One Wall Away: Campus Closures, Visitor Access, and the Micro-Geography of Innovation*

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Abstract

How much does local innovation depend on outsiders' in-person presence on university campuses? We exploit the nationwide closure of walled Chinese university campuses triggered by COVID-19, which sustained a block on outsider access well beyond the pandemic. We find that patenting in the innermost ring (0–2 km) fell by 5.8% relative to that in the outermost ring (8–10 km), with the magnitude decaying with distance. Both spillover and coordination-platform mechanisms likely operate: collaborative patents fell, including those without university inventors, while solo patents rose. Anonymized mobility data show that campus visits collapsed in the same pattern, accounting for a large share of the patent decline. Restricting in-person access to a university imposes substantial innovation costs on the surrounding economy.

Keywords: University campus access, patenting, geography of innovation, in-person interactions, foot traffic.

JEL classifications: O31, O33, R12, I23

*The analysis in this paper relies entirely on pre-existing secondary data. We request an exemption from submitting the proprietary mobile-phone data due to a restrictive purchase agreement. Temporary access to the data can be provided for reproducibility checks. We will provide all other data together with the complete set of code.

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1 Introduction

Universities are among the most durable institutions in modern society, with many having operated continuously for nearly a millennium (Cutler and Glaeser, 2026). Their persistence reflects their multifaceted value to society: educating students, conducting academic research, and serving as engines of local economic growth and innovation (Jaffe, 1989; Audretsch and Feldman, 1996; Liu, 2015). A growing empirical literature has identified several pathways by which universities raise innovation in the local economy, including the gradual buildup of population near colleges (Andrews, 2023), the formal transfer of knowledge to nearby firms through R&D partnerships and IP licensing (Hausman, 2022), and related contributions through graduates, research spending, and the entry of technologically related firms (Kantor and Whalley, 2014; Valero and Van Reenen, 2019).

This paper identifies a complementary channel of universities' impact on local innovation: the in-person interactions on campus through which outsiders come into contact with university resources and with one another. The premise that face-to-face contact transmits knowledge and seeds collaboration is well supported (Boudreau et al., 2017; Catalini, 2018; Atkin et al., 2022; Roche et al., 2024). What makes the university campus a particularly potent site for such contact is the dense concentration of knowledge and activity it assembles. The colocation of researchers, students, and laboratories, together with the seminars and casual conversations they sustain, creates an environment in which knowledge is, in Marshall's phrase, "in the air" (Marshall, 1890). Outsiders who come onto the campus are exposed to that same air, encountering specialists who match their interests, picking up ideas in passing, and forming partnerships they carry back into the surrounding economy. Because the ease of physical access attenuates sharply with distance, we examine the extent to which campus access generates innovation impacts that are spatially concentrated around universities. Answering this question matters for innovation policy: the value a university adds to the local economy depends not only on its presence but on how it organizes its physical interface with the surrounding economy, and in particular on how permeable that interface is to outsiders.

We exploit the sudden, nationwide closure of walled Chinese university campuses since the start of the COVID-19 pandemic to achieve identification. Unlike universities in North America and Europe, where campus boundaries are typically unmarked and freely traversable, Chinese campuses are physically enclosed by walls with guarded gates (Sun et al., 2018; Su et al., 2023). When the Ministry of Education ordered campuses to close in January 2020, access was cut off to outsiders. The walls draw a sharp line between inside and outside the campus, allowing us to examine spatial patterns around campus when visitor access is blocked. The Chinese setting is also well-suited for analyzing our research question because Chinese universities rank among the country's most prolific patent producers, and private firms draw heavily on this knowledge through cross-sector citation flows (Boeing et al., 2024; Fang et al., 2026), making this an unusually informative setting to study how in-person access to campus, and the interactions it enables, shapes nearby innovation.

Our empirical design is a difference-in-differences that compares patent density across concentric rings around each campus (0–2 km, 2–4 km, ..., 8–10 km, with the 8–10 km ring as the reference), drawing on the universe of invention patent filings recorded between 2017 and 2024 by the China National Intellectual Property Administration (CNIPA) for a nationwide sample of 270 campuses of 116 leading Chinese universities. Campus-by-year fixed effects absorb time-varying campus-level shocks, including local pandemic severity, economic conditions, and university-specific trends, so that identification comes from differential changes across distances within the same campus and year. The identification assumption is that, absent the closure, patent density in rings closer to the campus would have evolved in parallel with the reference ring.

We find that patent density near campus fell after closure, with the effect decaying monotonically with distance: a 5.8% decline within 2 km of campus, attenuating to insignificance beyond 4 km. Event-study estimates show flat pre-trends and a sharp break at the onset of closure that persists through the end of the sample, consistent with the parallel-trends assumption. As our conceptual framework predicts, the composition of the response is informative about how the university campus contributes. Collaborative patents declined sharply and account for the aggregate effect, while single-inventor patents rose, consistent with would-be collaborators reverting to solo work when they lost in-person access to campus. Not only collaborative patents involving university inventors fell, but also collaborative patents that do not involve university inventors also fell, especially among new collaboration pairs, suggesting that the campus likely matters as a coordination platform for interaction among outside inventors themselves besides as the conventional source of knowledge spillovers or collaboration. Because collaborative patents are typically associated with higher quality, the compositional shift implies a quality decline alongside the quantity decline.

To provide further evidence that closure affected patents through lost in-person interactions on campus, we use anonymized mobile-phone data from China Unicom for the area around 27 Shanghai campuses to measure visits to campus. The Shanghai patent regressions reproduce the national heterogeneity, particularly the decline in collaborative patents and in non-university collaborative patents. Visits to campus originating from the 0–2 km ring fell by 32–35% relative to that originating from the 8–10 km ring after closure, with similar declines across three margins of visitor activity (the number of visitors, visits per visitor, and visit-days per visitor) and the same monotonic spatial decay observed for patents. At the ring level, allowing visitor activity changes to absorb spatial variation reduces the distance-based patent effect by up to 97% for collaborative patents and 66% for non-university collaborative patents. This shows that the spatial pattern of access reduction accounts for nearly all of the spatial pattern of patent decline. At the finer scale of grid cells within rings, locations that experienced larger visitor declines also experienced larger patent declines, with the effect concentrated similarly on collaborative and non-university collaborative patents.

Our paper makes two primary contributions to the literature. First, we contribute to a growing literature on universities and local innovation (Jaffe, 1989; Audretsch and Feldman, 1996; Anselin et al., 1997; Kantor and Whalley, 2014; Kantor and Whalley, 2019; Valero and Van Reenen, 2019; Hausman, 2022; Andrews, 2023; Fan et al., 2026; Li et al., 2026).[1] We identify a complementary channel: the in-person interactions on campus that depend on outsiders being physically present, distinct from the population channel emphasized by Andrews (2023) and the formal technology-transfer channel emphasized by Hausman (2022). We detect this channel at refined within-city spatial resolution with visits tracked by mobile phone data. Our paper also joins a literature on the local effects of anchor-institution closures (Hooker and Knetter, 2001; Davis and Hausman, 2016; Jofre-Monseny et al., 2018; Fischer et al., 2024), to which we add the first systematic study of university campus closures with a spatial-decay design.

Second, we bridge the literature on face-to-face interactions and innovation (Boudreau et al., 2017; Catalini, 2018; Atkin et al., 2022; Roche et al., 2024; Koh et al., 2025; Gaetani et al., 2026) with work on the geography of innovation (Jaffe et al., 1993; Duranton and Puga, 2004; Rosenthal and Strange, 2020; Moretti, 2021; Kalyani et al., 2025). The first literature has shown that in-person encounters facilitate idea diffusion and collaboration formation; the second has documented that knowledge spillovers attenuate sharply with distance. However, these literatures typically do not speak to the specific institutional source of the in-person knowledge flows they document. We pinpoint the university as one such institutional source by combining the campus closure with anonymized mobile-phone data, linking the spatial pattern of visit decline directly to the spatial pattern of patenting decline.

Our findings carry implications for innovation policy and for the urban-planning decisions that shape access to universities. Universities contribute to the surrounding innovation ecosystem in part through in-person interactions on campus, whose value depends on access for outsiders. The innovation premium associated with proximity to a university (Hausman, 2022; Andrews, 2023) reflects, in part, this access channel. Campus design, transit infrastructure, and gate access policies shape the in-person channel wherever physical access to universities is constrained, including in settings where campuses are not formally walled. One direct application is the ongoing Chinese policy debate.

[1] The scope of "local" varies widely across the literature. While many previous works focus on broader spatial units such as counties or metropolitan regions, studies such as Li et al. (2026) use finer spatial units.

Whether Chinese university campuses should be reopened to outsiders has become a topic of national debate since 2023, when some institutions partially reopened with daily visitor caps and advance booking; the debate continues to balance concerns about security and operational pressure against universities' social mission as public institutions.[2] Our findings add a key consideration: there are real innovation costs to maintaining restrictive access.

The remainder of the paper is organized as follows. Section 2 describes the institutional background of walled campuses in China, the COVID-19 closure timeline, and the conceptual framework. Section 3 presents the data and measurement. Section 4 estimates the impact of campus closure on innovation using national patent data. Section 5 provides further evidence that closure affected patents through reduced campus visits. Section 6 concludes with policy implications.

2 Institutional Background and Conceptual Framework

2.1 The Walled-Campus Institution in China

Chinese university campuses are physically enclosed by perimeter walls or fences, with entry through a small number of guarded gates (Sun et al., 2018; Su et al., 2023). The perimeter draws a sharp line between "inside" and "outside," and when the gates close, the campus becomes inaccessible to outsiders. This form contrasts with the open-campus tradition common in North American and European universities, where campus boundaries are typically unmarked and the public can walk freely across the grounds. The contrast reflects a broader tradition of walled compounds in Chinese urban planning (Bray, 2005; Xu and Yang, 2009).

Despite the physical infrastructure, most campuses were de facto open prior to 2020. Outsiders could enter freely, with no identification check or registration required: local residents used the grounds for recreation, members of the public attended lectures and conferences, and industry professionals came for meetings and collaborations. How-

[2] For example, "Access to campuses sparks fierce debate," *China Daily*, February 26, 2024; "As China's Top Campuses Reopen, a Frenzy for Limited Visiting Slots," *Sixth Tone*, July 2023.

ever, this openness was governed by administrative policy, and the policy was readily reversible—Chinese universities operate within a centralized governance structure under the Ministry of Education, and directives issued by the Ministry on campus access are binding on all institutions.

2.2 The COVID-19 Closure and Sustained Restrictions on Outsiders

On January 27, 2020, in response to the spread of COVID-19, the Ministry of Education issued an emergency directive requiring all universities nationwide to postpone the spring semester and close their campuses.[3] The combination of pre-existing perimeter infrastructure and centralized authority allowed near-immediate enforcement.[4] Within days, all 2,738 regular higher-education institutions in China, enrolling more than 41 million students, had become inaccessible to outsiders.[5]

Re-opening proceeded in phases that applied unevenly to insiders and outsiders. From fall 2020, universities gradually allowed faculty, staff, and students to return for in-person instruction, subject to quarantine and testing requirements. Restrictions on outsiders did not ease in tandem: most universities maintained strict controls on non-affiliate entry throughout 2020 and 2021, requiring advance approval, negative COVID-19 tests, or an institutional reason for the visit, and casual access effectively ceased. A nationwide shift came in December 2022, when the State Council ended the zero-COVID regime. Restrictions on faculty, staff, and students were largely lifted, while controls on outsiders remained.[6] By 2023, many flagship universities, including Peking University and Tsinghua University, had institutionalized the new regime, reopening to outsiders only under daily caps and advance booking through dedicated mobile applications, with limited slots.[7] For

[3] Ministry of Education, "Notice on Postponing the Opening of the Spring Semester 2020," January 27, 2020. http://www.moe.gov.cn/jyb_xwfb/gzdt_gzdt/s5987/202001/t20200127_416672.html.

[4] Because the directive coincided with the Lunar New Year holiday, when most students had already returned home, implementation was nearly frictionless.

