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<https://doi.org/10.1057/s41599-025-06177-w>

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Peer effects in local government decision-making on new infrastructure investment: evidence from Chinese 258 cities

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Improving infrastructure investment efficiency is critical to address global investment gap and resource constraints, thereby promoting sustainable economic development. This study aims to explore the peer effects in local governments' new infrastructure investment (NII) decision-making and uncovers the underlying mechanisms driving these effects. Utilizing panel data from 258 Chinese prefecture-level cities (2012–2022), this study employs a spatial econometric model to examine how intergovernmental spatial interactions shape the NII decision-making. Furthermore, the impacts of learning mechanism, competition mechanism, and exogenous shocks on the peer effects are explored. The findings show that: (1) Significant peer effects exist in NII decision-making of local governments across all seven spatial correlation contexts, with transportation networks and industrial linkages exerting the strongest influence. (2) Cities exhibit asymmetric imitation patterns based on their level of economic development: underdeveloped cities exhibit stronger imitation of developed counterparts, which primarily serve as benchmarks. This behaviour reflects rational adaptation strategies under uncertainty, as local governments seek to minimise risks and leverage experiential learning. (3) Learning mechanisms reinforce irrational imitation through accumulated experience, leading to self-reinforcing path dependence. Competition mechanisms—especially industrial competition in central China—are major drivers, complemented by fiscal and talent competition in central and western regions. Moreover, national policy pilots (e.g. National Big Data Comprehensive Pilot Zones) serve as pivotal reference points, accelerating policy convergence among local governments. This study offers a comprehensive understanding of the existence, asymmetry, and multidimensional drivers of peer effects in NII decision-making. It provides both theoretical and policy insights for optimizing regional infrastructure coordination and promoting sustainable inclusive development.

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Introduction

Infrastructure development serves as a fundamental driver of global economic growth, improved livelihood, and enhanced social resilience (Thacker et al., 2019). In developing countries and emerging economies, infrastructure investment plays a critical role in advancing industrialization, promoting urbanization, and narrowing the digital divide (Han et al., 2025). With the rapid pace of technological advancement, New Infrastructure Investment (NII) has emerged as a strategic priority for nations seeking to achieve technological leadership, foster digital economy growth, and promote sustainable development (Vinuesa et al., 2020; Kirikkaleli et al., 2025). New Infrastructure encompasses cutting-edge sectors such as 5G networks, big data centres, artificial intelligence, industrial internet. As the world's largest developing economy and a leading digital economy, China has institutionalized NII development in the Central Economic Work Conference in 2018, positioning it as a national strategic priority (Wang et al., 2024a; Ma et al., 2025). This policy orientation reflects China's dual objective of accelerating its domestic transition toward high-quality development while proactively responding to global technological and industrial transformations (Li et al., 2024; Yao et al., 2025).

However, NII projects are marked by rapid technological iteration, high market uncertainty, and substantial upfront investment requirements (Liu et al., 2020), all of which pose considerable risks—particularly for local governments as primary investors. The prevailing financing model, which relies heavily on fiscal expenditures and government-issued special bonds (Guo and Hu, 2024), has significantly exacerbated local fiscal stress and debt risks, while also constraining the scale and long-term sustainability of NII. More concerningly, emerging issues such as indiscriminate construction, redundant investment, and structural imbalances in certain regions (Liu et al., 2020) underscore the inherent complexity and potential inefficiency of NII decision-making process. Against this backdrop of high risk and deep uncertainty, a critical research question emerges: What drives local governments to actively promote NII projects despite these challenges, and what mechanisms shape their decision-making behaviour?

Understanding the investment decision-making behaviour of the Chinese local governments requires careful consideration of their unique institutional context and interactive dynamics. The 'promotion tournament' theory elucidates the strong incentive structures for local officials embedded in China's political system, which strongly influence local officials' behaviour (Chen et al., 2017; Que et al., 2019; Liu et al., 2023b). As a national strategic priority, NII offers significant economic multiplier effects and observable performance outcomes. They have become an effective policy tool for local governments to concentrate fiscal and administrative resources in pursuit of favourable performance evaluations (Chen and Tang, 2024; Shang et al., 2024; Zeng and Zhou, 2024). Simultaneously, substantial theoretical and empirical evidence demonstrates significant spatial and strategic interaction in local government behaviour, particularly in the domain of investment decision-making (Brueckner, 2003; Yu et al., 2016; Yu and Zhou, 2024). When local officials observe that neighbouring or economically advanced cities are actively pursuing particular policies (e.g. investment in new infrastructure), they may adjust their own behaviour in response to yardstick competition, information learning, or peer pressure to avoid falling behind (Zhu and Wei, 2024). This form of intergovernmental behavioural interdependence lies at the heart of 'peer effects'—the systematic influence of neighbouring or similar entities on a government's own decision-making. Previous studies have investigated intergovernmental interactions in various domains, such as environmental governance, labour productivity, and

education (Falk and Ichino, 2006; Xu et al., 2022; Lenard and Silliman, 2025). However, a systematic application of peer effects theory to the context of strategically significant and high-risk NII decision-making remains underexplored. Moreover, prior research on NII often relies on national or provincial-level macro data (Shang, 2020), limiting granular insights into granular, dynamic, multi-dimensional nature of city-level intergovernmental interactions and their spatial linkages. Additionally, critical gaps remain in our understanding of the magnitude of the peer effects, transmission mechanisms (e.g. competitive imitation, information learning), and heterogeneity of these effects in the complex context of NII. To address these gaps, this study leverages a panel dataset of 258 Chinese prefecture-level cities (2012–2022) to systematically investigate peer effects of the NII decision-making for the local governments. Specifically, this study seeks to answer the following research questions: (1) Do significant peer effects exist in city-level NII decision-making for the government? (2) Do asymmetric imitative behaviour exist among cities with different levels of economic development? (3) What are the underlying mechanisms and the heterogeneity for such peer effects?

