' institutional and city affiliations, thereby identifying their inter-city mobility and providing a new data source for analyzing the mobility of high-level scientific talent in China.

Second, this paper reexamines the economic consequences of high-level talent mobility from the perspective of innovative entrepreneurship. Existing research has primarily focused on the impact of talent mobility on traditional innovation indicators such as patent output, journal publications, and R&D performance (Miguélez et al., 2010; Wei et al., 2020; Wang et al., 2025), but has rarely directly examined whether it promotes local innovative entrepreneurship. By matching business registration data with patent data to identify innovative and entrepreneurial firms and aggregating these at the city level, this paper maps the evolution of innovation and entrepreneurship in Chinese cities at a finer spatial scale, thereby offering a research approach that can serve as a reference for future studies.

Third, this paper deepens our understanding of the impact mechanisms of highly cited scientists. Unlike general talent mobility, the mobility of highly cited scientists is accompanied by shifts in cutting-edge knowledge, collaborative networks, academic reputation, and innovation resources (Miguélez & Morrison, 2023; Han et al., 2024; Prato, 2025; Giorgi et al., 2025). This paper analyzes the mechanisms through which the mobility of highly cited scientists influences innovation-driven entrepreneurship from three perspectives: the diffusion of cutting-edge knowledge, the clustering of innovative talent, and the attraction of innovation capital. It further examines heterogeneous factors such as "discipline-technology" matching, the influence of scientists, and the conditions of innovation infrastructure in destination locations, thereby revealing the intrinsic connections between these two phenomena more comprehensively.

2. Literature Review and Hypothesis Development

2.1 Literature Review

This paper draws on two core strands of literature. The first strand focuses on the impacts of talent mobility. On the one hand, research has examined the effects of talent migration on individuals' research activities and knowledge-production capabilities. Such studies suggest that inter-institutional mobility among researchers can help them access new knowledge resources, expand their collaborative networks, and enhance the efficiency of scientific knowledge creation. For example, Fernández-Zubieta et al. (2016) point out that researcher mobility can alter the structure of the knowledge networks in which they are embedded and influence the formation of academic collaborative relationships. Netz et al. (2020) found a significant link between researchers' career mobility and research productivity, noting that institutional transitions can provide researchers with new resource environments and knowledge opportunities. Researcher mobility not only affects publication output and academic influence but also facilitates the establishment of new collaborative relationships and interdisciplinary knowledge exchange (Miguélez et al., 2010; Qiao & Dong, 2026). On the other hand, research has focused on the impact of knowledge-based talent migration on the innovation performance of firms and regions. Based on the theory of knowledge spillovers, relevant studies argue that talent serves as a key vehicle for technical knowledge, experience, and social networks (Argote & Ingram, 2000; Dyer & Singh, 1998). The mobility of engineers and technical personnel can facilitate the cross-organizational dissemination of tacit knowledge and foster connections between knowledge systems in different regions (Almeida & Kogut, 1999). The mobility of inventors and R&D personnel can help firms break through existing knowledge-search boundaries and promote technological innovation and patent output through the introduction of external knowledge (Rahko, 2017; Aksnes et al., 2013; Baruffaldi & Landoni, 2012). Interregional talent migration is also considered a key mechanism for promoting knowledge diffusion and enhancing regional innovation capacity (Boschma et al., 2014; Wei et al., 2020; Wang et al., 2025). Overall, existing research has revealed the crucial role of talent mobility in knowledge creation, technology diffusion, and the enhancement of innovation performance, laying the foundation for understanding the relationship between knowledge flow and innovation development. However, there remains a lack of systematic research on whether and how the mobility of high-level scientists—a distinct group possessing the capacity for cutting-edge knowledge creation, academic reputation, and resource connectivity—drives innovative entrepreneurial activities.

The second body of literature focuses on the definition, characteristics, and influencing factors of innovative entrepreneurship. In terms of definition, innovative entrepreneurship is a knowledge-intensive form of entrepreneurship centered on the creation of new knowledge, technological breakthroughs, and the realization of market value (Baumol, 2010; Malerba & McKelvey, 2020). Unlike general entrepreneurial activities, which primarily rely on the integration of existing resources and the replication of business models, innovative entrepreneurship emphasizes the creation of new products, services, or industrial opportunities through scientific discoveries, technological innovations, and the reorganization of knowledge; its essence lies in transforming underutilized knowledge resources into new economic value (Acs et al., 2013). In terms of characteristics, innovative entrepreneurship is typically highly knowledge-intensive, technologically complex, and has high growth potential. First, innovative entrepreneurship often stems from emerging technologies, scientific breakthroughs, or interdisciplinary knowledge

combinations; therefore, entrepreneurs must possess strong capabilities in knowledge creation and technology absorption (Koellinger, 2008; Malerba & McKelvey, 2020). Second, because innovative entrepreneurship involves the development of new technologies and the cultivation of new markets, its future returns and commercialization pathways are subject to a high degree of uncertainty, and the entrepreneurial process faces greater technical and market risks (Block et al., 2017). Finally, innovative entrepreneurship exhibits high growth potential; its goal is not to maintain a small-scale operation but to achieve rapid expansion and market restructuring through technological advantages (Henrekson & Sanandaji, 2014). These characteristics determine that innovation-driven entrepreneurship relies more heavily on the participation of high-level knowledge-based talent. In particular, during the process of transforming scientific knowledge into industrial value, high-level scientists with deep research experience and professional networks can play crucial roles as knowledge producers, technology integrators, and opportunity discoverers (Marvel, 2013; Marvel et al., 2016). Therefore, understanding the formation mechanisms of innovation-driven entrepreneurship requires further attention to how high-level scientific talent influences such entrepreneurial activities.

2.2 Hypothesis Formulation

Compared to general entrepreneurial activities, innovative entrepreneurship not only requires identifying the practical value of new knowledge but also involves organizing specialized talent and capital to transform technological opportunities into viable entrepreneurial projects; as such, it is more susceptible to the impact of the influx of highly cited scientists. The influx of highly cited scientists leads to the spatial reorganization of cutting-edge knowledge, collaborative networks, and innovation resources (Miguélez & Morrison, 2023; Han et al., 2024; Prato, 2025; Giorgi et al., 2025). Based on this, this paper analyzes the mechanisms through which the inflow of highly cited scientists impacts local innovation-driven entrepreneurship from three perspectives: the diffusion of cutting-edge knowledge, the clustering of innovative talent, and the attraction of innovation capital.

2.2.1 Mechanism of Cutting-Edge Knowledge Diffusion

The non-rivalrous and non-exhaustible nature of knowledge makes its diffusion and reuse a vital source of innovation and entrepreneurial opportunities (Aghion & Jaravel, 2015). However, the public availability of knowledge does not necessarily imply its effective application. Scientific knowledge is typically highly specialized and context-dependent; relying solely on codified media such as papers and patents, potential entrepreneurs may not fully grasp its application conditions and technical value. Research collaboration, technical consulting, and joint R&D help convey relevant experience and reduce barriers to understanding and applying knowledge (Breschi & Lissoni, 2009). The inflow of highly cited scientists can create new conditions for local actors to access and utilize scientific knowledge. On the one hand, the inflow of scientists helps bridge the gap between entrepreneurs and the scientific frontier, making it easier for them to identify new technological opportunities, understand technical pathways, and reduce the costs of knowledge acquisition. On the other hand, after scientists move to a new city, they can promote the local diffusion of cutting-edge scientific knowledge through various channels—such as

technical consulting, patent applications, and project collaborations—thereby improving the conditions for the supply of knowledge to local innovative startups (Perkmann et al., 2013).

2.2.2 Mechanisms for the Aggregation of Innovation Talent

The commercialization of scientific knowledge requires the coordinated participation of multiple professional competencies (Moretti, 2021). While scientists can provide research direction and expert judgment, technological development, engineering implementation, and market application also require R&D personnel, engineering and technical staff, and professionals with industry experience. The mobility of highly cited scientists often extends beyond individual relocation; it is accompanied by the expansion of research teams, the deepening of project collaborations, and the establishment of innovation platforms, thereby attracting more talent to cluster in the destination city (Edler et al., 2011; Azoulay et al., 2017). For example, new research and technology development tasks require the participation of relevant personnel, and local enterprises will increase their R&D investment and recruitment for technical positions as a result of exposure to new technological opportunities; new research activities and career development opportunities will also enhance the region's appeal to relevant talent (Franzoni et al., 2014). Potential innovative startup teams can thus more easily access the specialized capabilities required for technology development and engineering applications, thereby reducing the costs associated with talent search, team formation, and R&D collaboration.

2.2.3 Mechanisms for Attracting Innovation Capital

Innovative entrepreneurship typically requires sustained investment at a time when technical feasibility and market prospects remain unclear. Particularly in the startup phase, innovative entrepreneurial firms generally lack a stable track record, collateral assets, and cash flow, while external investors find it difficult to accurately assess their technological value; consequently, these firms are prone to significant financing constraints (Evans & Jovanovic, 1989). Against this backdrop, the influx of highly cited scientists serves as a recognizable positive signal that improves local entrepreneurial capital support. For venture capital firms, industrial investors, and policymakers, the arrival of highly cited scientists in a city typically indicates that the region possesses a strong research foundation, robust knowledge-production capabilities, and a greater number of potential technological opportunities. This, in turn, helps reduce the uncertainty external capital and resource providers face when evaluating the local innovation environment and entrepreneurial projects (Samila & Sorenson, 2011). Furthermore, the influx of scientists will enhance the visibility and legitimacy of local innovation activities, attracting greater attention from the media, government agencies, investment institutions, and industry stakeholders toward local scientific and technological innovation and entrepreneurial developments (Clarysse et al., 2011). Based on the above analysis, this paper proposes the following hypotheses:

H1

The mobility of highly cited scientists significantly promotes local innovation-driven entrepreneurship.