[5] Ministry of Education, "2020 National Statistical Communiqué on Educational Development," August 2021. http://www.moe.gov.cn/jyb_sjzl/sjzl_fztjgb/202108/t20210827_555004.html.

[6] State Council Joint Prevention and Control Mechanism, "Notice on Implementing Class B Management for COVID-19," December 26, 2022. http://www.moe.gov.cn/srcsite/A17/moe_943/s3285/202212/t20221229_1037009.html.

[7] See, for example, "Why Is It So Hard to Get Tickets to Visit Elite Schools? An Exposé of the Criminal Industry Behind Ticket-Scalping Software," *CCTV News*, https://news.cctv.cn/2024/08/02/ARTIzuqO4nGtf0cZtUbXJIWM240802.shtml. The question of whether university campuses should

outsiders, the closure was not a transient pandemic measure but a sustained, multi-year reduction in campus access.

Crucially, this reduction in outsiders' access was not accompanied by a contraction of university activity. Total higher-education enrollment grew steadily from 19.1 million students in 2017 to over 24 million by 2024 (Online Appendix Figure A1). Patent applications filed from on-campus addresses also continued on its pre-closure growth trend throughout the closure window (Online Appendix Figure A2), indicating that university knowledge production continued despite restricted outsider access.[8]

Three features of this timeline make the COVID closure a useful setting for studying the impact of outsiders' access to campus. First, the closure was driven by a national public-health emergency unrelated to local innovation conditions, providing an exogenous source of variation. Second, the centralized governance of campus perimeters ensured that the closure applied uniformly across institutions, rather than selectively to specific universities. Third, restrictions on outsiders persisted well beyond the initial lockdown, so the closure represents a sustained change rather than a brief interruption. Throughout, university enrollment and university-affiliated patenting continued on their pre-closure trajectories, so the closure changed outsiders' access without changing the volume of university activity itself.

2.3 Conceptual Framework

We develop a simple framework to organize how campus access shapes the patenting decisions of outside inventors. Consider an outside inventor: an inventor not affiliated with the university whose ability to enter the campus depends on whether the gates are open to outsiders. Outside inventors at location i visit campus at intensity $v(d_i)$, where d_i is their distance from the campus and $v'(d_i) < 0$ reflects the well-documented spatial decay of in-person interactions (Jaffe et al., 1993; Catalini et al., 2020).

be open to the public has become a widely debated national issue. For example, "University Campuses Should Be Open to Public, Official Says," *China Daily*, August 19, 2023; "Xinhua Commentary: Why Is It So Difficult for University Campuses to Open to the Public?" *Xinhua*, July 2, 2025.

[8] The Shanghai pattern is even cleaner (Panel (b) of Online Appendix Figure A2): on-campus patenting at the 27 Shanghai sample campuses rose without interruption from 2019 to 2020 and continued to grow thereafter.

Higher v_i means higher in-person presence on campus, which exposes outside inventors to the campus environment (e.g. the seminars, conversations, and activities) and creates opportunities for interaction with university affiliates and other visitors. These interactions affect patenting through two channels. First, in-person presence on campus transmits frontier knowledge generated inside the university. We call this the *spillover* channel (Catalini, 2018; Atkin et al., 2022; Roche et al., 2024). Second, in-person presence raises the probability that an outside inventor finds collaborators, whether university researchers or other outsiders (Boudreau et al., 2017; Koh et al., 2025). We call this the *coordination-platform* channel. Let $p(v_i)$ denote the probability that an outside inventor with a project pursues it collaboratively, and $q(v_i)$ the probability that, conditional on collaborating, the partner is a university researcher; both are increasing in v_i. Matching is therefore endogenous to access: when the platform function weakens, projects can revert to solo work or shift to non-university partners.

The institutional features described in Sections 2.1 and 2.2 map onto the framework as follows. The closure drives v_i toward zero for outside inventors, while university enrollment and university-affiliated knowledge production continue on trend. Let Y_i denote patenting output by outside inventors at location i. Because $v(d_i)$ decreases in distance, locations closer to campus had higher pre-closure visit intensity and experience larger absolute reductions Δv_i after closure. To a first-order approximation,

$$\Delta Y_i \;\approx\; \phi \cdot \Delta v_i, \tag{1}$$

where ϕ summarizes the marginal effect of visits on innovation through both the spillover and coordination-platform channels. The expression implies that both Δv_i and ΔY_i should decay with distance from campus, with magnitude and sign determined by ϕ.

We classify outside-inventor patents into three categories: single-inventor (Y^S), multi-inventor with a university partner (Y^U), and multi-inventor without a university partner (Y^{NU}). The aggregate of all multi-inventor patents is $Y^M = Y^U + Y^{NU}$. Closure has different implications for each category. Y^M falls unambiguously: closure lowers p and reduces the productivity of each collaboration through diminished spillovers. Y^U also falls unambiguously: closure reduces p, q, and spillovers, so all three components push Y^U down. Y^S faces two opposing forces: lower spillovers reduce productivity even for solo projects, while unmatched would-be collaborators may revert to solo work, raising solo counts. The net effect on Y^S depends on which force is larger: an increase indicates that reallocation from collaborative to solo work outweighs the productivity loss, while a decrease indicates the opposite. The case of Y^{NU} is more nuanced. Substitution toward non-university partners would push Y^{NU} up as q falls, while reduced spillovers and lower p push it down. A decline in Y^{NU} would identify campus access as a source of positive externalities to the private sector beyond direct university partnership, whether by exposing outside inventors to university-derived knowledge that they then carry into non-university teams, or by serving as a platform where such teams form (in the spirit of the indirect spillovers in Anselin et al., 1997 and Kantor and Whalley, 2014). An increase in Y^{NU} would instead indicate that substitution toward non-university partners dominates the losses through the spillover and coordination-platform channels.

The framework yields two predictions, which we test in the empirical analysis.

Prediction 1 (Spatial gradient) *Campus closure changes nearby innovation in proportion to the change in visits, Δv_i. Because Δv_i decays with distance from campus, ΔY_i also decays with distance.*

Prediction 2 (Heterogeneity by patent type) *Campus closure unambiguously reduces Y^M and Y^U. The direction is ambiguous for Y^S: a rise indicates that reallocation to solo work dominates the productivity loss, while a decline indicates the opposite. The direction is also ambiguous for Y^{NU}: a decline indicates that spillover loss and reduced collaborative probability dominate substitution toward non-university partners, while a rise indicates the opposite.*

3 Data and Measurement

This section describes the sample of campuses and the two datasets used in our analysis: national patent records from CNIPA, and anonymized mobile-phone signaling data from

China Unicom for Shanghai.

3.1 Campus Sample and Spatial Units

Our sample comprises the 116 universities designated by China's Ministry of Education as top research institutions under Project 985 or Project 211.[9] Many Chinese universities operate multiple campuses as a result of mergers and urban expansion. We treat each campus as a separate observation. For each campus, we obtained geo-referenced Areas of Interest (AOIs), polygon boundaries authorized by both universities and municipal authorities, from China's leading digital mapping platforms.[10] The resulting national sample contains 270 campuses. The Shanghai subsample, used in the analysis with mobile-phone data, includes 27 campuses from nine universities. Appendix Figures A3 and A4 map the campus spatial distribution in the national sample and the Shanghai sample respectively.[11]

For each campus, we partition the surrounding area into 100 m-wide concentric rings extending out to 10 km from the campus boundaries. Outcome variables are aggregated to the ring–year level and expressed per (km^2) of ring area, since outer rings are larger than inner rings. For the regression analysis, we group these into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin serving as the reference category. This yields 216,000 ring–year observations in the national sample and 21,600 in the Shanghai sample.[12] For the more refined grid-level analysis in Section 5, we further partition the area around each Shanghai campus into Geohash-7 grid cells of approximately 152 m × 152 m. Each cell is assigned to the distance bin in which its centroid falls.

[9] Project 985 comprises 39 elite universities; Project 211 encompasses 116 institutions and includes all 39 Project 985 universities.

[10] AOI data are from Amap (akin to Google Maps). We excluded three military-affiliated universities whose AOIs are unavailable due to national security restrictions. These institutions had enforced strict access controls before COVID-19, so the pandemic-era closure did not change their access regime.

[11] The nine universities are Fudan University, Shanghai Jiao Tong University, Tongji University, East China Normal University, Shanghai University of Finance and Economics, East China University of Science and Technology, Shanghai International Studies University, Shanghai University, and Donghua University.

[12] 100 rings × 270 campuses × 8 years = 216,000; 100 rings × 27 campuses × 8 years = 21,600.

3.2 Patent Data

Our patent data come from CNIPA, which records the universe of patent applications filed in China. We restrict attention to invention patent applications, the category that undergoes substantive examination and most closely corresponds to inventive activity relevant to knowledge spillovers.[13] Each record contains the filing date, inventor name(s), and inventor address(es), which we geocode to obtain spatial coordinates. The sample covers applications filed between 2017 and 2024, providing three pre-closure years (2017–2019) and five post-closure years (2020–2024). We use the application date rather than the grant date because it more closely reflects when the underlying inventive activity occurred. Following the conceptual framework (Section 2.3), we count patents by inventor count and university affiliation, yielding four categories: Y^S (single-inventor), Y^U (multi-inventor with a university partner), Y^{NU} (multi-inventor without a university partner), and $Y^M = Y^U + Y^{NU}$.[14] For brevity, we refer to Y^U as university-collaborative patents and Y^{NU} as non-university-collaborative patents throughout the manuscript. The primary outcome is *patent density*: invention patent applications in a spatial unit (ring or grid cell) divided by its area in km^2, in natural logarithm.[15]

3.3 Mobile-Phone Data

To measure people's movement around campus, we use anonymized mobile-phone signaling data for Shanghai provided by China Unicom, one of China's three major telecommunications operators. The data consist of two cross-sectional snapshots from November 2019 (pre-closure) and November 2024 (post-closure), covering approximately 6.53 million users and constituting a representative sample of the Shanghai population. Each user's home and workplace locations are identified in the mobile-phone data.[16] A *campus*

[13] China's patent system distinguishes invention patents (novelty and inventiveness), utility model patents (lower inventiveness threshold), and design patents. We focus on invention patents following Boeing et al. (2024) and Fang et al. (2026).

[14] We follow the classification of university patents using the algorithm described in Boeing et al. (2024).

[15] Zero-value observations are rare at the ring–year level, so excluding them when taking logarithms has negligible effect on the results.

[16] Home location is defined as the most frequently observed nighttime (8 PM–5 AM) location over the preceding six months across the country, and workplace location is defined as the most frequently

visit is recorded when a user's signaling data places them within a campus AOI for more than 30 minutes and the user's home is not on that campus. This restriction excludes campus residents, providing an imperfect but workable proxy for the outside inventor of Section 2.3. It also excludes temporary visitors, such as couriers, who typically stay on campus for only a short period. A key advantage of the mobile-phone signaling data is that they allow us to track individuals' spatial movements throughout the day at large scale, making it possible to measure not only campus visits, but also visit frequency, exposure duration, and visitors' home and workplace locations within a consistent framework.

We construct three ring-level visitor measures, each capturing a different margin of adjustment: *visitor density* (distinct campus visitors with home in ring i, per km^2) for the extensive margin; *visits per visitor* for trip frequency; and *days per visitor* for exposure duration. All three enter regressions in logs.[17] Appendix Tables A1 and A2 report summary statistics at the ring and grid levels.

4 The Impact of Campus Closure on Innovation

4.1 Empirical Framework

Our research design is a DiD in which treatment intensity varies with distance to campus and treatment timing is set by the closure year. We estimate the following equation using ring–year level data:

$$y_{ict} = \alpha + \sum_{d} \beta_d \left[\mathbb{1}(t \geq 2020) \times \mathbb{1}(d)_{ic} \right] + \gamma_{ct} + \epsilon_{ict}, \tag{2}$$

where i, c, and t index the ring, university campus, and year, respectively. The dependent variable y_{ict} is the natural logarithm of patent density (patent applications per km^2) in ring i surrounding campus c in year t. Although the area around each campus

observed daytime (5 PM–8 PM) location over the same period.