Compared with existing research, this study makes three key contributions. *First*, this study introduces the peer effects theory into the field of new infrastructure for the first time and empirically reveals the existence of the peer effects in city-level NII decision-making. Further, we innovatively develop a multi-dimensional NII index at the city level, incorporating information infrastructure, integrated infrastructure, and innovation infrastructure. The composite index not only accurately captures the heterogeneous characteristics of NII across cities but also provides a solid empirical foundation for revealing peer effects. *Second*, this study employs a spatial econometric model to construct novel multi-dimensional spatial weight matrices and examine the NII decision-making process from the perspective of local government interactions. By incorporating the transportation networks and industrial linkages into the spatial matrices, the analysis more accurately reflects the complex spatial relationships among cities in the context of new infrastructure development. *Finally*, this study investigates the underlying mechanisms of the peer effects in the NII by local governments, focusing on learning mechanism, competition mechanism, and exogenous shocks. It further uncovers the significant heterogeneity in the strength and nature of the peer effects across regions, offering new insights into the behaviour logic of local governments operating in complex and uncertain policy environments.

The remainder of the paper is structured as follows: Section "Literature review" reviews the literature. Section "Theoretical framework and research hypothesis" outlines the theoretical framework and research hypotheses. Section "Methodology and data" describes the methodology and data. Section "Empirical results" presents the empirical results. Section "Mechanism test and exogenous shocks of the peer effects" examines the mechanisms underlying peer effects. Finally, Section "Conclusions and policy implications" provides the conclusions and policy implications.

Literature review

Peer effects in local government decision-making. Rooted in economics and sociology, peer effects theory posits that under conditions of uncertainty, individuals and organisations tend to imitate the behaviour of others rather than relying solely on independent judgement (Bursztyn et al., 2014; Dahl et al., 2014; Eckles et al., 2016). At the local government level, existing researches have documented the widespread mimetic behaviour

in traditional policy domains such as environmental governance, employment, and education (Falk and Ichino, 2006; Kondo and Shoji, 2019; Xu et al., 2022; Lenard and Silliman, 2025). Within China's distinctive system of fiscal decentralisation and political tournaments, local governments frequently engage in intense interjurisdictional competition through tax policy, fiscal spending, debt issuance, and infrastructure investment to maximise regional competitiveness (Li et al., 2019; Wu et al., 2020; Chen and Zhang, 2021; Du and Yi, 2022; Zeng and Zhou, 2024). Currently, investment in new infrastructure serves as a key driver for stimulating regional economic development. Compared to traditional infrastructure, NII is characterised by greater strategic importance, higher sunk costs, faster technological obsolescence, and greater uncertainty. All these features significantly amplify the decision-making risks and information asymmetries for local officials. In this complex and high-risk environment, local governments are increasingly compelled to observe and imitate the investment actions of spatially proximate or institutionally similar cities to avoid the costs of trial and error, safeguard political security, or gain a first-mover advantage (Yu et al., 2016). Despite the importance of this phenomenon, existing research has paid insufficient attention to whether and how local governments engage in such strategic interactive behaviour in the context of NII. Therefore, this study integrates peer effects theory into the field of new infrastructure, investigating whether such effects exist in the local government investment decision-making.

Measurement of new infrastructure investment level. The level of new infrastructure is typically measured using a range of proxy indicators, tailored to capture various dimensions of infrastructure development. International organisations such as the World Bank and the OECD typically employ indicators like Information and Communication Technology (ICT), broadband penetration and AI development index to approximate the level of digital transformation or the digital infrastructure investment. In academic research, researchers often use specific types of digital infrastructure as proxies for new infrastructure (Briglauer et al., 2021; Ahmad et al., 2024; Oughton, 2025). For instance, Ahmad et al. (2024) quantified the digital economy of 16 developing Asian countries using variables such as fixed-line telephone subscriptions, fixed broadband subscriptions, mobile phone subscriptions. Briglauer et al. (2021) then used variables such as broadband speed, broadband speed NB, and the duration of broadband deployment as proxy variables of high-speed broadband development in Germany. In the Chinese context, NII is typically measured by the capital stock of relevant industries based on different definitional scopes. The concept of new infrastructure first emerged in the 2018 Central Economic Work Conference, primarily referring to information infrastructure or digital infrastructure. Building on this foundation, several studies have conducted measures the national or provincial NII capital stock (Shang, 2020). The scope of the new infrastructure is further refined in 2020 by National Development and Reform Commission (NDRC), categorizing it into three main types: information, integrated, and innovation infrastructure. This classification has since been widely adopted in measuring provincial-level NII capital stock (Long et al., 2024). In addition, the scope of new infrastructure is also expanded with other specific types such as ultra-high-voltage power transmission, big data centres, and new energy vehicle charging stations (Yang et al., 2024). It is evident that most existing studies focused on national or provincial level, with scant attention devoted to city-level analysis. Such a limitation constrains our ability to uncover the true spatial heterogeneity and micro-mechanisms of policy effectiveness. Accordingly, we will develop a novel city-level,

multi-dimensional NII index covering information infrastructure, integrated infrastructure, and innovation infrastructure.