H2

The mobility of highly cited scientists promotes local innovative entrepreneurship through the diffusion of cutting-edge knowledge.

H3

The mobility of highly cited scientists promotes local innovative entrepreneurship through the clustering of innovative talent.

H4

The mobility of highly cited scientists promotes local innovative entrepreneurship through the attraction of innovation capital.

3. Empirical Models and Data Sources

3.1 Data Sources

First, data on scientist mobility were obtained from the “Highly Cited Chinese Scholars” list published by Elsevier and the information on the institutions listed as authors’ affiliations in their papers. This paper systematically compiles the list of China’s Highly Cited Scholars from 2014 to 2024 and, by combining this with information on the institutions listed in the scholars’ papers over the years, identifies their employing institutions and the cities where they are located. For scholars who did not publish any papers in certain years, this paper uses the year in which they first published a paper at their new institution to determine the timing of their mobility, in order to maximize the accuracy of mobility identification. Second, data on innovative entrepreneurship are primarily sourced from the China Business Registration Database and the China Patent Database. This study matches business registration data with patent data based on information such as company name, Unified Social Credit Code, registered address, and patent applicant, and identifies startups that obtained patents within two years of their establishment based on the company’s registration date and the date the patent was granted. On this basis, enterprise information is aggregated to the city-year level to form city-level innovative entrepreneurship indicators. Third, city-level control variables are primarily sourced from the *China Urban Statistical Yearbook*, the *China Urban Construction Statistical Yearbook*, local statistical yearbooks, city statistical bulletins, and relevant databases. Fourth, talent recruitment and investment data are primarily sourced from job recruitment databases and venture capital databases; data on technology transfer platforms and startup incubation platforms are compiled based on national and local platform directories and matched to the city level. This study ultimately constructs panel data at the city-year level. All continuous variables undergo truncation at the top and bottom 1% to reduce the impact of outliers on the estimation results. Standard errors are cluster-adjusted at the city level.

3.2 Variable Measurement

3.2.1 Dependent Variable: Innovative Entrepreneurship

Existing literature primarily measures innovative entrepreneurship using data from the Global Entrepreneurship Monitor (GEM), questionnaire surveys, and enterprise sample data (Darnihamedani et al., 2018; Low & Isserman, 2015; Kang et al., 2015; Giraudo et al., 2019). However, these methods have certain limitations regarding long-term comparisons and micro-level identification at the Chinese city level. Given that innovative activities—such as business model innovation, process innovation, and the development of new markets—are difficult to measure in a standardized manner, this study follows the approach in the economics of innovation that uses patents as a measure of innovation (Thompson, 2006) and matches the Chinese Business Registration Database with the Chinese Patent Database. Drawing on the truncation adjustment method commonly used in the literature (Akcigit et al., 2016), this study defines innovative startups as those that obtained a patent within two years of their registration, based on the average examination period for different types of patents during the sample period. The data are then categorized by city based on the enterprises' location and measured using the logarithm of the number of innovative startups.

3.2.2 Independent Variable: Scientist Mobility

Since 2014, Elsevier has consistently published the "China Highly Cited Researchers" list based on scholars' publication and citation records. Based on this, this study manually compiled a list of China's highly cited researchers from 2014 to 2024, yielding a sample of 7,541 highly cited researchers. Building on this, we further tracked the annual publication records of the scholars in the sample and identified changes in their affiliations based on the institutions listed in their paper bylines.

The reason for using the institution listed in the paper byline as the basis for identifying a scholar's affiliation is that this information is typically directly related to the attribution of research achievements, academic evaluation, and subsequent recognition, and can relatively accurately reflect the scholar's actual affiliation at the time of publication. Therefore, when a scholar's affiliation changes, the institution listed in their paper byline is usually adjusted accordingly. Given that highly cited scholars generally have a high frequency of research output, most scholars can provide relatively continuous annual affiliation information. Based on this, this study compares the affiliation listed on a scholar's paper in a given year with that of the previous year; if the affiliations differ between the two years, it is determined that the scholar experienced inter-institutional mobility in that year. For the small number of scholars who did not publish papers in certain years—resulting in gaps in their affiliation records—this study uses the year in which they first published a paper at their new institution as the year in which mobility occurred.

After identifying mobility at the individual level, this study further conducts manual matching and organization of scholars' affiliated institutions at the city level, converting individual-level changes in institutional affiliation into city-level scientist mobility data, and thereby constructs the core explanatory variables required for subsequent empirical analysis. Specifically, if a city experiences its first inflow of highly cited scientists during the sample period, that city is defined as a treatment city for scientist inflow, and the year of the first inflow is defined as the treatment year. The treatment variable is constructed as follows: when city i has experienced its first inflow of scientists and year t is not earlier than the year of that inflow, the core treatment variable DIDit takes the value 1; otherwise, it takes the

value 0. This variable reflects the persistent treatment effect experienced by the city following its first inflow of highly cited scientists.

3.2.3 Control Variables

Given that other city-level factors may also influence the formation and development of new firms—particularly innovative startups—this study further controls for the following variables: (1) Level of economic development, measured by the natural logarithm of a city's regional gross domestic product (GDP). A higher level of economic development indicates a larger local market and more abundant innovation resources, which are more conducive to innovative entrepreneurship. (2) Industrial structure, measured by the natural logarithms of the value added in the primary, secondary, and tertiary sectors, respectively. Industrial structure reflects the local industrial base, technological application scenarios, and industrial support capabilities. (3) Population size, measured by the natural logarithm of the city's year-end population. Cities with larger populations typically have greater market demand, a more abundant labor supply, and higher entrepreneurial activity. (4) Human capital reserves, measured by the logarithms of the number of students enrolled in middle and elementary schools, respectively.

3.3 Specification of the Econometric Model

The mobility of scientists is characterized by distinct cross-city and time-specific patterns; the fact that different cities experience their first inflow of highly cited scientists in different years exhibits certain characteristics of a quasi-natural experiment. Given that the inflow of highly cited scientists exhibits distinct patterns of phased and staggered entry, the following baseline difference-in-differences (DID) model is constructed to scientifically assess the impact of scientist mobility on urban innovation and entrepreneurship:

$$Y_{it} = \alpha + \beta DID_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where Y_{it} represents the level of innovative entrepreneurship in city i in year t; α is a constant term; DID_{it}t indicates whether city i experienced an inflow of scientists in year t; X_{it} is a set of city-level control variables; μ_i represents city fixed effects; λ_t represents year fixed effects; and ε_{it} is a random error term.

Regarding the construction of the treatment variable, this paper defines the year in which city i first experienced an inflow of highly cited scientists as the treatment year. Specifically, if city i first experienced an inflow of highly cited scientists in year T_i, the treatment variable is constructed as follows:

$$DID_{it} = Treat_i \times Post_{it}$$

where $Treat_i$ indicates whether city i experienced an inflow of highly cited scientists during the sample period; it takes the value 1 if an inflow occurred, and 0 otherwise; $Post_{it}$ indicates whether year t falls on or after the year of the city's first inflow of highly cited scientists; if $t \geq T_i$, it takes the value 1, otherwise 0. In other words, for cities experiencing their first inflow of scientists during the sample period, the

treatment variable takes the value 1 in the year of the inflow and all subsequent years, and 0 in years prior to the inflow; for cities that never experienced an inflow of scientists during the sample period, the treatment variable always takes the value 0.

It should be noted that the inflow of scientists into cities may not occur randomly; therefore, this study cannot rely solely on the baseline difference-in-differences (DID) model to completely rule out selection bias. To address this, the following tests will be conducted in the subsequent sections: First, an event study will be used to examine whether the treatment and control groups exhibited parallel trends prior to the treatment; second, propensity score matching combined with the difference-in-differences method will be employed to mitigate differences in observable characteristics between the treatment and control groups; third, conducting a placebo test by randomly assigning treatment years and treatment groups; fourth, employing a heterogeneous robust DID method suitable for multi-time-point treatments to eliminate estimation biases that may arise in traditional two-way fixed-effects models due to heterogeneity in treatment effects; and fifth, testing the robustness of the findings by varying the identification window for innovative startups.

4. Empirical Analysis

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables. The sample comprises a total of 23,550 city-year observations. The mean value for innovative entrepreneurship (lncountry2) is 2.113, with a standard deviation of 1.561; the minimum and maximum values are 0 and 6.457, respectively, indicating relatively significant differences in the level of innovative entrepreneurship across cities. The core treatment variable (did2) had a mean of 0.121, a standard deviation of 0.326, and a range from 0 to 1, indicating that approximately 12.1% of highly cited scientists experienced mobility during the sample period, and that there was good distinguishability between the treatment group and the control group.

Table 1
Descriptive Statistics of Key Variables

Variable	N	Mean	SD	Min	Max
lncountry2	23550	2.113	1.561	0	6.457
did2	23550	0.121	0.326	0	1
lngdp	23550	14.27	1.139	11.12	16.93
lnmiddle	23550	9.672	1.035	6.472	11.50
lnprim	23550	10.07	0.967	7.252	11.91
lnthird	23550	13.41	1.205	10.17	16.37
lnsec	23550	13.20	1.367	9.468	16.05
lnfirst	23550	12.04	1.203	7.863	13.94
lnpop	23550	3.587	0.892	0.693	5.147

4.2 Baseline Regression

Table 2 reports the results of the baseline regression on the impact of the inflow of highly cited scientists on local innovation and entrepreneurship. In Column (1), which does not include control variables, the estimated coefficient for did2 is 2.1132 and is significant at the 1% level. In Column (2), after controlling for covariates, the coefficient for did2 decreased to 1.1890 but remained significant at the 1% level, indicating that this result is not entirely driven by differences in observable regional characteristics. In Column (3), after further controlling for city fixed effects and year fixed effects, the estimated coefficient for did2 was 0.6250, which remained significant at the 1% level. In Column (4), the standard errors are adjusted to city-level cluster-robust standard errors, and the core conclusions remain unchanged. Overall, the baseline regression results indicate that the mobility of scientists significantly promotes innovative entrepreneurship in destination cities, and H1 is supported.

