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From Network Deployment to AI Industry Location: How Mobile Broadband Shapes the County-Level Geography of AI Firms in China

Junjie Ruan
Zhongnan University of Economics and Law
Tian Cheng
1029168434@qq.com
Guilin University of Electronic Technology

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Abstract

Digital networks reduce the costs of communication and coordination across distance, but their spatial consequences remain ambiguous. This study examines whether mobile broadband allows artificial intelligence (AI) firms to escape local constraints or instead reconfigures county-level locational advantage by improving the complementary conditions needed for financing, staffing, and innovation. We assemble a balanced panel of 1,866 county-level administrative units in China from 2015 to 2022. Geocoded LTE base-station records from OpenCelliD are matched to county boundaries to measure deployment intensity, and Tianyancha business-registration data are used to identify AI firms and construct their density per square kilometer. Two-way fixed-effects estimates show that more intensive observed LTE deployment is associated with greater AI-firm density. Instrumental-variable estimates and multiple robustness checks provide additional support. Mechanism-consistent evidence indicates that deployment is associated with broader digital financial inclusion and stronger bank competition, greater digital-labor supply and recruitment demand, and denser university-industry and interfirm innovation links. The association is stronger in non-resource-dependent areas, localities with denser road networks, and counties with greater economic resilience. The findings suggest that mobile broadband does not erase geography. It changes the basis of locational advantage by improving how complementary resources are identified, matched, and coordinated.

1. Introduction

Mobile broadband reduces the costs of transmitting information and collaborating remotely, but its spatial-economic consequences are ambiguous. One view holds that digital connectivity allows firms to obtain customers, services, and some production inputs across distance, thereby weakening their dependence on particular places. Another argues that lower communication costs increase the efficiency with which highly connected locations organize specialized talent, capital, and knowledge collaboration, thereby reconfiguring rather than eliminating locational advantage (Gaspar & Glaeser, 1998; Leamer & Storper, 2001; Goldfarb & Tucker, 2019). Related research finds that broadband is closely associated with the distribution of knowledge-intensive firms, firm creation, and digital entrepreneurship, but that its returns vary with city size, industrial foundations, educational conditions, urban-rural context, and venture type (Mack & Rey, 2014; Hasbi, 2020; Luo et al., 2022; Strover et al., 2024). The more consequential question, therefore, is no longer whether network access is beneficial on average, but how mobile broadband changes firm location: is it a remote-substitution technology that enables firms to escape local constraints, or an industrial platform that helps places organize complementary inputs?

AI firms provide a particularly revealing setting in which to examine this tension. Algorithms, software, data, and some R&D outputs can be transmitted digitally, giving firms substantial capacity for remote service delivery and collaboration. Yet AI development also involves long R&D cycles, rapid technological iteration, high intangible-asset intensity, and continuing reliance on risk-bearing finance, specialized digital skills, and repeated interaction among firms, universities, and research institutes. The formation of China's AI innovation ecosystem likewise depends on the continuing combination of government, firms, universities, venture capital, talent, and knowledge (Arenal et al., 2020). AI thus combines two features: its outputs are

highly transmissible, while its production process remains dependent on complementary inputs. If mobile broadband continues to be systematically associated with the local distribution of such firms, digitalization has not made location irrelevant; it has changed the sources of locational advantage.

This question is especially important at the county level in China. The 2025 Government Work Report called for deeper implementation of the "AI Plus" initiative (State Council of the People's Republic of China, 2025). By the end of 2024, China had deployed 4.251 million 5G base stations, and more than 90% of administrative villages had access to 5G services (National Data Administration, 2025). Expanded coverage, however, does not necessarily mean that firms can use networks effectively. Rural and peripheral areas may simultaneously face gaps in availability, adoption, quality, affordability, and skills (Prieger, 2013), while the economic returns to communications infrastructure depend on local capabilities and demand-side support (Henderson, 2020; de Clercq et al., 2023). Counties are not closed factor markets, but base-station deployment, business registration, public services, industrial policy, and the connectivity between central urban districts and peripheral areas vary substantially at this scale. County-level analysis can therefore reveal local differences in deployment and firm-location intensity that prefecture-level averages tend to conceal.

We study this question using a balanced panel of 1,866 county-level administrative units in China from 2015 to 2022. We extract geocoded LTE base-station records from OpenCelliD, match them to county boundaries, and measure mobile broadband deployment intensity as the number of observed LTE stations per 10,000 residents. We also use a keyword-based identification procedure to classify AI firms in Tianyancha business-registration records and measure county-level AI-firm location intensity as the number of firms per square kilometer. The analysis addresses two connected questions. Is more intensive mobile broadband deployment associated with greater AI-firm location intensity within a county-level unit? Is this relationship accompanied by improvements in the local financing environment, digital labor market, and innovation-network connections? Two-way fixed-effects estimates, instrumental-variable estimates, and multiple robustness checks show a stable positive association between LTE deployment intensity and AI-firm density. Six supplementary outcomes are consistent with improvements in three sets of local complementary conditions, and the baseline association is stronger in non-resource-dependent areas, localities with denser road networks, and counties with greater economic resilience. AI-firm density captures local location intensity and cannot directly establish whether nationwide concentration is rising or falling. The complementary-factor estimates are mechanism-consistent evidence rather than a complete identification of mediation.