Impact effects of new infrastructure investment. Current research on NII primarily focuses on its economic and social impacts, such as contributions towards achieving sustainable development goals (Vinuesa et al., 2020), fostering high-quality economic growth (Habibi and Zabardast, 2020), upgrading industrial structures (Ma and Lin, 2023), and potential effects on labour markets (Agrawal et al., 2019). For example, Kirikkaleli et al. (2025) find that AI and green electricity investments advance sustainable development in the US, whereas economic growth may hinder it. Cross-national research shows ICT investments boost economic growth in both Middle Eastern and OECD countries, with particularly strong effects observed from mobile subscriptions in Middle Eastern contexts (Habibi and Zabardast, 2020). Gong et al. (2023) further demonstrate that new infrastructure promotes industrial upgrading. However, despite revealing valuable insights into the investment effects and operational mechanisms of NII, existing literature has overlooked the motivations behind local governments' NII decision-making. Understanding why local governments invest in new infrastructure is as important as evaluating investment outcomes, especially in light of observed issues such as indiscriminate investment and redundant infrastructure projects (Arbolino et al., 2025). Although some studies have tried to explore the peer effects of local government decision-making through constructing weighting matrices based on geographic proximity (Xu et al., 2022; Yuan et al., 2023), these efforts provide only a partial picture. In fact, the drivers of peer effects exhibit multi-dimensional complexity. The spatial interaction behaviours of local governments are not solely determined by geographic proximity but are deeply embedded within regional economic networks and administrative hierarchies (Qin et al., 2024). Notably, transport network connectivity and industrial linkage are also key factors influencing local governments' spatial decision-making, yet these aspects have received relatively limited scholarly attention. Thus, this study constructs multi-dimensional spatial weight matrices to explore the peer effects in NII decision-making. To date, the formation mechanisms underlying NII decision-making remain underexplored in depth. Therefore, building on this foundation, this study further investigates the mechanisms of peer effects.

Theoretical framework and research hypothesis

Peer effects theory originates from sociology and behavioural economics. It posits that under conditions of incomplete information and outcome uncertainty, individuals or organisations tend to observe and imitate the behaviours of their peers with geographical proximity, administrative equivalence, or comparable economic status (Manski, 1993). Such behavioural imitation serves as a strategy to mitigate decision-making risks, acquire actionable information, and shape future expectations. This foundational theory elucidating how social interactions shape decision-making has been extensively validated across domains including education (Bursztyn et al., 2014), corporate management (Eckles et al., 2016), and consumer behaviour (Cao et al., 2019). Peer effects are particularly salient in public-sector decision-making. As key decision-makers, local governments often regard their counterparts as important reference points. By closely observing their peers' policy implementation, performance outcomes, and resulting impacts, they adjust their own resource allocation, policy direction, and investment scale—engaging in a learning process largely driven by imitation (Xu et al., 2022; Yuan et al., 2023).

Such emulative behaviour among local governments directly propels policy diffusion. Policy diffusion is a process where policy concepts, instruments, or solutions are replicated and disseminated across regions via observational learning and imitation (Zhu, 2014; Qamar et al., 2023). Within China's distinct political-administrative framework, policy diffusion transcends beyond top-down directives, exhibiting two salient mechanisms (Zhang and Zhu, 2018): (1) Demonstration-Learning: Successful pilot programs or model cities (e.g. "Broadband China" demonstration cities, smart cities) attract voluntary emulation by other regions (Tavares et al., 2023); (2) Competition-Convergence: Intense intergovernmental competition over developmental resources, policy advantages, or performance rankings accelerates the adoption of policies—often exceeding initiatives in proximate or comparable regions (Li and Wang, 2024). This results in strategic convergence, particularly evident in domains like NII. Fiscal incentives (e.g. earmarked intergovernmental transfers), demonstration effects among peer governments, and regional economic competition constitute the primary drivers of these mechanisms (Chen and Huang, 2021). Consequently, policy diffusion—particularly via China-specific 'demonstration-learning' and 'competition-convergence' pathways—provides a critical framework for examining how peer effects operate within local government decision-making, especially in the field of NII.

China's hybrid system of political centralization and fiscal decentralisation grants local governments autonomy over infrastructure investments (Jiang, 2018), while subjecting them to stringent growth-oriented performance evaluations (Lei and Zhou, 2022). The capital-intensive and technologically complex nature of new infrastructure projects, combined with rapid technological change and market uncertainty, create significant decision-making challenges for local governments. This dual pressure encourages local officials to monitor the NII decision-making of their peers closely, particularly in cities with similar economic profiles or within the same provincial jurisdiction (Yu et al., 2016; Xu et al., 2022). Additionally, geographical proximity and transport connectivity facilitate communication and the rapid diffusion of investment strategies (Bu and Tang, 2025). Similarly, cities connected through industrial similarity or supply chain integration tend to emulate each other's development policies to maintain competitive parity (Wang et al., 2022a). In this context, peer cities serve as strategic benchmarks for evaluating the feasibility and outcomes of NII projects (Xu et al., 2022). Motivated by tournament-style intergovernmental competition, local governments may replicate or even seek to outperform their peers. Therefore, this study proposes Hypothesis 1.

H1: The NII decision-making of a city is significantly influenced by its peer cities.