[17]Visitors are assigned to rings by home location. Section 5 reanchors visitors by workplace location as a robustness check and finds consistent results; Appendix Table A3 reports workplace-based summary statistics at both the ring and grid-cell levels.

is partitioned into 100m-wide rings, we group these into five 2km bins for the regression specification: $d \in \{0\text{–}2, 2\text{–}4, 4\text{–}6, 6\text{–}8, 8\text{–}10\}$ km, where $\mathbb{1}(d)_{ic}$ indicates that ring i around campus c falls into bin d. The 8–10 km bin is omitted as the reference category, so each β_d measures the differential change in log patent density in bin d relative to the 8–10 km bin after closure.

The inclusion of campus-by-year fixed effects (γ_{ct}) is central to identification. These fixed effects absorb all time-varying shocks at the campus level, including city-level pandemic severity, local economic conditions, and university-specific trends, so that β_d is identified purely from differential changes across distance bins around the same campus in the same year. The identifying assumption is that, absent campus closure, patent density would have evolved in parallel across rings around the same campus. We assess this assumption using event-study specifications below. Standard errors are clustered at the campus level to allow for arbitrary spatial and serial correlation across rings within the same campus.

4.2 Baseline Results

Table 1 reports the estimated coefficients from Equation (2). Columns 1–4 estimate the model on paired samples: each column uses one inner bin (0–2, 2–4, 4–6, or 6–8 km) plus the 8–10 km reference bin. Column 5 includes all four inner bins simultaneously in the full sample, and we focus our discussion on this column. The results reveal a clear spatial gradient. In the 0–2 km bin, patent density declined by approximately 5.8 percent relative to the 8–10 km bin after closure (Column 5, $\hat{\beta} = -0.058$, $p < 0.05$). The effect attenuates monotonically with distance: the 2–4 km bin shows a decline of 4.1 percent ($p < 0.05$), while the 4–6 km and 6–8 km bins show smaller and statistically insignificant declines of 2.1 and 1.2 percent, respectively. The paired-sample estimates in Columns 1–4 yield similar magnitudes and the same monotonic pattern. This pattern is consistent with Prediction 1: ΔY_i decays with distance from campus, with the negative sign reflecting reduced spillovers and a net negative effect from the coordination-platform channel.

Table 1: Impact of Campus Closure on Patent Density

	(1)	(2)	(3)	(4)	(5)
0–2 km	0.807***				0.798***
	(0.064)				(0.064)
2–4 km		0.482***			0.481***
		(0.058)			(0.058)
4–6 km			0.330***		0.330***
			(0.049)		(0.049)
6–8 km				0.199***	0.196***
				(0.036)	(0.036)
Post × 0–2 km	−0.061***				−0.058**
	(0.023)				(0.023)
Post × 2–4 km		−0.039*			−0.041**
		(0.020)			(0.020)
Post × 4–6 km			−0.018		−0.021
			(0.018)		(0.018)
Post × 6–8 km				−0.015	−0.012
				(0.016)	(0.016)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.44	0.51	0.55	0.58	0.48
Observations	75,194	78,880	79,904	78,243	188,882

Note: This table reports estimates of Equation (2). The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level, computed for 270 university campuses across China over 2017–2024. Each campus is partitioned into five concentric distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates years from 2020 onward. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all five bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A 5.8 percent decline in patent density in the 0–2 km bin represents a substantial loss of innovative activity in the immediate vicinity of campus. Andrews (2023) estimates that the establishment of a US college increased local patenting by 62 percent, and Furman et al. (2021) find that after patent library opening, local patenting increases by 8–20 percent relative to similar regions. Our estimate suggests that the innovation premium associated with proximity to a university is reversible: it can be created by opening campus access (as Furman et al. (2021) and Andrews (2023) document) but also undone by restricting it. The monotonic decay across distances is difficult to attribute to a general pandemic effect on innovation.

Figure 1 presents the event-study counterpart of Table 1, plotting year-specific coefficients from full-sample regressions of each inner distance bin against the 8–10 km reference bin. Two features stand out. First, the pre-2020 coefficients are close to zero and statistically insignificant across all bins, supporting the parallel trends assumption

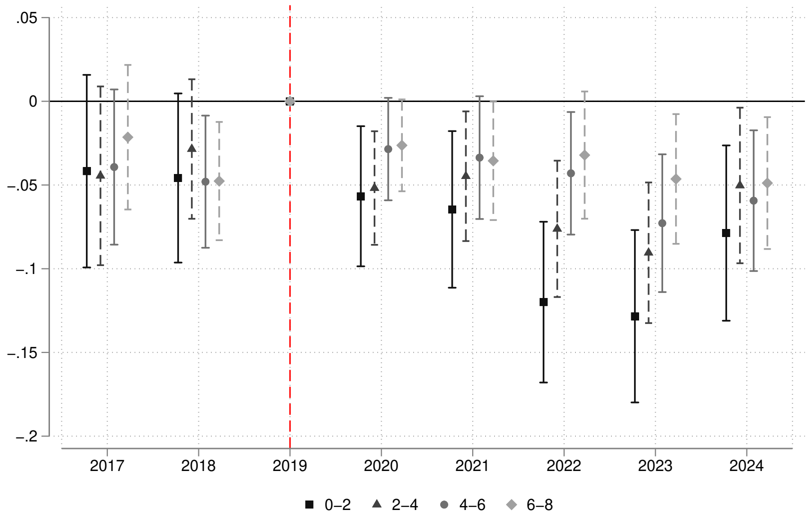


Figure 1: Event Study: Impact of Campus Closure on Patent Density

Note: This figure plots year-specific coefficients from an event-study version of Equation (2), in which the post-2020 indicator is replaced by year dummies interacted with distance-bin indicators. The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level, for 270 university campuses across China over 2017–2024. The four series show the 0–2, 2–4, 4–6, and 6–8 km bins; the 8–10 km bin is the omitted distance reference and 2019 (the last pre-closure year) is the omitted year reference, indicated by the vertical dashed line. All specifications include campus×year fixed effects. Vertical lines denote 95% confidence intervals based on standard errors clustered at the university-campus level.

underlying our identification strategy. Second, the effects emerge sharply in 2020 (the year campuses closed) and persist through the end of the sample period. The persistence of the effect through 2024 indicates that the innovation decline was not transient but reflected the sustained restriction of outsider access, consistent with the timeline described in Section 2.2.

4.3 Heterogeneity by Patent Type

Table 2 decomposes the baseline result by patent type, testing Prediction 2. The four columns correspond to single-inventor patents (Y^S), all multi-inventor patents (Y^M), university collaborative patents (Y^U), and non-university collaborative patents (Y^{NU}). Single-inventor patents (Y^S) show no decline near campus after closure; the 0–2 km coefficient is in fact positive and significant ($\hat{\beta} = 0.064$, $p < 0.05$) In contrast, multi-inventor patents (Y^M) decline substantially: the 0–2 km coefficient is -0.143 ($p < 0.01$), more than twice the magnitude of the overall effect in Table 1. The effect decays monotonically

Table 2: Impact of Campus Closure on Patent Density by Types

	(1) Y^S	(2) Y^M	(3) Y^U	(4) Y^{NU}
0–2 km	0.882***	0.967***	1.893***	0.850***
	(0.055)	(0.061)	(0.068)	(0.061)
2–4 km	0.500***	0.552***	1.103***	0.491***
	(0.051)	(0.056)	(0.074)	(0.054)
4–6 km	0.333***	0.368***	0.643***	0.320***
	(0.044)	(0.049)	(0.073)	(0.047)
6–8 km	0.189***	0.211***	0.307***	0.187***
	(0.034)	(0.038)	(0.057)	(0.038)
Post × 0–2 km	0.064**	−0.143***	−0.067*	−0.160***
	(0.030)	(0.020)	(0.035)	(0.019)
Post × 2–4 km	0.032	−0.092***	−0.048	−0.113***
	(0.025)	(0.019)	(0.032)	(0.019)
Post × 4–6 km	0.032	−0.054***	0.001	−0.062***
	(0.023)	(0.017)	(0.032)	(0.017)
Post × 6–8 km	0.013	−0.035**	−0.002	−0.041***
	(0.021)	(0.015)	(0.029)	(0.016)
Campus × year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.46	0.44	0.18	0.45
Observations	165,433	179,945	91,094	176,381

Note: The dependent variable is the natural logarithm of patent density (patent applications per km^2) for the patent type indicated in each column at the ring–year level, computed for 270 university campuses across China over 2017–2024. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates years from 2020 onward. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with distance and remains significant through the 6–8 km bin ($\hat{\beta} = -0.035$, $p < 0.05$).

This result is consistent with Prediction 2 and is informative about operative channels. The decline in Y^M alone is consistent with either the spillover or the coordination-platform channel. The rise in Y^S, however, identifies the coordination-platform channel: under a pure-spillover interpretation, lower productivity from reduced co-presence would push solo work down. Because innovation has become increasingly team-based (Wuchty et al., 2007; Jones, 2009), disruptions to team formation are especially costly. Our finding that the patent decline is concentrated in multi-inventor work underscores this point.

In column 3, Y^U shows a marginally significant decline in the 0–2 km bin ($\hat{\beta} = -0.067$, $p < 0.10$) and no significant effects at greater distances. Y^{NU} in column 4 shows a substantially larger and more persistent decline: the 0–2 km coefficient is -0.160 ($p < 0.01$), and the effect remains significant at $p < 0.01$ through the 6–8 km bin ($\hat{\beta} = -0.041$). The empirical finding that Y^{NU} falls by more than Y^U rules out two simple alternatives:

(i) closure shuts off only research collaborations involving the university (which would leave Y^{NU} unaffected), and (ii) closure merely redirects matches from university to non-university partners (which would raise Y^{NU}). Combined with the rise in Y^{S}, which pins down the coordination-platform channel, the decline in Y^{NU} shows that this channel operates not only for outsider–university pairings but also for collaborations among outside inventors themselves.[18]

The spillover channel likely contributes to the decline in Y^{NU} as well: outsiders carrying university-derived knowledge into non-university teams would push Y^{NU} in the same direction. The reduced-form design cannot fully separate the two channels, but the broader implication is clear: campus access matters for collaborations that need not include the university. This complements the cross-sector citation evidence in Fang et al. (2026), who document that Chinese private firms actively cite university-held patents. Our findings provide causal evidence that this dependence operates in part through in-person presence on campus.

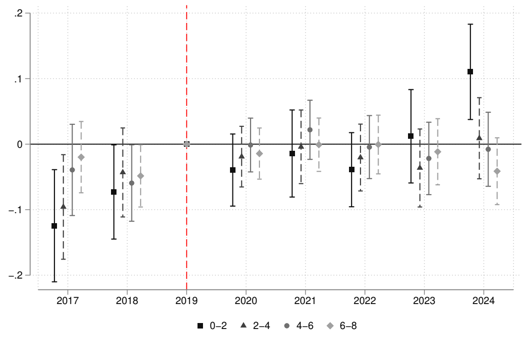
Figure 2 presents the event-study counterparts of the patent-type results, plotting year-specific coefficients for each patent type and inner distance bin relative to the 8–10 km reference bin. The patterns reinforce Table 2. For Y^{S} (Panel a), the post-2020 coefficients are close to zero or slightly positive, with no evidence of a decline. For Y^{M} (Panel b), the coefficients drop sharply in 2020 and remain negative throughout the post-period, with no pre-trend. Panels (c) and (d) confirm that the decline in Y^{NU} is both more persistent and more precisely estimated than the decline in Y^{U}.[19]

The heterogeneous response also implies a compositional shift in the quality of nearby innovation. Figure 3 shows that, in the pre-closure period (2017–2019), Y^{M} received significantly more forward citations than Y^{S}, with Y^{U} being cited the most.[20] Because

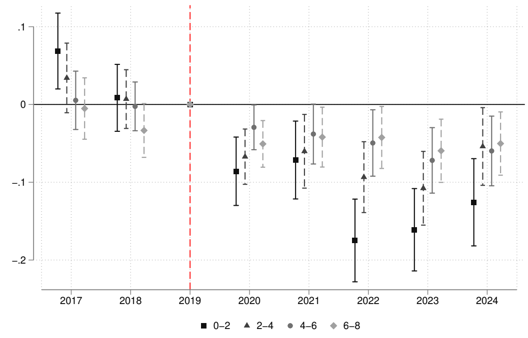
[18]When we further decompose the impact on Y^{NU} into that of existing collaborations or newly-formed collaborations available in the Shanghai sample in Section 5.1 later, we find that the impact is mainly driven by the fall of newly-formed collaborations, which is more in line with the coordination-platform channel.