This study makes three contributions. First, it extends the spatial debate in research on the economic consequences of broadband to the location of AI firms. Prior work already shows that broadband can affect the distribution of knowledge-intensive firms, firm creation, and entrepreneurship (Mack & Rey, 2014; Hasbi, 2020; Luo et al., 2022); the proposition that broadband promotes firm entry is therefore not, by itself, novel. Our contribution is to exploit AI firms' dual dependence on digital transmission and locally organized complementary inputs to distinguish remote substitution from location reconfiguration. The results suggest that mobile broadband is more likely to change how local advantage is formed than to make firm activity placeless.

Second, we provide evidence based on physical network deployment and fine spatial units. Compared with policy-pilot indicators, general coverage rates, or prefecture-level averages, geocoded LTE records more closely approximate the physical footprint of mobile broadband and reveal differences between central urban districts and peripheral counties within the same prefecture-level city. We do not equate base-station counts with speed, latency, adoption, or service quality, nor do we treat counties as closed markets. The measurement contribution lies in consistently matching observable network deployment to the registered location of firms at the county level. Third, we connect communications networks to local complementary conditions. Network deployment is not sufficient to generate AI firms. It is more likely to translate into financing, digital-labor, and innovation-collaboration opportunities when it increases the visibility of market participants, expands the set of potential matches, and reduces post-match coordination costs. This account offers a testable explanation for why similar infrastructure supply can produce different industrial returns across places and shifts telecommunications policy from coverage counts alone toward coordination between network rollout and local conditions for industrial development.

2. Theoretical analysis and hypotheses

2.1. Mobile broadband deployment and the reconfiguration of AI-firm location

By location reconfiguration, we do not mean that mobile broadband necessarily increases the nationwide concentration of AI firms. Rather, digital connectivity changes the foundations on which locational advantage is built. Traditional locational advantages derive primarily from market size, transport accessibility, resource endowments, and geographic proximity. Mobile broadband reduces the costs of information transmission and cross-regional collaboration, thereby improving firms' ability to obtain and organize production inputs. As some conventional distance constraints weaken, network connectivity and a locality's ability to organize capital, specialized talent, and innovation partnerships become increasingly important to AI-firm location. Mobile broadband therefore does not simply make geography irrelevant; it makes digital connectivity a new component of location.

AI firms are especially suitable for examining this change. Algorithms, software, data, and some R&D outputs can travel through digital channels, allowing firms to serve customers remotely, obtain data, and purchase standardized technical services. At the same time, AI firms are R&D intensive, iterate rapidly, face substantial commercialization uncertainty, and hold a large share of their value in intangible assets. They consequently need continuing access to capital able to bear technological risk, specialized digital skills, and stable knowledge partnerships. Standardized information can be transmitted remotely, but judging technical quality, recognizing complex skills, building trust, and exchanging contextual knowledge still require sustained interaction. AI products are highly digitally transmissible, but the production process has not escaped its dependence on complementary inputs.

Mobile broadband changes access to these inputs in three ways. First, reliable connectivity increases the observability of firms' operations, funding needs, vacancies, and technical capabilities, making it easier for capital providers, workers, and innovation actors to identify potential counterparties. Second, digital

platforms enlarge the pool of funding sources, talent, and partners that firms can reach, increasing the probability of finding suitable resources. Third, mobile broadband reduces communication, monitoring, and joint-development costs after a match is formed, allowing cross-regional contacts to develop into relatively stable financing, employment, and innovation relationships. Network deployment therefore does more than lower the communication costs of individual firms; it improves a locality's ability to organize the complementary inputs that AI firms require.

The locational value of mobile broadband is unlikely to be uniform across places. The relationship between broadband and the distribution of knowledge-intensive firms varies with city size and industrial foundations (Mack & Rey, 2014); the effect of very high-speed broadband on firm creation differs by industry and education (Hasbi, 2020); and the returns to rural digital entrepreneurship depend jointly on network quality, venture type, and local business capability (Strover et al., 2024). The economic returns to mobile broadband may also emerge only after organizational adjustment and complementary investment (Edquist, 2022). These studies indicate that physical network deployment does not automatically create firms, but it can change the relative conditions under which places attract and sustain firm activity.

Compared with firms in general, AI firms' continuing reliance on capital, specialized digital talent, and innovation partnerships makes them particularly likely to incorporate network connectivity into location decisions. When mobile broadband deployment raises the visibility of relevant actors, broadens access to complementary inputs, and lowers the cost of sustained collaboration, county-level units with more intensive deployment should be more likely to attract new AI firms and support the continued operation of incumbent firms. Mobile broadband should therefore increase the local location intensity of AI firms. We propose:

H1. Mobile broadband deployment intensity is positively associated with county-level AI-firm density.

2.2. Mobile broadband and local complementary conditions for AI-firm location

2.2.1. Improving the local financing environment

AI firms typically face severe financing constraints. Their R&D investments are large, returns take time to materialize, and both technological trajectories and commercialization outcomes are highly uncertain. Firm value resides mainly in algorithms, data, software, and team capabilities rather than in tangible assets that can be pledged as collateral. Capital providers cannot readily assess technical quality and future cash flows from conventional financial information alone and therefore incur high costs of information search, risk identification, pricing, and continuing monitoring. In counties with few financial-service outlets and limited capacity for specialized technical assessment, financing difficulties may arise not because capital is entirely absent, but because information between firms and capital providers is incomplete.