According to organisational learning theory, decision-makers often imitate the strategies of more successful peers to reduce uncertainty and avoid potential losses (Lieberman and Asaba, 2006; Yuan et al., 2023). In China's decentralised yet highly competitive governance system, local officials are incentivized to replicate infrastructure initiatives pioneered by more developed cities. NII require advanced technical capabilities, long-term policy commitment, and sustained fiscal inputs. Developed cities are more capable of initiating and sustaining such projects due to their stronger administrative capacity, stronger financial base, and superior access to technological resources. In this context, developed cities often serve as credible demonstrators in NII. Extensive empirical research supports this pattern. When a province or city leads in areas like renewable energy (Liu et al., 2023a), high-speed rail (Yuan et al., 2023), public-private partnerships (PPPs) (Xiong et al., 2025) or climate governance (An et al., 2023), their policies are often emulated by peers or underdeveloped regions. Such imitation enables follower cities

to avoid falling behind in regional competition. Therefore, this study proposes Hypothesis 2.

H2: NII decision-making in economically developed cities are more likely to be imitated by their peers.

The theory of peer posits suggests that behavioural convergence among peers mainly stem from two drivers: learning and competition (Feld and Zöllitz, 2017; Cao et al., 2019). First, local officials engage in learning-by-watching under uncertainty. Given the technological novelty and uncertain outcomes of new infrastructure projects, officials often observe and emulate the successful initiatives of their peers as an information shortcut to reduce risk (Shang et al., 2024). Such imitation can lower decision-making costs and enhance policy legitimacy, allowing officials to 'follow the leader' rather than undertake untested projects independently. Second, the competition arises from China's decentralised promotion system, which fosters intense intergovernmental rivalry. Because local officials are evaluated based on growth and investment performance (Yuan et al., 2023), they engage in yardstick competition—adopting similar infrastructure projects to match or surpass their peers. Consequently, if peer cities successfully launch new infrastructure project, other cities are motivated to follow suit to avoid lagging behind in economic development or technological progress. In sum, local governments emulate their peers both to learn effective strategies and to maintain competitiveness in a tournament-style environment. Accordingly, this study proposes Hypothesis 3.

H3: Peer effects in NII decision-making operate through learning and competition.

Major policy interventions, as exogenous shocks, reshape the information environment and the structure of competition (Xu et al., 2022), thereby influencing peer effects among local governments. NII involves high technological complexity, substantial capital intensity, and rapid technological iteration, all of which substantially heighten decision-making risks. When the technological paths are unclear and market prospects remain uncertain, local officials increasingly rely on peer behaviour for credible references. For example, the National Big Data Comprehensive Pilot Zones (NBDP) policy, launched in 2015, endowed selected cities with special resources and policy status, explicitly leveraging their demonstrative role (Zhou et al., 2025). Similarly, the "Broadband China" strategy (BCS) (2014–2016) designated pilot cities as benchmarks for diffusion (Yang and Zhang, 2025). The smart city pilot (SCP) policy (2012–2013) was integrated into national strategies and performance evaluations (Wang et al., 2023). Such policies share two salient features. First, they generate explicit incentive signals. Pilot cities receive central resources and political recognition, signalling policy priorities to other jurisdictions. Second, they establish observable benchmarks. The progress of pilot cities provides tangible reference points for non-pilot regions. Under the combined influence of these informational and incentive mechanisms, local governments become more likely to follow their peers. Successful pilots encourage voluntary imitation, while performance assessment pressures may force officials to track peer progress to avoid falling behind. Therefore, this study proposes Hypothesis 4.

H4: Exogenous shocks influence peer effects in NII decision-making.

In summary, this study investigates the peer effects in NII decision-making of local governments based on the above research hypothesis. The research framework is presented in Fig. 1. First, the study adopts the perpetual inventory method to measure the city-level NII which includes three components of information infrastructure, integrated infrastructure, and innovation infrastructure. Next, the spatial benchmark regression model is employed to verify the peer effects with seven different spatial weight matrices. The complementarity test model is