[19]We further assess robustness using the approach of Roth (2022). Figure A5 shows that, for multi-inventor and non-university collaborative patents, our estimates are unlikely to be driven by spurious pre-trends.

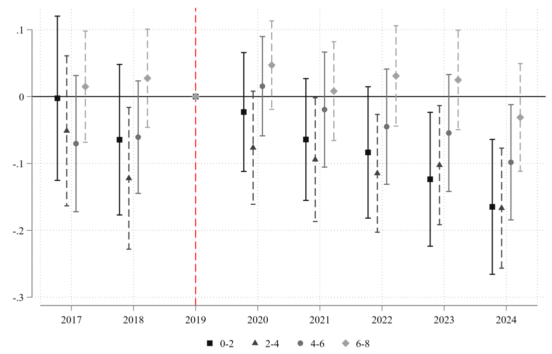
[20]Figure A6 presents analogous results using ln(citations) as the dependent variable and a Poisson pseudo-maximum likelihood (PPML) estimator. The patterns are consistent across specifications.



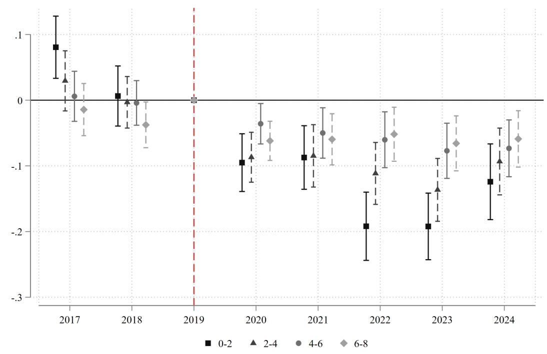
(a) Single-inventor patents (Y^S)



(b) Multi-inventor patents (Y^M)



(c) Univ. collaborative patents (Y^U)



(d) Non-univ. collaborative patents (Y^{NU})

Figure 2: Event Study: Impact of Campus Closure on Patent Density by Type

Note: This figure plots year-specific coefficients from an event-study version of Equation (2), estimated separately for each patent type, where the post-2020 indicator is replaced by year dummies interacted with distance-bin indicators. The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level, for 270 university campuses across China over 2017–2024. The four series show the 0–2, 2–4, 4–6, and 6–8 km bins; the 8–10 km bin is the omitted distance reference and 2019 (the last pre-closure year) is the omitted year reference, indicated by the vertical red dashed line. All specifications include the remaining inner-bin indicators and campus×year fixed effects. Vertical lines denote 95% confidence intervals based on standard errors clustered at the university-campus level.

closure raised Y^S and reduced Y^M in the inner bins, the composition of local innovation shifted toward less-cited categories, implying a quality decline beyond the documented quantity decline. Table A4 confirms this directly: mean forward citations per patent in the 0–2 km bin fell by 0.133 relative to the 8–10 km reference after closure ($p < 0.01$), with the effect decaying monotonically with distance. The closure thus reduced not only the quantity but also the quality of innovation near campus.

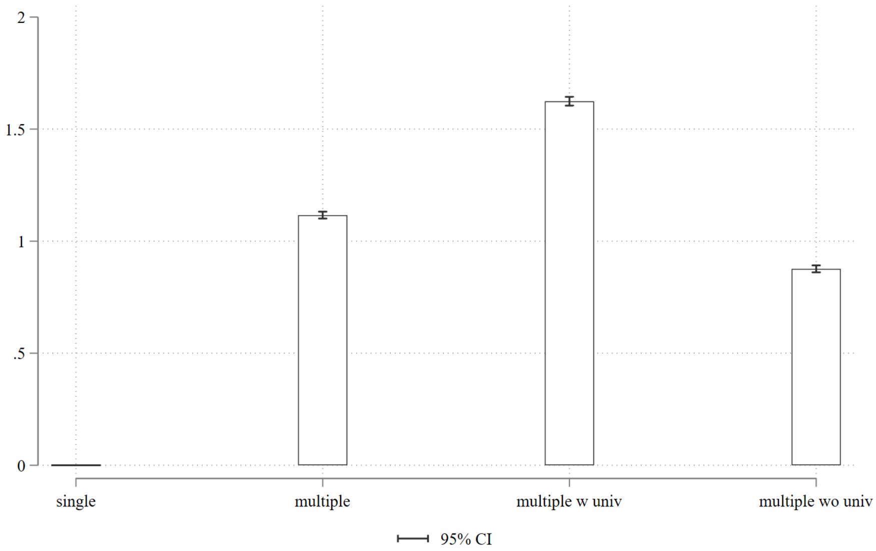


Figure 3: Forward Citations by Patent Type, 2017–2019 (Pre-Closure)

Note: This figure plots coefficients and 95% confidence intervals from patent-level regressions of forward citation counts on patent-type indicators, with Y^S as the omitted reference. The first bar is the reference (zero by construction). The second bar reports the coefficient on the Y^M. The third and fourth bars report coefficients for the two multi-inventor subsets: Y^U and Y^{NU}. Each bar is interpreted as the difference in mean forward citations relative to single-inventor patents, holding year fixed. The sample comprises CNIPA invention patent applications filed during 2017–2019, the three-year pre-closure period. All regressions include year fixed effects.

5 Linking Patent Declines to Visit Declines

The previous section showed that campus closure reduced nearby patenting using national patent data. This section uses mobile-phone data for Shanghai to provide further evidence that the closure affected patents through reduced campus visits. Visits are an imperfect but informative measure of in-person presence on campus. We do not observe the interactions themselves (e.g. conversations, chance encounters, and exposures through which knowledge is transmitted), but we observe the visits that make those interactions possible. In the spirit of Marshall's "knowledge in the air," visits capture the extent to which outsiders are physically positioned to draw on the campus environment. If closure reduces visits, it reduces the opportunities for the in-person interactions through which the campus contributes to local innovation.

The analysis proceeds in three steps. Because the mobile-phone data are available only for Shanghai, we first verify that the patent results replicate in the Shanghai subsample.

We then show that campus visits declined more at closer distances, with a spatial pattern similar to patents. Finally, we link visit declines to patent declines at two spatial scales (rings and grid cells), showing that locations with larger visit declines also experienced larger patent declines.

5.1 Replication in the Shanghai Subsample

We check whether the patent decline documented nationally also appears in the Shanghai subsample. Table 3 reports estimates of Equation (2) on the Shanghai subsample. Column 1 reports results for all patents. The point estimates display the same distance gradient as the national results: the Post × 0–2 km coefficient is −0.083 and the Post × 2–4 km coefficient is −0.070, with magnitudes decaying at greater distances. The Post × 0–2 km coefficient is marginally above conventional levels of significance, reflecting the substantially smaller sample: the Shanghai analysis draws on 27 campuses compared to 270 in the national sample.

The remaining columns decompose by patent type and closely mirror the national results. The estimated effects in the 0–2 km bin after closure are: Y^S in Column 2 shows a positive coefficient ($\hat{\beta} = 0.098$, $p < 0.10$); Y^M in Column 3 declines sharply ($\hat{\beta} = -0.171$, $p < 0.01$); Y^U in Column 4 declines at $\hat{\beta} = -0.176$ ($p < 0.05$); and Y^{NU} in Column 5 declines more sharply at $\hat{\beta} = -0.190$ ($p < 0.01$). As in the national sample, Y^S rises while all collaborative patents fall, with the largest decline in Y^{NU}.

Given the limited sample size in the Shanghai subsample, we adopt a more parsimonious specification to address potential collinearity. Appendix Table A5 restricts the regression to the 0–2 km bin relative to the 8–10 km reference bin. The results confirm a consistent pattern: Y^M and Y^{NU} near campus decline by approximately 12% and 15%, respectively, magnitudes comparable to the corresponding national estimates in Table 2. When we further decompose the impact on Y^{NU} into that of existing collaborations or newly-formed collaborations, we find that the impact is mainly driven by the fall of newly-formed collaborations (Online Appendix Table A6). Overall, the Shanghai patent results replicate the national distance gradient and patent-type decomposition, with broadly

Table 3: Impact of Campus Closure on Patent Density: Shanghai Subsample

	(1) All patents	(2) Y^S	(3) Y^M	(4) Y^U	(5) Y^{NU}
0–2 km	0.462**	0.720***	0.677***	1.929***	0.649***
	(0.189)	(0.142)	(0.197)	(0.204)	(0.179)
2–4 km	0.227	0.323***	0.305*	0.916***	0.279*
	(0.155)	(0.112)	(0.160)	(0.229)	(0.143)
4–6 km	0.362***	0.379***	0.398***	0.379*	0.395***
	(0.103)	(0.079)	(0.108)	(0.200)	(0.096)
6–8 km	0.148**	0.101	0.152*	0.372**	0.110
	(0.070)	(0.068)	(0.075)	(0.165)	(0.078)
Post × 0–2 km	−0.083	0.098*	−0.171***	−0.176**	−0.190***
	(0.051)	(0.057)	(0.060)	(0.069)	(0.056)
Post × 2–4 km	−0.070	−0.015	−0.125**	−0.110	−0.122**
	(0.046)	(0.048)	(0.054)	(0.065)	(0.054)
Post × 4–6 km	−0.038	0.028	−0.076*	−0.117	−0.056
	(0.034)	(0.047)	(0.038)	(0.077)	(0.037)
Post × 6–8 km	−0.018	0.018	−0.020	−0.181**	−0.004
	(0.034)	(0.055)	(0.037)	(0.084)	(0.037)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.34	0.28	0.32	0.11	0.33
Observations	20,658	19,283	20,081	8,663	20,005

Note: This table replicates Equation (2) on the Shanghai subsample of 27 university campuses over 2017–2024. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates years from 2020 onward. The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level. Column 1 includes all patents. Columns 2–5 are estimated separately for the four patent-type outcomes. All specifications include campus×year fixed effects. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

similar magnitudes but less precision.

5.2 Campus Visits and Distance

We document the spatial gradient in baseline visit intensity. Appendix Figure A7 plots visitor density as a function of distance from campus using home locations, showing a steep decline with distance. A similar pattern emerges when using workplace locations (Appendix Figure A8). This baseline gradient is what generates spatial variation in post-closure visit declines. Locations near campus had more visits to lose, so they experienced larger declines after closure.

We now examine how visits to campus changed after closure across distances. We estimate Equation (2) with three visit outcomes, each capturing a different margin of adjustment.

Extensive margin: visitor density. Table 4 reports results where the dependent variable is the natural logarithm of visitor density (number of distinct campus visitors per km^2). The effects are statistically significant across all bins, with consistent magnitudes across the paired-sample and joint specifications. After closure, visitor density of trips originating from the 0–2 km bin declined by 42.3 percent relative to that originating from the 8–10 km bin (Column 5, $p < 0.01$). The effect decays monotonically: 39.2 percent in the 2–4 km bin, 29.2 percent in 4–6 km, and 12.5 percent in 6–8 km, all statistically significant at the 1 percent level. The spatial gradient in visitor decline closely parallels the gradient in patent decline (Table 1), consistent with reduced in-person presence on campus driving the spatial pattern of innovation decline.

