

Who Benefits from Urban AI Industry Density? Firm Value Creation and the Absorptive Capacity Threshold

Rongrong LI

Soochow University

Rui YANG

ryang@suda.edu.cn

Soochow University

Research Article

Keywords: AI industry density, entrepreneurial ecosystems, absorptive capacity, knowledge spillovers, firm value creation

Posted Date: September 30th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10980625/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Who Benefits from Urban AI Industry Density?

Firm Value Creation and the Absorptive Capacity Threshold

Abstract Artificial intelligence (AI) is widely expected to widen the gap between dominant firms and the rest, because the knowledge needed to deploy it is produced in a concentrated upstream sector while its value needs to be realized downstream by heterogeneous firms. Whether less resource-rich firms can share in AI's gains may therefore depend on where they are located. This study conceptualizes urban AI industry density (UAID) as a spatial organizational carrier, a regional knowledge transfer infrastructure that concentrates, translates, and transmits AI knowledge from upstream producers to downstream firms. Using panel data on Chinese A-share listed firms spanning 288 cities from 2007 to 2024, we show that both the spatial and economic dimensions of UAID significantly enhance relative value creation, operating through two patent-based pathways: technological evolution, which expands and deepens firms' internal AI knowledge, and technological integration, which broadens cross-domain linkages. UAID also generates a spatial compensatory effect. The gains concentrate among moderately endowed firms: firms below an absorptive capacity threshold fail to benefit, very small firms most clearly and low-innovation firms only directionally, and highly innovative firms respond more modestly. Regional infrastructure thus substitutes for the scale-intensive self-provisioning of AI capabilities but not for the baseline absorptive capacity that participation requires. These findings contribute to research on entrepreneurial ecosystems and knowledge spillovers by showing how the regional organization of AI supply shapes which firms can participate in AI diffusion.

Plain English Summary Being surrounded by AI firms helps mid-sized companies thrive, but does little for the smallest ones. Tracking Chinese listed firms across 288 cities from 2007 to 2024, we find that a city's AI industry density works like a regional delivery system for AI knowledge: it pools local AI capabilities, turns generic algorithms into usable applications, and channels them to nearby firms, which then create more value by deepening their own AI expertise and by linking AI to their existing technologies. The benefits, however, concentrate among moderately equipped firms: very small and less innovative firms lack the baseline capabilities to absorb what the region supplies. The key policy implication is that simply attracting AI firms or subsidizing adoption is not enough; cities also need to build the transfer channels that move AI knowledge to ordinary firms and help small firms reach the capability threshold that participation in the AI economy requires.

Keywords AI industry density; entrepreneurial ecosystems; absorptive capacity; knowledge spillovers; firm value creation

JEL Classification O33 · R12 · O31

1 Introduction

Artificial intelligence (AI) is widely expected to deliver its gains disproportionately to a minority of dominant firms (Babina et al., 2024). Behind this expectation lies a structural asymmetry in how AI creates value: the knowledge underpinning AI applications is produced in a concentrated upstream sector, whereas its economic value needs to be realized downstream by heterogeneous firms whose capabilities span a wide range. Smaller and less resource-rich firms, in particular, lack the scale to build proprietary AI capabilities and risk being excluded from AI-driven value creation. Whether these firms can participate may depend not only on their own investments but also on where they are located. Firm-level research on AI-era knowledge sourcing shows that AI investment pays off primarily when it complements firms' own R&D (D'Amico et al., 2025; Zhou et al., 2026), yet this firm-choice perspective presumes that external AI knowledge is there to be chosen. It leaves untheorized the regional supply-side conditions that determine whether such knowledge is locally available, in what form, and at what cost. AI knowledge production is geographically concentrated in a limited number of urban industrial ecosystems (Balland et al., 2020; Kogler et al., 2013), so the effective supply of transferable AI knowledge varies substantially across the locations in which firms operate.

This asymmetry is compounded by AI's character as a general-purpose technology (GPT): its value-creating potential is realized not through standalone adoption but through recombination with complementary, domain-specific innovations (Bresnahan & Trajtenberg, 1995; David, 1990; Gambardella et al., 2021). This poses a knowledge transfer problem. The GPT literature has established that realizing such complementarities requires organizational adaptation and complementary assets within firms (Brynjolfsson et al., 2021; Teece, 1986), but says little about how the AI knowledge that feeds such recombination reaches heterogeneous firms in the first place. Regional industrial ecosystems offer a natural setting for pursuing this question: AI-related firms function as primary sources of tacit technological solutions for downstream industries, yet such knowledge diffuses with friction, and its transmission depends on the geographic clustering of AI activities (Audretsch & Feldman, 1996; Klinger et al., 2021). As Scott's (2006) notion of the creative field makes clear, geographic concentration creates

only the potential for knowledge exchange; the actual flow of tacit knowledge requires organizational arrangements that co-location alone does not supply. These considerations generate three interrelated questions: Which firms benefit from the geographic concentration of AI activities, and which are left behind? How does this concentration convert AI's latent potential into firm-level value creation? And through what micro-level mechanisms, which we term complementary technology-knowledge recombination (CTKR), does this conversion operate?

Three literatures converge on this transfer problem, each illuminating one of its constitutive elements: the movement of knowledge across boundaries, its embedding in interdependent organizational systems, and its concentration in space. Yet each stops short of the junction where these elements meet. The knowledge transfer literature has long recognized that effective transfer depends on the characteristics of the transfer agent, the transfer medium, and the recipient (Argote & Ingram, 2000; Bozeman, 2000), and that crossing knowledge boundaries requires not mere movement but translation across syntactic and semantic differences (Carlile, 2004). Yet this literature theorizes transfer as a dyadic, intentional, and organizationally bounded event between identifiable senders and recipients, offering limited leverage on settings where the “sender” is an entire upstream industry and the potential recipients are anonymous, heterogeneous firms that never enter formal collaboration. The innovation ecosystem literature theorizes this organizational embedding, emphasizing multilateral interdependencies and complementarity-based value creation (Adner & Kapoor, 2010; Jacobides et al., 2018), but adopts a focal-firm perspective that implicitly assumes sufficient strategic leverage to navigate complex ecosystem structures, an assumption that leaves it ill-equipped to account for moderately endowed firms: those possessing baseline absorptive capacity yet lacking the scale to self-provision AI capabilities. For entrepreneurship research, this gap is consequential: if entrepreneurial ecosystems supply not only venture opportunities (Autio et al., 2018) but also the AI knowledge on which incumbent smaller firms depend, then the regional organization of AI supply becomes a condition of their participation in the digital economy. Economic geography theorizes the spatial element, documenting that

concentration generates localized knowledge spillovers (Audretsch & Feldman, 1996), yet it treats such spillovers as passive, undirected exposure, knowledge “in the air,” rather than as a structured process that renders AI knowledge deployable. Neither the dyadic logic of knowledge transfer, the focal-firm logic of innovation ecosystems, nor the passive logic of agglomeration externalities explains how a region’s AI industrial base, through CTKR, converts latent AI potential into firm-level value creation for firms across the capability spectrum.

We address this gap by conceptualizing urban AI industry density (UAID) as a spatial organizational carrier, defined as a regional knowledge transfer infrastructure that channels AI knowledge from its upstream producers to heterogeneous downstream firms. A region does not merely hold AI knowledge; it carries knowledge across organizational and sectoral boundaries. This infrastructure performs three transfer functions: concentration (pooling dispersed AI capabilities into a locally accessible knowledge reservoir), translation (adapting generic algorithms into modular, domain-specific applications), and transmission (routing these translated modules to heterogeneous firms through supply chains, labor mobility, and technical standards). These functions correspond to the boundary-spanning processes through which knowledge is rendered transferable across cognitive distance (Carlile, 2004; Hansen, 1999); in our account, however, this boundary work is located in the region’s organizational thickness (the density and diversity of organizational actors that perform the transfer functions) rather than in any single firm. Our argument draws on the knowledge-based view (KBV), which treats knowledge as the “glue” binding strategic resources into productive capabilities (Bergh et al., 2025; Grant, 1996), and extends this logic to the regional level: the carrier is this knowledge glue in spatial form, operating through this thickness rather than inter-firm relational governance or passive ambient exposure. If regions perform transfer work, density should behave as infrastructure: its returns should substitute for what firms cannot self-provision, peaking below the self-provisioning frontier rather than rising monotonically with absorptive capacity.

We posit that the carrier’s transfer work reaches firms through CTKR, which operates along two distinct pathways. The technological evolution pathway captures the expansion of a

firm's internal AI knowledge base in both breadth and depth. It embodies the enabling role of GPTs: UAID reduces search costs, allowing firms to accumulate complementary AI knowledge and harness AI's generic potential. The technological integration pathway captures the cross-domain embedding of AI knowledge into non-AI fields, in both breadth (recombination across technological domains) and depth (embeddedness within industrial applications). It reflects the bridging role of GPTs, as UAID provides the knowledge nodes that lower the coordination costs of recombining AI with domain-specific technologies. Together, these pathways channel regional AI density into firm value creation.

We test these arguments using panel data on Chinese A-share listed firms spanning 288 cities from 2007 to 2024. The results support the carrier account: UAID enhances firm value creation through both recombination pathways, and its returns exhibit the predicted threshold pattern, concentrating among moderately endowed firms rather than rising with absorptive capacity.

Our study offers four theoretical contributions. First, we identify a spatial compensatory effect governed by an absorptive capacity threshold. Whereas firm-level studies show that AI investment pays off when it complements internal R&D (D'Amico et al., 2025), we identify the regional counterpart: the transfer infrastructure compensates most effectively for moderate capability deficits, so that moderately endowed firms, rather than the most resource-constrained, benefit from AI diffusion, a pattern statistically robust in the size dimension and directionally consistent in the innovation dimension. This compensatory effect recasts the AI productivity paradox in spatial terms, explaining why aggregate AI potential materializes unevenly across firms and places.

Second, we theorize the regional infrastructure of knowledge transfer. Classic accounts conceptualize knowledge transfer as a dyadic, intentional event whose effectiveness hinges on the attributes of specific agents, media, and recipients (Argote & Ingram, 2000; Bozeman, 2000), while spillover accounts relax intentionality only to dissolve structure, treating regional knowledge as ambient exposure. The spatial organizational carrier bridges these poles: it is structured yet non-dyadic, performing concentration, translation, and transmission functions

that convert passive spillovers into structured transfer for anonymous, heterogeneous recipients. This shifts the analytical focus from who transfers to what infrastructural conditions make transfer possible at scale.

Third, we extend the GPT literature by identifying the spatial-organizational conditions of AI value realization. While classic GPT accounts define the intrinsic attributes of general-purpose innovations, namely pervasiveness, inherent potential for technical improvements, and innovation complementarity (Bresnahan & Trajtenberg, 1995; David, 1990), they remain silent on the spatial and organizational frictions that govern their micro-level diffusion. By conceptualizing UAID as a regional knowledge transfer infrastructure, we show that this infrastructure is not an incidental backdrop but a structural condition shaping the conversion of latent AI potential into firm value creation.

Fourth, we operationalize the two recombination pathways as empirically tractable, patent-based measures, thereby providing micro-level, replicable evidence of how GPT potential is recombined into value-creating capabilities.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and hypotheses. Section 3 describes the research design. Section 4 presents the baseline results, tests of the absorptive capacity threshold and the mechanism of CTKR. Section 5 presents robustness results. Section 6 discusses the findings. Section 7 outlines implications, limitations, and future research. Section 8 concludes.

2 How urban ai industry density creates value: the spatial organizational carrier

2.1 The carrier: transfer functions and density dimensions

Firm value creation is a process of knowledge integration (Grant, 1996), the mechanism through which strategic resources are configured into productive capabilities (Bergh et al., 2025). AI exhibits pervasiveness and innovation complementarity (Bresnahan & Trajtenberg, 1995; Rosenberg & Trajtenberg, 2004), yet these attributes do not automatically translate into firm value creation; realizing AI's potential rests on the recombination of complementary knowledge and on organizational adaptations (David, 1990; Jovanovic & Rousseau, 2005).

Such recombination depends on firms' capacity to access, absorb, and embed AI knowledge. While generic AI algorithms are highly codified and globally mobile, the knowledge required to adapt them to specific operational contexts remains tacit and spatially sticky (Szulanski, 1996), embedded in the regional ecosystems where it is produced. Firms therefore engage in localized search to integrate it into their production systems, a process constrained by the availability of local AI knowledge infrastructure.