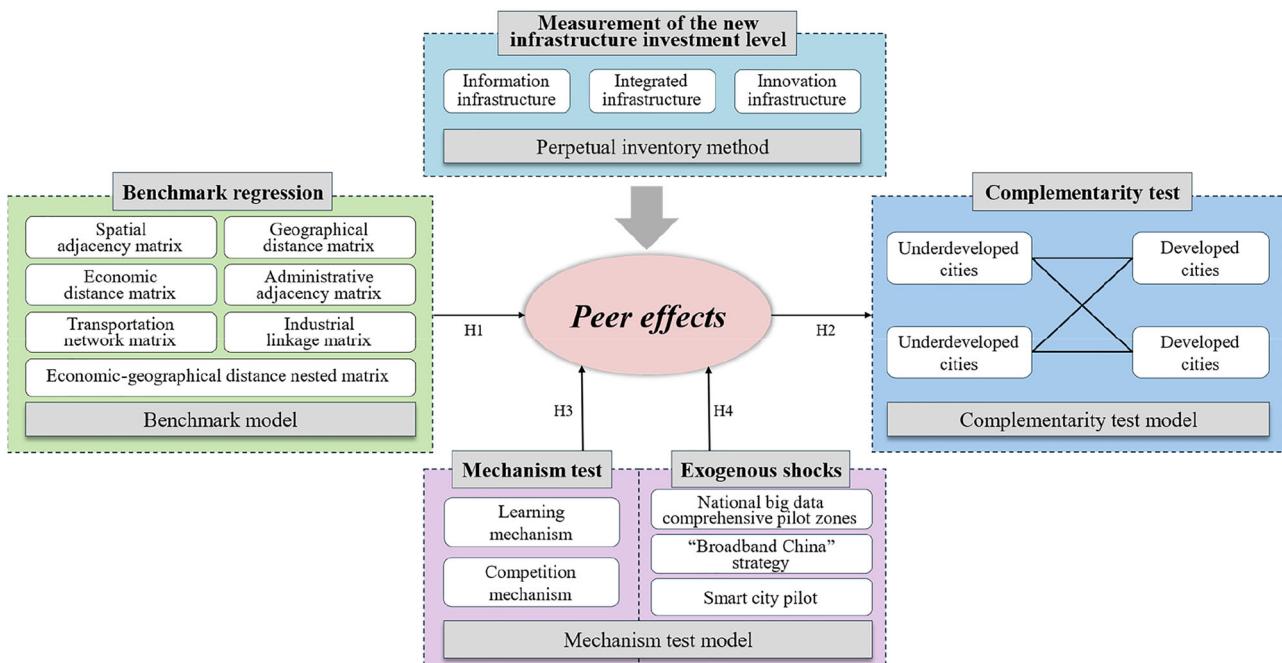


Fig. 1 Research framework of peer effects in local government decision-making on new infrastructure investment. The top panel applies the perpetual inventory method to measure city-level NII. The left panel employs the spatial benchmark regression model to verify the peer effects with seven different spatial weight matrices. The right panel explores peer effects between cities with different economic development levels. The bottom-left panel examines the influence of learning and competition mechanisms on peer effects. The bottom-right panel explores the impact of exogenous shocks on peer effects. Arrows indicate the logical flow of the research framework.

further used to explore the peer effects between cities with different economic development levels, focusing on imitation behaviours between underdeveloped and developed cities. Additionally, the mechanism test model is utilized to examine the influence of learning mechanism and competition mechanism on peer effects. Finally, the study explores the impact of exogenous shocks on peer effects, including the NBDP, BCS, and SCP policy.

Methodology and data

Methodology. Spatial econometric models provide an effective framework for identifying peer effects (Lee et al., 2010; Lee and Yu, 2010). This study employs a spatial econometric model incorporating a lagged dependent variable to examine peer effects in NII decision-making. The model is specified as follows:

$$\ln NII_{it} = \alpha + \rho W \ln NII_{it} + \beta \ln X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

Here, i and t denote city and year, respectively. NII_{it} represents the level of NII for city i in year t , while X_{it} is a vector of control variables. W is an $N \times N$ standardized matrix with zero diagonals, where the elements w_{ij} represent the spatial relationships between city i and city j . $W \ln NII_{it}$ as the spatial lag term, represents the weighted average of NII levels in all peer cities excluding city i , thereby capturing peer influences on city i 's NII decision-making. μ_i and η_t are the fixed effects of city i and year t , respectively, while ε_{it} is the error term. The coefficients α , ρ and β correspond to the constant, the spatial regression parameter, and the effects of control variables. Notably, ρ serves as both the spatial autoregressive coefficient and the measure of peer effects. A significantly positive ρ , after controlling for other variables, provides evidence of peer effects in NII decision-making.

To ensure robust model estimation and address potential endogeneity concerns, this study adopts several strategies. First, the definition of 'neighbours' in all spatial weight matrices is determined exogenously, thereby minimizing the risk of self-selection bias. Second, the Quasi-Maximum Likelihood Estimator

(QMLE) proposed by Lee and Yu (2010) is employed. Unlike the Least Square Dummy Variables method, which is prone to autocorrelation and variance inconsistency, QMLE employs orthogonal transformations to eliminate individual and time-fixed effects, thereby ensuring unbiased and consistent estimates. Finally, to mitigate potential heteroskedasticity, continuous variables are log-transformed.

Considering that differences in economic development levels may influence peer effects, the complementarity test is used to examine how economic development disparities influence these peer effects. Specifically, prefecture-level cities are categorized into developed cities (H) and underdeveloped cities (L) based on the 50th percentile of GDP per capita. Such complementarity test model enables us to explore the imitation patterns between developed (H) and underdeveloped (L) cities. Following Yuan et al. (2023), we extend the benchmark model into a complementarity test model, which is specified as follows:

$$\ln NII_m = \alpha + \rho W \ln NII_m + \beta \ln X_{it} + \varepsilon_i, m = L, H \quad (2)$$

Here, NII_m represents the level of NII in regions with either higher (H) or lower (L) economic development. W is an $N \times N$ standardized spatial weight matrix with zero diagonals, where each element w_{ij} captures the spatial relationships between city i and city j . $W \ln NII_{it}$ as the spatial lag term, represents the weighted average of NII levels in all peer cities excluding city i , thereby capturing the influence of peer cities' NII on city i . Specifically, L-L represents mutual imitation among underdeveloped cities, L-H captures the imitation of underdeveloped cities by developed cities. H-H indicates mutual imitation among developed cities, and H-L represents the imitation of developed cities by underdeveloped cities.

To examine the mechanisms and exogenous shocks influencing peer effects in NII decision-making, this study constructs an empirical model drawing on Lieberman and Asaba (2006). Three aspects are considered in this part: the learning mechanism, the

competition mechanism, and exogenous shocks. The specified mechanism test model is as follows:

$$W\ln NII_{it} = \alpha + \delta V_{it} + \beta \ln X_{it} + \varepsilon_i \quad (3)$$