Table 2
Baseline Regression Results

Variable	(1)	(2)	(3)	(4)
	No controls	Controls	HC robust	Cluster(city)
did2	2.1132***	1.1890***	0.6250***	0.6250***
	(86.0976)	(34.1201)	(9.3239)	(7.9114)
lngdp		-0.3756***	-0.1757	-0.1757
		(-4.8785)	(-1.3492)	(-1.1092)
lnmiddle		-0.4076***	0.1855***	0.1855***
		(-13.2706)	(4.8290)	(4.0004)
lnprim		0.7126***	-0.0878	-0.0878
		(22.8850)	(-1.3875)	(-1.1602)
lnthird		0.8813***	0.1329*	0.1329
		(19.5445)	(1.9091)	(1.5022)
lnsec		0.2531***	0.1005*	0.1005
		(8.4078)	(1.8407)	(1.5330)
lnfirst		-0.1651***	-0.1875***	-0.1875***
		(-11.8870)	(-4.6152)	(-3.8554)
lnpop		-0.6554***	0.2471*	0.2471
		(-19.1296)	(1.7924)	(1.4815)
City F.E.	No	No	Yes	Yes
Year F.E.	No	No	Yes	Yes
Constant	1.7865***	-6.9378***	1.1096	1.6415
	(185.1112)	(-25.2080)	(1.2570)	(1.5007)
N	23550	23550	23550	23550
Adj_R^2	0.2394	0.3555	0.7424	0.7420
Note: t statistics in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01; The same applies below.				

4.3 Parallel Trend Test

Given that the timing of the first influx of scientists varied across cities, this study cannot simply designate a single year as the uniform policy shock point. Instead, it is necessary to construct dynamic dummy variables relative to the actual year of the scientist influx in each city and conduct event study analysis based on these variables. To this end, this study estimates the following model:

$$Y_{it} = \alpha + \sum_{k \neq -1} \beta_k D_{it}^{k} + \gamma X_{it} + CityFE_i + YearFE_t + \varepsilon_{it}$$

Here, D_{it}^{k} represents the dummy variable for city i in year t relative to the kth period before or after the first influx of scientists. This study treats the period immediately preceding the event as the baseline period and omits it. The definitions of the other variables are consistent with those in the baseline regression. Given that an insufficient sample size for periods far removed from the event may lead to excessive volatility in the estimates, the figures report only the dynamic effects from the 5 periods before the treatment to the 5 periods after the treatment, as shown in Fig. 1. The results indicate that, prior to the scientist inflow, the estimated coefficients for each period generally fluctuated slightly around 0, and most were not significantly different from 0. This suggests that there were no significant divergent trends between the treatment group and the control group before the inflow event occurred, and the parallel trends assumption is generally supported.

4.4 Robustness Tests

This paper conducts robustness tests from multiple perspectives, including the comparative structure of two-way fixed-effects estimates, treatment-time heterogeneity, alternative identification strategies, the exclusion of random shocks, and the substitution of the dependent variable.

4.4.1 Goodman-Bacon Decomposition

To further examine whether the traditional two-way fixed-effects DID estimate is affected by treatment-time heterogeneity and inappropriate comparisons, this paper employs the Goodman-Bacon decomposition method to diagnose the baseline results. The results are shown in Fig. 2. The decomposition results indicate that the overall estimate of the TWFE-DID is 0.579, suggesting that the overall treatment effect is positive. From the decomposition structure, the estimated values for comparisons between the “never-treated group and the phased-in treatment group” are generally concentrated in the positive range, and some comparisons carry relatively high weights. This suggests that the positive conclusion of the baseline regression is largely supported by the comparison between the treatment group and the never-treated group, which has a clear identification meaning. At the same time, the comparisons between the “always-treated group and the phased-in treatment group” are mainly concentrated in the lower-weight region, indicating that their impact on the overall estimate is relatively limited. It should be noted that the distribution of comparison results among different treatment-timing groups is relatively dispersed, with some estimates significantly higher or lower than the overall estimate. This suggests that the innovation effects of scientist inflows may exhibit some treatment-

timing heterogeneity or dynamic heterogeneity. Therefore, it is necessary to conduct supplementary tests using robust DID methods suitable for multi-time-point treatment scenarios.

4.4.2 Heterogeneity-Robust DID for Treatment Effects

To mitigate the weighted bias that may arise in traditional two-way fixed-effects models under a multi-time-point treatment design, this paper further employs various DID estimation methods that are more robust to heterogeneous treatment effects, including the interpolation method by Borusyak et al. (2024), the dynamic DID by de Chaisemartin and D'Haultfoeuille (2020), the cohort-time-averaged treatment effect method by Callaway and Sant'Anna (2021), and Stacked DID. Table 3 reports the aggregated effect estimates obtained using the different methods. Figure 3 displays the dynamic treatment effects estimated using various DID methods robust to heterogeneity. The results indicate that the dynamic treatment effects obtained from different robust estimation methods are generally consistent: prior to the treatment event, the estimated coefficients for each period do not deviate significantly from zero overall and do not exhibit any obvious pre-event trends; after the treatment event, the average treatment effects estimated by various methods are mostly positive, and the majority show a trend of gradually increasing as the event period extends. This suggests that the promotional effect of highly cited scientists' mobility on innovative entrepreneurship is not driven by heterogeneity bias in the traditional TWFE model but is consistently supported across various identification methods. In other words, the benchmark conclusions of this paper are highly robust.

Table 3
DID Estimation Results Considering Heterogeneous Treatment Effects

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	BJS	**CS**	**CDH**	**Stacked DID**
did2	0.6385***	0.5947***	0.6723***	0.6158***
	(8.4261)	(7.5834)	(8.9175)	(7.9462)
Controls	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	23550	23550	23550	23550
Adj_R^2	0.7418	0.7412	0.7425	0.7410

4.4.3 Placebo Test

To further examine whether the baseline regression results are influenced by random factors, contemporaneous shocks, or model specification biases, this study conducts a placebo test. If the

promotional effect of highly cited scientists' mobility on innovative entrepreneurship truly stems from talent mobility shocks, then after randomly generating a treatment event with no real economic significance, the dummy treatment variable should not have a systematic and significant impact on innovative entrepreneurship. Specifically, while maintaining the baseline difference-in-differences (DID) model specification, this study randomly permuted treatment-group firms and treatment years to construct a dummy treatment variable, "Placebo DID," which was then substituted for the true treatment variable in the baseline model for regression estimation. This randomization process was repeated 500 times to obtain the empirical distribution of the placebo treatment effect. As shown in Fig. 4, the mean of the estimated coefficients for the randomly generated placebo treatment variable is close to 0, a marked deviation from the estimated coefficient for the mobility of highly cited scientists in the baseline regression. Thus, the core conclusion of this paper is further supported.

4.4.4 Propensity Score Matching–Double Difference Method

To mitigate estimation bias that may arise from initial differences in observable characteristics between the treatment group and the control group, this study further employs propensity score matching–double difference (PSM-DID) to conduct robustness tests. Specifically, using 2014 as the matching base year, we constructed matched samples based on covariates such as population size, economic level, and human capital, employing various methods including 1:1, 1:2, 1:3, and 1:10 nearest-neighbor matching as well as kernel matching. We then performed DID regression on the matched samples. The results are shown in Table 4. The balance test results following kernel matching indicate that the standardized bias for most covariates decreased significantly: the average bias of the sample fell from 28.2% to 9.2%, and the median bias dropped from 31.6% to 5.9%. Furthermore, the explanatory power of the propensity score model decreased markedly after matching, suggesting that the matching process effectively improved the comparability between the treatment and control groups. Although some variables still exhibited certain biases after matching, the overall quality of the match improved significantly. Therefore, this study further conducted a DID regression on the matched samples as a supplementary robustness test. The regression results showed that the direction and significance of the estimated coefficients for the core explanatory variables were essentially consistent with those of the baseline regression, indicating that the study's conclusions are highly robust.