Mobile broadband can increase the digital traceability of operating, transaction, and performance information, improve the observability of firm conditions, and give financial institutions more information for pre-loan screening and post-loan monitoring. In this way, it can reduce the distance-related information costs of lending (Petersen & Rajan, 2002). Online financial services can also lower the marginal cost of

reaching dispersed clients and give county-level firms access to providers beyond traditional branches. As the serviceable market expands, more financial institutions may be able to enter county markets, potentially intensifying competition for promising innovation projects. Mobile broadband does not directly provide finance to AI firms, but it can improve the conditions under which financial institutions identify, reach, and monitor them.

An improved financing environment can affect both entry and continued operation. For potential entrants, accessible and predictable financial services lower the up-front funding threshold for initiating R&D, purchasing equipment, and recruiting talent. For incumbent firms, funding continuity helps bridge long development cycles and reduces the risk that cash-flow interruptions terminate technical projects. Prior research identifies financial development as an important pathway through which broadband influences entrepreneurship in China (Luo et al., 2022). For AI firms, improvements in the local financing environment are thus an important condition through which digital connectivity can become a county-level locational advantage. We propose:

H2. More intensive mobile broadband deployment is associated with a more favorable local financing environment.

2.2.2. Expanding the local digital labor market

AI innovation and production depend on digital workers with differentiated skills. Algorithm development, data processing, software engineering, model deployment, and application in specific settings require different capabilities. Firms need not only a sufficient number of workers but also people whose skill profiles match particular vacancies at the right time. In relatively small county-level labor markets, digital workers and specialized vacancies may be scarce, and neither worker quality nor job prospects are fully observable. Firms struggle to assess candidates' actual capabilities, while job seekers struggle to evaluate project quality, career growth, and employment stability. These information problems raise the cost of assembling and adjusting teams.

Recruitment platforms, professional networks, and online communication tools supported by mobile broadband make worker profiles and vacancies more visible. They enlarge the pool of candidates available to firms and allow workers to identify more opportunities both within and beyond the county. Broader information and lower communication costs can improve two-sided matching between firms and digital workers. Broadband adoption is also complementary to skill demand: firms that use digital technologies tend to increase their demand for digital occupations (Akerman et al., 2015). Parallel growth in the supply of digital workers and demand for digital jobs can support a more stable specialized labor market.

A larger and deeper digital labor market affects not only entry but also firms' ability to adjust teams as technologies evolve. A broader range of skills makes it easier to fill temporarily scarce roles and reduces the organizational risk created by key-worker departures or persistent vacancies. A continuing flow of job opportunities also increases digital workers' willingness to enter and remain in the local market. Entrepreneurial human capital is closely associated with firm entry and subsequent development (Queiró, 2022). By expanding the visible range of digital workers and vacancies, mobile broadband can improve the county-level digital labor market and increase its attractiveness to AI firms. We propose:

H3. More intensive mobile broadband deployment is associated with a larger local digital labor market.

2.2.3. Strengthening local innovation-network connections

AI technologies are complex and evolve rapidly. Their development and application often require firms, universities, research institutes, and other organizations to combine algorithms, data, engineering knowledge, and application settings. Standardized code, papers, and models can travel through digital channels, but understanding a specific use case, validating technical performance, addressing data-governance problems, and revising engineering solutions require repeated interaction among multiple actors. Even as the cost of transmitting formal information falls, knowledge spillovers remain strongly localized geographically (Jaffe et al., 1993). When innovation actors are few, partner capabilities are difficult to observe, and collaborative rules are unclear, county-level AI firms may struggle both to identify complementary organizations and to bear the communication, experimentation, and trust-building costs of joint R&D.

Mobile broadband increases the visibility of firms, universities, research institutes, and their patents, projects, and technical capabilities, helping AI firms identify potential innovation partners. After collaboration begins, reliable connectivity supports continuing exchange of technical materials, feedback on experimental results, and coordination of R&D tasks, reducing the communication and project-management costs of joint development across organizations. Digital communication cannot fully replace face-to-face interaction, but it can increase the organizational efficiency of limited in-person contact and extend the geographic range over which innovation partnerships can be maintained. County-level firms may thereby become more deeply embedded in university-industry-research and interfirm collaboration networks.

Innovation-network connections raise a locality's expected value to AI firms. For potential entrants, access to technical knowledge, application settings, and partnership opportunities increases the expected return to innovation. For incumbent firms, continuing knowledge exchange and collaborative validation can shorten technological iteration cycles and reduce the risk of R&D failure. By improving the identification of innovation actors and the conditions for sustained collaboration, mobile broadband can strengthen county-level university-industry-research links and innovation ties among AI firms. We propose:

H4. More intensive mobile broadband deployment is associated with stronger local innovation-network connections.

3. Research design

3.1. Variables

3.1.1. Dependent variable

AI-firm density (Density). Following the identification approach of Liu and Ma (2025), we use Tianyancha's business-registration database and the keyword set established in the original data construction to identify AI-related firms. Records from 2015 to 2022 are assigned to county-level administrative units according to each firm's registered location. Compared with samples limited to listed firms or firms above a designated

size, business-registration records include more firms, smaller firms, and firms at earlier stages, making them better suited to examining the entry and geography of an emerging industry at a fine spatial scale. Keyword identification, however, captures AI-related attributes reported in registration information and cannot guarantee that AI constitutes the principal revenue source or actual R&D focus of every classified firm.