Where W is an $N \times N$ row-standardized matrix with zero diagonals; whose elements w_{ij} represent the spatial relationships between cities i and j . $W\ln NII_{it}$ is the dependent variable, representing the weighted average of NII levels in all peer cities excluding city i , thereby reflecting the influence of peer cities' NII levels on city i . X_{it} represents covariates controlling for the socioeconomic characteristics of the region. δ is the core coefficient, quantifying the mechanisms underlying peer effects. V_{it} represents intrinsic mechanism variables driving peer effects, encompassing the learning, competition, and exogenous shocks. Specifically, the learning mechanism is captured by two components: *internal learning*, represented by a dummy variable indicating whether NII increased compared to the previous year, and *external demonstration*, measured by the number of prefecture-level cities within the same province. The competition mechanism is operationalized through fiscal, talent and industrial competition. *Fiscal competition* is measured by the rank of fiscal expenditure in the same province. *Talent competition* is reflected by the rank of R&D personnel to total employees. *Industrial competition* is captured by the rank of the tertiary sector's added value to GDP. These variables collectively link the theoretical constructs of learning and competition to empirically observed peer effects. Additionally, exogenous policy shocks are incorporated by including dummy variables for the NBDP, BCS, and SCP policies, coded as 1 for cities designated as pilots from the year of designation onward and 0 otherwise. By integrating these mechanisms and policy shocks into V_{it} , the model provides a comprehensive framework to examine how learning, competition, and exogenous shocks jointly influence peer effects in NII decision-making, thereby enhancing both its analytical depth and empirical validity.

Spatial weight matrices. Constructing appropriate spatial weight matrices is essential for incorporating spatial externalities into the model and accurately identifying causal effects in empirical analyses (Zhang et al., 2025). Since NII decision-making could be influenced by interactions along multiple dimensions, we incorporate several types of spatial weight matrices into the analysis.

- (1) *Spatial adjacency matrix* (W_{01}): This contiguity-based matrix is constructed using the Queen criterion which defines regions i and j as neighbours if they share a common border or vertex, assigning $w_{ij} = 1$ in such cases and 0 otherwise. This matrix reflects the essential 'visible and learnable' interactions among proximate cities. Highly observable infrastructure—such as 5G base stations and data centres—facilitates on-site visits by local officials, which in turn encourages imitation or induces competitive responses aimed at preventing relative decline.
- (2) *Geographical distance matrix* (W_d): In this matrix, spatial weights decline with increasing distance between cities. Specifically, we define $w_{ij} = d_{ij}^{-\varphi}$, where d_{ij} denotes the Euclidean distance between cities i and j , and φ is a distance-decay parameter (typically set to 0.5, 1, or 2). Different values of φ reflect varying rates of spatial attenuation, with larger values indicating a faster decline in influence over distance. This matrix captures the intuition that spatial spillovers—such as the diffusion of technology or knowledge—diminish as geographical separation increases.
- (3) *Economic distance matrix* (W_e): This matrix assigns greater weights to city-pairs with similar levels of economic development. Specifically, we define

$W_e = 1 / |PGDP_i - PGDP_j| (i \neq j)$, where $PGDP_i$ and $PGDP_j$ represent the average per capita real GDP of city i and city j , respectively, over the period 2012–2022 (adjusted to 2012 constant prices). The underlying assumption is that cities with comparable economic conditions are likely to view each other as benchmarks and engage in yardstick competition, particularly in terms of NII-related performance such as GDP growth or innovation performance. Accordingly, W_e captures competitive pressure among economically similar peers.

- (4) *Administrative adjacency matrix* (W_a): This binary matrix captures intra-provincial linkages, where $w_{ij} = 1$ if cities i and j belong to the same province ($i \neq j$), and 0 otherwise. It reflects spatial dependence arising from shared provincial governance. Cities within the same provincial administrative region often share fiscal resources, development plans and performance evaluation system, which foster direct competition and policy coordination. Thus, NII-related decision-making tends to exhibit stronger spatial correlation among cities governed by the same provincial authority.
- (5) *Economic-geographical distance nested matrix* (W_{de}): This matrix integrates both economic size and geographical distance, drawing on the logic of the gravity model. We compute $W_{de} = (PGDP_i \times PGDP_j) / d_{ij}^2 (i \neq j)$. The product of PGDP assigns greater weight to interactions between economically larger cities, while the squared distance term captures the decay of influence with spatial separation. This formulation reflects the mechanism by which economically dominant hub cities (e.g. first-tier cities) can stimulate NII in surrounding areas, although their influence diminishes with increasing distance.
- (6) *Transportation network matrix* (W_t): This matrix replaces straight-line (Euclidean) distance with actual highway travel distances between cities. It is defined as $w_{ij} = D_{ij}^{-\varphi}$, where D_{ij} denotes the highway distance between cities i and j , and φ (e.g. 0.5, 1, or 2) is the decay parameter, consistent with that used in W_d . By incorporating real-world transport connectivity, W_t provides a more accurate representation of inter-city accessibility. It captures the fact that spillover effects from NII are channelled through transportation corridors, with their intensity diminishing as travel distance increases—an effect that becomes more pronounced with larger values of φ .
- (7) *Industrial linkage matrix* (W_{ind}): This matrix combines industrial structure with transportation connectivity. It is defined as $W_{ind} = (industry_i \times industry_j) / D_{ij}^2 (i \neq j)$, where $industry$ represents the share of tertiary industry added value in GDP for a city, and D_{ij} is the transportation distance between cities i and j . This specification assigns greater weights to city-pairs that have service-oriented economies but are also well connected via highways. It captures a nuanced form of interdependence: cities with similar industrial profiles and strong transport links exert particularly strong mutual influence on each other's NII decisions.

Variable definition and data description

Definitions of variables. The National Development and Reform Commission categorizes new infrastructure into three components: information infrastructure, integrated infrastructure, and innovation infrastructure (Ma et al., 2025). Due to the absence of official statistics on investment amounts in each component or their aggregate total, we use capital stock as a proxy to estimate

Table 1 Variable definitions and measurements.