Table 4
PSM-DID Estimation Results Under Different Matching Methods

Variable	(1)	(2)	(3)	(4)	(5)
	NN(1:1)	NN(1:2)	NN(1:3)	NN(1:10)	Kernel
did2	0.532***	0.510***	0.507***	0.543***	0.620***
	(5.613)	(5.627)	(5.707)	(6.393)	(5.845)
lngdp	0.169	0.127	0.166	0.028	-0.128
	(0.451)	(0.366)	(0.499)	(0.112)	(-0.339)
lnmiddle	-0.041	0.024	0.046	0.053	-0.007
	(-0.226)	(0.144)	(0.323)	(0.614)	(-0.038)
lnprim	0.071	-0.016	-0.028	0.047	0.077
	(0.306)	(-0.082)	(-0.152)	(0.413)	(0.336)
lnthird	0.361*	0.287	0.193	0.107	0.373*
	(1.680)	(1.511)	(1.073)	(0.826)	(1.762)
lnsec	-0.046	-0.038	-0.033	0.052	0.017
	(-0.232)	(-0.214)	(-0.197)	(0.451)	(0.091)
lnfirst	0.160	0.161	0.173*	0.054	0.082
	(1.364)	(1.479)	(1.672)	(0.645)	(0.590)
lnpop	-0.617**	-0.564*	-0.487*	-0.416*	-0.224
	(-1.976)	(-1.911)	(-1.728)	(-1.869)	(-0.725)
Constant	-4.762	-3.252	-3.173	-1.021	-2.646
	(-1.559)	(-1.182)	(-1.245)	(-0.570)	(-0.837)
N	2438	3657	4876	13409	8965
Adj_R^2	0.7015	0.7277	0.7376	0.7557	0.5926

4.4.5 Changing the Dependent Variable

Given that the baseline regression's definition of innovative startups relies on the criterion of obtaining patents within a certain period after a firm's establishment, and that the scope of identification for innovative startups may vary across different time windows, this paper further changes the dependent variable to conduct a robustness test of the baseline conclusions. Specifically, this paper defines firms

that obtain patents within 1, 3, and 4 years after incorporation as innovative startups, respectively, and reconstructs the city-level innovative startup index accordingly. The results are shown in Table 5.

The regression results show that regardless of whether innovative startups are defined as those obtaining patents within 1 year, 3 years, or 4 years after incorporation, the estimated coefficient of the core explanatory variable did2 is consistently significantly positive and maintains a high level of significance under both heteroskedasticity-robust standard errors and city-cluster-robust standard errors. For example, under the 1-year criterion, the estimated coefficient of did2 was 0.5117; under the 3-year criterion, it rose to 0.7675; and under the 4-year criterion, it further increased to 0.8920. These results indicate that the promotional effect of scientist mobility on innovative startups does not depend on the specific time window set, and the conclusions of this paper are highly robust.

Table 5
Effects of Innovative Startups Under Different Patent Identification Windows

Variable	One-Year Window		Three-Year Window		Four-Year Window	
	HC robust	Cluster(city)	HC robust	Cluster(city)	HC robust	Cluster(city)
did2	0.5117***	0.5117***	0.7675***	0.7675***	0.8920***	0.8920***
	(7.4305)	(6.6627)	(11.6650)	(9.6566)	(13.3727)	(10.7687)
lngdp	-0.2049	-0.2049	-0.2903**	-0.2903*	-0.2514*	-0.2514
	(-1.3744)	(-1.3121)	(-2.0967)	(-1.6838)	(-1.7677)	(-1.3768)
lnmiddle	0.0947**	0.0947**	0.1996***	0.1996***	0.1840***	0.1840***
	(2.4874)	(2.2079)	(5.0076)	(4.1472)	(4.4702)	(3.6185)
lnprim	0.0431	0.0431	-0.1061*	-0.1061	-0.1661***	-0.1661**
	(0.6669)	(0.6010)	(-1.6634)	(-1.3672)	(-2.5985)	(-2.1470)
lnthird	0.1589**	0.1589*	0.1280*	0.1280	0.1216*	0.1216
	(2.1059)	(1.9580)	(1.7983)	(1.3885)	(1.6590)	(1.2471)
lnsec	0.1407**	0.1407**	0.1467**	0.1467**	0.1177*	0.1177
	(2.2017)	(2.1284)	(2.4894)	(2.0034)	(1.9583)	(1.5294)
lnfirst	-0.0638	-0.0638	-0.1871***	-0.1871***	-0.1922***	-0.1922***
	(-1.5557)	(-1.4251)	(-4.4636)	(-3.6107)	(-4.6213)	(-3.6996)
lnpop	-0.1320	-0.1320	0.3648***	0.3648*	0.3865***	0.3865**
	(-1.0289)	(-0.9234)	(2.5771)	(1.9387)	(2.7960)	(2.0963)
Constant	-0.4164	0.1597	2.0672**	2.6076**	2.9115***	3.4347***
	(-0.4672)	(0.1499)	(2.2397)	(2.1768)	(3.0973)	(2.7907)
N	19455	19455	25035	25035	25961	25961
Adj_R^2	0.7536	0.7535	0.7455	0.7453	0.7465	0.7464

5. Mechanism Analysis

Based on the preceding analysis, it is evident that the impact of the inflow of highly cited scientists on local innovation and entrepreneurship is not the result of a single channel but may operate through multiple mechanisms, such as the diffusion of cutting-edge knowledge, the clustering of innovative talent, and the attraction of innovation capital. This paper treats each mechanism variable as a

dependent variable to examine whether the inflow of highly cited scientists can significantly influence the corresponding mechanism indicators. The econometric model is specified as follows:

$$\mathrm{Mechanism}_{\mathrm{it}}=\alpha+\beta\mathrm{DID}_{\mathrm{it}}+\mathrm{X}\prime_{\mathrm{it}}\gamma+\mu_{\mathrm{i}}+\lambda_{\mathrm{t}}+\varepsilon_{\mathrm{it}}$$

Where $\mathrm{Mechanism}_{\mathrm{it}}$represents the mechanism variable for city i in year t; $\mathrm{DID}_{\mathrm{it}}$ represents the treatment variable for the inflow of highly cited scientists; $\mathrm{X}\prime_{\mathrm{it}}$represents city-level control variables; μ_{i} and λ_{t}represent city fixed effects and year fixed effects, respectively; and $\varepsilon_{\mathrm{it}}$is the random error term. Standard errors are cluster-adjusted at the city level. The results are shown in Table 6.

5.1 Diffusion of Cutting-Edge Knowledge

To examine the knowledge diffusion mechanism through which scientist mobility promotes innovation-driven entrepreneurship, this study constructs a knowledge diffusion indicator system by integrating OpenAlex academic data with patent data. First, the number of citations in papers and patents is used to measure the extent to which local technological innovation activities absorb and transform scientific knowledge, thereby characterizing the process by which scientific research outcomes diffuse into the field of technological innovation; Second, we use the number of joint university-enterprise patent applications to measure the level of local industry-academia-research collaborative innovation, reflecting the degree of connection between university research resources and corporate technological needs, as well as the capacity for technology transfer. A higher value for the former indicates that local technological innovation is increasingly grounded in scientific knowledge, and that the conversion of scientific knowledge into technological knowledge is more advanced; a higher value for the latter suggests closer interaction between scientific research entities and technology application entities, as well as smoother channels for local knowledge spillovers and technology transfer. In the empirical analysis, this paper uses the logarithmic forms of the two aforementioned indicators for estimation. Columns (1) and (2) report the test results for the mechanism of cutting-edge knowledge diffusion. Specifically, Column (1) uses the logarithm of the number of citations for papers and patents as the dependent variable, while Column (2) uses the logarithm of the number of joint university-enterprise patent applications as the dependent variable. The results show that the estimated coefficients for the core explanatory variable did2 are 1.8551 and 0.2365, respectively, and both are significantly positive at the 1% level. This indicates that the inflow of highly cited scientists can create a more favorable knowledge environment and source of technology for innovative entrepreneurship by enhancing local knowledge spillovers and the level of industry-academia-research collaboration. Thus, H2 is supported.

5.2 Aggregation of Innovation Talent

To examine the mechanism of innovation talent aggregation, this study utilizes data from online recruitment platforms to construct a regional talent demand indicator system. Specifically, two indicators are selected for measurement: the region's annual total recruitment volume and the number of technical job openings. The region's annual total recruitment volume is used to characterize the overall level of local talent demand and the vitality of the labor market, reflecting the region's comprehensive

ability to attract external talent resources; the number of technical job openings focuses on the demand for specialized talent in R&D, engineering, and technology transfer, and is used to measure the region's capacity to attract highly skilled talent for local innovation activities. Given that recruitment data typically exhibits a pronounced right-skewed distribution, this study takes the natural logarithm of the relevant variables before including them in the regression. Columns (3) and (4) report the test results for the innovation talent agglomeration mechanism. The results show that the inflow of highly cited scientists has a significant positive impact on both total recruitment and the number of technical job openings; the estimated coefficients for did2 are 0.1588 and 0.2345, respectively, and both are significant at the 1% level. This indicates that the inflow of highly cited scientists significantly enhances local talent demand and the ability to attract technical talent, thereby promoting further talent agglomeration within the local innovation system. Consequently, H3 is supported.

5.3 Attraction of Innovation Capital

To test the mechanism for attracting innovation capital, this paper utilizes regional venture capital data from the Qianke Database to construct a capital support indicator system, selecting two indicators for measurement: the total annual investment amount and the number of investment transactions. The total annual investment amount is used to characterize the scale of financial support provided by external capital to local entrepreneurial activities, reflecting the regional entrepreneurial ecosystem's ability to attract capital resources; the number of investments is used to measure the capital market's level of attention toward local startup projects, reflecting the level of market connectivity between investment institutions and startup entities. Given that investment indicators may take on zero values, this study treats missing values as 0, adds 1 to the relevant variables, and then calculates their natural logarithms. Columns (5) and (6) report the estimation results for the innovation capital attraction mechanism. The results show that the estimated coefficients for did2 regarding investment amount and number of investments are 1.3273 and 0.5897, respectively, and both are significant at the 1% level. This indicates that the inflow of highly cited scientists significantly enhances the region's attractiveness to external capital and increases the capital market's attention to and support for local innovation and entrepreneurship projects. Thus, H4 is supported.