When AI firms co-locate in a city, they generate a local pool of AI knowledge (Autio et al., 2018; Balland et al., 2020; Kogler et al., 2013). Yet such a pool is only a stock; what moves it across firm boundaries is the relational structure in which it is embedded. UAID thus denotes not merely a geographic pattern but a spatial organizational carrier: a structurally embedded arrangement of inter-organizational relations (specialized labor markets, supplier–customer interfaces, and technical standards) that concentrates dispersed AI capabilities, translates generic algorithms into deployable modules (Carlile, 2004), and transmits these modules to heterogeneous firms (Dyer & Singh, 1998; Uzzi, 1997). In performing these functions, the carrier channels the AI industry's accumulated knowledge base across firm boundaries within the region (Bergh et al., 2025). It is the organizational thickness, not just spatial proximity, that enables the carrier to perform its translating and transmitting functions. Proximity without thickness would leave AI knowledge ambient, requiring each firm to search, decode, and assemble it on its own; thickness converts that ambient stock into deployable form, so the carrier's returns should substitute for firm-level provisioning rather than compound with it. This account resonates with Autio et al.'s (2018) observation that entrepreneurial ecosystems exploit digital affordances to facilitate knowledge exchange, yet extends their logic beyond entrepreneurial opportunity discovery to the systematic recombination of AI with established technological domains. It also aligns with the concept of bridging technologies, which occupy central positions in regional knowledge spaces by connecting otherwise distant fields (Basilico & Graf, 2023), but shifts the analytical focus from the structural position of individual technologies to the spatial-organizational conditions that enable heterogeneous firms to access and deploy such bridging potential.

The carrier manifests itself through two complementary structural dimensions, which transform AI knowledge from dispersed and tacit to localized and deployable. Spatial density reflects the vitality and knowledge spillover potential of the regional AI ecosystem, namely the extent to which AI ventures constitute a significant segment of the city's entrepreneurial landscape. This dimension primarily performs the concentration function: by pooling a large share of AI ventures within this landscape, it exposes firms to a cognitively accessible reservoir of emergent algorithmic capabilities, reducing the spatial scope of knowledge search. Economic density captures the structural penetration and commercial maturity of the AI sector within the local economy, namely the concentration of AI-specialized supply capabilities relative to the region's overall economic scale. This dimension performs the translation and transmission functions: by embedding AI activities deeply into local supply chains, labor markets, and technical standards (Audretsch & Feldman, 1996; Dyer & Singh, 1998; Teece, 1986), it generates the organizational thickness required to adapt generic algorithms into modular, domain-specific applications and to diffuse these translated capabilities across heterogeneous firms. Together, these two dimensions determine the carrier's effectiveness and shape the regional cost structure for CTKR.

Specifically, the three transfer functions lower the costs of accessing, absorbing, and embedding AI knowledge. The concentration function mitigates search costs, the friction of locating relevant AI knowledge among dispersed sources. The translation function mitigates absorption costs, the cognitive and technical effort required to internalize tacit AI knowledge. The transmission function mitigates coordination costs, the transactional frictions of assembling complementary assets across domains. By lowering the threshold for CTKR, UAID enables firms to bind AI knowledge into productive capabilities (Bergh et al., 2025; Grant, 1996), so that firms in denser regions should exhibit superior value creation relative to peers in less dense regions. We therefore propose the following hypothesis:

H1: Urban AI industry density (UAID) positively affects firm value creation.

While H1 predicts a positive average effect, its magnitude should vary with firms' internal capability endowments. On this point, passive exposure and transfer infrastructure diverge: the

former predicts returns that rise with absorptive capacity, whereas the latter predicts returns that peak where baseline absorptive capacity meets the inability to self-provision. Innovation ecosystem research typically assumes that benefiting from external knowledge networks requires substantial absorptive capacity and complementary assets (Cohen & Levinthal, 1990; Teece, 1986). However, the spatial organizational carrier lowers the threshold for complementary recombination, enabling moderately endowed firms to capture disproportionate value from UAID, a spatial compensatory effect whereby regional infrastructure offsets their capability deficits. At the same time, the compensatory effect is bounded at both ends of the capability spectrum: below a minimum absorptive capacity threshold, very small firms may lack the capacity to decode and internalize translated AI modules; at the upper end, large incumbents can rely on internal pipelines and may therefore depend less on regional density, muting their marginal gains from it, and highly innovative firms can self-provision AI knowledge, reducing their reliance on it. We therefore expect the compensatory effect to be strongest for moderately endowed firms that combine baseline absorptive capacity with organizational flexibility.

H2: The positive effect of UAID on firm value creation is strongest for medium-sized and moderately innovative firms, consistent with an absorptive capacity threshold.

2.2 How UAID activates CTKR

As illustrated in **Figure 1**, the spatial organizational carrier drives firm value creation through CTKR, a process by which firms acquire, deepen, and embed AI knowledge across domains to generate value-creating capabilities. This process reflects the dual attributes of GPTs and operates through two distinct pathways. The technological evolution pathway captures the expansion and deepening of a firm's internal AI knowledge base, embodying the pervasiveness and dynamism of GPTs (the enabling mechanism): UAID reduces search and absorption costs, allowing firms to build foundational AI capabilities and harness AI's generic potential. The technological integration pathway captures the cross-domain embedding of AI knowledge into non-AI fields, reflecting the innovation complementarity of GPTs (the bridging mechanism): UAID provides knowledge nodes and intermediary resources that facilitate the recombination

of AI with domain-specific technologies. Together, these pathways constitute the micro-level channels through which UAID generates firm value creation.

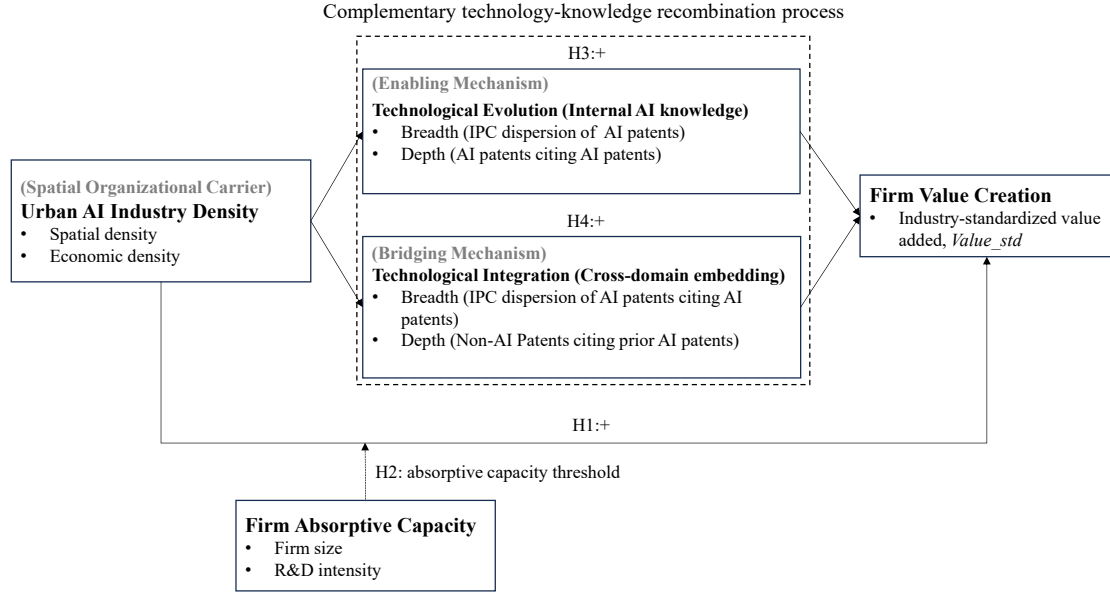


Figure 1 Urban AI industry density, complementary technology-knowledge recombination, and firm value creation

2.2.1 The technological evolution pathway: the enabling mechanism

As an “invention of a method of invention” (Cockburn et al., 2018), AI exhibits pervasiveness and sustained dynamism, driving novel combinations within the knowledge space (Qu et al., 2026). However, internalizing this rapidly evolving technology is resource-intensive and risky. While firms may pursue idiosyncratic, frontier AI capabilities in search of competitive differentiation, this strategy triggers the technological uniqueness paradox: excessive uniqueness increases cognitive distance from the industry frontier, elevates capital expenditure, and impairs external absorptive capacity (Fan et al., 2026).

We argue that UAID mitigates this paradox by reducing the marginal costs of knowledge acquisition and absorption, thereby enabling firms to accumulate AI capabilities without bearing the full cognitive and capital burden of technological distinctiveness. The two dimensions of UAID differentially enable the evolution pathway. Spatial density performs the concentration function, pooling dispersed AI knowledge into localized, cognitively accessible reservoirs. By reducing the search costs of locating relevant AI capabilities, high spatial density

allows firms to identify, track, and capture iterative advancements in AI technologies, thereby augmenting their internal AI knowledge base (evolutionary depth). This localized accessibility partially offsets the reduced incoming spillovers that firms would otherwise suffer when pursuing technologically distinctive AI strategies (Fan et al., 2026).

Economic density performs the translation function, converting generic AI algorithms into modular, domain-specific applications through technical intermediaries and labor mobility. By reducing the absorption costs of understanding AI's diverse application scenarios, high economic density expands the firm's technological opportunity set (Kogler et al., 2013), enabling it to diversify its AI knowledge portfolio across related technological fields (evolutionary breadth). In line with relatedness theory in evolutionary economic geography (Boschma et al., 2013; Boschma & Capone, 2015), these translation-generated modular applications reveal trajectories connected to the firm's existing technological base, broadening its cognitive horizon.

By mitigating knowledge acquisition barriers and triggering cumulative learning, the evolution pathway enhances firm value creation. Depth captures technical mastery, enabling firms to optimize core operational processes and enhance productivity. Breadth enriches the technological search space, facilitating the configuration of non-substitutable digital assets. According to the KBV, the joint accumulation of evolutionary depth and breadth enhances the firm's combinative capacity to bind strategic resources into productive capabilities, sustaining superior value creation (Bergh et al., 2025; Grant, 1996).

H3: UAID promotes the evolution of firms' AI knowledge.

2.2.2 The technological integration pathway: the bridging mechanism

Beyond driving internal knowledge evolution, AI, as a bridging technology, facilitates recombination across disparate technological domains (Basilico & Graf, 2023; Qu et al., 2026). This cross-domain recombination reflects the broader logic of sectoral innovation systems, where vertical linkages and inter-sectoral knowledge flows constitute critical channels for technological diffusion and value creation (Castellacci, 2008). Such recombination is

constrained by the cognitive distance between technological domains (Boschma, 2005) and by the technological specificity that elevates cross-domain coordination costs (Teece, 1986). AI mitigates both frictions, acting as a shared layer that reshapes the architecture of recombination and inventive activity (Qu et al., 2026). It reduces cognitive distance by translating heterogeneous domain-specific inputs into unified algorithmic architectures, enabling knowledge exchange across cognitively distant fields. It lowers the costs of coordinating these inputs by making their interactions more predictable, rendering cross-domain knowledge integration feasible.

For firms to access this bridging potential at tolerable cost, however, the technology-level work of AI must be complemented at the regional level. Economic density performs the translation and transmission functions central to this pathway, while spatial density, through the concentration function, raises the encounter rate between AI knowledge and non-AI domains. By embedding AI activities deeply into local supplier networks, skilled labor pools, and technical standards, it generates standardized interfaces, modular algorithmic architectures, and interoperable labor skills that reduce the coordination costs of cross-domain recombination. This localized translation produces shared solution representations, algorithmic response templates that dampen uncertainty and render previously unrelated technological domains newly combinable.

These translated modules are codified and non-rival (Fan et al., 2026; Romer, 1990), unlike firm-level capabilities, which are non-scale-free (Levinthal & Wu, 2010). They can therefore diffuse across heterogeneous firms without diminishing in value, lowering the marginal cost of complementary recombination for each additional adopter. Such representations lower the threshold for structural citation (non-AI inventions building on AI knowledge), but the actual volume of cross-domain linkage depends on the rate at which firms encounter and access these translated AI capabilities. The integration enabled along this pathway unfolds in two dimensions. Integration breadth reflects the scope of cross-boundary knowledge linkages: as UAID increases the encounter rate between AI knowledge and non-AI technological domains, firms can more readily establish structural citations to AI patents within

their technological portfolios. Integration depth reflects the degree of structural embeddedness of AI knowledge within the firm's non-AI operations: while UAID generates the modular, pre-translated interfaces necessary for cross-domain embedding, achieving deep structural coupling ultimately depends on firms' internal capacity to reconfigure existing operational architectures and sustain cross-functional coordination. Consequently, UAID supplies the regional infrastructure for cross-domain integration, but the depth of structural embedding remains contingent on internal managerial commitment.