Table 4: Impact of Campus Closure on Visitor Density: Shanghai

	(1)	(2)	(3)	(4)	(5)
0–2 km	3.613***				3.634***
	(0.136)				(0.136)
2–4 km		2.163***			2.155***
		(0.107)			(0.108)
4–6 km			1.268***		1.255***
			(0.079)		(0.079)
6–8 km				0.508***	0.499***
				(0.045)	(0.045)
Post × 0–2 km	−0.403***				−0.423***
	(0.070)				(0.066)
Post × 2–4 km		−0.400***			−0.392***
		(0.061)			(0.063)
Post × 4–6 km			−0.304***		−0.292***
			(0.057)		(0.060)
Post × 6–8 km				−0.133***	−0.125***
				(0.036)	(0.037)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.90	0.90	0.89	0.90	0.89
Observations	2,140	2,131	2,109	2,044	5,235

Note: This table reports estimates of Equation (2) using Shanghai mobile-phone data at the ring–year level for two cross-sectional snapshots, November 2019 (pre-closure) and November 2024 (post-closure). The sample comprises 27 university campuses. The dependent variable is the natural logarithm of visitor density, defined as ln(distinct campus visitors/ring area in km^2). Visitors are anchored to rings by home location. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Intensive margin: visit frequency. Table 5 uses the natural logarithm of visits per visitor as the dependent variable, capturing how often each visitor goes to campus. The estimates are consistent across the paired-sample and joint specifications, and we focus on Column 5. After closure, the 0–2 km bin experienced a 42.0 percent decline in visit frequency ($p < 0.01$), with the effect decaying to 19.4 percent at 2–4 km and 11.5 percent at 4–6 km. The 6–8 km coefficient is effectively zero ($\hat{\beta} = -0.000$). This suggests that not only did fewer people visit campus from nearby locations (the extensive margin), but those who continued to visit did so less frequently. This intensive-margin pattern reinforces the spatial gradient in reduced in-person presence on campus.

Table 5: Impact of Campus Closure on Visit Frequency per Visitor: Shanghai

	(1)	(2)	(3)	(4)	(5)
0–2 km	1.252***				1.272***
	(0.065)				(0.063)
2–4 km		0.612***			0.613***
		(0.054)			(0.054)
4–6 km			0.289***		0.283***
			(0.044)		(0.046)
6–8 km				0.068	0.068
				(0.049)	(0.051)
Post × 0–2 km	−0.400***				−0.420***
	(0.068)				(0.067)
Post × 2–4 km		−0.193***			−0.194***
		(0.067)			(0.067)
Post × 4–6 km			−0.121*		−0.115*
			(0.059)		(0.061)
Post × 6–8 km				−0.000	−0.000
				(0.061)	(0.063)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.44	0.28	0.21	0.17	0.36
Observations	2,140	2,131	2,109	2,044	5,235

Note: This table reports estimates of Equation (2) using Shanghai mobile-phone data at the ring–year level for the November 2019 (pre-closure) and November 2024 (post-closure) snapshots. The sample comprises 27 university campuses. The dependent variable is the natural logarithm of visit frequency per visitor, defined as ln(total campus visits by ring residents/distinct visitors). Visitors are anchored to rings by home location. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Intensive margin: visit days. Table 6 uses the natural logarithm of visit days per visitor, measuring the number of distinct days each visitor spent on campus. The pattern closely tracks visit frequency: a sharp decline near campus that decays monotonically with distance, with no significant effect in the 6–8 km bin.

Table 6: Impact of Campus Closure on Visit Days per Visitor: Shanghai

	(1)	(2)	(3)	(4)	(5)
0–2 km	1.032***				1.049***
	(0.055)				(0.054)
2–4 km		0.513***			0.513***
		(0.048)			(0.049)
4–6 km			0.253***		0.248***
			(0.039)		(0.040)
6–8 km				0.065	0.065
				(0.044)	(0.044)
Post × 0–2 km	−0.374***				−0.392***
	(0.052)				(0.052)
Post × 2–4 km		−0.160***			−0.161***
		(0.054)			(0.054)
Post × 4–6 km			−0.108**		−0.104**
			(0.043)		(0.045)
Post × 6–8 km				−0.014	−0.015
				(0.048)	(0.049)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.45	0.26	0.17	0.11	0.36
Observations	2,140	2,131	2,109	2,044	5,235

Note: This table reports estimates of Equation (2) using Shanghai mobile-phone data at the ring–year level for the November 2019 (pre-closure) and November 2024 (post-closure) snapshots. The sample comprises 27 university campuses. The dependent variable is the natural logarithm of visit days per visitor, defined as ln(distinct days on which ring residents visit campus/distinct visitors). Visitors are anchored to rings by home location. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tables 4–6 establish that campus closure reduced visitor activity on all three margins and that these reductions were concentrated at close distances, precisely mirroring the spatial pattern of patent declines. This evidence supports Prediction 1: Δv_i decays with distance from campus. The magnitudes of the visit decline are large: visitor density in the 0–2 km ring fell by 42 percent. Similar reductions hold for the other two visit measures. This indicates that the closure comprehensively disrupted outsiders' in-person presence on campus and the opportunities for in-person interactions that this presence enables.[21]

[21] We obtain similar results when defining visitors based on workplace location rather than home location (Online Appendix Tables A7–A9).

5.3 Linking Visit Declines to Patent Declines: Ring Level Evidence

We now examine whether the spatial pattern of visit decline accounts for the spatial pattern of patent decline. We augment the Shanghai patent regression with visitor-change controls. Specifically, we interact the post-2020 indicator with ring-level measures of pre-closure visitor activity (visitor density, visit days per visitor, and visit frequency per visitor), allowing these controls to capture the differential visitor decline across rings. If the spatial pattern of visit decline accounts for the patent decline, adding these controls should shrink the 0–2 km distance coefficient — the bin where the patent decline was largest — toward zero. We focus on Y^M and Y^{NU}, the two categories that showed the strongest effects in both the national (Table 2) and Shanghai (Table A5) analyses.

Multi-inventor patents. Panel A of Table 7 reports the results. Column 1 reproduces the baseline Shanghai specification for Y^M (from Table A5): the Post $\times$ 0–2 km coefficient is -0.118 ($p < 0.05$). Adding visitor density instead as a control (Column 2) reduces the coefficient to -0.072, a 39 percent reduction, and it becomes statistically insignificant. Adding visit days per visitor (Column 3) instead reduces it further to -0.025, a 79 percent reduction. Adding visit frequency per visitor (Column 4) yields -0.038, a 68 percent reduction. When all three visitor measures are included simultaneously (Column 5), the distance coefficient shrinks to -0.003, essentially zero, representing a 97 percent reduction from the baseline. Differential visit declines across rings absorb nearly the entire distance-based effect on Y^M, meaning the spatial pattern of Y^M decline is almost entirely attributable to the loss of in-person presence on campus. This provides evidence that in-person presence is the foundation through which collaborative innovation is generated.

Non-university collaborative patents. Panel B of Table 7 repeats the exercise for Y^{NU}. The baseline coefficient is -0.146 ($p < 0.05$, Column 1). Adding visitor density (Column 2) reduces the coefficient by 32.2%. Controlling for visit days per visitor instead (Column 3) yields a 51.4% reduction, while controlling for visit frequency instead (Column 4) yields a 45.9% reduction. When all three visitor measures are included simultaneously (Column 5), the coefficient falls to -0.049, implying a 66.4% reduction, and becomes sta-

Table 7: Innovation Decline Explained by Visitor Changes: Ring-Level Analysis

Panel A: Multi-inventor patents (Y^M)

	(1)	(2)	(3)	(4)	(5)
Post × 0–2 km	−0.118**	−0.072	−0.025	−0.038	−0.003
	(0.055)	(0.062)	(0.064)	(0.063)	(0.068)
Post × visitor density		0.179*			0.127
		(0.096)			(0.095)
Post × visit days per visitor			0.302***		0.401
			(0.104)		(0.371)
Post × visit frequency per visitor				0.246**	−0.128
				(0.090)	(0.319)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.32	0.32	0.32	0.32	0.32
Observations	20,081	20,069	20,069	20,069	20,069

Panel B: Non-university collaborative patents (Y^{NU})

	(1)	(2)	(3)	(4)	(5)
Post × 0–2 km	−0.146**	−0.099	−0.071	−0.079	−0.049
	(0.056)	(0.066)	(0.066)	(0.065)	(0.072)
Post × visitor density		0.186*			0.143
		(0.092)			(0.089)
Post × visit days per visitor			0.244**		0.226
			(0.098)		(0.393)
Post × visit frequency per visitor				0.206**	−0.030
				(0.084)	(0.333)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.32	0.32	0.32	0.32	0.32
Observations	20,005	19,993	19,993	19,993	19,993

Note: This table augments the parsimonious Shanghai patent regression (Table A5) with ring-level visitor controls. The dependent variable in Panel A is the natural logarithm of multi-inventor patent density; in Panel B, it is the natural logarithm of multi-inventor patent density without a university inventor. Column 1 reproduces the baseline specification (0–2 km bin vs. 2–10 km reference) with no visitor controls. Columns 2–4 add one pre-closure (2019) visitor measure at a time, interacted with the post-2020 indicator: visitor density (Column 2), visit days per visitor (Column 3), and visit frequency per visitor (Column 4). Column 5 includes all three simultaneously. The sample is the Shanghai subsample of 27 university campuses, 2017–2024. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

tistically insignificant. While differential visit declines absorb less of the distance effect than for Y^M, they still explain a substantial share of the distance effect.

These results are consistent with Prediction 1: campus closure changes nearby innovation in proportion to the change in visits. The near-complete absorption for Y^M is particularly notable. Multi-inventor patents depend on the in-person presence on campus that enables both knowledge spillovers and the coordination of collaborators — and the closure's loss of this presence accounts for nearly all of the spatial pattern of Y^M

decline. More generally, this result shows that the spatial pattern of patent decline is not driven by distance per se, but by the underlying loss of in-person presence on campus. The results are robust to defining visitors based on workplace location rather than home location.

5.4 Additional Variation at the Grid Level

We now examine a finer scale: among grid cells at the same distance from campus, do cells that lost more visitors also lose more patents? We include Cell×campus fixed effects, which absorb each cell's time-invariant characteristics including its distance from campus. Any remaining association between visitor declines and patent declines cannot be driven by the spatial gradient.

We first show that visitor decline varies across grid cells. In Table 8, Panel A, we regress post-closure visitor outcomes at the grid-cell level on pre-closure (2019) visitor levels, interacted with a post-2020 indicator. The interaction coefficient captures whether cells with higher pre-closure visitor activity experienced larger post-closure declines. A one-log-point increase in 2019 visitor count is associated with a 0.60-log-point larger decline in visitor counts after 2020 ($p < 0.01$, Column 1). The intensive margins show similar or stronger patterns: a one-log-point increase in pre-closure visit days per visitor predicts a 0.83-log-point larger decline ($p < 0.01$, Column 2), and pre-closure visit frequency per visitor predicts a 0.80-log-point larger decline ($p < 0.01$, Column 3). Grid cells with higher pre-closure campus visitor activity experienced disproportionately larger visitor losses after closure, even at the same distance from campus.[22]

Panel B tests the link between visit decline and patent decline at the grid level. We classify grid cells into above- and below-median groups based on their pre-closure (2019) visitor count, then estimate whether above-median cells experienced a differential change in patent activity after 2020. The dependent variable is an indicator for whether any patent was filed in the grid cell (extensive margin), and all specifications include cell×campus fixed effects, so the comparison absorbs each cell's time-invariant location

[22] We obtain similar results when defining visitors, visit frequency, and visit days based on workplace location rather than home location (Online Appendix Table A11).