Table 6
Mechanism Test

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	lninv	lncop	lnallrec	lntechrec	lninvsum	lninvcount
did2	1.8551***	0.2365***	0.1588***	0.2345***	1.3273***	0.5897***
	(0.1337)	(0.0701)	(0.0495)	(0.0566)	(0.2767)	(0.0908)
lngdp	0.0436	0.3861	0.0659	0.1147	-0.4798	0.0010
	(0.1364)	(0.2627)	(0.0759)	(0.0806)	(0.2993)	(0.0634)
lnmiddle	0.0275	-0.0678	-0.0039	-0.0334*	0.1196*	0.0186
	(0.0417)	(0.0737)	(0.0189)	(0.0195)	(0.0674)	(0.0258)
lnprim	-0.3260***	0.2700**	0.1869***	0.1903***	-0.3670***	0.0040
	(0.0695)	(0.1200)	(0.0409)	(0.0420)	(0.1207)	(0.0388)
lnthird	0.0486	-0.1399	-0.0183	-0.0457	0.2986**	0.0156
	(0.0800)	(0.1473)	(0.0383)	(0.0417)	(0.1267)	(0.0305)
lnsec	0.0277	-0.0788	0.0229	0.0029	0.1518	0.0016
	(0.0524)	(0.1123)	(0.0270)	(0.0288)	(0.1028)	(0.0224)
lnfirst	0.2103***	-0.0751	-0.3251***	-0.2867***	0.5408***	0.0199
	(0.0502)	(0.0625)	(0.0412)	(0.0405)	(0.1592)	(0.0313)
lnpop	-0.1488	0.3834	0.5790***	0.5342***	-0.3489	0.0607
	(0.1553)	(0.2380)	(0.1335)	(0.1379)	(0.2777)	(0.0723)
City F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.0986***	-3.8193**	3.9844***	2.6934***	-1.6585	-0.7940
	(1.0397)	(1.6333)	(0.6000)	(0.6393)	(1.5829)	(0.5176)
N	23550	23550	23550	23550	23550	23550
Adj_R^2	0.7815	0.6812	0.5491	0.4330	0.4665	0.4814

6. Heterogeneity Analysis

6.1 Degree of “Discipline-Technology” Match

When there is a strong correlation between a scientist's research field and local technological activities, enterprises find it easier to understand the content and practical value of the research. It also becomes easier for both parties to engage in technology transfer activities—such as technology licensing and consulting partnerships—centered on shared R&D goals, thereby strengthening the entrepreneurial promotion effect (Boschma, 2005; Perkmann et al., 2013). Conversely, if there is a significant disparity between the two, local enterprises may struggle to effectively absorb relevant knowledge due to insufficient absorptive capacity, a lack of supporting R&D infrastructure, and limited application scenarios, thereby weakening the entrepreneurial spillover effect of scientist mobility. To identify the matching relationship between the inflow of highly cited scientists and the local technological structure, this study constructs a "discipline-technology" correspondence based on the linkages between scientific papers and technological applications. Specifically, this study first utilizes the citation relationships between academic papers and patents to establish a mapping between scientists' disciplinary affiliations and patent classifications, thereby characterizing the correspondence between knowledge from different disciplines and technological fields. Building on this foundation, the study further identifies the characteristics of each city's existing technological structure, defining the top 50% of a city's primary patent classification codes as its core technological fields. If there is a correspondence between the disciplines of incoming scientists and the city's core technological fields, the inflow of such scientists is defined as a "matched inflow"; otherwise, it is defined as a "mismatched inflow."

Table 7 examines the impact of the degree of alignment between the disciplinary fields of highly cited scientists and the local technological structure on the entrepreneurial effects of scientist mobility. The results show that in the high-match group, the estimated coefficient for did2 is 1.2949 and is significant at the 1% level; whereas in the low-match group, the estimated coefficient for did2 is only 0.1621 and is significant only at the 10% level. Further tests of the difference in coefficients between the two groups revealed a p-value of 0.000, indicating a significant difference in treatment effects between the high-match and low-match groups. This suggests that scientist mobility has a markedly stronger promotional effect on innovative entrepreneurship in the high-match group; that is, the degree of alignment between the local technological structure and scientists' research fields significantly influences the efficiency of knowledge transfer and technology commercialization.

Table 7
Differences in the Effects of Innovative Entrepreneurship Under “Discipline-Technology” Matching Conditions

Variable	(1)	(2)
	High-Match Group	Low-Match Group
did2	1.2949***	0.1621*
	(9.7815)	(1.6898)
lngdp	-0.2015	-0.1786
	(-1.2478)	(-1.1364)
lnmiddle	0.1779***	0.1632***
	(3.8502)	(3.5217)
lnprim	-0.0944	-0.0815
	(-1.2493)	(-1.0768)
lnthird	0.1467*	0.1324*
	(1.6638)	(1.5189)
lnsec	0.1054	0.0981
	(1.5947)	(1.4836)
lnfirst	-0.1526***	-0.1387***
	(-3.0681)	(-2.7984)
lnpop	0.1595	0.1438
	(0.9305)	(0.8441)
City F.E.	Yes	Yes
Year F.E.	Yes	Yes
Constant	1.7941	1.6527
	(1.6178)	(1.4895)
N	23187	22694
Adj_R^2	0.7486	0.7359
(p-value)	0.000	

6.2 Differences in the Influence of Highly Cited Scientists

Although highly cited scientists generally possess strong knowledge-creation capabilities and the ability to mobilize resources, significant differences still exist among them in terms of academic influence and research output; these differences may further affect their impact on entrepreneurship. Scientists with higher influence typically possess stronger knowledge spillover capabilities, broader collaboration networks, and higher academic reputations, and are therefore more likely to promote local innovative entrepreneurship through mechanisms such as knowledge provision, resource integration, and signal transmission (Franzoni et al., 2014; Azoulay et al., 2017). To this end, this study uses both the h-index and the number of published papers to measure the academic influence of highly cited scientists and divides them into high-influence and low-influence groups based on their mean values.

As shown in Table 8, on the h-index dimension, the estimated coefficient for did2 in the high h-index group is 0.8125 and is significant at the 1% level, while the estimated coefficient for did2 in the low h-index group is 0.4368 and is also significant at the 1% level. Further tests of the difference in coefficients between the groups showed that the p-value for the difference between the two groups' coefficients was 0.001, indicating a significant difference in the mobility effects among scientists with different levels of academic influence. Under the dimension of number of publications, the results showed a similar trend. In the high-publication-output group, the estimated coefficient for did2 was 0.7689, which was significant at the 1% level; in the low-publication-output group, the estimated coefficient for did2 was 0.3826, which was also significantly positive. The results of the test for differences in coefficients between the two groups showed a p-value of 0.001, indicating significant heterogeneity in the impact of scientist mobility on innovative entrepreneurship across different levels of publication output. In other words, scientists with higher h-indexes and greater publication output typically possess a richer knowledge base, broader academic collaboration networks, and higher social recognition; they have a greater reach in knowledge dissemination and stronger resource-linking capabilities, making them better positioned to drive local innovative entrepreneurship.

Table 8
Differences in the Effects of Innovative Entrepreneurship Across Different Levels of Influence

Variable	(1)	(2)	(3)	(4)
	High h-index Group	Low h-index Group	Papers—High Group	Papers—Low Group
did2	0.8125***	0.4368***	0.7689***	0.3826***
	(9.8963)	(5.4947)	(9.2205)	(4.6831)
lngdp	-0.1798	-0.1690	-0.1764	-0.1718
	(-1.1328)	(-1.0664)	(-1.1107)	(-1.0827)
lnmiddle	0.1856***	0.1860***	0.1842***	0.1871***
	(4.0086)	(4.0162)	(3.9784)	(4.0349)
lnprim	-0.0858	-0.0909	-0.0871	-0.0896
	(-1.1340)	(-1.2016)	(-1.1512)	(-1.1840)
lnthird	0.1356	0.1309	0.1341	0.1328
	(1.5322)	(1.4792)	(1.5163)	(1.5006)
lnsec	0.1021	0.0967	0.1012	0.0985
	(1.5561)	(1.4756)	(1.5442)	(1.5038)
lnfirst	-0.1902***	-0.1872***	-0.1891***	-0.1883***
	(-3.9388)	(-3.8519)	(-3.9162)	(-3.8765)
lnpop	0.2349	0.2411	0.2376	0.2385
	(1.4024)	(1.4485)	(1.4207)	(1.4316)
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Constant	1.6979	1.6666	1.6838	1.6752
	(1.5497)	(1.5239)	(1.5384)	(1.5307)
N	22896	21965	22807	22054
Adj_R^2	0.7422	0.7423	0.6721	0.6592
(p-value)	0.001		0.001	

6.3 Differences in Innovation Infrastructure in Destination Locations

The mobility of scientists is not merely a process of spatial relocation of talent, but rather a complex innovation activity embedded within local research infrastructure, technology transfer systems, and entrepreneurial support environments (Edler et al., 2011; Rasmussen & Wright, 2015). For highly cited scientists in particular, knowledge creation and technology transfer typically rely on supporting facilities such as laboratories, research centers, scientific instruments, data platforms, pilot production facilities, and technology transfer organizations. Consequently, the level of local innovation infrastructure may influence the absorption, transformation, and commercialization of external scientific knowledge, thereby determining whether scientist mobility can be further transformed into innovative entrepreneurial activities. Based on this, this paper utilizes Amap POI data to construct an index of local innovation infrastructure. Specifically, the number of technology transfer platforms is identified based on the number of POIs whose geographic names contain keywords such as “laboratory,” “research center,” “technology transfer center,” “pilot plant,” “proof-of-concept platform,” and “experimental platform,” and is used to measure the foundation for local technology transfer; the number of entrepreneurial incubation platforms is identified based on the number of POIs whose geographic names contain keywords such as “incubator,” “co-working space,” “accelerator,” and “startup park,” and is used to measure the local entrepreneurial support environment. Furthermore, this paper divides the sample into high-level and low-level groups based on the median values of these two indicators to examine the impact of differences in local innovation infrastructure on the effect of scientist mobility on entrepreneurship.