We divide the number of identified AI firms by the land area of the administrative unit to obtain AI firms per square kilometer. Area normalization captures the spatial intensity of firm activity within a unit and prevents geographically larger counties from mechanically recording more firms simply because they cover more land. The measure is closer to a local hosting density, but it has clear limits. Registered location need not coincide with all R&D and operating activities; geographically large and sparsely populated counties may show low density; and the measure cannot directly establish whether firms are becoming more concentrated or dispersed nationwide. We therefore interpret it as the observable county-level location intensity of AI firms rather than as a complete index of industrial agglomeration.

3.1.2. Core explanatory variable

Observed LTE base-station deployment intensity (DI). Following Chao et al. (2024), we extract Chinese records from the global OpenCelliD open base-station database, retain observations with mobile country code 460 and LTE as the network standard, and form the raw LTE station dataset. Each record contains geographic coordinates and a Unix timestamp. We convert timestamps to China Standard Time (UTC + 8) and treat the first year in which a station appears in OpenCelliD as the year it enters the observable database, thereby constructing county-year observations for 2015–2022. In ArcGIS, station coordinates are projected into the coordinate system used by the county boundary polygons, and spatial joins identify the county-level administrative unit containing each station record.

After spatial matching, we aggregate the annual number of observed LTE stations in each county-level administrative unit and divide it by contemporaneous population to obtain LTE stations per 10,000 residents. Population normalization makes the measure more closely reflect relative network supply faced by residents and firms and reduces the mechanical influence of population size on station counts. Compared with city-level policy indicators such as the Broadband China pilots, geocoded station records reveal observable differences in physical network deployment within counties and preserve changes in deployment over time.

The measure captures the physical footprint of mobile broadband deployment recorded by OpenCelliD rather than a composite index of all digital infrastructure. It does not directly observe download speed, latency, dropped connections, prices, adoption, traffic load, 5G coverage, data-center capacity, or AI computing power. A station's first appearance in the database may also differ from its construction or commissioning date, and the completeness of crowdsourced records may vary across places. We therefore consistently refer to the core explanatory variable as observed LTE base-station deployment intensity and limit the interpretation to physical mobile-broadband deployment rather than generalizing to all digital infrastructure.

3.1.3. Control variables

The regressions include time-varying county-level characteristics that may be associated with both network deployment and AI-firm location: economic development (the natural logarithm of county GDP), service-sector share (tertiary-industry value added divided by GDP), consumption capacity (retail sales of consumer goods divided by GDP), health-service supply (hospital and township-health-center beds per 10,000 residents), mobile-phone penetration (mobile subscribers per resident multiplied by 100), fiscal expenditure (general public budget expenditure divided by GDP), and innovation potential (the natural logarithm of secondary vocational-school enrollment per 10,000 residents). These controls reduce observable confounding but do not establish exogeneity.

The controls address several major sources of confounding. Economic development, the service-sector share, and consumption capacity capture changes in market size and industrial structure because richer and more service-oriented areas may attract both base-station investment and AI firms. Health-service supply represents local public-service conditions. Mobile-phone penetration distinguishes network demand and device adoption from physical station supply. Fiscal expenditure captures local-government resource-mobilization capacity, while innovation potential proxies the local foundation for skills formation. These variables can reduce bias from observed characteristics but cannot eliminate contemporaneous industrial policy, land supply, talent policy, or other unobserved shocks. The analysis therefore combines controls with fixed effects, instrumental variables, and multiple robustness checks and interprets the evidence cautiously.

3.2. Data sources and sample

The balanced panel covers 1,866 county-level administrative units from 2015 to 2022, yielding 14,928 unit-year observations in the baseline specification. AI-firm records come from Tianyancha, LTE station records from OpenCelliD, patent data from IncoPat, road-network data from OpenStreetMap, county-level socioeconomic variables from the China County Statistical Yearbook and local statistical yearbooks, and firm-level information from CSMAR and the Chinese Research Data Services Platform (CNRDS). Missing values in selected series are filled by linear interpolation. Data management and estimation are conducted in Stata 18.0. Because the sample includes counties, county-level cities, and urban districts, we use "county-level administrative unit" as the general term and do not treat administrative boundaries as closed economic markets.

The use of multiple sources broadens measurement coverage but also creates consistency challenges. We rely on the administrative-boundary matching completed in the original data construction and apply the common term "county-level administrative unit" to counties, county-level cities, and urban districts. Linear interpolation helps retain a balanced panel for selected series, but interpolated values estimate trends between adjacent years rather than provide direct observations and may smooth genuine fluctuations. These variables should therefore be interpreted within the sample-construction rules. Counties are not closed capital, labor, or knowledge markets; the estimates capture common changes in registered firm locations and observable deployment at the county scale and do not imply that all inputs originate within the administrative boundary.

3.3. Empirical specifications

To examine the relationship between LTE deployment intensity and AI-firm density, we estimate the following two-way fixed-effects model:

$$Density_{ct} = \alpha + \beta\, DI_{ct} + \gamma' X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct} \quad (1)$$

In Eq. (1), Density_ct denotes AI-firm density in county-level administrative unit c and year t; DI_ct is the number of observed LTE base stations per 10,000 residents; X_ct is the vector of controls; mu_c and lambda_t denote unit and year fixed effects; and epsilon_ct is the error term. The coefficient of interest is beta. Conditional on the included controls and fixed effects, a positive estimate is consistent with H1. The fixed-effects design absorbs time-invariant local characteristics and common year shocks, but causal interpretation still depends on the treatment of time-varying confounding and reverse causality.