The integration pathway enhances firm value creation. High integration breadth expands the firm's recombinant search space beyond domain boundaries, enabling the synthesis of novel technological solutions. High integration depth facilitates the structural coupling of AI with core business architectures, triggering process reengineering and the transition from static products to data-driven service ecosystems (Clough & Wu, 2022). According to the KBV, these deeply coupled, cross-domain configurations assemble disparate technological resources into coherent, path-dependent, and causally ambiguous capabilities that are difficult to imitate, thereby sustaining superior value creation (Barney, 1991; Bergh et al., 2025; Grant, 1996).

H4: UAID promotes the cross-domain integration of AI knowledge.

3 Research design

3.1 Empirical specification

3.1.1 Baseline model

To examine the impact of UAID on firm value creation (H1), we estimate the following fixed-effects panel specification:

$$Value_std_{i,j,t} = \alpha_0 + \alpha_1 UAID_{c,t} + \mathbf{X}_{i,j,t} \alpha_2 + \mathbf{Z}_{c,t} \alpha_3 + \mu_i + \gamma_t + \varepsilon_{i,j,t} \quad (1)$$

where i , j , c , and t index firms, industries, cities, and years; $Value_std_{i,j,t}$ is firm i 's standardized value creation in year t ; $UAID_{c,t}$ is our core independent variable at the city-year level, operationalized as spatial density and economic density in separate regressions; $\mathbf{X}_{i,j,t}$ and $\mathbf{Z}_{c,t}$ are vectors of firm- and city-level control variables capturing time-varying micro- and macro-level factors; μ_i and γ_t denote firm and year fixed effects, absorbing time-invariant

unobserved firm heterogeneity and macroeconomic shocks common to all firms, respectively; and $\varepsilon_{i,j,t}$ is the random error term. Standard errors are clustered at the firm level to address within-firm serial correlation. We also report the baseline specification with city-level and two-way (firm and city) clustering in **Table A3**; the coefficients remain significant at the 1% level.

3.1.2 Mechanism model

To trace the mechanisms linking UAID to firm value creation, we estimate the effect of UAID on the two CTKR pathways (H3 and H4) using the following specification:

$$M_{i,j,t} = \beta_0 + \beta_1 UAID_{c,t} + \mathbf{X}_{i,j,t} \beta_2 + \mathbf{Z}_{c,t} \beta_3 + \mu_i + \gamma_t + \varepsilon_{i,j,t} \quad (2)$$

where $M_{i,j,t}$ represents the mechanism variables: (1) the evolutionary breadth and depth of a firm's internal AI knowledge stock (the technological evolution pathway, H3); and (2) the integration breadth and depth of AI knowledge into non-AI technological fields (the technological integration pathway, H4). We supplement these estimates with instrumental variable specifications to address endogeneity, reported in Panels B of **Tables 12** and **13**. Standard errors are clustered at the firm level. **Tables A6** and **A7** report the mechanism estimates under city-level and two-way (firm and city) clustering, respectively: the technological evolution results are unchanged, whereas the marginal OLS effect on integration breadth is sensitive to the clustering scheme. We therefore base inference for the integration pathway primarily on the IV estimates.

The coefficient of interest is β_1 , the effect of UAID on firm-level knowledge recombination. The onward link from these mechanisms to firm value creation is established by the deductive logic developed in Sections 2.2.1 and 2.2.2: technological evolution optimizes processes and builds non-substitutable digital assets, while cross-domain integration drives structural reengineering and ecosystem-based value capture.

3.2 Variable definitions

3.2.1 Urban AI industry density (UAID)

Enterprise registration records come from the CNRDS database, which compiles firm-level information from the national industrial and commercial registration system. We identify AI-

related firms through feature-keyword extraction from registered business scopes: a firm is classified as an AI firm if its business scope contains AI-related keywords such as image recognition, computer vision, speech recognition, or sensors. We retain only active firms, excluding those with liquidated, suspended, or revoked registrations. Firm registrations are traced from 2000 onward and aggregated to the city-year level; the analysis sample spans 288 Chinese prefecture-level cities from 2007 to 2024.

We proxy the carrier's organizational thickness with the density of active AI firms rather than sectoral output value or firm quality metrics for two reasons. First, localized knowledge spillovers and technological translation depend on the density and diversity of organizational actors; high output concentrated in a few dominant firms may fail to generate the communicative networks that downstream firms rely on. This measurement strategy aligns with Autio et al.'s (2018) emphasis on actor density and diversity as a defining feature of ecosystems, yet captures the broader industrial base rather than exclusively entrepreneurial activity. Second, organizational thickness is a structural property that precedes quality deepening: specialized labor pools, supplier networks, and technical interoperability presuppose a critical mass of AI enterprises, and firm-level scale and technological leadership are typically built atop this organizational base. In this sense, the density of active AI firms captures the foundational organizational infrastructure upon which the three carrier functions operate.

Spatial density

We operationalize spatial density as the stock of active AI firms scaled by the city's cumulative number of newly founded firms.

$$Spatial\ density_{c,t} = \frac{Active\ AI\ Firms_{c,t}}{Cumulative\ New\ Firms_{c,t}} \quad (3)$$

Two features of this construction warrant emphasis. First, the numerator counts only active AI firms, because inactive firms cannot supply transferable knowledge. Second, the denominator cumulates all new firm registrations, proxying the scale of the city's accumulated entrepreneurial foundation.¹ Rather than scaling by land area, which fails to capture the dynamic density of organizational activities, this scaling standardizes the accessible AI

knowledge base against the city’s entrepreneurial baseline. A higher value indicates a larger reservoir of accessible AI capabilities relative to this foundation, from which downstream firms can source emergent algorithmic capabilities.

Economic density

We operationalize economic density as the ratio of active AI firms to GDP in city c in year t . Prefecture-level statistics in China do not report standardized, long-term annual output values for the AI sector, so constructing active firm stock from registration records ensures measurement consistency across cities and years.

$$Economic\ density_{c,t} = \frac{Active\ AI\ Firms_{c,t}}{City\ GDP_{c,t}} \quad (4)$$

This metric captures the structural penetration of the AI sector relative to the region’s overall economic scale. A higher ratio indicates that the regional economy is proportionally more invested in AI-related supply capabilities. In Equation (4), city GDP is expressed in millions of RMB; this rescales the coefficient away from near-zero values, improving computational convergence and the readability of the estimates.

These two dimensions scale the same stock of active AI firms by different regional baselines, and thus offer complementary characterizations of the carrier: spatial density reflects the variety and accessibility of AI knowledge sources relative to the entrepreneurial foundation, while economic density reflects the structural embeddedness and commercial maturity of AI activities relative to the region’s economic scale. A region with high spatial but low economic density may host a large AI firm stock relative to its entrepreneurial base yet lack the stable intermediate-input infrastructure that sustains firm-level recombination; conversely, high economic density without spatial vitality may indicate a commercially embedded but stagnant AI sector with limited knowledge spillovers. Each dimension thus captures a distinct functional facet of the carrier, and estimating them separately allows us to assess whether the concentration function or the translation and transmission functions are more strongly associated with firm-level value creation.

3.2.2 Firm value creation

We conceptualize firm value creation as the economic wealth a firm generates through the transformation of inputs into outputs, treating value as a surplus distributed among employees, the government, and the firm. We operationalize this construct using firm value added (VA), calculated as the sum of employee compensation, net production taxes, operating surplus, and depreciation of fixed assets.

Unlike financial market-based metrics such as Tobin's Q or cumulative abnormal returns (CAR), which are susceptible to macroeconomic noise and investor expectations, VA isolates the surplus generated within the real production system. This measurement strategy aligns with our theoretical focus on how UAID enhances firm-level productive capabilities through complementary technology-knowledge recombination.

We calculate value added of firm i in industry j and year t as follows:

$$Value_{i,j,t} = EC_{i,j,t} + NPT_{i,j,t} + OS_{i,j,t} + DFA_{i,j,t} \quad (5)$$

The four components are operationalized as follows:

- Employee compensation ($EC_{i,j,t}$) is measured as the current-period additions to the “Employee Benefits Payable” account.
- Net production taxes ($NPT_{i,j,t}$) is proxied by “Taxes and Surcharges” from the Income Statement.
- Operating surplus ($OS_{i,j,t}$) is calculated as the sum of operating profits and financial expenses.
- Depreciation of fixed assets ($DFA_{i,j,t}$) is calculated as the sum of depreciation of fixed assets, depletion of oil and gas assets, and amortization of productive biological assets from the Cash Flow Statement.

To eliminate industry-specific scale effects and ensure cross-sectoral comparability, we apply an industry-year Min-Max standardization to construct our dependent variable, $Value_std_{i,j,t}$, bounded between $[0, 1]$:

$$Value_std_{i,j,t} = \frac{Value_{i,j,t} - Value_{j,t}^{Ind_Min}}{Value_{j,t}^{Ind_Max} - Value_{j,t}^{Ind_Min}} \quad (6)$$

where i , j , and t denote the firm, industry (CSRC 2-digit level), and year, respectively. $Value_{j,t}^{Ind_Min}$ and $Value_{j,t}^{Ind_Max}$ represent the minimum and maximum firm value added within industry j in year t . A higher value of $Value_std_{i,j,t}$ reflects a higher relative standing in value creation within the industry, indicating a stronger capability to generate economic surplus. We also verify in Section 4.2.1 that the baseline results hold under two alternative transformations of value added: an industry-year Z-score and a Min-Max transformation using the full-sample minimum and maximum (**Table A2**).

3.2.3 Control variables

To mitigate confounding bias and isolate the net impact of UAID on firm-level value creation, we incorporate covariates at both the firm and city levels.

Firm-level controls

At the firm level, we control for operational, financial, and governance characteristics:

- Operational & Financial Status: Firm size (*Size*), firm age (*Age*), operating cash flow (*OCF*), leverage (*LEV*), return on equity (*ROE*), and Tobin's Q.
- Corporate Governance & Ownership: Ownership concentration (*Own_Con*) and a state-owned enterprise dummy (*SOE*).
- Supply Chain Bargaining Power: Supplier bargaining power (*SBP*) and buyer bargaining power (*BBP*).
- Internal AI Technology Investment (*AI_Asset*).

City-level controls

At the city level, we control for local economic, structural, and innovation environments:

- Innovation & Talent Ecology: The listing rate of high-tech firms (*HT_Share*).
- Economic Vibrancy: GDP growth (*GDP_Gr*) and regional financial development (*Fin_Dev*).
- Policy & Industrial Structure: Municipal scientific support (*Gov_ST*) and tertiary sector share (*Serv_Share*).

Table 1 summarizes the definitions and measurements for all variables.

Table 1 Definitions of variables

Variable	Measures
Firm value creation (<i>Value_std</i>)	The sum of employee compensation, net production taxes, operating surplus, and depreciation of fixed assets, standardized by industry.
Economic Value Added (EVA)	Net operating profit after tax – (total capital × weighted average cost of capital), standardized by industry.
AI spatial density (<i>AI_Spat</i>)	The ratio of active AI firms to the cumulative new firms in the city.
AI economic density (<i>AI_Econ</i>)	The number of active AI firms per million RMB of city GDP.
Firm size (<i>Size</i>)	The natural logarithm of total assets.
Firm age (<i>Age</i>)	The number of years since the firm's initial public offering (IPO).
Operating cash flow (<i>OCF</i>)	Net operating cash flow scaled by total assets.
Debt-to-asset ratio (<i>LEV</i>)	Total liabilities divided by total assets.
Return on equity (<i>ROE</i>)	Net income divided by the average of opening and closing balances of shareholders' equity.
Ownership concentration (top-10 shareholders) (<i>Own_Con</i>)	The Herfindahl-10 index of shareholding percentage among the top ten shareholders.
State-Owned Enterprise (<i>SOE</i>)	A dummy variable equal to 1 if the firm is state-owned, and 0 otherwise.
Supplier bargaining power (<i>SBP</i>)	Net trade payables (accounts payable minus prepayments) scaled by total assets.
Buyer bargaining power (<i>BBP</i>)	Net trade receivables (accounts receivable minus contract liabilities and advances received) scaled by operating revenue.
Tobin's Q	The ratio of market capitalization of equity to total assets net of intangible assets and goodwill.
Internal AI technology investment (<i>AI_Asset</i>)	AI-related intangible and fixed assets scaled by total assets.
The share of high-tech firms (<i>HT_Share</i>)	The number of listed companies with high-tech qualifications in the city, scaled by the total number of high-tech enterprises in the city.
The annual growth rate of GDP (<i>GDP_Gr</i>)	The annual growth rate of GDP of the city where the firm is located.
The level of regional financial development (<i>Fin_Dev</i>)	The year-end financial institution loan balance scaled by city GDP.
Municipal scientific support (<i>Gov_ST</i>)	Public science and technology expenditures scaled by city GDP.
The share of the tertiary sector (<i>Serv_Share</i>)	Tertiary industry GDP divided by total city GDP.