Table 9 examines the impact of local innovation infrastructure on the effect of scientist mobility on entrepreneurial activity. The results show that in the high-level group for technology transfer platforms, the estimated coefficient for did2 is 0.8564, which is significant at the 1% level; whereas in the low-level group for technology transfer platforms, the estimated coefficient for did2 is 0.3927, which is also significant at the 1% level. Furthermore, the results of the test for differences between the two groups’ coefficients show that the p-value for the intergroup difference is 0.004, indicating that the level of technology transfer platforms significantly enhances the promotional effect of scientist mobility on innovation-driven entrepreneurship. In the high-level group for startup incubation platforms, the estimated coefficient for did2 is 0.7926 and is significant at the 1% level; in the low-level group for startup incubation platforms, the estimated coefficient for did2 is 0.4583 and is also significant at the 1% level. Further tests of the difference in coefficients between the two groups showed a p-value of 0.025. This indicates that the entrepreneurial effects of scientist mobility differ significantly across regions with varying levels of entrepreneurial infrastructure.

Table 9
Differences in the Effects of Innovation-Driven Entrepreneurship Under Local Innovation Infrastructure Conditions

Variable	(1)	(2)	(3)	(4)
	Technology Transfer Platform—High-Level Group	Technology Transfer Platform—Low-Level Group	Startup Incubation Platform—High-Level Group	Startup Incubation Platform—Low-Level Group
did2	0.8564***	0.3927***	0.7926***	0.4583***
	(10.4275)	(2.8126)	(9.6534)	(3.6821)
lngdp	-0.1635	-0.1827	-0.1712	-0.1768
	(-1.0254)	(-1.1478)	(-1.0786)	(-1.1115)
lnmiddle	0.1824***	0.1887***	0.1849***	0.1868***
	(3.9127)	(4.0625)	(3.9764)	(4.0196)
lnprim	-0.0865	-0.0912	-0.0879	-0.0903
	(-1.1416)	(-1.2079)	(-1.1623)	(-1.1948)
lnthird	0.1398*	0.1315	0.1372*	0.1321
	(1.6428)	(1.4865)	(1.6124)	(1.5013)
lnsec	0.1036	0.0987	0.1018	0.0995
	(1.5749)	(1.5068)	(1.5527)	(1.5194)
lnfirst	-0.1869***	-0.1895***	-0.1876***	-0.1890***
	(-3.8531)	(-3.9217)	(-3.8715)	(-3.9096)
lnpop	0.2268	0.2416	0.2315	0.2398
	(1.3574)	(1.4527)	(1.3898)	(1.4416)
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Constant	1.6725	1.6859	1.6798	1.6814
	(1.5312)	(1.5489)	(1.5403)	(1.5441)
N	22941	22941	22941	22941
Adj_R^2	0.7441	0.7417	0.7438	0.7420
(p-value)	0.004		0.025	

7. Further Analysis

Table 10 reports the impact of the outflow of highly cited scientists on innovation and entrepreneurship in their former cities. The results show that the estimated coefficient for $dout$ did not reach statistical significance under any model specification. After controlling for control variables, city fixed effects, and year fixed effects, the coefficient for $dout$ was 0.0527 but was not statistically significant, indicating that the outflow of highly cited scientists did not significantly reduce the level of innovation and entrepreneurship in their former cities. This suggests that the inter-city mobility of highly cited scientists does not result in a simple “brain drain” effect; innovative and entrepreneurial activities in the cities they leave are not significantly suppressed by the departure of key talent. These findings are consistent with the conclusions of Agrawal et al. (2006) regarding talent mobility and enduring social relationships. In other words, the impact of scientist mobility is not manifested as a unidirectional transfer of human capital, but rather as a process of restructuring cross-regional knowledge networks. Although highly cited scientists have changed their geographic locations, their long-term research collaborations, academic networks, and industrial connections remain intact. Through joint research, technological cooperation, and resource linkages, they generate knowledge inflows and network spillovers back to their original regions, thereby mitigating the potential negative impacts of talent outflow.

Table 10
Impact of the Outflow of Highly Cited Scientists on Innovation and Entrepreneurship in Their Original Cities

Variable	(1)	(2)	(3)	(4)
	No controls	Controls	HC robust	Cluster(city)
did_out	0.0865	0.0527	0.0527	0.0527
	(1.2146)	(0.7638)	(0.7638)	(0.6985)
lngdp	-0.2146*	-0.1867	-0.1867	-0.1867
	(-1.7264)	(-1.3948)	(-1.3948)	(-1.2815)
lnmiddle	0.1768***	0.1825***	0.1825***	0.1825***
	(3.8214)	(3.9475)	(3.9475)	(3.6218)
lnprim	-0.0912	-0.0845	-0.0845	-0.0845
	(-1.2147)	(-1.1275)	(-1.1275)	(-1.0356)
lnthird	0.1426*	0.1358*	0.1358*	0.1358*
	(1.6735)	(1.5864)	(1.5864)	(1.4827)
lnsec	0.1047	0.1013	0.1013	0.1013
	(1.5846)	(1.5268)	(1.5268)	(1.4175)
lnfirst	-0.1538***	-0.1495***	-0.1495***	-0.1495***
	(-3.1014)	(-3.0165)	(-3.0165)	(-2.7846)
lnpop	0.1637	0.1548	0.1548	0.1548
	(0.9564)	(0.9037)	(0.9037)	(0.8426)
City F.E.	No	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes
Constant	1.8236	1.7468	1.7468	1.7468
	(1.9215)	(1.6884)	(1.6884)	(1.5627)
N	23550	23550	23550	23550
Adj_R^2	0.2387	0.7415	0.7415	0.7415

8. Conclusions and Implications

8.1 Research Conclusions

Innovative entrepreneurship serves as a vital link between scientific knowledge, technological development, and industrial applications, and is a key driver for enhancing regional innovation capacity. Against the backdrop of increasingly intense competition in science and technology, the question of whether the mobility of highly cited scientists can stimulate local innovative entrepreneurship holds significant theoretical and practical implications. Based on Elsevier's "China Highly Cited Scholars" list from 2014 to 2024, combined with data on business registrations, patents, and city-level characteristics, this study identifies instances of highly cited scientists moving between cities. Using a multi-period difference-in-differences method, we examine the impact of these movements on local innovation and entrepreneurship, as well as the underlying mechanisms.

The study reaches the following main conclusions: First, the inflow of highly cited scientists significantly promotes local innovation and entrepreneurship, and this finding remains robust after controlling for city fixed effects, year fixed effects, and observable local characteristics. Further tests using the Goodman-Bacon decomposition, heterogeneous treatment effects robust DID, placebo tests, PSM-DID, and replacement of the dependent variable confirm the validity of these findings. Mechanism analysis indicates that the inflow of highly cited scientists primarily promotes local innovation and entrepreneurship through the diffusion of cutting-edge knowledge, the aggregation of innovative talent, and the attraction of innovation capital. Specifically, the inflow of scientists significantly increased the number of citations for papers and patents as well as the number of joint patent applications between universities and enterprises, thereby enhancing local knowledge spillovers and industry-academia-research collaboration; simultaneously, it significantly boosted total hiring and the number of technical job openings, driving further aggregation of innovative talent; Furthermore, the inflow of scientists significantly increased both the amount and frequency of regional investment, indicating that it attracted more external capital by improving the region's innovation reputation and capital expectations. Heterogeneity analysis revealed that the entrepreneurial promotion effect of scientist mobility is jointly influenced by the compatibility of knowledge structures and the characteristics of the scientists. When the disciplinary focus of incoming scientists aligns more closely with the local technological structure, their role in promoting innovation-driven entrepreneurship is significantly stronger; The inflow of scientists with varying levels of influence all significantly promotes innovation-driven entrepreneurship, though the intensity of this effect varies depending on the dimension of influence; at the same time, the better the innovation infrastructure in the receiving region, the more pronounced the promotional effect of scientist mobility. Further analysis indicates that the inter-city mobility of highly cited scientists does not come at the expense of innovation-driven entrepreneurship in the originating region.

8.2 Policy Implications

First, optimize the allocation of high-level scientific talent and improve the alignment of talent policies with the local knowledge base. The entrepreneurial impact of scientist inflows is stronger when the "discipline-technology" match is higher, suggesting that talent policies should not rely solely on the number of recruits or academic titles as evaluation criteria, but should also focus on the connections between research directions and local technological capabilities, industrial needs, and application

scenarios. Localities can conduct assessments of talent allocation and collaboration needs based on existing technological strengths and industrial upgrading requirements, supporting scientists and research teams in establishing substantive ties with local enterprises. At the same time, talent allocation should remain open, reserving space for interdisciplinary collaboration and the exploration of emerging technologies, and avoiding the simplistic interpretation of “matching” as merely reinforcing the existing industrial structure. In terms of policy implementation, various approaches—such as long-term appointments, joint research, and cross-regional collaboration—can be combined to improve access to specialized knowledge, rather than treating permanent relocation as the sole objective.