To assess whether mobile broadband improves the complementary conditions proposed in the theoretical analysis, we further estimate:

$$M_{ct} = \alpha + \theta\, DI_{ct} + \gamma' X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct} \quad (2)$$

In Eq. (2), M_ct denotes one of six indicators of the local financing environment, digital labor market, or innovation network. The remaining terms are defined as in Eq. (1). Eq. (2) tests whether network deployment changes the proposed complementary conditions and provides mechanism-consistent evidence. It does not formally identify the complete mediation pathway from deployment, through each mechanism, to AI-firm density.

4. Empirical results

4.1. Baseline estimates

Table 1 reports the baseline estimates. Column (1) includes only LTE deployment intensity. Column (2) adds the controls, columns (3) and (4) separately add unit and year fixed effects, and column (5) includes both sets of fixed effects. The coefficient on DI is positive in every column and statistically significant at the 1% level. In the preferred two-way fixed-effects specification in column (5), the estimate is 0.0507 with a standard error of 0.0085. The result supports H1: after accounting for common year shocks and the included time-varying controls, years with more intensive observed LTE deployment within the same county-level unit are associated with higher AI-firm density.

Table 1
Baseline estimates

Variable	(1)	(2)	(3)	(4)	(5)
DI	0.0567***	0.0445***	0.0453***	0.0483***	0.0507***
	(0.0063)	(0.0050)	(0.0050)	(0.0083)	(0.0085)
Controls	No	Yes	Yes	Yes	Yes
Unit fixed effects	No	No	Yes	No	Yes
Year fixed effects	No	No	No	Yes	Yes
Constant	0.0030	-1.1399***	-1.0865***	-1.5827***	-0.2448
	(0.0026)	(0.1059)	(0.1119)	(0.1600)	(0.1685)
Observations	14,928	14,928	14,928	14,928	14,928
R^2	0.0911	0.1264	0.1363	0.4471	0.4598
*Notes: Coefficient standard errors are reported in parentheses. * p < .10; ** p < .05; *** p < .01.*					

4.2. Instrumental-variable estimates

Reverse causality and omitted time-varying factors remain concerns. Places that attract AI firms may receive more network investment, while unobserved development policies, industrial-park construction, or investment-promotion activities may affect both network deployment and firm registration. To reduce these concerns, we report two instrumental-variable strategies. IV1 interacts year indicators with terrain ruggedness and uses differential changes in network-deployment costs across terrain conditions during the nationwide rollout to predict county-level LTE deployment intensity. IV2 is a shift-share instrument. We first calculate each county's share of base stations within its prefecture-level city at the beginning of the sample and then combine this initial share with the city's annual base-station total, following the construction logic discussed by Goldsmith-Pinkham et al. (2020).

Table 2 shows that both instruments significantly predict DI. The reported underidentification and weak-identification statistics meet conventional thresholds, and the second-stage coefficients remain positive. The IV results make it less likely that the baseline association is driven entirely by contemporaneous reverse causality, but first-stage relevance does not establish instrument exogeneity. IV1 requires the interaction between terrain ruggedness and year not to affect AI-firm location directly through transport, construction costs, or other industrial trends. IV2 requires the combination of initial shares and prefecture-level network growth not to capture other development shocks with the same spatial allocation pattern. We therefore treat the IV estimates as supplementary evidence closer to a causal interpretation while retaining caution about the exclusion restrictions.

Table 2
Instrumental-variable estimates

Variable / statistic	IV1 first stage	IV1 second stage	IV2 first stage	IV2 second stage
DI		0.4597***		0.0750**
		(0.0595)		(0.0306)
IV1	-0.0163***			
	(0.0018)			
IV2			4.2179***	
			(0.2648)	
Controls	Yes	Yes	Yes	Yes
Unit fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic		75.080 (0.00)		106.778 (0.00)
Cragg-Donald Wald F statistic		80.751 (16.38)		49,000 (16.38)
Observations		14,904		11,969

*Notes: Coefficient standard errors are reported in parentheses. Parentheses following the Kleibergen-Paap rk LM statistics contain p-values; parentheses following the Cragg-Donald Wald F statistics contain the corresponding critical values. * p < .10; ** p < .05; *** p < .01.*

4.3. Robustness checks

Table 3 reports five robustness checks. Column (1) clusters standard errors at the prefecture-city level, allowing arbitrary correlation across counties and years within the same city. Column (2) uses two-way clustering by county-level unit and year. The estimated coefficient remains positive under both adjustments.

Column (3) lags DI by one year to reduce concerns about contemporaneous reverse causality and to allow time for network planning, construction, adoption, and organizational adjustment. Column (4) excludes Beijing, Tianjin, Shanghai, and Chongqing because their administrative status, fiscal capacity, industrial planning, and network-approval processes differ from those of ordinary prefecture-level cities. Column (5) aggregates the data to the prefecture-city level. Across these checks, the coefficient on DI remains positive and statistically significant. The baseline association is therefore robust to alternative dependence structures, timing assumptions, sample coverage, and spatial aggregation, although these tests do not eliminate every source of endogeneity.

The five checks address different risks and are not substitutes for one another. Alternative clustering changes the assumed error-correlation structure. A one-year lag improves temporal ordering but does not remove persistent omitted variables. Excluding centrally administered municipalities tests whether special

administrative units drive the result. Prefecture-level aggregation assesses whether the conclusion depends on the county as the spatial unit. Together, the checks show that the findings are not mechanically produced by a single standard-error specification, a contemporaneous relationship, a special subsample, or a particular spatial scale; they do not imply that all identification threats have disappeared.