GDP_Gr is computed as the growth rate of real (constant-price) GDP.

3.3 Data sources and sample selection

This study constructs a panel dataset of Chinese A-share listed firms from 2007 to 2024. The sample starts in 2007, when China's revised Accounting Standards for Business Enterprises took effect, ensuring the consistency of the financial items underlying our value-added measure. The sample period spans multiple macroeconomic cycles and policy shifts in the AI industry, encompassing the deep learning breakthrough circa 2012, the elevation of AI to national policy priority post-2014, and AI's transition from scientific breakthrough to large-scale application, thereby enabling robustness checks across distinct AI development regimes (see **Table A1**).

Firm-level financial, operational, and governance data come from the China Stock Market & Accounting Research (CSMAR) database. Enterprise registration records, used to construct

UAID, come from the CNRDS database, which compiles national business registration information. Urban macroeconomic indicators come from the China City Statistical Yearbook and the CSMAR database. Patent application data come from the China National Intellectual Property Administration and the CNRDS database. Patent citation data come from the incoPat and CNRDS databases.

We apply the following sample filters: (1) excluding Special Treatment (ST and *ST) firms; (2) excluding financial institutions due to their distinct accounting standards; and (3) excluding singleton observations, that is, firm-years in which a firm appears only once in the sample. To mitigate outlier influence, all continuous variables are winsorized at the 1st and 99th percentiles. The final unbalanced panel consists of 51,795 firm-year observations.

3.4 Descriptive statistics

Table 2 presents the descriptive statistics. The standardized firm-level value creation (*Value_std*) has a mean of 0.1671 and a median of 0.0899. The right-skewed distribution indicates that high value-added generation remains concentrated in a small group of high-efficiency firms.

Similarly, our core independent variables exhibit substantial right-skewness: the mean of spatial density (*AI_Spat*) is 0.0099 (median = 0.0054), and that of economic density (*AI_Econ*) is 0.0140 (median = 0.0076). This pattern reflects the geographic concentration of China's AI industry, in which a few leading digital hubs possess highly concentrated AI knowledge bases while most cities are in the early stages of building local AI ecosystems. This substantial cross-regional variation underpins our identification strategy.

Table 2 Descriptive statistics

Variable	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>p25</i>	<i>Median</i>	<i>p75</i>	<i>Max</i>
<i>Value_std</i>	51795	0.1671	0.2117	0.0000	0.0344	0.0899	0.2041	1.0000
<i>AI_Spat</i>	51795	0.0099	0.0108	0.0000	0.0021	0.0054	0.0139	0.0452
<i>AI_Econ</i>	51795	0.0140	0.0150	0.0000	0.0026	0.0076	0.0216	0.0881
<i>Size</i>	51795	22.1693	1.2952	19.3502	21.2382	21.9609	22.8876	26.4838
<i>Age</i>	51795	9.9594	7.8738	0.0000	3.0000	8.0000	15.0000	31.0000
<i>OCF</i>	51795	0.0460	0.0698	-0.2228	0.0077	0.0457	0.0864	0.2825
<i>LEV</i>	51795	0.4197	0.2070	0.0274	0.2527	0.4124	0.5744	0.9204
<i>ROE</i>	51795	0.0563	0.1471	-1.2086	0.0244	0.0704	0.1212	0.4574
<i>Own_Con</i>	51795	0.5823	0.1561	0.1946	0.4696	0.5915	0.7048	0.9097
<i>SOE</i>	51795	0.3389	0.4733	0.0000	0.0000	0.0000	1.0000	1.0000
<i>SBP</i>	51795	0.0735	0.0753	-0.2141	0.0247	0.0603	0.1102	0.3578
<i>BBP</i>	51795	0.1657	0.3187	-1.5361	0.0198	0.1426	0.2953	1.6338
<i>Tobin's Q</i>	51795	2.1746	1.4522	0.8247	1.3222	1.7227	2.4753	19.0305
<i>AI_Asset</i>	51795	0.0042	0.0081	0.0000	0.0002	0.0013	0.0043	0.0695
<i>HT_Share</i>	51795	0.0008	0.0006	0.0000	0.0003	0.0006	0.0010	0.0043
<i>GDP_Gr</i>	51795	0.0918	0.0623	-0.3591	0.0552	0.0869	0.1218	0.4191
<i>Fin_Dev</i>	51795	1.7291	0.7014	0.1814	1.2030	1.7759	2.2111	4.1413
<i>Gov_ST</i>	51795	0.1486	0.0549	0.0575	0.1107	0.1355	0.1798	0.6918
<i>Serv_Share</i>	51795	0.5474	0.1196	0.1199	0.4633	0.5325	0.6359	0.7820

4 Results

4.1 Baseline results

Table 3 reports the baseline results, with firm- and city-level controls introduced sequentially. Columns (1) and (4) report specifications with only firm and year fixed effects: *AI_Spat* (0.6510, $p < 0.05$) and *AI_Econ* (0.6885, $p < 0.01$) are both positively associated with firm value creation. Columns (2) and (5) add firm-level controls; the coefficients remain positive and significant (0.6798, $p < 0.05$; 0.6630, $p < 0.01$). Columns (3) and (6) further add city-level controls; the coefficients hold at 0.7169 ($p < 0.01$) and 0.6591 ($p < 0.01$), suggesting that the effect is not an artifact of the observed local macroeconomic conditions and innovation environment.

The positive effect of UAID on firm value creation is stable across all specifications, supporting H1. Economically, a one-standard-deviation (interquartile-range) increase in spatial density raises standardized value creation by approximately 4.6% (5.1%) of the sample mean; the corresponding figures for economic density are 5.9% and 7.5%. These magnitudes indicate that UAID exerts a moderate yet non-negligible effect on firms' relative standing within their industries.

Table 3 Baseline Estimates: UAID and Firm Value Added

Variable	<i>Value std</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>AI_Spat</i>	0.6510** (0.2813)	0.6798** (0.2705)	0.7169*** (0.2772)			
<i>AI_Econ</i>				0.6885*** (0.2211)	0.6630*** (0.2116)	0.6591*** (0.2136)
<i>Size</i>		0.0540*** (0.0039)	0.0539*** (0.0039)		0.0540*** (0.0039)	0.0540*** (0.0039)
<i>Age</i>		-0.0301 (0.0315)	-0.0302 (0.0316)		-0.0300 (0.0315)	-0.0299 (0.0316)
<i>OCF</i>		0.0904*** (0.0140)	0.0896*** (0.0140)		0.0899*** (0.0140)	0.0892*** (0.0140)
<i>LEV</i>		0.0075 (0.0118)	0.0073 (0.0117)		0.0068 (0.0117)	0.0067 (0.0117)
<i>ROE</i>		0.0900*** (0.0083)	0.0897*** (0.0083)		0.0899*** (0.0083)	0.0895*** (0.0083)
<i>Own_Con</i>		0.0119 (0.0152)	0.0116 (0.0151)		0.0110 (0.0152)	0.0107 (0.0151)
<i>SOE</i>		-0.0075 (0.0069)	-0.0076 (0.0069)		-0.0076 (0.0069)	-0.0076 (0.0069)
<i>SBP</i>		-0.0308 (0.0314)	-0.0290 (0.0314)		-0.0296 (0.0314)	-0.0284 (0.0314)
<i>BBP</i>		0.0270*** (0.0062)	0.0270*** (0.0062)		0.0266*** (0.0062)	0.0267*** (0.0062)
<i>TobinsQ</i>		0.0026*** (0.0009)	0.0026*** (0.0009)		0.0026*** (0.0009)	0.0026*** (0.0009)
<i>AI_Asset</i>		0.1353 (0.1791)	0.1365 (0.1796)		0.1416 (0.1789)	0.1426 (0.1794)
<i>HT_Share</i>			10.2705*** (3.9394)			9.8570** (3.9372)
<i>GDP_Gr</i>			0.0315* (0.0186)			0.0316* (0.0186)
<i>Fin_Dev</i>			0.0048 (0.0063)			0.0017 (0.0063)
<i>Gov_ST</i>			0.0337 (0.0595)			0.0226 (0.0583)
<i>Serv_Share</i>			-0.0038 (0.0372)			0.0024 (0.0371)
<i>_cons</i>	0.1909*** (0.0056)	-0.9882*** (0.0850)	-1.0012*** (0.0900)	0.1909*** (0.0056)	-0.9879*** (0.0849)	-1.0000*** (0.0900)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795	51795	51795
Adj.R ²	0.0339	0.0773	0.0777	0.0342	0.0774	0.0778

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

4.2 Absorptive capacity threshold effect

To identify the boundary conditions under which UAID enhances firm value creation, we examine two firm-level proxies of absorptive capacity (firm size and R&D intensity), a capability that shapes the marginal returns to external AI knowledge. As formalized in H2, we expect the spatial compensatory effect to exhibit a threshold pattern: firms with moderate absorptive capacity should benefit most, whereas firms below the threshold lack the capacity

to decode and internalize localized AI knowledge, and firms well above it can self-provision AI knowledge.

4.2.1 Absorptive capacity proxied by firm size

We begin by constructing a dummy variable *FirmSize* that equals 1 if a firm's size exceeds the annual median, using total assets and the number of employees as alternative measures. This dichotomization aligns with the theoretical distinction between small-to-medium enterprises and large incumbents in the innovation ecosystem literature. Columns (1) and (2) of **Table 4** report results using the asset-based measure. The coefficients on *AI_Spat* (1.1768, $p < 0.01$) and *AI_Econ* (0.9988, $p < 0.01$), which represent the effects for below-median firms, are positive, while the interaction terms are significantly negative (-0.6545, $p < 0.01$; -0.4862, $p < 0.01$). Columns (3) and (4) report results using the employee-based size measure, with the same pattern: positive coefficients on *AI_Spat* (1.6033, $p < 0.01$) and *AI_Econ* (1.3758, $p < 0.01$), and significantly negative interaction terms (-1.4264, $p < 0.01$; -1.0979, $p < 0.01$). On average, the marginal effect of UAID declines with firm size.

Table 4 Moderating role of firm size: dummy specification

Variable	<i>Value_std</i>			
	Asset-based firm size		Employee-based firm size	
	(1)	(2)	(3)	(4)
<i>AI_Spat</i>	1.1768*** (0.3016)		1.6033*** (0.2893)	
<i>FirmSize</i> × <i>AI_Spat</i>	-0.6545*** (0.2441)		-1.4264*** (0.2492)	
<i>AI_Econ</i>		0.9988*** (0.2261)		1.3758*** (0.2286)
<i>FirmSize</i> × <i>AI_Econ</i>		-0.4862*** (0.1622)		-1.0979*** (0.1677)
<i>FirmSize</i>	0.0016 (0.0047)	0.0019 (0.0047)	0.0176*** (0.0046)	0.0184*** (0.0046)
_cons	-1.0354*** (0.0994)	-1.0364*** (0.0995)	-1.0017*** (0.0940)	-1.0071*** (0.0940)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795
Adj.R ²	0.0780	0.0782	0.0796	0.0801

The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

The dichotomous specification, however, imposes a single step at the median and thus captures only the average decline; it cannot detect nonlinearity at the lower tail of the size

distribution. We therefore divide the sample into small, medium, and large groups based on annual terciles of total assets and estimate the baseline model separately for each group. The results, presented in **Table 5**, reveal a pronounced lower-tail threshold. The smallest tercile shows statistically insignificant coefficients (-0.1642 and 0.3333 , both $p > 0.10$), the middle tercile exhibits the strongest response (1.5467 and 1.2705 , both $p < 0.01$), and the largest tercile also responds positively (1.0458 and 0.8524 , both $p < 0.10$). Chow-type tests indicate that the difference between the medium and small groups is statistically significant ($p = 0.0085$ for *AI_Spat*; $p = 0.0460$ for *AI_Econ*), whereas the difference between the medium and large groups is not ($p = 0.5103$ and 0.4767 , respectively). The evidence thus points to an absorptive capacity threshold at the lower end of the size distribution: very small firms lack the absorptive capacity to decode and internalize localized AI knowledge, while firms at or above the middle tercile respond comparably.