Second, improve organizational support for the integration of scientific knowledge into the entrepreneurial process and strengthen the linkage between talent and complementary resources such as capital. Mechanism analysis shows that the inflow of scientists is accompanied by enhanced knowledge connections, talent demand, and capital support. Therefore, talent recruitment policies should be integrated with joint R&D, technology validation, team building, and financing services. Support can be provided for universities, research institutions, and enterprises to collaborate on specific technical issues, improve systems for technology transfer, intellectual property management, and the distribution of returns on research outcomes, thereby reducing the costs of collaboration between research entities and entrepreneurial entities. To address the demand for technical talent, efforts should focus on strengthening professional training, job matching, and engineering capacity building. The effectiveness of policies should be evaluated using metrics such as actual hiring, skill alignment, and team stability, rather than using recruitment numbers as a substitute for the actual effectiveness of talent supply. Regarding early-stage startup financing, mechanisms for technical due diligence, project screening, and professional investment matching should be improved to help investors identify technological value and commercial risks, and avoid relying solely on a scientist’s academic reputation as a sufficient basis for project investment value.

Third, the service capacity of local innovation support facilities should be enhanced, rather than simply increasing the number of platforms. The better the innovation infrastructure in a destination region, the stronger the promotional effect of highly cited scientists’ mobility on innovative entrepreneurship; this suggests that local knowledge transfer requires corresponding enabling conditions. Localities should, in line with technology development and industrialization needs, improve services such as proof-of-concept, pilot-scale refinement, testing and inspection, technology transfer, and shared laboratories to reduce costs and uncertainties for startup teams during the technology validation and product development stages. For incubators, co-working spaces, and startup parks, the focus should be on improving the quality of professional services, the openness of facilities, and the ability to connect talent with capital, thereby reducing redundant construction and inefficient operations. Platform evaluations should place greater emphasis on actual services provided to projects, facility utilization efficiency, and the effectiveness of technology transfer, rather than measuring achievements solely by the number of registered entities or the size of the space.

8.3 Limitations of the Study and Future Directions

This study still has several limitations. First, regarding variable measurement, this study constructs an innovative entrepreneurship index based on patent activity within a certain period after a firm's establishment; however, it struggles to capture technological innovations for which no patents have been filed, as well as other forms of innovative entrepreneurship such as business model, organizational, and service innovations. Future research could integrate information on new product development, R&D investment, software copyrights, and innovation surveys to construct a multidimensional innovative entrepreneurship index and improve the accuracy of the variables. Second, regarding the mechanism analysis, this study examines the impact of scientist inflows on variables such as the diffusion of cutting-edge knowledge, the clustering of innovative talent, and the attraction of innovation capital, providing channel evidence consistent with theoretical expectations. However, it has not directly revealed how these changes influence the processes of entrepreneurial team formation, technology development, and new firm formation, nor has it been able to distinguish the relative roles of each channel. Future research could further match microdata on scientist-firm collaborations, actual personnel mobility, and project financing to trace the specific processes of scientific knowledge commercialization and test the causal effects and synergistic relationships among different channels. Third, regarding the research focus, this paper primarily examines the impact of scientist inflows on local innovation-driven entrepreneurship. Although it further analyzes entrepreneurial changes in the regions of origin, it has not directly identified the continuation of collaborations or knowledge outflow following migration, nor has it examined the long-term performance of newly established firms. Future research could construct cross-regional networks of scientific research and industrial collaboration and extend the enterprise tracking period to examine the impact of scientist mobility on enterprise survival, growth, and innovation quality, thereby providing a more comprehensive assessment of its cross-regional spillovers and long-term economic consequences.

Declarations

Author Contribution

Tianxu Li contributed to conceptualization, data curation, methodology, software, formal analysis, investigation, visualization, and writing—original draft. Liangliang Lu contributed to conceptualization, supervision, project administration, validation, writing—review and editing, and served as the corresponding author. All authors reviewed and approved the final manuscript.

Data Availability

The data used in this study are obtained from publicly available and licensed databases, including the Elsevier "Highly Cited Chinese Researchers" list, the China Business Registration Database, the China Patent Database, Chinese urban statistical yearbooks, recruitment platforms, venture capital databases, OpenAlex, and Amap POI data. The processed data are available from the corresponding author upon reasonable request.