Table 3
Robustness checks

Variable	SEs clustered by prefecture-level city	Two-way clustering by unit and year	DI lagged one year	Municipalities excluded	Prefecture-level sample
DI	0.0507***	0.0507**	0.0589***	0.0429***	0.1417***
	(0.0161)	(0.0164)	(0.0108)	(0.0082)	(0.0433)
Controls	Yes	Yes	Yes	Yes	Yes
Unit fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	-0.2448	-0.2448	-0.0492	-0.1371	2.2669*
	(0.3503)	(0.2840)	(0.1977)	(0.1617)	(1.3142)
Observations	14,928	14,928	13,062	14,632	2,368
R^2	0.4598	0.4597	0.4988	0.4886	0.6402

*Notes: Coefficient standard errors are reported in parentheses. Column headings identify the adjustment relative to the baseline specification. * p < .10; ** p < .05; *** p < .01.*

5. Evidence on local complementary factors

AI firms are sensitive to local financing conditions because R&D is intensive, returns are delayed, and commercialization is uncertain. We examine the financing environment through financial-service reach and banking-market structure. First, Peking University's county-level Digital Financial Inclusion Index captures the coverage and development of digital financial services. It reflects financial access beyond traditional branches but does not directly record loans or equity finance actually obtained by AI firms. Second, following Jiang et al. (2019), we use the share of branches belonging to the three largest banks to characterize local banking-market structure. A lower share indicates a less concentrated supply of banking services and is interpreted as stronger bank competition. The measure represents the potential competitive environment rather than the loan rate or credit outcome faced by an individual AI firm.

Column (1) of Table 4 shows a positive association between DI and digital financial inclusion, indicating broader digital-finance coverage in counties with more intensive observed LTE deployment. In column (2), DI is negatively associated with the top-three bank branch share; given the direction of the indicator, this pattern is consistent with stronger local bank competition. The two measures capture complementary

dimensions: whether financial services can reach more firms and whether service supply is sufficiently competitive. They support the financing-environment account in H2. Because the analysis does not observe firm-level credit, financing costs, or the use of funds, it cannot establish that the financing constraints of AI firms have been directly relaxed.

AI firms also depend on specialized digital workers and effective job matching. We measure the local digital labor market from both the supply and demand sides. Labor supply is proxied by the natural logarithm of employment in information transmission, computer services, and software. This measure captures a stock of workers related to digital technology, but its scope is broader than AI specialists and does not distinguish skill levels. On the demand side, following Tan et al. (2025), we use listed-firm recruitment data to identify positions related to digital transformation and count posted vacancies. This measure reflects firms' publicly expressed demand for digital skills, but it is affected by the spatial distribution of listed firms and platform coverage and does not represent all county-level labor demand.

Columns (3) and (4) of Table 4 show positive associations between DI and both information-sector employment and digital-vacancy recruitment. Parallel expansion of supply and demand is more consistent with the formation of a labor market than movement on either side alone. More workers without vacancies may not remain locally, while more vacancies without workers can leave firms with persistent shortages. The two results jointly support H3's prediction that network deployment expands the local digital labor market. The information-employment outcome, however, contains only 2,368 observations, far fewer than the baseline sample. It should therefore be treated as supplementary rather than decisive evidence for the labor channel.

Finally, we use the intensity of university-industry-research collaboration and an indicator of cooperative innovation among AI firms to capture innovation-network connections. The former follows the patent-based identification logic of Zhou et al. (2025) and reflects observable joint innovation between universities, research institutes, and industry. The latter focuses on cooperative innovation involving AI firms. These indicators provide evidence on both the general regional innovation network and connections within the AI industry and are more closely aligned with the theoretical emphasis on collaboration, learning, and coordination than a simple patent count. Patent collaboration nevertheless covers only formal innovative activity that generates patentable outputs and cannot observe technical exchanges that do not lead to applications, failed experiments, or informal knowledge sharing.

Columns (5) and (6) of Table 4 show positive associations between DI and both innovation-network indicators. The estimates are consistent with H4: places with more intensive network deployment also exhibit more observable university-industry-research and interfirm collaboration. Taken together, the six outcomes move in directions consistent with improvements in local financing, labor, and innovation conditions and with the proposed account of how places become better able to host AI activity. Eq. (2), however, estimates only the relationship between DI and each complementary condition. It does not identify the complete indirect effect from network deployment through those conditions to AI-firm density, nor does it directly observe cross-regional flows of capital, workers, or knowledge. Table 4 should therefore be interpreted as mechanism-consistent evidence rather than as a formal mediation or spatial-flow test.