Table 5 Subsample regressions by terciles of firm size

Variable	Value std					
	Small		Medium		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>AI_Spat</i>	-0.1642 (0.4370)		1.5467*** (0.4807)		1.0458* (0.5896)	
<i>AI_Econ</i>		0.3333 (0.2965)		1.2705*** (0.3643)		0.8524* (0.4610)
_cons	-0.0616 (0.1063)	-0.0479 (0.1061)	0.1619*** (0.0537)	0.1673*** (0.0532)	0.2360 (0.2288)	0.2438 (0.2289)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16970	16970	16974	16974	17137	17137
Adj.R ²	0.0971	0.0972	0.0692	0.0692	0.0478	0.0477

Based on the annual terciles of firm size (assets) across the entire sample, the sample was divided into three groups (small, medium, and large). The set of control variables is identical to that in Table 3. Chow-type tests indicate significant coefficient differences between small and medium firms ($p < 0.05$ for *AI_Spat*; $p < 0.10$ for *AI_Econ*), whereas medium and large firms exhibit statistically indistinguishable responses ($p > 0.10$). The p -values for the Chow test between column (1) and column (3), column (1) and column (5), and column (3) and column (5) are as follows: 0.0085, 0.0992 and 0.5103; the p -values for the Chow test between column (2) and column (4), column (2) and column (6), and column (4) and column (6) are as follows: 0.0460, 0.3436 and 0.4767. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

As a robustness check, we replace the dummy variable with the natural logarithms of total assets and employee headcount. The results, reported in **Table A4** of the Appendix, corroborate the average negative gradient: the interaction term is negative and significant for *AI_Econ* (-0.1488 , $p < 0.10$ with the asset-based measure; -0.1926 , $p < 0.05$ with the employee-based

measure) and for AI_Spat using the employee-based measure ($-0.2745, p < 0.05$), though it is statistically indistinguishable from zero for AI_Spat using the asset-based measure ($-0.1999, p > 0.10$). Consistent with the tercile evidence, these linear specifications capture the average decline in marginal effects but mask the lower-tail nonlinearity documented above.

4.2.2 Absorptive Capacity Proxied by R&D Intensity

We proxy absorptive capacity by R&D intensity (RDI), calculated as R&D expenditures scaled by operating revenue. To net out industry differences in innovation norms, we construct an industry-adjusted measure, $IndAdj.RDI_{i,t} = \frac{RDI_{i,t} - Ind.meanRDI_j}{Ind.sdRDI_j}$, where $Ind.meanRDI_j$ and $Ind.sdRDI_j$ denote the mean and standard deviation of RDI among firms in industry j (CSRC 2-digit level), respectively. We divide the sample into low, medium, and high groups based on terciles of industry-adjusted RDI within each industry–year cell and re-estimate the baseline model for each group; the industry-adjusted measure enters the interaction specifications reported below. As reported in **Table 6**, point estimates are largest in the middle tercile ($0.8421, p < 0.10$ for AI_Spat ; $0.7139, p < 0.05$ for AI_Econ) and smaller in both tails: the high-RDI tercile yields statistically insignificant coefficients (0.4029 and 0.5534 , both $p > 0.10$), while the low-RDI tercile yields an insignificant estimate for AI_Spat ($0.6424, p > 0.10$) and a marginally significant one for AI_Econ ($0.5648, p < 0.10$). This ordering is directionally consistent with the threshold pattern documented for firm size. At the same time, Chow-type tests do not reject coefficient equality across the three groups ($p > 0.10$ for all pairwise comparisons), so we interpret the RDI pattern as suggestive rather than conclusive: directionally consistent with, but statistically weaker than, the size-based threshold.

Table 6 Subsample regressions by industry–year terciles of r&d intensity

Variable	<i>Value std</i>					
	Low <i>IndAdj.RDI</i>		Medium <i>IndAdj.RDI</i>		High <i>IndAdj.RDI</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>AI_Spat</i>	0.6424 (0.4561)		0.8421* (0.4621)		0.4029 (0.4080)	
<i>AI_Econ</i>		0.5648* (0.3290)		0.7139** (0.3369)		0.5534 (0.3695)
_cons	-1.1325*** (0.1634)	-1.1300*** (0.1638)	-0.8795*** (0.1486)	-0.8756*** (0.1491)	-0.6565*** (0.2094)	-0.6514*** (0.2050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13983	13983	13461	13461	13194	13194
Adj.R ²	0.0848	0.0849	0.0853	0.0854	0.0857	0.0860

Based on the “industry–year” terciles of the industry-adjusted RDI in the sample, the sample was divided into three groups (low *IndAdj.RDI*, medium *IndAdj.RDI*, and high *IndAdj.RDI*). The set of control variables is identical to that in Table 3. A Chow-type test fails to reject equality of coefficients across subsamples ($p > 0.10$). The p -values for the Chow test between column (1) and column (3), column (1) and column (5), and column (3) and column (5) are as follows: 0.7584, 0.6955 and 0.4761; the p -values for the Chow test between column (2) and column (4), column (2) and column (6), and column (4) and column (6) are as follows: 0.7515, 0.9817 and 0.7483. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

Table A5 in the Appendix reports the corresponding linear interaction specification. The coefficients on $IndAdj.RDI \times AI_Spat$ (0.1649, $p < 0.10$) and $IndAdj.RDI \times AI_Econ$ (0.1327, $p < 0.05$) are positive, indicating that, on average, R&D intensity amplifies the marginal effect of UAID. Set against the tercile evidence, however, this average gradient appears to be driven primarily by the contrast between low- and medium-RDI firms: once firms attain moderate innovation capability, additional R&D intensity no longer strengthens the response, plausibly because highly innovative firms possess sufficient internal pipelines to self-provision AI knowledge and thus rely less on regional density.

The analyses across firm size and R&D intensity reveal a consistent cross-dimensional pattern: the spatial compensatory effect is not monotonically increasing in resource scarcity but peaks among moderately endowed firms. Firms below the threshold (very small firms and, directionally, low-RDI firms) lack the capacity to decode and internalize localized AI knowledge, and the statistical support for this lower-tail threshold is strongest in the size dimension, where the contrast between the medium and small groups is significant. At the upper end of the distribution, large incumbents continue to benefit at levels statistically comparable to medium-sized firms, whereas highly innovative firms exhibit weaker and imprecisely estimated responses, hinting at self-provisioning of AI knowledge. Medium-sized and

moderately innovative firms, those possessing baseline absorptive capacity and organizational flexibility yet lacking the scale to self-provision AI capabilities, thus appear to capture a disproportionate share of the value. This cross-dimensional convergence supports the spatial compensatory effect with an absorptive capacity threshold, largely consistent with H2, though the statistical support is stronger in the size-based tests than in the RDI-based tests.

4.3 Mechanism Analysis: CTKR

4.3.1 Technological Evolution

Following Qu et al. (2026), we construct an AI dictionary using machine learning methods and search patent titles and abstracts for AI-related keywords to identify firms' annual AI patent filings. This keyword-based approach aligns with validated AI patent classification methodologies that combine machine learning with expert human coding (Giczy et al., 2022). We then decompose this evolution into breadth and depth.

Evolutionary breadth captures diversification across IPC subclasses:

$$Evolution_Breadth_{i,t} = 1 - \sum_{p=1}^n \left(\frac{x_{i,p,t}}{X_{i,t}} \right)^2 \quad (7)$$

where $x_{i,p,t}$ is the number of AI patents under IPC subclass p , and $X_{i,t}$ is the total number of AI patents. Higher values indicate a broader cognitive horizon.³

Evolutionary depth captures the cumulative deepening of a firm's AI knowledge, reflected in the extent to which its new AI patents build upon the prior stock of AI knowledge in the field, whether that stock was developed by the firm itself or by other actors.

$$Evolution_Depth_{i,t} = \ln(New\ AI\ Patents\ Citing\ AI\ Patents_{i,t} + 1) \quad (8)$$

Table 7 reports the results. *AI_Spat* significantly increases both evolutionary breadth (1.4385, $p < 0.01$) and evolutionary depth (5.4314, $p < 0.01$). *AI_Econ* shows similar effects (1.4806 and 4.0693, both $p < 0.01$). These results support H3: UAID promotes the diversification and deepening of firms' AI knowledge. The findings remain significant in the IV estimates (Panel B of **Table 7**).

Table 7 How UAID shapes internal ai knowledge: the evolution pathway

Panel A: The impact of UAID on internal technology evolution (OLS)				
Variable	<i>Evolution_Breadth</i> (1)	<i>Evolution_Depth</i> (2)	<i>Evolution_Breadth</i> (3)	<i>Evolution_Depth</i> (4)
<i>AI_Spat</i>	1.4385*** (0.3872)	5.4314*** (1.3629)		
<i>AI_Econ</i>			1.4806*** (0.3191)	4.0693*** (1.0230)
_cons	-1.4610*** (0.0882)	-5.6660*** (0.3463)	-1.4575*** (0.0883)	-5.6638*** (0.3463)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795
Adj.R ²	0.1845	0.1884	0.1849	0.1882
Panel B: Second-stage IV estimates				
Variable	<i>Evolution_Breadth</i> (1)	<i>Evolution_Depth</i> (2)	<i>Evolution_Breadth</i> (3)	<i>Evolution_Depth</i> (4)
<i>AI_Spat</i>	3.8361*** (1.0373)	15.9944*** (3.4616)		
<i>AI_Econ</i>			3.8993*** (1.0537)	16.2576*** (3.5314)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795

First-stage results and diagnostic tests are reported in Table 13. The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

4.3.2 Technological integration

AI can serve as a “bridge” between previously unconnected fields (Qu et al., 2026), helping inventors discover unrecognized knowledge combinations in high-dimensional spaces by escaping local search traps (Agrawal et al., 2024). The second pathway through which the carrier activates GPT potential is technological integration: the embedding of AI knowledge into non-AI technological domains through cross-domain recombination. Patent citations trace such knowledge combinations, allowing us to observe AI integration into firms’ wider technological portfolios.

Integration breadth captures the scope of cross-boundary recombination:

$$Integration_Breadth_{i,t} = 1 - \sum_{p=1}^n \left(\frac{q_{i,p,t}}{Q_{i,t}} \right)^2 \quad (9)$$

where $q_{i,p,t}$ is the number of new non-AI patents citing AI patents under IPC subclass p , and $Q_{i,t}$ is the total number of new non-AI patents citing AI patents. Higher values indicate that AI-linked recombination spans a wider range of technological fields.⁴

Integration depth captures how deeply AI is embedded in the firm's non-AI technological domains:

$$Integration_Depth_{i,t} = \ln(New\ Non\text{-}AI\ Patents\ Citing\ AI\ Patents_{i,t} + 1) \quad (10)$$

Table 8 reports the results. *AI_Spat* marginally increases integration breadth (0.6742, $p < 0.10$) but has no statistically significant effect on integration depth (-0.2959, $p > 0.10$). *AI_Econ* shows the same ordering at smaller magnitudes (0.3558, $p > 0.10$; 0.1533, $p > 0.10$). These estimates suggest that UAID primarily broadens the scope of cross-boundary technology integration, while its effect on deep structural embedding is statistically indistinguishable from zero. The marginal OLS effect on integration breadth is sensitive to the clustering scheme (**Tables A6 and A7**), whereas the IV estimates reported below are significant at the 1% level.

Panel B reports the IV estimates. The coefficients on integration breadth become significant at the 1% level (3.0309 for *AI_Spat*; 3.0808 for *AI_Econ*), suggesting that the OLS estimates are attenuated; as in Section 4.3, we interpret these IV coefficients as local average treatment effects bearing on the direction and robustness of the breadth effect rather than its population magnitude. The coefficients on integration depth remain insignificant (4.5599 for *AI_Spat*; 4.6350 for *AI_Econ*). These results provide partial support for H4: UAID broadens the scope of cross-domain technology-knowledge recombination, but we find no robust evidence that it deepens structural embedding.