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Figures

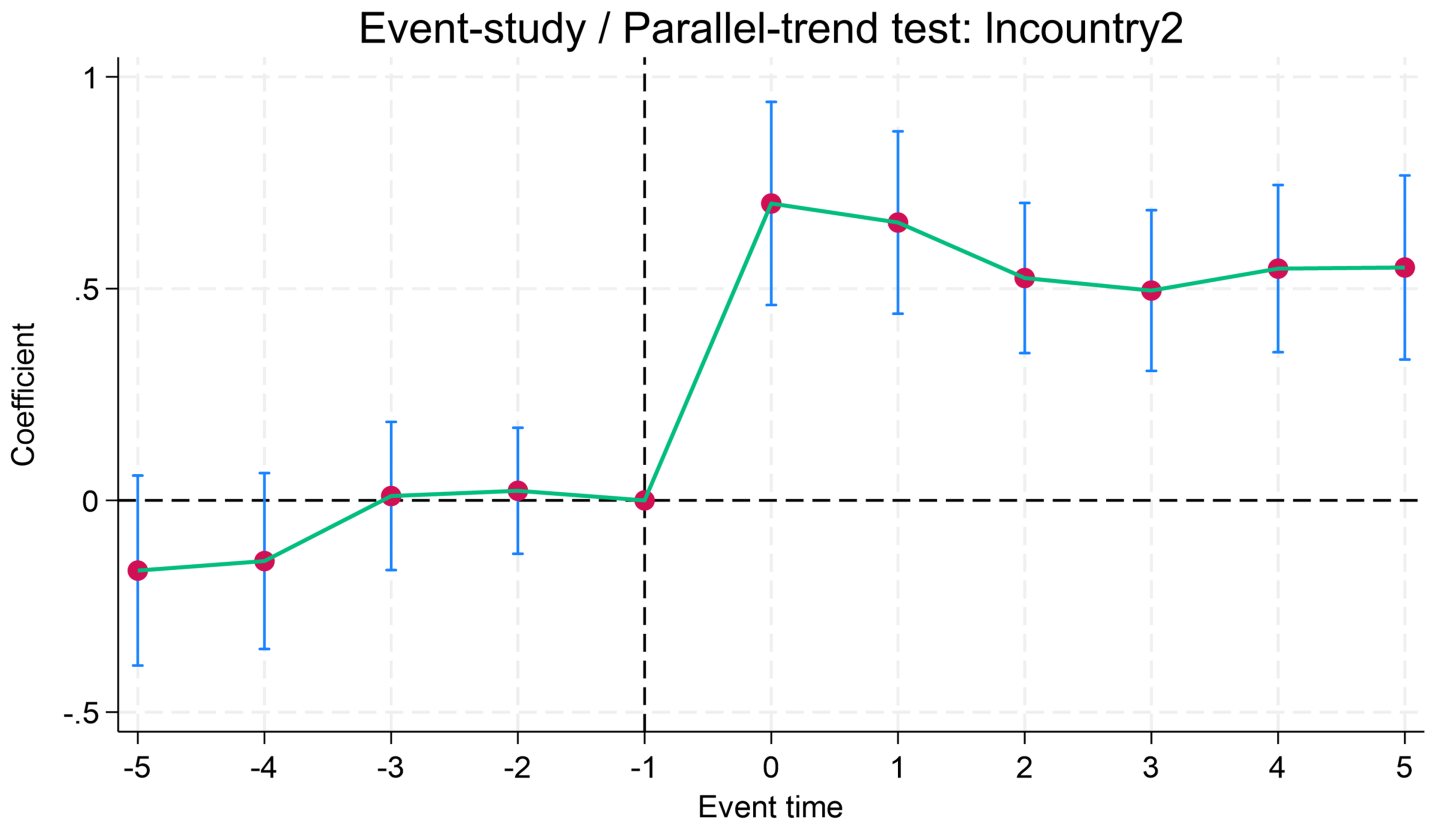


Figure 1

Test for Parallel Trends

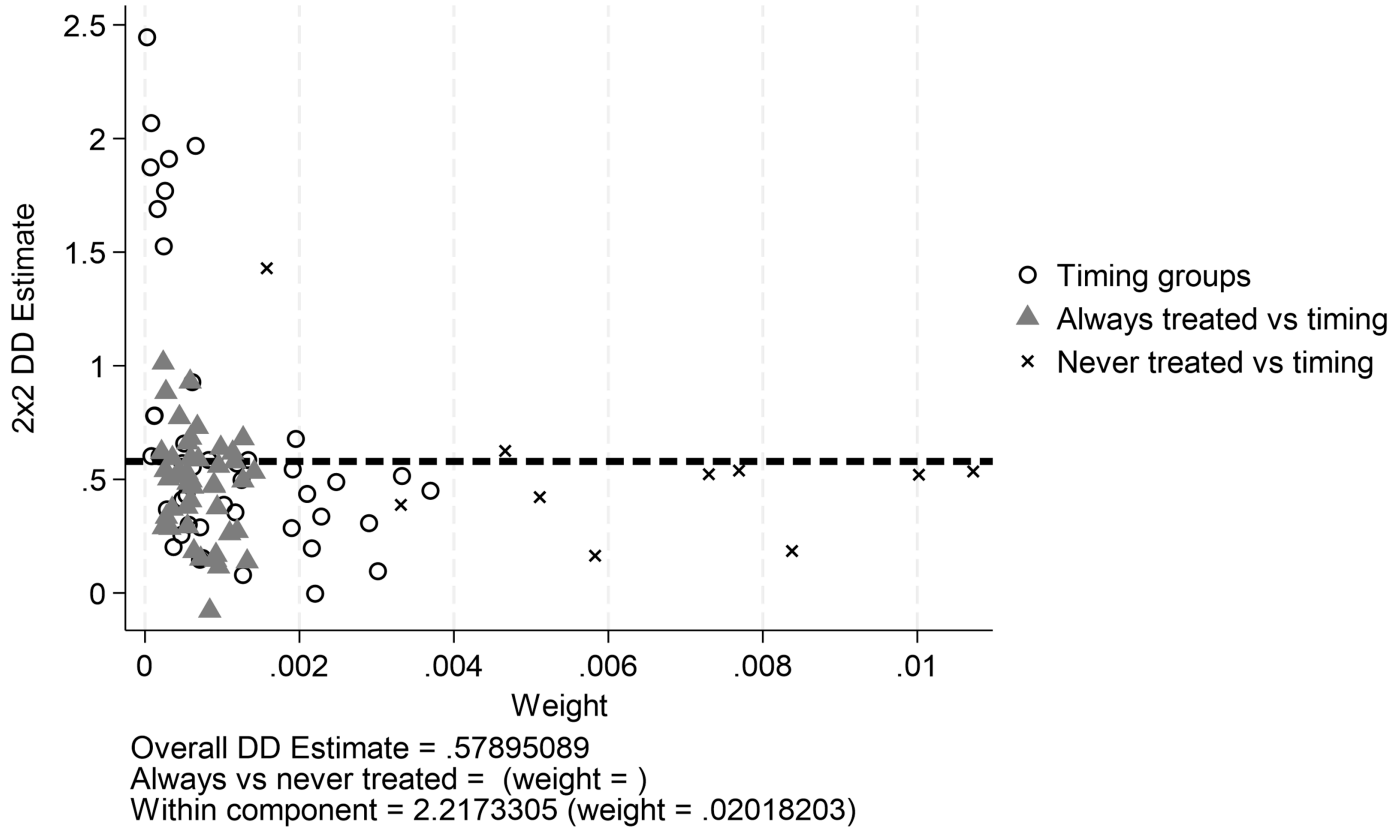


Figure 2

Goodman-Bacon Decomposition

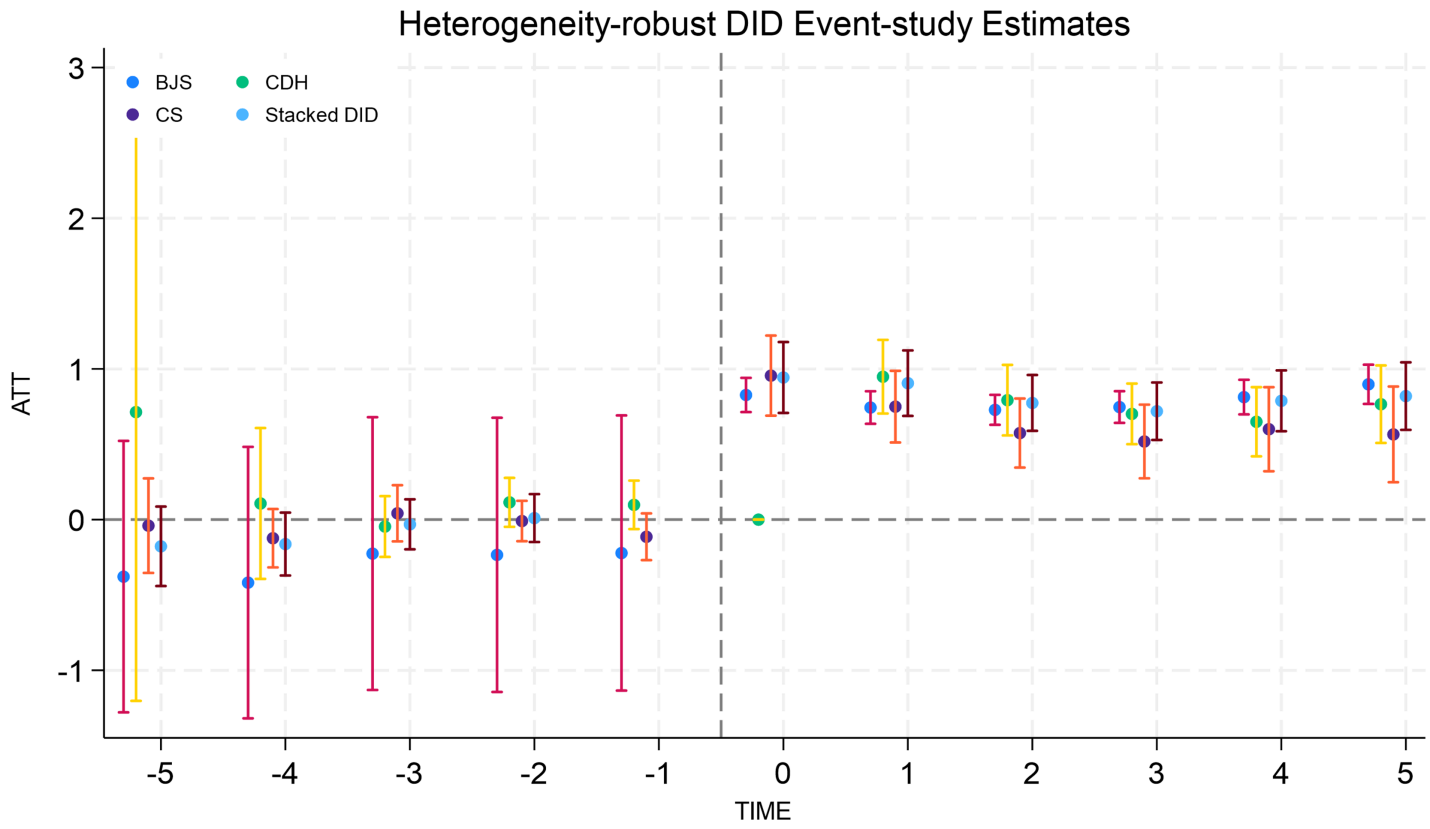


Figure 3

Robust DID for Multiple Heterogeneous Treatment Effects

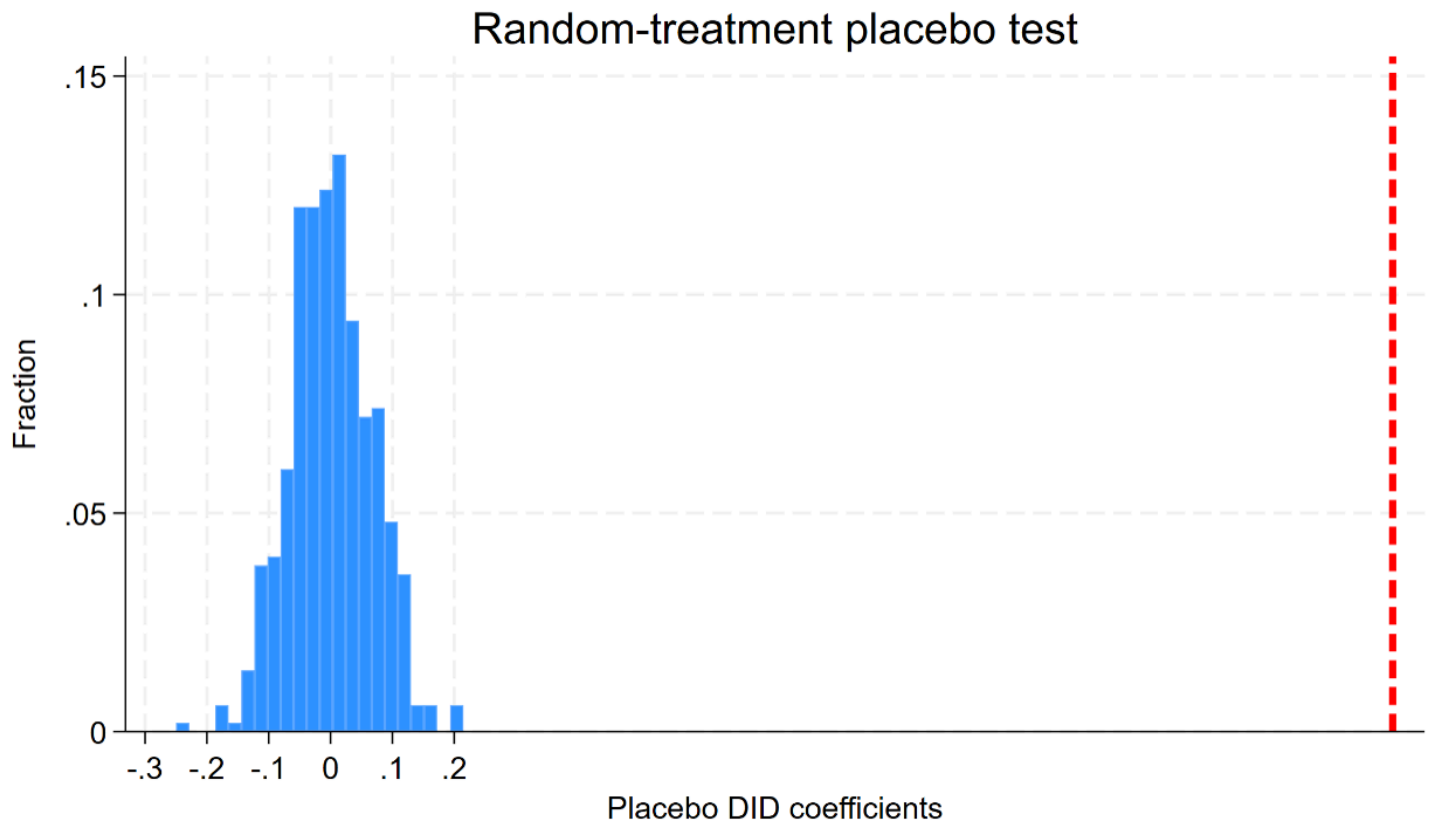


Figure 4

Placebo Test