Table 8: Linking Patent Declines to Visit Declines: Grid Level

Panel A: Grid-level visitor decline

	(1) ln visitor count	(2) ln visit days per visitor	(3) ln visit freq. per visitor
Post × ln 2019 visitor count	−0.599***		
	(0.008)		
Post × ln 2019 visit days per visitor		−0.830***	
		(0.006)	
Post × ln 2019 visit freq. per visitor			−0.804***
			(0.006)
Campus × year FE	Yes	Yes	Yes
Cell × campus FE	Yes	Yes	Yes
Adjusted R^2	0.51	0.57	0.52
Observations	61,138	61,138	61,138

Panel B: Visitor decline and patent activity

	(1) All	(2) Y^S	(3) Y^M	(4) Y^U	(5) Y^{NU}
Post × Above Median (2019)	−0.010***	0.002*	−0.016***	−0.003***	−0.016***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Cell × campus FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.41	0.30	0.47	0.46	0.47
Observations	984,248	984,248	984,248	984,248	984,248

Note: This table reports grid-cell-level mediation analyses for the 27 Shanghai university campuses. In Panel A, the dependent variable in each column is regressed on the interaction between the post-2020 indicator and the corresponding pre-closure (2019) visitor measure. Panel B reports patent-outcome regressions in which the dependent variable is an indicator for whether any patent of the specified type was filed in the grid cell (extensive margin). "Above Median (2019)" is an indicator for grid cells with above-median pre-closure visitor counts. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

characteristics including distance from campus. The key coefficient (the interaction between the post-2020 indicator and the above-median visitor indicator) is negative and significant for all categories except for Y^S. Y^M (Column 3) and Y^{NU} (Column 5) show a 1.6 percentage point larger decline ($p < 0.01$). This pattern mirrors the ring-level findings: grid cells that lost the most visitors are the same cells that lost the most patents, and the relationship is concentrated in collaborative patents (Y^M and Y^{NU}).[23] Together with the ring-level evidence, this confirms that the spatial pattern of patent decline reflects the loss of in-person presence on campus — the foundation through which collaborative innovation is generated.

[23] We obtain similar results when defining visitors, visit frequency, and visit days based on workplace location rather than home location (Online Appendix Table A11).

6 Conclusion

This paper identifies in-person presence on campus as a quantitatively important driver of local innovation. By coming onto the campus, outsiders gain access to the in-person interactions through which knowledge is transmitted and collaborations form. The Chinese pandemic-era closure of walled campuses provides a well-identified source of variation: a sustained, nationwide reduction in outsider entry without a contraction of university research output. We document sharp distance gradients in both patenting and visitor activity, a decline concentrated in collaborative patents, and near-complete absorption of the distance effect by differential visit declines. The patent-type heterogeneity — particularly the rise in single-inventor patents and the decline in non-university collaborative patents — is consistent with the coordination-platform channel operating, although our reduced-form design cannot separate spillover from coordination-platform channels.

The decline in non-university collaborative patents shows that private-sector inventors depend on physical access to the university environment for knowledge that feeds into their own work, whether through informal absorption of university research or through finding collaborators on campus. This in-person channel is complementary to the population channel emphasized by Andrews (2023) and the formal technology-transfer channel emphasized by Hausman (2022).

Our findings carry implications for innovation policy and the urban-planning decisions that shape access to universities, particularly given the evolving role of universities in the local economy. As universities increasingly engage with surrounding production ecosystems rather than function as isolated ivory towers, their accessibility to outsiders becomes central to the value they create. Campus design, transit infrastructure, and gate access policies are direct levers that shape this in-person access channel. The results also speak to ongoing debates in China, where many universities have yet to restore pre-pandemic openness following the 2020–2022 closures. Public discussion has focused on security, congestion, and administrative cost; our results add the innovation costs of restrictive access.

While our empirical context is based on China, the underlying logic generalizes: physical access to a university enables in-person interactions between outsiders and the campus environment, and these interactions operate wherever universities exist. Our reduced-form design shows that this in-person access matters but cannot fully separate its two underlying mechanisms: knowledge spillovers from university research, and the campus's role as a coordination platform for outsider-to-outsider collaboration. Distinguishing the two more sharply remains an open question for future work.

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Online Appendix [For Online Publication]

List of Figures

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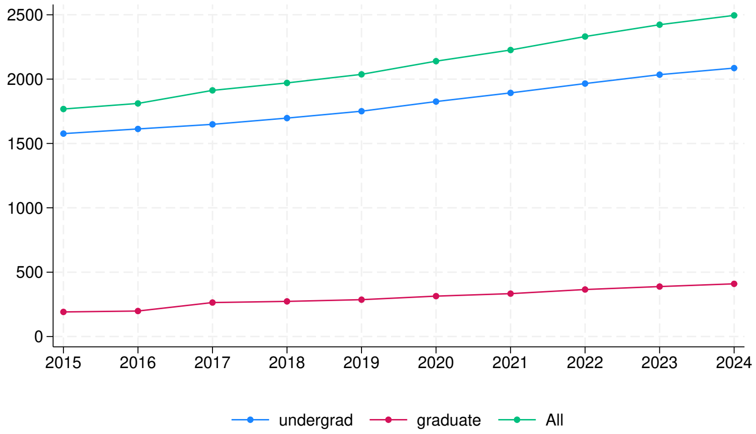
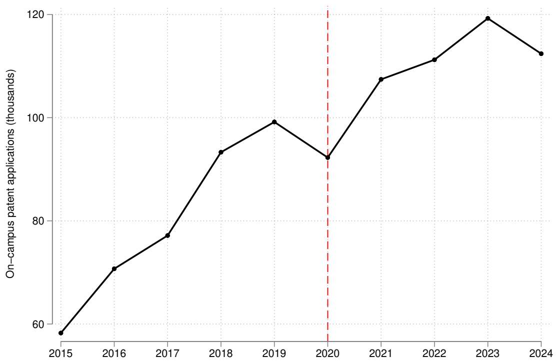
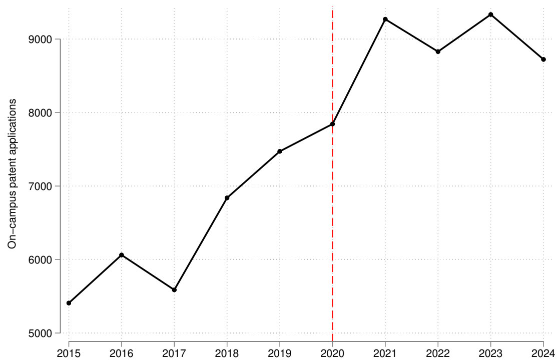


Figure A1: Higher-Education Enrollment in China, by Degree Type, 2015–2024

Note: This figure plots total student enrollment in regular higher-education institutions in China, in units of 10,000 students, separately for the total (All), undergraduate, and graduate populations. Source: *Educational Statistics*, Ministry of Education of the People's Republic of China.



(a) National



(b) Shanghai

Figure A2: On-Campus Patent Applications, 2015–2024

Note: This figure plots the total number of CNIPA invention patent applications filed inside the university campuses, summed across campuses, by application year. Patents filed at on-campus addresses originate exclusively from the universities and their affiliated entities, so each series serves as a proxy for university-affiliated patent output. The vertical dashed line at 2020 marks the year of the nationwide campus closure. Panel (a) reports patent applications for 270 campuses across China, while Panel (b) reports the corresponding figures for 27 campuses in Shanghai.

Figure A3: Geographic Distribution of Sample University Campuses Across China

Note: This figure plots the locations of the 270 campuses in our national sample, drawn from 116 universities designated under Project 985 or Project 211 (China's two tiers of nationally designated top research institutions). Each red dot represents one campus centroid; black lines mark provincial boundaries. Provincial boundary data are from the National Platform for Common Geospatial Information Services for Geographic Information, Ministry of Natural Resources of China; campus locations are from official university websites cross-referenced with Amap.

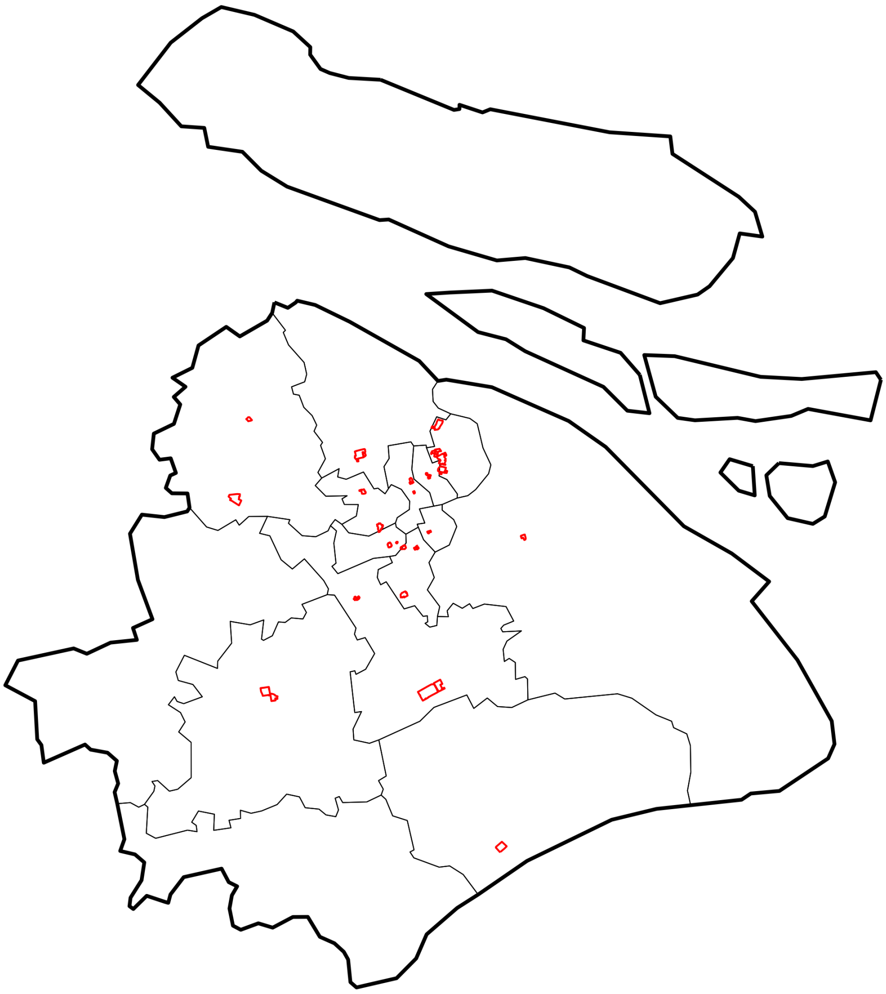
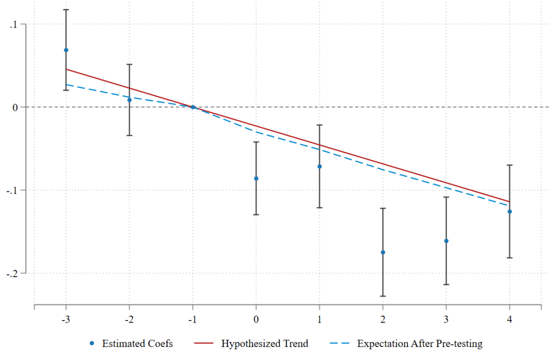
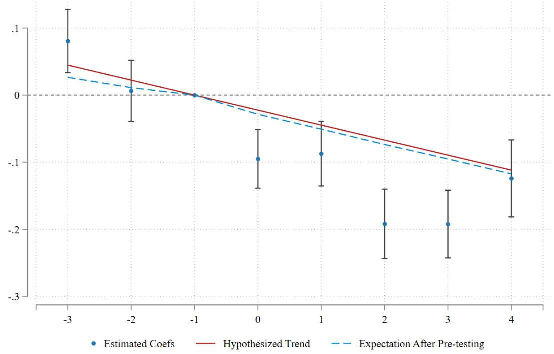


Figure A4: Geographic Distribution of Sample University Campuses in Shanghai

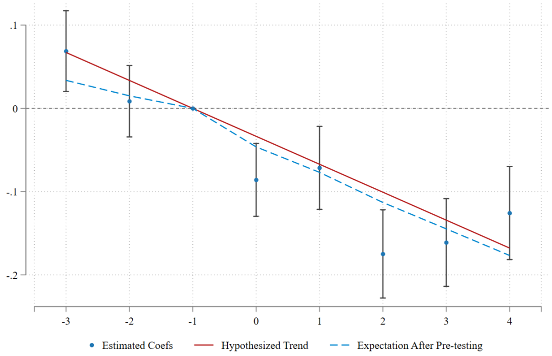
Note: This figure plots the 27 university campuses in Shanghai used in the analysis of campus visits (Section 5), drawn from nine universities designated under Project 985 or Project 211. Each red polygon outlines the Area of Interest (AOI) boundary of one campus; black lines mark Shanghai's district boundaries. District boundary data are from the National Platform for Common Geospatial Information Services, Ministry of Natural Resources of China; campus AOIs are from Amap.