Table 4
Evidence on local complementary factors

Variable	Digital financial inclusion	Top-three bank branch share	Information-sector employment	Digital-vacancy recruitment	University-industry-research collaboration	Cooperative innovation among AI firms
DI	0.6912*	-0.0007*	0.0416***	0.1229***	0.0500***	0.0708***
	(0.4029)	(0.0004)	(0.0137)	(0.0277)	(0.0088)	(0.0101)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Unit fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	59.1608***	0.7237***	1.2127	-0.6100	0.3109	-0.3241
	(15.6233)	(0.0488)	(0.8007)	(0.5234)	(0.2239)	(0.3715)
Observations	14,928	14,928	2,368	14,928	14,928	14,928
R^2	0.8302	0.9759	0.3845	0.7665	0.5310	0.5590

*Notes: Each column reports a separate outcome regression based on Eq. (2). Coefficient standard errors are reported in parentheses. * p < .10; ** p < .05; *** p < .01.*

6. Heterogeneity analyses

6.1. Resource dependence

Resource dependence may constrain the conversion of digital connectivity into an emerging-industry advantage. In resource-based areas, capital, labor, and policy attention may remain locked into extraction and established industrial paths, limiting the development of capabilities required by AI firms. Non-resource-dependent areas generally have more flexible industrial structures and stronger demand for digital services, specialized skills, and collaborative innovation. Following Liu and Deng (2023), we divide the sample into resource-based and non-resource-based areas. Columns (1) and (2) of Table 5 show positive coefficients in both groups, but the estimate is substantially larger in non-resource-based areas, and the reported between-group difference is significant at the 1% level. Existing industrial paths therefore condition the locational value of network deployment for AI firms.

The difference does not imply that resource-based areas cannot develop AI industries. It indicates that network rollout must be coordinated with industrial restructuring. If capital, skills training, and application settings remain organized around extraction and primary processing, additional connectivity may mainly improve the efficiency of existing industries without creating a diversified market suitable for AI-firm entry. More flexible structures in non-resource-dependent areas, together with service industries and emerging

manufacturing, are more likely to supply varied application settings, allowing connectivity to translate into jobs, collaborative projects, and business demand.

6.2. Road-network density

Mobile broadband improves informational connectivity, but workers, equipment, business travel, and some collaborative activities still depend on physical accessibility. Digital and transport networks may therefore be complementary. Denser road networks can reduce the cost of installing and maintaining base stations and make firms, workers, and partners easier to reach offline, allowing online connections to translate into actual matches and operating activity. Following Chen et al. (2022), we measure road density as total road-network length divided by land area and split the sample at the median. Columns (3) and (4) show positive coefficients in both groups, but the estimate is substantially larger in high-road-density areas; the between-group difference is significant at the 1% level. Mobile broadband therefore appears to complement rather than replace physical accessibility.

The road-network result provides direct counterevidence to a simple "death of distance" account. Digitizable information transmission must still be combined with movements of people, equipment maintenance, and on-site services that cannot be fully digitized. Connectivity can reduce unnecessary travel but cannot eliminate all face-to-face contact. Where physical accessibility is better, opportunities discovered online are more readily converted into in-person communication, contract execution, and sustained operations. Digital and transport networks are therefore better understood as complements than as simple substitutes.

6.3. Economic resilience

Economic resilience captures a locality's ability to absorb shocks, adjust its industrial structure, and reallocate resources. More resilient county-level units typically possess stronger supporting industries, public services, and risk-management capabilities and can therefore convert connectivity into financing, skills, and innovation partnerships more effectively. Following Xia and Liu (2024), we construct a county-level economic-resilience indicator and split the sample at the median. Columns (5) and (6) show positive coefficients in both groups, with a larger estimate for high-resilience areas; the reported between-group difference is significant at the 10% level. The result further supports the central argument that the industrial returns to network deployment depend on local absorptive and coordinating capacity.

Highly resilient areas can adjust resource allocation, maintain public services, and respond to changes in external demand more quickly, making them more likely to convert network access into stable business expectations. In counties with weaker risk-response capacity, firms may postpone entry despite additional base stations because of disruptions in supporting services, demand volatility, or inadequate organizational coordination. Economic resilience may also reflect broader governance capacity and development levels. The split-sample result reveals conditional differences but cannot independently identify a causal moderating effect of resilience.

Table 5
Heterogeneity analyses

Variable	Resource-based areas	Non-resource-based areas	High road density	Low road density	High economic resilience	Low economic resilience
DI	0.0056**	0.0666***	0.0617***	0.0004**	0.0604***	0.0332*
	(0.0026)	(0.0117)	(0.0123)	(0.0002)	(0.0129)	(0.0181)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Unit fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.4383**	0.0399	-1.0677**	-0.0173***	-1.2390***	-0.3820**
	(0.1873)	(0.3484)	(0.5382)	(0.0037)	(0.3909)	(0.1853)
Observations	4,960	7,848	7,278	7,222	7,349	7,343
R^2	0.3397	0.4708	0.4409	0.5618	0.4710	0.3221
Between-group difference p-value	0.006***	0.006***	0.003***	0.003***	0.095*	0.095*

*Notes: Coefficient standard errors are reported in parentheses. The final row reports the between-group coefficient-difference tests from the original analysis. * p < .10; ** p < .05; *** p < .01.*

The three heterogeneity analyses point to a common conclusion: the industrial return to network deployment is not a fixed parameter independent of place. Industrial structure determines whether diversified demand and convertible resources are available; road networks determine whether online connections can be linked to offline activity; and economic resilience determines whether a locality can continue organizing these inputs under uncertainty. Mobile broadband is therefore better understood as a foundational platform that can amplify the value of complementary conditions than as a sufficient condition for AI-firm agglomeration on its own.

7. Conclusions and policy implications

7.1. Main conclusions

This study asks whether mobile broadband weakens locational constraints or creates new county-level locational advantages by improving local complementary conditions. We use a balanced panel of 1,866 county-level administrative units in China from 2015 to 2022, geocoded OpenCelliD LTE station records, and Tianyancha business-registration data. Observed LTE stations per 10,000 residents measure mobile broadband deployment intensity, while AI firms per square kilometer capture local firm-location intensity. We

examine the baseline relationship, instrumental-variable estimates, three sets of local complementary factors, and heterogeneity across local conditions.