Table 8 How UAID shapes cross-domain embedding: the integration pathway

Panel A: The impact of UAID on cross-domain technology-knowledge recombination (OLS)				
Variable	<i>Integration_Breadth</i>	<i>Integration_Depth</i>	<i>Integration_Breadth</i>	<i>Integration_Depth</i>
	(1)	(2)	(3)	(4)
<i>AI_Spat</i>	0.6742*	-0.2959		
	(0.3781)	(1.0609)		
<i>AI_Econ</i>			0.3558	0.1533
			(0.3104)	(0.8350)
_cons	-1.5678***	-4.1901***	-1.5685***	-4.1876***
	(0.0906)	(0.2894)	(0.0907)	(0.2893)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795
Adj.R ²	0.1886	0.2109	0.1885	0.2109
Panel B: Second-stage IV estimates				
Variable	<i>Integration_Breadth</i>	<i>Integration_Depth</i>	<i>Integration_Breadth</i>	<i>Integration_Depth</i>
	(1)	(2)	(3)	(4)
<i>AI_Spat</i>	3.0309***	4.5599		
	(1.0285)	(2.8527)		
<i>AI_Econ</i>			3.0808***	4.6350
			(1.0454)	(2.8983)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795

First-stage results and diagnostic tests are reported in Table 13. The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

5 Robustness checks

5.1 Alternative measurement of core variables

To mitigate potential measurement error, we reconstruct both explanatory and dependent variables. First, we replace the baseline independent variables with the growth rate of AI-related enterprises in each city to capture the dynamic expansion of the AI industry. Columns (1) and (2) in **Table 9** report the coefficients of 0.3016 ($p < 0.01$) for *AI_Spat* and 1.4263 ($p < 0.01$) for *AI_Econ*, both significantly positive.

Second, we employ the relative share of AI-related patents as an alternative proxy:

$$AI_patent_{c,t} = \frac{AI \text{ Patents Filed or Granted}_{c,t}}{Total \text{ Patents Filed or Granted}_{c,t}}. \text{ Columns (3) and (4) report coefficients of 0.0938 (} p$$

< 0.01) and 0.2082 ($p < 0.01$) for *AI_Patent*, confirming that the positive effect remains robust.

Third, we substitute the dependent variable with non-standardized value added (*Value*) and Economic value added (*EVA*). Columns (5) and (6) report coefficients of 0.2386 ($p < 0.01$) for *AI_Spat* and 0.1821 ($p < 0.05$) for *AI_Econ* with non-standardized value added, confirming that the baseline conclusions hold for this alternative metric. Columns (7) and (8) report that *AI_Spat* significantly enhances *EVA* (1.4494, $p < 0.01$), whereas the coefficient for *AI_Econ* (0.5307, $p > 0.1$) is statistically indistinguishable from zero. We also re-standardize firm value added using two alternative transformations: a Z-score within industry-year cells and a Min-Max transformation using the full-sample minimum and maximum. The coefficients remain significant in both cases (at least at the 5% level; see **Table A2**).

Table 9 Robustness: alternative measures of key variables

Variable	<i>Value std</i>				<i>Non-standardized VA</i>		<i>EVA</i>	
	Growth-rate measures		Patent-share proxy					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>AI_Spat</i>	0.3016*** (0.0967)				0.2386*** (0.0781)		1.4494*** (0.4342)	
<i>AI_Econ</i>		1.4263*** (0.5429)				0.1821*** (0.0538)		0.5307 (0.3447)
<i>AI_Patent</i>			0.0938*** (0.0363)	0.2082*** (0.0582)				
_cons	-0.9986*** (0.0899)	-1.0011*** (0.0900)	-0.9984*** (0.0895)	-0.9985*** (0.0895)	-0.3182*** (0.0225)	-0.3181*** (0.0224)	0.2671*** (0.0987)	0.2637*** (0.0987)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	51795	51795	51795	51795	51795	51795	51795	51795
Adj.R ²	0.0778	0.0775	0.0775	0.0778	0.2642	0.2639	0.0777	0.0771

The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

5.2 Controlling for high-dimensional fixed effects

To address potential bias from unobserved time-invariant heterogeneity at the industry and regional level, we introduce high-dimensional fixed effects (**Table 10**). Because firm fixed effects absorb time-invariant industry and locational attributes only for firms that never change industry or city, we additionally incorporate industry and city fixed effects to absorb heterogeneity arising from industry reclassification and firm relocation. Columns (1) and (2) incorporate industry fixed effects to absorb time-invariant industry heterogeneity. Columns (3) and (4) add city fixed effects to absorb time-invariant city characteristics. Columns (5) and (6) simultaneously include industry and city fixed effects alongside firm and year fixed effects.

Across all specifications, the coefficients for AI_Spat (e.g., 0.6769, $p < 0.05$ in column 5) and AI_Econ (e.g., 0.5367, $p < 0.01$ in column 6) remain positive and significant. This indicates that the baseline effect is not driven by time-invariant industry or city heterogeneity.

Table 10 Robustness: high-dimensional fixed effects

Variable	<i>Value std</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
AI_Spat	0.6634** (0.2624)		0.6730** (0.2809)		0.6769** (0.2652)	
AI_Econ		0.5622*** (0.1976)		0.5983*** (0.2151)		0.5367*** (0.1983)
_cons	-0.8655*** (0.0881)	-0.8649*** (0.0881)	-0.9579*** (0.0908)	-0.9534*** (0.0909)	-0.8356*** (0.0933)	-0.8309*** (0.0934)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes
City FE	No	No	Yes	Yes	Yes	Yes
N	51795	51795	51795	51795	51795	51795
Adj.R ²	0.1835	0.1835	0.0829	0.0830	0.1876	0.1875

The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

5.3 Controlling for concurrent policies

During our sample period (2007–2024), several national digital economy initiatives may confound the relationship between UAID and firm value creation. We explicitly control for three major policies in **Table 11**.

$$Value_std_{i,j,t} = \alpha_0 + \alpha_1 UAID_{c,t} + \alpha_2 Policy_{c,t}^{(m)} + \sum_k \gamma_k X_{i,t}^{(k)} + \mu_i + \gamma_t + \varepsilon_{i,j,t} \quad (11)$$

where $Policy_{c,t}^{(m)}$ denotes one of the following policy regimes: the “Innovative Industrial Clusters Policy” (general technology agglomeration), the “Broadband China” Pilot Strategy (basic network infrastructure), or the construction of “National Next-Generation AI Innovation and Development Pilot Zones” (targeted AI policy).

Across columns (1) to (6), the coefficients for AI_Spat and AI_Econ remain positive and significant (at least at the 5% level). The net effect of UAID operates independently of these concurrent policies.

Table 11 Robustness: controlling for concurrent national policies

Variable	<i>Value_std</i>					
	IICP	IICP	BCPS	BCPS	AIPZ	AIPZ
	(1)	(2)	(3)	(4)	(5)	(6)
AI_Spat	0.6421** (0.2760)		0.6623** (0.2766)		0.6047** (0.2981)	
AI_Econ		0.5924*** (0.2109)		0.6192*** (0.2132)		0.5778*** (0.2235)
$Policy$	0.0089 (0.0054)	0.0085 (0.0054)	0.0064 (0.0055)	0.0065 (0.0055)	0.0038 (0.0050)	0.0040 (0.0049)
$_cons$	-0.9996*** (0.0899)	-0.9987*** (0.0899)	-0.9989*** (0.0899)	-0.9978*** (0.0898)	-0.9994*** (0.0901)	-0.9981*** (0.0901)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	51795	51795	51795	51795	51795	51795
Adj.R ²	0.0779	0.0779	0.0777	0.0779	0.0777	0.0778

The set of control variables is identical to that in Table 3. IICP: Innovative Industrial Clusters Policy; BCPS: Broadband China Pilot Strategy; AIPZ: National Next-Generation AI Innovation and Development Pilot Zones; ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

5.4 Subsample Tests

To ensure that our findings are not driven by specific firm types or sectors, we conduct subsample tests (**Table 12**). First, we exclude “SRUI” (Specialized, Refined, Unique, and Innovative) firms, whose designation confers direct government support such as subsidies and preferential financing; this checks whether the baseline effect hinges on this policy-favored subgroup. Second, we exclude high-tech firms to ensure results are not driven by industry-specific tax incentives. Third, we exclude AI firms² to ensure results are not driven by the unique characteristics of the AI sector. Columns (1) to (6) show coefficients for AI_Spat and AI_Econ that remain positive and significant (at least at the 5% level), confirming that the

findings hold across different firm types and sectors.

Finally, we restrict the sample to manufacturing firms, the sector where downstream AI application is most consequential and our value-added measure is most reliably constructed. Columns (7) and (8) show coefficients for *AI_Spat* and *AI_Econ* that remain positive and significant (at the 10% level), confirming that the baseline effect holds within manufacturing and is not driven by service-sector firms.

Table 12 Robustness: subsample tests

Variable	<i>Value_std</i>							
	Excluding SRUI Firms	Excluding SRUI Firms	Excluding High- Tech Firms	Excluding High- Tech Firms	Excluding AI Firms	Excluding AI Firms	Manufact uring Firms Only	Manufact uring Firms Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>AI_Spat</i>	0.7044** (0.3383)		0.6240** (0.3041)		0.7852*** (0.2845)		0.5230* (0.2777)	
<i>AI_Econ</i>		0.6134** (0.2570)		0.6022** (0.2383)		0.7465*** (0.2254)		0.3881* (0.2078)
_cons	-1.0092*** (0.1001)	-1.0079*** (0.1001)	-0.9864*** (0.0924)	-0.9851*** (0.0924)	-0.9428*** (0.0957)	-0.9428*** (0.0955)	-0.8742*** (0.1295)	-0.8746*** (0.1296)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	40411	40411	45333	45333	46634	46634	34158	34158
Adj.R ²	0.0762	0.0762	0.0763	0.0764	0.0769	0.0770	0.1130	0.1130

The set of control variables is identical to that in Table 3. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

5.5 Addressing endogeneity: instrumental variable estimates

To address potential endogeneity, such as omitted variable bias and reverse causality, we employ a two-stage least squares (2SLS) approach. We construct the instrumental variable ($IV_{c,t}$) as the interaction between a city's university endowment in AI and digital majors and whether it is a backbone city of China's national fiber optic transmission network:

$$IV_{c,t} = PCT_c \times AI\ Major_{c,t} \quad (12)$$

where $PCT_c = 1$ if the city is a backbone city of the national fiber optic network, and $AI\ Major_{c,t}$ captures the university's AI program endowment in city c by year t .

The relevance and exclusion restriction are justified as follows. For relevance, universities offering AI and digital programs supply technological talent and knowledge that directly foster

local AI industry growth, and the strong first-stage estimates reported below bear this out. For exclusion, the approval of university majors rests with national education authorities and follows medium-to-long-term strategic plans rather than contemporaneous firm-level conditions, while the fiber-optic backbone cities were designated in the 1990s on geographic and communication grounds, well before the AI era. The interaction thus isolates variation in AI industry density produced by layering a policy-regulated educational expansion onto a predetermined infrastructure endowment. Two qualifications apply. University AI programs could in principle affect firms directly through graduate labor supply and university-industry collaboration; our city-level controls, including the high-tech firm share and government S&T support, absorb the broad innovation-environment component of such channels, and any residual direct effect would bias the estimates away from a pure density interpretation only insofar as it operates independently of local AI industry scale. Likewise, the predetermined backbone endowment is plausibly unrelated to current firm value creation except through local digital conditions, which we account for by controlling for the Broadband China pilots.

Table 13 presents the 2SLS results. Panel A uses the cumulative number of AI or digital majors established in city c by year t as the university component, denoted $AI\ Major_{c,t}$. Columns (1) and (3) report the first-stage regressions: the coefficients of the instrumental variable are positive and significant (0.0070 and 0.0068, both $p < 0.01$). Columns (2) and (4) report the second-stage results: after addressing endogeneity, the coefficients of AI_Spat (1.6200, $p < 0.05$) and AI_Econ (1.6467, $p < 0.05$) remain positive and significant. Panel B replaces the count with a dummy, $AI\ Major_{c,t} = 1$ if city c has established any AI or digital majors by year t . The second-stage coefficients (5.6148 and 5.0878, both $p < 0.05$) corroborate the Panel A findings.

The 2SLS coefficients exceed their OLS counterparts, a pattern typical of local average treatment effects (LATE): the instrument isolates density variation driven by educational and digital infrastructure endowments rather than by endogenous demand pressures, and such infrastructure-driven expansions may yield larger marginal returns for the affected firms.

Attenuation from measurement error in the density proxies would produce the same pattern. We therefore read the 2SLS estimates as confirming the sign and robustness of the baseline effect rather than as a precise estimate of its population magnitude.