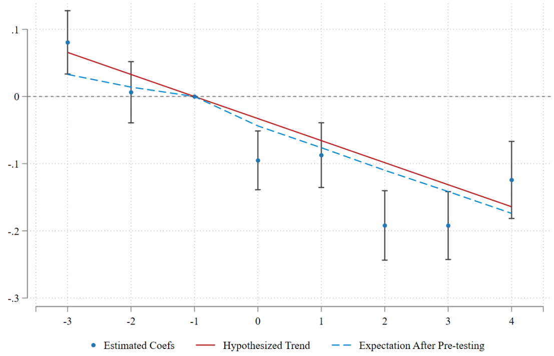
(a) Y^{M}, 50% power



(b) Y^{NU}, 50% power



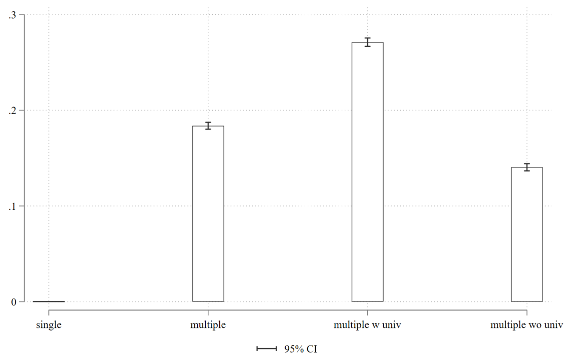
(c) Y^{M}, 80% power



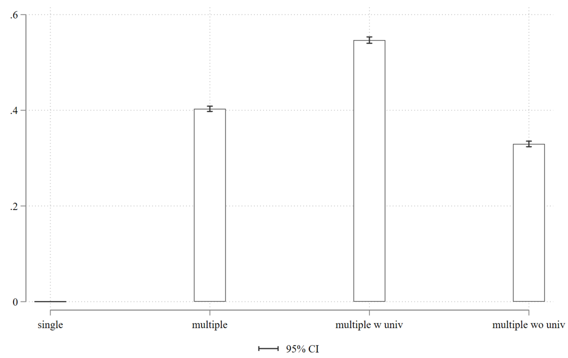
(d) Y^{NU}, 80% power

Figure A5: Pre-Trend Sensitivity Analysis: Impact of Campus Closure on Patent Density by Type

Note: This figure reports sensitivity analyses based on the pre-trend testing method of Roth (2022), which assesses how robust the estimated treatment effects are to potential violations of parallel trends. The method constructs confidence sets for the post-treatment coefficients conditional on a hypothesized linear pre-trend slope that would not have been detected by a pre-test at a given power level. The dependent variable is the natural logarithm of patent density. Panels (a) and (b) use 50% power; Panels (c) and (d) use 80% power. In each panel, coefficients correspond to the 0–2 km bin relative to the 8–10 km reference bin.



(a) ln(citations) as outcome



(b) Poisson pseudo-maximum likelihood

Figure A6: Forward Citations by Patent Type, 2017–2019: Alternative Specifications

Note: This figure reports robustness checks for the citation premia documented in Figure 3, under alternative outcome specifications. Panel (a) uses ln(forward citations) as the dependent variable in a linear regression. Panel (b) uses raw forward citations as the dependent variable in a Poisson pseudo-maximum likelihood (PPML) regression. In both panels, single-inventor patents are the omitted reference; the first bar is the reference (zero by construction), and the subsequent bars report coefficients on the collaborative patent indicator, the university collaborative patent indicator, and the non-university collaborative patent indicator. The sample comprises CNIPA invention patent applications filed during 2017–2019, the three-year pre-closure period. All regressions include year fixed effects. Bars are accompanied by 95% confidence intervals.

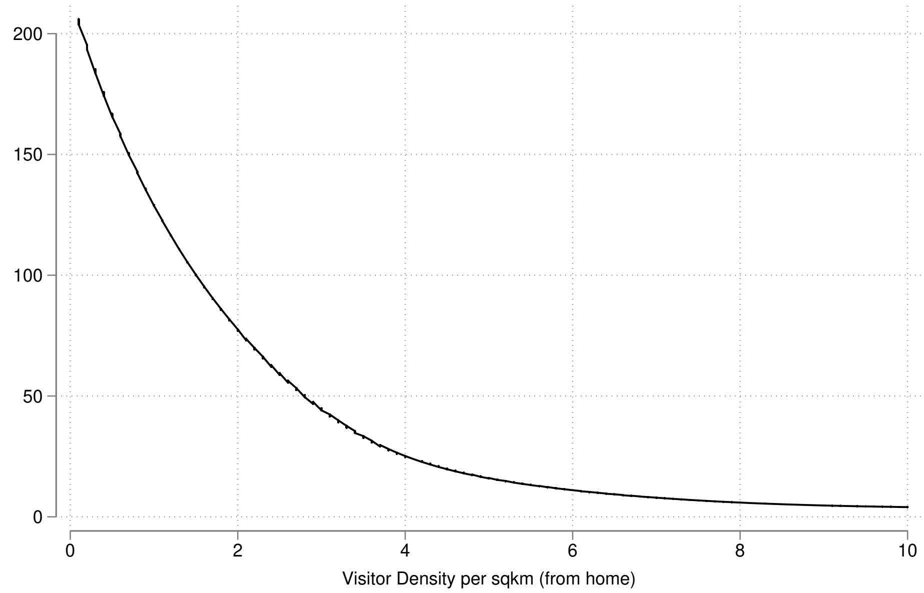


Figure A7: Visitor Density by Distance to Campus: Shanghai, Home-Anchored

Note: This figure plots the spatial gradient in campus-visitor density across the 27 Shanghai university campuses in our sample. The horizontal axis is distance from the campus boundary. The vertical axis is the average number of distinct campus visitors per km^2 in each ring. Visitors are anchored to rings by home location. Data are from China Unicom mobile-phone signaling records, drawn from the November 2019 and November 2024 snapshots.

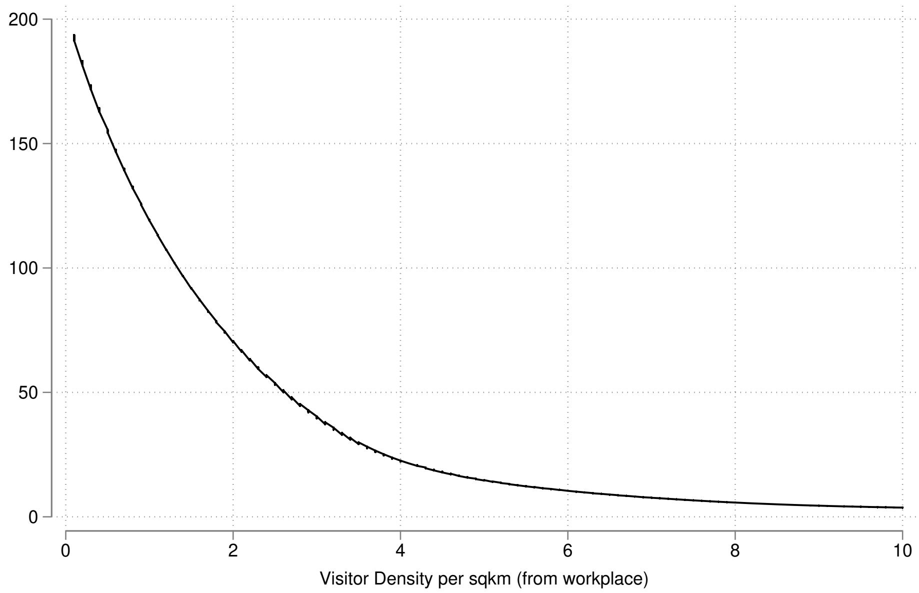


Figure A8: Visitor Density by Distance to Campus: Shanghai, Workplace-Anchored

Note: This figure plots the spatial gradient in campus-visitor density across the 27 Shanghai university campuses in our sample, anchoring each visitor to a ring by workplace location rather than home location. The horizontal axis is distance from the campus boundary. The vertical axis is the average number of distinct campus visitors per km^2 in each ring. This figure is the workplace-anchored counterpart to Appendix Figure A7.

Table A1: Summary Statistics: Patent and Visitor Variables at the Ring Level

Variable	Mean	Std. Dev.	Obs.
Panel A. Patents			
Patent density	47.80	162.05	216,000
Y^S	7.91	30.10	216,000
Y^M	39.89	146.67	216,000
Y^U	14.77	113.16	216,000
Y^{NU}	25.12	82.06	216,000
Panel B. Visitor Activity			
Visitor density	35.00	79.93	5,358
Visits per visitor	6.09	6.42	5,235
Days per visitor	4.00	3.11	5,235

Note: This table reports summary statistics for the variables used in the empirical analysis at the ring level. *Panel A* covers patent density (patent applications per km^2 of ring area), broken down by inventor count and university affiliation, for the national sample of 270 campuses over 2017–2024. *Panel B* covers ring-level visitor activity constructed from two cross-sectional mobile-phone snapshots (November 2019 and November 2024) for the 27 Shanghai sample campuses; visitors are assigned to rings by their home location. *Visitor Density* is the number of distinct campus visitors per km^2 of ring area; *Visits per Visitor* is total visits divided by the number of distinct visitors; *Days per Visitor* is total distinct days on campus divided by the number of distinct visitors.

Table A2: Summary Statistics: Patent and Visitor Variables at the Grid-Cell Level

Variable	Mean	Std. Dev.	Obs.
Panel A. Patents			
Patent Count	2.36	25.86	984,248
Y^S	0.45	4.97	984,248
Y^M	1.91	24.01	984,248
Y^U	0.49	20.19	984,248
Y^{NU}	1.42	12.35	984,248
Panel B. Visitor Activity			
Visitor count	1.01	2.84	246,062
Visits per visitor	5.85	11.41	90,258
Days per visitor	3.88	5.07	90,258

Note: This table reports summary statistics for the variables used in the within-ring mediation analysis (Section 5) at the Geohash-7 grid-cell level (approximately 152 m × 152 m). Both panels cover the 27 Shanghai sample campuses. *Panel A* reports patent application counts per grid cell over 2017–2024, broken down by inventor count and university affiliation. *Panel B* reports visitor activity from the November 2019 and November 2024 mobile-phone snapshots, with visitors assigned to grid cells by their home location. The number of observations is larger for visitor counts than for visits per visitor and days per visitor because the visitor-count sample includes grid cells with zero visitors, whereas the per-visitor measures are only defined for grid cells with at least one visitor.

Table A3: Summary Statistics: Workplace-Based Visitor Variables, Shanghai Subsample

Panel A: Ring Level

Variable	Mean	Std. Dev.	Obs.
Visitor Activity (Workplace-Based)			
Visitor Density	32.13	75.07	5,358
Visits per Visitor	6.25	6.03	5,233
Days per Visitor	4.02	2.96	5,233

Panel B: Grid-Cell Level

Variable	Mean	Std. Dev.	Obs.
Visitor Activity (Workplace-Based)			
Visitor Count	0.92	2.47	246,062
Visits per Visitor	5.93	11.67	89,969
Days per Visitor	3.88	5.38	89,969

Note: This table reports summary statistics for the workplace-based visitor measures used as a robustness check in Section 5. Visitors are assigned to spatial units by their workplace location, rather than home location as in Tables A1 and A2. The sample covers the 27 Shanghai campuses over the November 2019 and November 2024 mobile-phone snapshots. Panel A reports ring-level statistics; Panel B reports Geohash-7 grid-cell-level statistics (approximately 152 m $\times$ 152 m).