Variables	Definitions	Measurements
InNII	New infrastructure investment	Natural logarithm of the new infrastructure investment level
InFD	Fiscal decentralisation	Natural logarithm of the ratio of local government fiscal expenditure to central government fiscal expenditure
InED	Economic development level	Natural logarithm of GDP per capita
InCS	City size	Natural logarithm of the built-up urban area
InIS	Industrial structure	Natural logarithm of the ratio of the added value of the tertiary sector to regional GDP
InFS	Fiscal self-sufficiency	Natural logarithm of the ratio of public budget revenue to public budget expenditure
<i>promotion</i>	Promotion of local officials	Dummy variables: 1 if the party secretary of the prefecture-level city is promoted in year t , 0 otherwise
<i>Internal</i>	Internal learning effect	Dummy variables (0, 1): 1 if the NII of a city is higher than the previous year, 0 otherwise
<i>External</i>	External demonstration effect	Number of prefecture-level cities within the same province
<i>Fiscal</i>	Fiscal competition	Rank of fiscal expenditure in the same province (lower rank = higher spending)
<i>Talent</i>	Talent competition	Rank of the proportion of R&D personnel to total employees within the same province
<i>Industrial</i>	Industrial competition	Rank of the proportion of the added value of the tertiary sector to GDP within the same province
NBDP	National big data comprehensive pilot zones	Dummy variables (0, 1): 1 if designated as a pilot city from the year of inclusion onward, 0 otherwise
BCS	“Broadband China” strategy	Dummy variables (0, 1): 1 if designated as a pilot city from the year of inclusion onward, 0 otherwise
SCP	Smart city pilot	Dummy variables (0, 1): 1 if designated as a pilot city from the year of inclusion onward, 0 otherwise

the level of NII. A higher value of this indicator reflects greater level of investment, with total fixed asset investment in relevant industries serving as the proxy variable. Among them, information infrastructure primarily includes information technology and software services. It is measured by fixed asset investment in ‘*Information transmission, software and information technology services*.’ Integrated infrastructure refers to the digital transformation of traditional infrastructure. It is measured by the sum of fixed asset investments in ‘*Production and supply of electricity, heat, gas and water*’ and ‘*Transport, storage, and postal services*.’ Innovation infrastructure encompasses scientific and technological innovation and public services, supporting various public welfare initiatives. It is measured by the sum of fixed asset investments in ‘*Scientific research and technical services*’ and ‘*Education*.’ The overall level of NII is calculated as the sum of these three components. To estimate the capital stock, we apply the perpetual inventory method proposed by Zhang et al. (2004). The specific equation is as follows:

$$K_t = (1 - \delta) \times K_{t-1} + \frac{I_t}{P_t} \quad (4)$$

Here, K_t and K_{t-1} represent the physical capital stock for the current and previous periods, respectively. P_t is the capital price index (with 2012 as the base year), I_t denotes fixed asset formation for the current period, and δ is the depreciation rate. The perpetual inventory method is applied to calculate the capital stock. Fixed asset investments in information, integrated, and innovation infrastructure are recorded annually. To account for inflation, a deflator with 2012 as the base year is used to adjust investment figures to constant prices by dividing nominal investments by the deflation index. The capital stock for each year is calculated using Eq. (4), assuming a depreciation rate of 9.6%. Finally, the accumulated capital stocks for the three infrastructures are aggregated to derive the overall level of new infrastructure capital stock.

This study incorporates several characteristic variables of prefecture-level cities as control variables, drawing on prior research (Xu et al., 2022; Yuan et al., 2023). (1) Fiscal Decentralisation (FD). Greater fiscal autonomy typically intensifies inter-jurisdictional competition, incentivizing local governments to invest in high-profile, technology-driven projects like

new infrastructure. (2) Economic Development Level (ED). Economically advanced regions with more developed industries tend to have stronger demand for digital infrastructure and greater financial capacity to support such investments. (3) City Size (CS). Larger cities benefit from agglomeration economies and face increased pressure to upgrade infrastructure, making new infrastructure a strategic priority. (4) Industrial Structure (IS). A higher share of the tertiary sector reflects a service-oriented economy, which increases demand for digital and information-intensive infrastructure—core components of new infrastructure. (5) Fiscal Self-Sufficiency (FS). Cities with higher self-sufficiency are better able to fund infrastructure projects independently, reducing reliance on central government transfers. (6) Promotion of officials (*promotion*). In the Chinese context, local officials often prioritize NII to signal administrative competence and align with central government policy agendas, thereby improving their prospects for promotion. Definitions and detailed calculations of variables are provided in Table 1.

Data source. Due to major updates in China’s national economic industry classification standards in 2011 and the availability of prefecture-level data, this study focuses on the period from 2012 to 2022. The final sample includes 258 prefecture-level and above cities over this timeframe. The variables involved in this study are primarily derived from the *Statistical Yearbook of the Chinese Investment in Fixed Assets*, the *Statistical Yearbook of the Chinese Investment Field*, the *China City Statistical Yearbook*, and the respective Statistical Yearbooks of each city. To address limited missing data, we apply linear interpolation by calculating the average growth rate between the preceding and subsequent years, following the approach of Yuan et al. (2023). Such treatment ensures data continuity and supports the use of strongly balanced spatial panel models. To reduce the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Descriptive statistics for the main variables are reported in Table 2.

Empirical results

Spatial correlation test. Spatial correlation is a key prerequisite for the application of spatial econometric models. To assess the suitability of using such models in our analysis, we first examine

the presence of spatial dependence in NII across cities, following the approach of Elhorst (2003). Using seven spatial weight matrices, we calculate Moran's I for NII levels across 258 Chinese prefecture-level cities from 2012 to 2022. As reported in Table 3, Moran's I values are consistently positive and statistically significant across all matrices and years, indicating strong positive spatial clustering in NII. These findings provide robust support for the use of spatial econometric methods. Moreover, the upward trend in Moran's Index over time further demonstrates spatial dependence in NII has intensified throughout the study period.