Diagnostic tests assess the instrument's identification strength. The Kleibergen-Paap rk LM statistics (727.2404 and 599.7070 in Panel A; 68.1073 and 53.8927 in Panel B, all $p < 0.01$) strongly reject underidentification. The Kleibergen-Paap rk Wald F-statistics (1069.3071 and 816.6643 in Panel A; 76.1434 and 58.1044 in Panel B) substantially exceed the Stock-Yogo 10% critical value, ruling out weak instrument concerns. Together, these diagnostics lend credibility to the 2SLS estimates.

Table 13 Endogeneity: 2SLS instrumental variable estimates

Panel A: IV = PCT × cumulative number of AI/digital majors				
Variable	<i>AI_Spat</i>	<i>Value std</i>	<i>AI Econ</i>	<i>Value std</i>
	First	Second	First	Second
	(1)	(2)	(3)	(4)
<i>IV</i>	0.0070*** (0.0002)		0.0068*** (0.0002)	
<i>AI_Spat</i>		1.6200** (0.7245)		
<i>AI_Econ</i>				1.6467** (0.7359)
<i>N</i>	51795	51795	51795	51795
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	727.2404*** [0.0000]		599.7070*** [0.0000]	
Kleibergen-Paap rk Wald F statistic	1069.3071		816.6643	
Panel B: IV = PCT × dummy for any AI/digital majors				
Variable	<i>AI_Spat</i>	<i>Value std</i>	<i>AI Econ</i>	<i>Value std</i>
	First	Second	First	Second
	(1)	(2)	(3)	(4)
<i>IV</i>	0.0013*** (0.0001)		0.0014*** (0.0002)	
<i>AI_Spat</i>		5.6148** (2.7090)		
<i>AI_Econ</i>				5.0878** (2.4766)
<i>N</i>	51795	51795	51795	51795
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	68.1073*** [0.0000]		53.8927*** [0.0000]	
Kleibergen-Paap rk Wald F statistic	76.1434		58.1044	

The set of control variables is identical to that in Table 3. The instrumental variable is constructed as $IV_{c,t} = PCT_c \times AI\ Major_{c,t}$, where $PCT_c = 1$ if the city is a backbone city of the national fiber optic network. In Panel A, $AI\ Major_{c,t}$ denotes the cumulative number of AI and digital majors established in city c by year t . In Panel B, $AI\ Major_{c,t} = 1$ if city c has established any AI or digital majors by year t . ***, **, and * denote significance levels of

1%, 5%, and 10%, respectively; the values in parentheses are robust standard errors clustered at the firm level.

6 Discussion

For a general-purpose technology such as AI, technical potential translates into firm value creation only when firms can access and recombine complementary knowledge produced beyond their boundaries (Bresnahan & Trajtenberg, 1995; Cockburn et al., 2018). Our results show that urban AI industry density (UAID) supplies precisely such a condition: firms located in cities with denser AI industries exhibit significantly higher value creation. This effect operates through complementary technology-knowledge recombination (CTKR): the evolution of firms' AI knowledge and its cross-domain integration. UAID therefore functions not merely as a co-location pattern but as a spatial organizational carrier, suggesting that it lowers the search, absorption, and coordination costs of accessing external AI knowledge. Its benefits are unevenly distributed, however: the value effect is strongest among firms with moderate endowments, those possessing baseline absorptive capacity yet lacking the scale to self-provision AI capabilities, and weakens at both ends of the distribution. Absent such infrastructural conditions, AI-driven value creation tends to concentrate within a minority of dominant firms (Babina et al., 2024); UAID thus shapes not only whether AI creates value but also how that value is distributed across heterogeneous firms.

6.1 Discussion of core findings

Our baseline results support the conceptualization of UAID as a spatial organizational carrier. Both density dimensions exert positive effects on firm value creation that are robust across specifications and under instrumental-variable estimation. Whereas strategic management research traditionally emphasizes internal complementary assets (Bresnahan et al., 2002; Teece, 1986), these findings qualify this boundary-centric assumption: complementary assets need not be owned to be productive, as UAID concentrates them regionally and renders them accessible to firms that cannot self-provision. Teece's (2018) account of value creation in the digital economy points the same way: strategic success increasingly depends on external facilitators rather than isolated internal assets. Because the knowledge required to adapt generic algorithms

to specific operational contexts is tacit and spatially sticky, absorption hinges on local interactions, collaborative networks, and localized human capital (Almeida & Kogut, 1999; Boschma, 2005). Technical intermediaries, the actors through which the local AI sector reaches downstream industries, plausibly serve as the operational agents of the carrier's translation function, converting complex algorithms into domain-specific, deployable applications for heterogeneous firms. The carrier account extends entrepreneurial ecosystem research beyond venture creation: the same regional organization that supplies entrepreneurial opportunities (Autio et al., 2018) also conditions which incumbent firms can access AI knowledge.

The efficacy of the carrier, however, is not uniform across the firm capability spectrum. Our threshold tests reveal a critical boundary condition: the spatial compensatory effect does not increase monotonically with resource scarcity. The most robust evidence concerns the lower tail: the effect is absent for very small firms and directionally absent for low-innovation firms, while moderately endowed firms exhibit clear positive responses. At the upper end, the pattern is directionally consistent but statistically weaker: large incumbents benefit at levels comparable to medium-sized firms, whereas highly innovative firms exhibit weaker, imprecisely estimated responses, plausibly because they can self-provision AI knowledge. This pattern refines absorptive capacity theory (Cohen & Levinthal, 1990; Teece, 1986): absorptive capacity operates as a participation threshold governing the returns to regional knowledge transfer infrastructure, not merely as a performance gradient. The result is a pattern of selective substitution: the carrier substitutes for the scale-intensive self-provisioning of AI capabilities, but not for the baseline absorptive capacity that participation requires. External infrastructure and internal capability thus operate as substitutes above the threshold and as complements below it.

For these moderately endowed firms, the carrier operates as an external substitute for self-provisioning: lacking the scale to build proprietary AI capabilities, they can leverage the carrier's pre-translated modules to embed AI directly into value-creating activities. Large incumbents benefit comparably but are plausibly less dependent on the carrier, given their internal pipelines; the carrier's distinctive contribution thus lies in widening participation in AI

diffusion for firms below the self-provisioning frontier. This finding extends innovation ecosystem research, which typically adopts a focal-firm perspective and presumes sufficient strategic leverage to orchestrate multilateral complementarities (Adner & Kapoor, 2010; Jacobides et al., 2018): regional industry density itself, absent any focal orchestration, lowers the marginal cost of complementary innovation for moderately endowed firms.

Our findings also speak to emerging firm-level evidence on knowledge sourcing in the AI era. D’Amico et al. (2025) show that AI adoption enhances innovation performance when it complements internal R&D, and that it can substitute for knowledge collaboration with certain external partners, framing external knowledge as an object of strategic choice. Our results provide the regional supply-side condition under which such choices operate. The option to substitute AI adoption for external collaboration, or to combine the two, presupposes that external AI knowledge is available, intelligible, and affordable; the carrier shapes these parameters, plausibly by lowering the search, absorption, and coordination costs of accessing it. In low-density regions, the substitution-complementarity calculus collapses, not because firms choose poorly, but because the external option is effectively unavailable. Our absorptive capacity threshold echoes their complementarity logic at the regional level: just as AI adoption pays off only atop internal R&D in their setting, the carrier yields disproportionate returns only for firms with baseline internal capabilities in ours. Together, these findings suggest that AI-era knowledge sourcing is best understood as a firm-level choice made on a regionally given cost curve, and that regional transfer infrastructure shifts that curve, while absorptive capacity determines whether a firm can climb it.

6.2 Mechanisms: micro-dynamics of complementary recombination

Our mechanism analysis identifies two micro-level pathways: technological evolution (expanding internal AI knowledge) and technological integration (embedding AI into non-AI domains through cross-domain recombination). This dual-pathway structure also gives empirical content, at the firm level, to GPT attributes that have proven difficult to operationalize: the evolution pathway corresponds to pervasiveness, and the integration pathway to innovation complementarity (Bresnahan & Trajtenberg, 1995; Cockburn et al., 2018; David, 1990). The

two pathways appear to draw on different regional inputs: localized spillovers of tacit AI know-how feed internal knowledge accumulation (the enabling mechanism), whereas the carrier's translated, modular outputs lower the cost of linking AI to non-AI domains (the bridging mechanism).

Whereas UAID significantly expands both dimensions of technological evolution, its effect on integration is uneven: it expands integration breadth, an effect that is weak in OLS but becomes robustly significant in the IV estimates, while its effect on integration depth remains statistically indistinguishable from zero across both density measures and both estimators. The breadth expansion reflects a process akin to triadic closure (cf. Qu et al., 2026): as heterogeneous non-AI domains individually integrate locally translated AI knowledge, they become “bridgeable” through shared AI nodes. The contrast between the two depth effects is instructive: deepening AI knowledge within the firm's existing technological trajectory requires only cumulative internal search, whereas embedding AI deeply into non-AI domains requires reconfiguring the architectures of those domains themselves.

Our measure captures the intensity of codified cross-domain embedding, the volume of non-AI patents building on AI knowledge, so the null strictly indicates that firms in denser regions do not exhibit detectably more intensive citation-based coupling; it does not speak directly to organizational reconfiguration. Within this limit, an organizational account is plausible: deep structural embedding of AI knowledge into core non-AI domains requires more than accessible regional knowledge nodes; it demands sustained managerial commitment, cross-functional coordination, and fundamental reconfiguration of existing operational architectures, conditions that are inherently firm-specific, path-dependent, and socially complex. Moreover, as bridging technologies shift their central positions within regional knowledge spaces over time (Basilico & Graf, 2023), any completed embedding depreciates; deep integration therefore requires continuous organizational adaptation rather than one-time reconfiguration. UAID can facilitate but not substitute for these internal transformations, and the depth of structural embedding remains contingent on internal organizational readiness, pointing to firm-level factors, such as dynamic capabilities or top management team

composition, as boundary conditions for future research.

The two pathways thus mark the boundary between what UAID can externalize and what remains for firms to internalize. The carrier can fully supply the inputs for internal knowledge accumulation: both the breadth and depth of technological evolution respond to density. For cross-domain integration, by contrast, UAID externalizes access but not embedding: it broadens the set of domains that become bridgeable through shared AI knowledge, while the depth of structural embedding remains, so far as our citation-based measure can detect, the firm's own work.

7 Implications, limitations and future research

7.1 Theoretical implications

Identifying a spatial compensatory effect with an absorptive capacity threshold. The threshold pattern documented in Section 4.4 moves absorptive capacity theory (Cohen & Levinthal, 1990) from a continuous performance gradient to a discrete participation threshold, and thereby recasts what regions do for firms: the spatial organization of AI supply is not an exogenous backdrop but an active structural force that widens participation in AI diffusion, reconfiguring the competitive boundaries between dominant incumbents and mid-sized competitors. This pattern also extends the KBV's knowledge-glue logic to the spatial-industrial domain (Bergh et al., 2025; Grant, 1996): the carrier functions as a spatial glue whose efficacy is contingent on the recipient's baseline absorptive capacity. For research on small-to-medium enterprises, the threshold specifies the capability floor below which even a well-developed ecosystem cannot help.

Theorizing the regional infrastructure of knowledge transfer. Classic transfer research locates the boundary work of translation within dyadic, intentional relationships (Argote & Ingram, 2000; Carlile, 2004), while spillover accounts relax intentionality only by dissolving structure (Audretsch & Feldman, 1996). The carrier bridges these poles: structured yet non-dyadic, it performs concentration, translation, and transmission at the regional level for anonymous, heterogeneous recipients who never enter formal collaboration. The analytical

question thus shifts from “who transfers knowledge to whom?” to “what regional infrastructural conditions make transfer possible at scale?”, making the measurement and explanation of regional variation in transfer infrastructure a prerequisite for understanding the uneven spatial diffusion of general-purpose technologies.

Reconceptualizing GPT realization through a spatial-organizational lens. Classic GPT accounts define the intrinsic attributes of general-purpose innovations (Bresnahan & Trajtenberg, 1995; David, 1990) but treat their micro-level diffusion as spatially frictionless. By showing that the regional organization of AI supply conditions the conversion of latent AI potential into firm-level value, we reframe the foundational inquiry from “What constitutes a GPT?” to “What regional organizational structures actualize GPT properties for heterogeneous firms?”, offering a spatial-organizational reading of the productivity paradox. This lens opens two avenues: carrier deficiency may explain why GPTs fail to diffuse in certain regions, extending the productivity paradox from a firm-level failure to a spatial-structural failure; and if carrier efficacy depends on how completely the three transfer functions are performed, carrier design becomes a question for theory and policy in its own right: what mix of spatial and economic density minimizes the marginal cost of complementary recombination for different firm types?