Table A4: Impact of Campus Closure on Mean Forward Citations per Patent

	(1)	(2)	(3)	(4)	(5)
0–2 km	0.161***				0.158***
	(0.034)				(0.033)
2–4 km		0.135***			0.136***
		(0.029)			(0.029)
4–6 km			0.071***		0.073***
			(0.024)		(0.024)
6–8 km				0.056**	0.055**
				(0.023)	(0.023)
Post × 0–2 km	−0.135***				−0.133***
	(0.029)				(0.029)
Post × 2–4 km		−0.117***			−0.118***
		(0.026)			(0.026)
Post × 4–6 km			−0.054***		−0.056***
			(0.021)		(0.021)
Post × 6–8 km				−0.048**	−0.048**
				(0.021)	(0.021)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.51	0.54	0.59	0.59	0.53
Observations	75,194	78,880	79,904	78,243	188,882

Note: This table reports estimates of Equation (2) with the dependent variable redefined as the mean number of forward citations received by patents filed in each ring–year cell, computed for 270 university campuses across China over 2017–2024. Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates years from 2020 onward. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all five bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of Campus Closure on Patent Density: Shanghai, Parsimonious 0–2 km Specification

	(1) All patents	(2) Y^S	(3) Y^M	(4) Y^U	(5) Y^{NU}
0–2 km	0.280*	0.524***	0.468***	1.536***	0.457***
	(0.162)	(0.123)	(0.168)	(0.149)	(0.157)
Post × 0–2 km	−0.052	0.090*	−0.118**	−0.070	−0.146**
	(0.044)	(0.046)	(0.055)	(0.070)	(0.056)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.33	0.27	0.32	0.09	0.32
Observations	20,658	19,283	20,081	8,663	20,005

Note: This table reports a parsimonious version of Table 3, restricting Equation (2) to the 0–2 km bin relative to the 2–10 km reference bin. The sample is the Shanghai subsample of 27 university campuses over 2017–2024. The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level. Column 1 includes all patents. Columns 2–5 are estimated separately for the four patent-type outcomes. "Post" indicates years from 2020 onward. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Impact of Campus Closure on Non-University Collaborative Patents by Pair History: Shanghai

	(1) Existing pair	(2) New pair	(3) Existing pair	(4) New pair
0–2 km	1.535***	1.597***	1.138***	1.249***
	(0.204)	(0.101)	(0.146)	(0.097)
2–4 km	0.999***	0.865***		
	(0.201)	(0.072)		
4–6 km	0.596***	0.510***		
	(0.129)	(0.070)		
6–8 km	0.219**	0.179***		
	(0.098)	(0.050)		
Post × 0–2 km	−0.044	−0.244***	−0.036	−0.248***
	(0.138)	(0.081)	(0.121)	(0.077)
Post × 2–4 km	−0.064	−0.172**		
	(0.148)	(0.071)		
Post × 4–6 km	−0.093	0.057		
	(0.106)	(0.073)		
Post × 6–8 km	0.088	0.073		
	(0.107)	(0.071)		
Campus × year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.12	0.24	0.08	0.20
Observations	4,561	10,393	4,561	10,393

Note: This table decomposes Y^{NU} into two collaboration types based on applicant-pair history: "Existing pair" patents have at least one applicant pair that appeared on an earlier patent within the 2019–2024 classification window, while "New pair" patents have no applicant pair with any such prior co-filing. The sample is the Shanghai subsample of 27 university campuses over 2019–2024. The dependent variable is the natural logarithm of patent density (patent applications per km^2) at the ring–year level for the indicated subset. Columns 1–2 estimate Equation (2) jointly across the four inner distance bins (0–2, 2–4, 4–6, 6–8 km) relative to the 8–10 km reference. Columns 3–4 estimate the parsimonious specification restricting to the 0–2 km bin relative to the 8–10 km reference. "Post" indicates years from 2020 onward. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Impact of Campus Closure on Visitor Density: Shanghai, Workplace-Anchored

	(1)	(2)	(3)	(4)	(5)
0–2 km	3.499***				3.532***
	(0.118)				(0.118)
2–4 km		2.068***			2.061***
		(0.076)			(0.077)
4–6 km			1.273***		1.258***
			(0.068)		(0.070)
6–8 km				0.502***	0.495***
				(0.046)	(0.046)
Post × 0–2 km	−0.316***				−0.348***
	(0.074)				(0.069)
Post × 2–4 km		−0.355***			−0.347***
		(0.060)			(0.061)
Post × 4–6 km			−0.291***		−0.276***
			(0.064)		(0.067)
Post × 6–8 km				−0.119***	−0.113***
				(0.037)	(0.037)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.90	0.91	0.91	0.90	0.89
Observations	2,143	2,132	2,112	2,041	5,233

Note: This table reports the workplace-anchored counterpart to Table 4, with visitors assigned to rings by their workplace location rather than home location. The sample comprises 27 Shanghai university campuses observed in two cross-sectional snapshots, November 2019 (pre-closure) and November 2024 (post-closure). The dependent variable is the natural logarithm of visitor density, defined as ln(distinct campus visitors/ring area in km^2). Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Impact of Campus Closure on Visit Frequency per Visitor: Shanghai, Workplace-Anchored

	(1)	(2)	(3)	(4)	(5)
0–2 km	1.337***				1.349***
	(0.073)				(0.073)
2–4 km		0.610***			0.608***
		(0.052)			(0.053)
4–6 km			0.254***		0.240***
			(0.051)		(0.052)
6–8 km				0.083*	0.084*
				(0.043)	(0.044)
Post × 0–2 km	−0.500***				−0.512***
	(0.071)				(0.070)
Post × 2–4 km		−0.211***			−0.209***
		(0.050)			(0.051)
Post × 4–6 km			−0.044		−0.031
			(0.064)		(0.067)
Post × 6–8 km				0.076	0.076
				(0.064)	(0.063)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.45	0.26	0.20	0.18	0.36
Observations	2,143	2,132	2,112	2,041	5,233

Note: This table reports the workplace-anchored counterpart to Table 5, with visitors assigned to rings by their workplace location rather than home location. The sample comprises 27 Shanghai university campuses observed in two cross-sectional snapshots, November 2019 (pre-closure) and November 2024 (post-closure). The dependent variable is the natural logarithm of visit frequency per visitor, defined as ln(total campus visits by ring residents/distinct visitors). Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Impact of Campus Closure on Visit Days per Visitor: Shanghai, Workplace-Anchored

	(1)	(2)	(3)	(4)	(5)
0–2 km	1.099***				1.109***
	(0.054)				(0.054)
2–4 km		0.492***			0.491***
		(0.040)			(0.040)
4–6 km			0.200***		0.188***
			(0.040)		(0.041)
6–8 km				0.068*	0.068*
				(0.036)	(0.036)
Post × 0–2 km	−0.442***				−0.453***
	(0.051)				(0.050)
Post × 2–4 km		−0.147***			−0.145***
		(0.039)			(0.039)
Post × 4–6 km			−0.022		−0.010
			(0.049)		(0.052)
Post × 6–8 km				0.055	0.054
				(0.048)	(0.048)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.27	0.19	0.15	0.39
Observations	2,143	2,132	2,112	2,041	5,233

Note: This table reports the workplace-anchored counterpart to Table 6, with visitors assigned to rings by their workplace location rather than home location. The sample comprises 27 Shanghai university campuses observed in two cross-sectional snapshots, November 2019 (pre-closure) and November 2024 (post-closure). The dependent variable is the natural logarithm of visit days per visitor, defined as ln(distinct days on which ring residents visit campus/distinct visitors). Each campus is partitioned into five 2 km distance bins (0–2, 2–4, 4–6, 6–8, and 8–10 km), with the 8–10 km bin as the reference category. "Post" indicates the November 2024 snapshot. Columns 1–4 estimate the model on a paired sample (one inner bin plus the 8–10 km reference); Column 5 estimates the model jointly on all four inner bins. All specifications include campus×year fixed effects. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Innovation Decline Explained by Visitor Changes: Workplace-Anchored Mediation

Panel A: Multi-inventor patents (Y^M)

	(1)	(2)	(3)	(4)	(5)
Post × 0–2 km	−0.118**	−0.075	−0.089	−0.085	−0.065
	(0.055)	(0.061)	(0.058)	(0.061)	(0.063)
Post × visitor density		0.221**			0.206**
		(0.104)			(0.100)
Post × visit days per visitor			0.069		−0.094
			(0.062)		(0.395)
Post × visit frequency per visitor				0.070	0.106
				(0.056)	(0.320)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.32	0.32	0.32	0.32	0.32
Observations	20,081	20,081	20,081	20,081	20,081

Panel B: Collaborative non-university patents (Y^{NU})

	(1)	(2)	(3)	(4)	(5)
Post × 0–2 km	−0.146**	−0.103	−0.128*	−0.116*	−0.108
	(0.056)	(0.064)	(0.065)	(0.068)	(0.070)
Post × visitor density		0.227**			0.201**
		(0.101)			(0.097)
Post × visit days per visitor			0.045		−0.294
			(0.063)		(0.365)
Post × visit frequency per visitor				0.063	0.251
				(0.056)	(0.298)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.32	0.32	0.32	0.32	0.32
Observations	20,005	20,005	20,005	20,005	20,005

Note: This table reports the workplace-anchored counterpart to Table 7, with visitors assigned to rings by their workplace location rather than home location. The dependent variable in Panel A is the natural logarithm of multi-inventor patent density; in Panel B, it is the natural logarithm of multi-inventor patent density without a university inventor. Column 1 reproduces the baseline specification (0–2 km bin vs. 2–10 km reference) with no visitor controls. Columns 2–4 add one pre-closure (2019) visitor measure at a time, interacted with the post-2020 indicator: visitor density (Column 2), visit days per visitor (Column 3), and visit frequency per visitor (Column 4). Column 5 includes all three simultaneously. The sample is the Shanghai subsample of 27 university campuses, 2017–2024. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Grid-Level Mediation: Workplace-Anchored Visitor Decline and Patent Activity

Panel A: Grid-level visitor decline

	(1) ln visitor count	(2) ln visit days pp	(3) ln visit freq. pp
Post × ln 2019 visitor count	−0.590***		
	(0.008)		
Post × ln 2019 visit days per visitor		−0.859***	
		(0.005)	
Post × ln 2019 visit freq. per visitor			−0.849***
			(0.006)
Campus × year FE	Yes	Yes	Yes
Cell × campus FE	Yes	Yes	Yes
Adjusted R^2	0.49	0.59	0.57
Observations	59,810	59,810	59,810

Panel B: Visitor decline and patent activity

	(1) All	(2) Y^S	(3) Y^M	(4) Y^U	(5) Y^{NU}
Post × Above Median (2019)	−0.009***	0.002	−0.015***	−0.003***	−0.014***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Campus × year FE	Yes	Yes	Yes	Yes	Yes
Cell × campus FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.41	0.30	0.47	0.46	0.47
Observations	984,248	984,248	984,248	984,248	984,248

Note: This table reports the workplace-anchored counterpart to Table 8, with visitors assigned to grid cells by workplace location rather than home location. Panel A reports separate regressions for three visitor outcomes: log visitor count (Column 1), log visit frequency per visitor (Column 2), and log visit days per visitor (Column 3). In each column, the dependent variable is regressed on the interaction between the post-2020 indicator and the corresponding pre-closure (2019) measure. Panel B reports patent-outcome regressions in which the dependent variable is an indicator for whether any patent of the specified type was filed in the grid cell. "Above Median (2019)" is an indicator for grid cells with above-median pre-closure visitor counts. Standard errors clustered at the university-campus level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.