Three findings stand out. First, observed LTE base-station deployment intensity is positively associated with AI-firm density. In the two-way fixed-effects model, the coefficient on DI is 0.0507 with a standard error of 0.0085. The direction of the result remains stable under alternative clustering, a one-year lag, exclusion of centrally administered municipalities, aggregation to the prefecture-city level, and two instrumental-variable strategies. Second, deployment is associated with broader digital financial inclusion, stronger bank competition, larger supplies of digital workers and demand for digital vacancies, and denser university-industry-research and AI-firm innovation ties. These results support the proposed financing, digital-labor, and innovation-network explanations but do not constitute complete identification of mediation.

Third, the positive association between mobile broadband and AI-firm density is stronger in non-resource-dependent areas, places with denser road networks, and counties with greater economic resilience. These differences correspond to industrial path dependence, physical accessibility, and absorptive and coordinating capacity, respectively, showing that the industrial return to network deployment depends on a locality's ability to organize complementary inputs. Overall, mobile broadband has not allowed AI firms to escape geography. It has changed the sources of locational advantage, making network connectivity and its combination with local conditions an important foundation for county-level AI-firm location.

7.2. Policy implications

First, policy should move from "completing network coverage" to improving business usability. County-level mobile-broadband investment should continue to fill coverage gaps, but evaluation should move beyond base-station counts to include speed, latency, reliability, recovery from outages, affordability, and continuous coverage in industrial parks. Areas with concentrated business activity, industrial parks, and public technology-service platforms can establish network-quality monitoring and service-response mechanisms oriented toward production and operations. Mobile communications networks, data centers, and computing facilities perform different functions and are not interchangeable. Localities should coordinate investment according to the actual operating needs of AI firms rather than equating construction counts with the capacity to host industry.

Second, network rollout should be coordinated with financing services for AI firms. Subject to compliance and privacy safeguards, financial institutions can use digital records of operations, transactions, and performance to improve project screening, credit assessment, and post-loan monitoring. Credit arrangements for firms with long R&D cycles and high intangible-asset intensity can be linked to cash flow and R&D milestones. Local governments can build standardized interfaces for bank-firm matching and credit-information services to reduce repeated reporting and verification costs while maintaining a multi-tier supply of banking services and avoiding excessive concentration in a single institution. Public risk-sharing instruments should focus on early-stage technological uncertainty and projects with strong public benefits and should apply transparent entry, exit, and performance-evaluation rules.

Third, county-level digital labor markets should be developed from both the supply and demand sides. On the supply side, vocational colleges, application-oriented universities, and firm training programs can provide

updatable curricula and certification in data processing, software engineering, model deployment, equipment maintenance, and industry applications. On the demand side, regional recruitment platforms and vacancy-information standards should make skill requirements, pay ranges, and career paths more transparent. Counties unable to attract a complete R&D team immediately can first connect to external talent through cross-county recruitment services, flexible work arrangements, and remote collaboration, while improving housing, education, and health services to support long-term retention in core positions. Policy should shift from short-term competition for talent toward a continuing flow of jobs and career opportunities.

Fourth, localities should establish low-cost and durable interfaces for university-industry-research collaboration. Around existing industrial use cases, they can build shared testing environments, public services for compliant data use, and technology-validation platforms with clear rules for data access, intellectual property, cost sharing, and commercialization. For counties, identifying specific problems in manufacturing, agriculture, logistics, health care, or public governance is more important than pursuing an all-encompassing AI platform. Repeatable procedures for project solicitation, joint development, and impact evaluation can help small but stable collaboration networks accumulate trust and reusable knowledge.

Fifth, policy packages should be differentiated according to local conditions. Non-resource-dependent, accessible, and resilient areas may use existing industries and innovation networks to develop clusters of AI R&D and applications. Resource-dependent areas should prioritize industrial diversification and begin with real needs in production safety, equipment maintenance, and energy management to cultivate demand for digital services. Areas with weak road networks should combine network rollout with improvements in maintenance access, public transport, and logistics. Low-resilience counties should first strengthen public services, risk response, and business-support capacity. Differentiated policy does not mean replicating the same AI industry in every county; its purpose is to reduce mismatches between network supply and local business demand.

7.3. Limitations and future research

Several limitations qualify the findings. First, an OpenCelliD timestamp records when a station first becomes visible in that database, which may differ from its official commissioning date, and the completeness of crowdsourced records may vary across places. Future research should cross-validate the measure against operator or official infrastructure records. Second, station counts proxy the physical deployment footprint rather than speed, latency, reliability, traffic, adoption, or actual service quality and do not capture data centers or AI computing capacity. Future work can integrate network quality, price, and firm-usage data into the same analysis.

Third, AI-firm density is based on registered location, which may not correspond to actual R&D sites and cannot establish nationwide concentration trends. Future research should identify firm births, relocations, and exits. Fourth, the complementary-factor regressions do not observe actual financing, worker-job matches, or knowledge flows and do not identify indirect effects. Linking firm loans, worker histories, recruitment records, and collaborative projects would provide a more direct test of the proposed pathways.

Declarations

Author Contribution

J.R. and T.C. conceived the research design, performed empirical analysis, and drafted the main manuscript. J.R. prepared the figures and tables. All authors reviewed and approved the final version of the manuscript.

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