Operationalizing GPT complementary recombination through two patent-based pathways. Prior work treats GPT-driven organizational adjustment as an unobservable black box (Brynjolfsson et al., 2017; Cockburn et al., 2018) or locates AI’s bridging potential at the invention level without examining its spatial accessibility (Qu et al., 2026). Our two patent-based pathways, technological evolution and technological integration, provide replicable micro-level measures that trace how macro-level regional density gives rise to micro-level technological recombination, complementing firm-level accounts of AI adoption and search (Zhou et al., 2026).

7.2 Practical implications

For policymakers, our findings recast the policy problem: the bottleneck in AI-driven

productivity is often not the supply of AI producers but the effectiveness of the regional transfer infrastructure that moves AI knowledge to adopters. Policy focus should therefore shift from subsidizing individual firm adoption, or merely attracting AI firms to raise local headcounts, toward cultivating the carrier's three transfer functions. Concentration can be supported by co-locating AI knowledge providers with traditional industrial firms. Translation can be strengthened by investing in technical intermediaries, demonstration platforms, and standards-setting bodies that convert generic algorithms into domain-specific, deployable modules. Transmission can be reinforced via supplier–customer interfaces, labor-market mobility, and technical standards, the channels through which translated knowledge reaches heterogeneous firms. By the same logic as our threshold results, such functional investments can lower the effective participation threshold itself, bringing more firms within reach of the compensatory effect and broadening the distribution of AI's economic dividends beyond the most resource-rich incumbents. For SME policy, the implication is that adoption subsidies and ecosystem cultivation are complements rather than substitutes: subsidies without transfer infrastructure leave below-threshold firms unable to absorb what they are given.

For managers, the prescriptions vary by endowment. Medium-sized and moderately innovative firms, the primary beneficiaries of the spatial compensatory effect, can exploit their organizational flexibility to absorb and deploy the carrier's translated modules; locating in regions with well-developed transfer infrastructure lets them tap localized tacit knowledge spillovers instead of building costly proprietary AI assets from scratch. Very small firms should prioritize building baseline absorptive capacity, including technical personnel training and foundational digital infrastructure, before expecting co-location to generate value. Large incumbents continue to benefit from regional density, though they are plausibly less dependent on it given their internal pipelines; for them, the carrier's value lies less in substituting for proprietary capability than in widening the range of bridgeable domains. Across all firm types, geographic proximity alone is insufficient: because UAID expands the breadth of cross-domain linkages but not the depth of structural embedding, co-location must be coupled with purposeful organizational learning that builds internal absorptive capacity and carries external AI

knowledge into core domains.

7.3 Limitations and future research

First, our measurement strategy captures scale better than depth on both sides of the relationship. The UAID measures capture regional organizational scale rather than technological depth, and the operationalization of CTKR relies exclusively on patent-based metrics, omitting non-technological complementarities such as organizational redesign, managerial practices, and business model innovation that are vital for GPT value capture. Future research could employ more granular regional indicators, such as AI R&D expenditures or open-source developer contributions, and survey-based or text-mined firm data to examine whether these non-technological complementarities substitute for or complement the technological pathways identified in this study.

Second, our mechanism evidence traces the effect of UAID to the two recombination pathways, but the onward link from these pathways to value creation is established deductively rather than tested, and the micro-processes underlying our account, the carrier's cost reductions and firms' organizational readiness for deep embedding, are inferred rather than directly observed. Future research could subject the full causal chain to formal mediation tests and measure these processes more proximally, for example through surveys of knowledge search or fine-grained data on firm–intermediary interactions.

Third, our analysis is static in two respects. We do not examine how the evolution and integration pathways interact over time, for instance whether firms must first accumulate internal AI knowledge through the evolution pathway before engaging in cross-domain recombination; and we treat the carrier's efficacy as fixed even though bridging technologies shift their central positions within regional knowledge spaces over time (Basilico & Graf, 2023), so that it may decay or renew. Longitudinal case studies and dynamic structural modeling could address both forms of dynamics.

Fourth, our threshold evidence rests on tercile splits and linear interaction specifications: while the lower-tail threshold is statistically robust in the size dimension, the upper-end decline

(self-provisioning among highly innovative firms) is directionally consistent but not statistically confirmed, particularly in the R&D intensity dimension. Moreover, our sample comprises Chinese A-share listed firms, whose smallest members remain far larger than typical small and medium-sized enterprises; the threshold we identify is therefore relative to the listed-firm population, and its relevance to unlisted SMEs awaits direct testing. Future research could employ formal threshold regression models and extend the analysis to unlisted firms and other institutional settings to test the generality of the carrier framework.

8 Conclusion

As AI integrates into industrial landscapes, the asymmetry between concentrated upstream knowledge production and dispersed downstream value realization becomes economically consequential. This study demonstrates that overcoming this asymmetry is neither automatic nor uniform; it depends on a regional knowledge transfer infrastructure. Urban AI industry density functions as a spatial organizational carrier that concentrates, translates, and transmits AI knowledge from its upstream producers to downstream adopters, activating the potential of a general-purpose technology through CTKR. Firms in denser regions expand and deepen their internal AI knowledge bases and broaden the embedding of AI into non-AI technological domains; yet these benefits hinge on the carrier's effectiveness rather than on mere geographic proximity, and the depth of structural embedding remains contingent on firm-specific organizational readiness.

For moderately endowed firms, regional density substitutes for the scale-intensive self-provisioning of AI capabilities, though not for baseline absorptive capacity itself. This spatial compensatory effect is subject to an absorptive capacity threshold at the lower end of the capability spectrum: very small firms, and directionally low-innovation firms, fail to exploit localized AI knowledge, whereas moderately endowed firms benefit substantially. At the upper end, highly innovative firms respond more modestly, consistent with self-provisioning, while large incumbents benefit at levels comparable to medium-sized firms. The carrier thus widens participation in AI diffusion above the threshold, flattening the capability gradient that would otherwise reserve AI's gains for the best-endowed firms. Ultimately, our findings reframe the

productivity paradox: the disconnect between AI potential and value creation reflects not merely a failure of firm-level technology adoption but also a structural deficit in regional knowledge transfer infrastructure. Closing this deficit requires cultivating the carrier's transfer functions (concentration, translation, and transmission) so that complementary knowledge recombination becomes accessible and actionable for moderately endowed firms. For firms without the scale to build AI capabilities of their own, the region may be the only balance sheet on which such capabilities can be found.

Notes

¹ While our empirical estimation panel covers 2007–2024, cumulative stocks for both the numerator (active AI firms) and the denominator (all new firm registrations) are traced from 2000 onward to establish a robust pre-sample baseline and mitigate left-censoring bias.

² We first draw on Han et al. (2025) to classify industries (CSRC 2-digit level) as AI-using or AI-producing, setting $TreatAI = 1$ for firms in such industries and 0 otherwise. Building on this, we identify a firm’s entry into the AI sector by the first mention of AI technology in the “construction-in-progress” section of its financial statement notes, setting $PostAI = 1$ from the year of entry onward and 0 before. When $TreatAI \times PostAI = 1$, the firm is classified as an AI firm; otherwise, it is classified as a non-AI firm.

³ If a firm files no AI patent in year t (i.e., $X_{i,t} = 0$), we set $Evolution_Breadth_{i,t}$ to 0, reflecting an absence of codified AI knowledge output.

⁴ If none of a firm’s non-AI patent applications in year t cites any AI patents (i.e., $Q_{i,t} = 0$), we set $Integration_Breadth_{i,t}$ to 0, reflecting an absence of cross-domain AI knowledge recombination in codified form.

References

- Adner, R., & Kapoor, R. (2010). Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal*, 31(3), 306-333.
- Agrawal, A., McHale, J., & Oettl, A. (2024). Artificial intelligence and scientific discovery: A model of prioritized search. *Research Policy*, 53(5), 104989.
- Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7), 905-917.
- Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes*, 82(1), 150-169.
- Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, 86(3), 630-640.
- Autio, E., Nambisan, S., Thomas, L. D., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, 12(1), 72-95.
- Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745.
- Balland, P. A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P., Rigby, D. L., & Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3), 248-254.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Basilico, S., & Graf, H. (2023). Bridging technologies in the regional knowledge space: measurement and evolution. *Journal of Evolutionary Economics*, 33(4), 1085-1124.
- Bergh, D. D., D'Oria, L., Crook, T. R., & Roccapiore, A. (2025). Is knowledge really the most important strategic resource? A meta-analytic review. *Strategic Management Journal*, 46(1), 3-18.
- Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies*, 39(1), 61-74.
- Boschma, R., & Capone, G. (2015). Institutions and diversification: Related versus unrelated diversification in a varieties of capitalism framework. *Research Policy*, 44(10), 1902-1914.
- Boschma, R., Minondo, A., & Navarro, M. (2013). The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. *Economic Geography*, 89(1), 29-51.
- Bozeman, B. (2000). Technology transfer and public policy: A review of research and theory. *Research Policy*, 29(4-5), 627-655.
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: 'Engines of growth'? *Journal of Econometrics*, 65(1), 83-108.
- Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1), 339-376.

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *The Economics of Artificial Intelligence: An Agenda* (pp. 23-57). *University of Chicago Press*.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1), 333-372.

Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science*, 15(5), 555-568.

Castellacci, F. (2008). Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. *Research Policy*, 37(6-7), 978-994.

Clough, D. R., & Wu, A. (2022). Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. *Academy of Management Review*, 47(1), 184-189.

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation: An exploratory analysis. In *The Economics of Artificial Intelligence: An Agenda* (pp. 115-146). *University of Chicago Press*.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128-152.

D'Amico, E., Belitski, M., Braga, A., & Savoie, R. (2025). Enhancing knowledge spillover of innovation through artificial intelligence: an empirical investigation. *The Journal of Technology Transfer*. <https://doi.org/10.1007/s10961-025-10217-7>.

David, P. A. (1990). The dynamo and the computer: an historical perspective on the modern productivity paradox. *The American Economic Review*, 80(2), 355-361.

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of Management Review*, 23(4), 660-679.

Fan, Y., Litov, L., Yang, M. J., & Zenger, T. (2026). The technological uniqueness paradox. *Strategic Management Journal*, 47(5), 1211-1243.

Gambardella, A., Heaton, S., Novelli, E., & Teece, D. J. (2021). Profiting from enabling technologies? *Strategy Science*, 6(1), 75-90.

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *The Journal of Technology Transfer*, 47(2), 476-505.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Han, M., Shen, H., Wu, J., & Zhang, X. (2025). Artificial intelligence and firm resilience: Empirical evidence from natural disaster shocks. *Information Systems Research*, 36(4), 2116-2133.

Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44(1), 82-111.

Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, 39(8), 2255-2276.

Jovanovic, B., & Rousseau, P. L. (2005). General purpose technologies. In *Handbook of Economic Growth* (Vol. 1, pp. 1181-1224). *Elsevier*.

Klinger, J., Mateos-Garcia, J., & Stathoulopoulos, K. (2021). Deep learning, deep change? Mapping the evolution and geography of a general purpose technology. *Scientometrics*, 126(7), 5589-5621.

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies*, 21(9), 1374-1391.

Levinthal, D. A., & Wu, B. (2010). Opportunity costs and non-scale free capabilities: Profit maximization, corporate scope, and profit margins. *Strategic Management Journal*, 31(7), 780-801.

Qu, X., Eggers, J. P., & Kumar, M. S. (2026). Unlocking novel knowledge recombinations: The effect of artificial intelligence on inventive activity. *Strategic Management Journal*. <https://doi.org/10.1002/smj.70080>.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2), S71-S102.

Rosenberg, N., & Trajtenberg, M. (2004). A general-purpose technology at work: The Corliss steam engine in the late-nineteenth-century United States. *The Journal of Economic History*, 64(1), 61-99.

Scott, A. J. (2006). Entrepreneurship, innovation and industrial development: Geography and the creative field revisited. *Small Business Economics*, 26(1), 1-24.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal*, 17(S2), 27-43.

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285-305.

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, 47(8), 1367-1387.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly*, 42(1), 35-67.

Zhou, Y. E., Xu, J. D., & Liu, Z. (2026). Harnessing artificial intelligence for ambidextrous innovation: Contingent roles of complementary investments. *Technovation*, 151, 103475.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterial.docx](#)