Benchmark regression. Table 4 reports the results of benchmark regressions under the seven different spatial weight matrices. Across all model specifications, the coefficients for peer effects are consistently positive and statistically significant, providing strong evidence for the existence of peer effects in NII decision-making. These results confirm that a city's NII strategy is significantly influenced by the investment behaviours of peer cities, regardless of whether these cities are connected by geographical proximity, economic similarity, administrative affiliation, transportation networks, or industrial linkages. This finding provides empirical support for Hypothesis 1. The practical implications of this result are noteworthy. The presence of peer effects indicates that policy coordination among cities can help reduce redundant investments and facilitate more efficient regional resource allocation, ultimately enhancing the effectiveness of NII initiatives.

A comparison of the peer effects coefficients across different spatial weight matrices reveals that the transportation network matrix yields the largest coefficient, followed by the industrial linkage matrix and the geographical distance matrix. This indicates that peer effects are most pronounced not simply among geographically proximate cities, but more significantly among those that are functionally connected by transportation networks and industrial structures. In contrast, the coefficient for the economic distance matrix and the administrative adjacency

matrix are smaller. While there is evidence of mimicry within provincial boundaries or among economically similar cities, these effects are less pronounced than those driven by functional connectivity. Taken together, these findings underscore the critical role of functional connectivity—particularly in terms of transportation infrastructure and industrial relationships—in shaping peer effects in NII.

The regression results show that fiscal decentralisation is consistently positive and statistically significant across all models. This suggests that local governments are more incentivized to promote regional economic development through NII under a decentralised system. The coefficient for economic development is significantly positive in all models, confirming that economically developed regions provide more favourable conditions for NII. Similarly, the significantly positive coefficient for city size is significantly positive implies that larger cities enjoy greater advantages in resource allocation, which supports their investment in infrastructure upgrading. The positive effect of industrial structure on investment suggests that cities with a more developed tertiary sector are more likely to invest in new infrastructure to facilitate industrial upgrading and support economic transformation. The coefficient for fiscal self-sufficiency is also significantly positive across all models, indicating that fiscally autonomous local governments are more susceptible to the investment behaviours of neighbouring cities. This may lead to convergent behaviour in NII, which often driven by imitation rather than local needs, thereby increasing the risks of resource misallocation and redundant investment. Interestingly, after incorporating control variables into the model, the coefficient of officials' promotion incentives becomes statistically insignificant. This does not imply the absence of political motivation, but rather suggests that its influence may be indirect. Specifically, promotion incentives are often realized through performance-based 'hard indicators' such as expanding the overall economic scale. This underscores the dominance of economic and fiscal 'hard constraints' in guiding investment decision-making in the new infrastructure field. It highlights the complexity of local government decision-making, where political objectives must be achieved through economic and fiscal instruments. Overall, although the magnitudes of the regression coefficients for control variables vary across models, their direct effects on NII remain consistent, reinforcing the robustness of the empirical results.

Robustness test. To further validate the robustness of the benchmark regression results, this study conducts a series of robustness tests. The detailed results are reported in Table 5.

Table 2 Descriptive statistics for main variables.

Variables	Obs	Mean	Std. dev	Min	Max
InNII	2838	16.575	0.775	14.604	18.406
InFD	2838	-4.45	0.613	-5.739	-2.751
InED	2838	10.859	0.557	9.670	12.242
InCS	2838	4.641	0.784	3.144	6.833
InIS	2838	3.747	0.221	3.138	4.245
InFS	2838	-0.905	0.517	-2.325	-0.002
promotion	2838	0.324	0.468	0	1

Table 3 Spatial correlation test.

Year	W_{01} Moran's I	W_d Moran's I	W_e Moran's I	W_{de} Moran's I	W_a Moran's I	W_t Moran's I	W_{ind} Moran's I
2012	0.205***	0.113***	0.264***	0.097***	0.148***	0.100***	0.111***
2013	0.208***	0.115***	0.273***	0.099***	0.153***	0.103***	0.113***
2014	0.211***	0.119***	0.278***	0.102***	0.157***	0.105***	0.116***
2015	0.217***	0.121***	0.287***	0.104***	0.165***	0.108***	0.118***
2016	0.222***	0.125***	0.293***	0.106***	0.172***	0.110***	0.121***
2017	0.233***	0.132***	0.301***	0.113***	0.185***	0.116***	0.128***
2018	0.237***	0.139***	0.312***	0.119***	0.202***	0.122***	0.134***
2019	0.233***	0.143***	0.320***	0.123***	0.219***	0.126***	0.138***
2020	0.231***	0.147***	0.324***	0.127***	0.229***	0.130***	0.142***
2021	0.230***	0.149***	0.331***	0.130***	0.241***	0.132***	0.145***
2022	0.228***	0.152***	0.337***	0.133***	0.247***	0.135***	0.148***

* , ** , *** denote significant levels at 10%, 5%, and 1%, respectively.

Table 4 Estimation results of the benchmark model.

Variables	W_{01}	W_d	W_e	W_{de}	W_d	W_t	W_{ind}
ρ	0.380*** (0.022)	0.689*** (0.034)	0.352*** (0.020)	0.649*** (0.036)	0.467*** (0.023)	0.707*** (0.035)	0.701*** (0.034)
InFD	0.175*** (0.030)	0.177*** (0.030)	0.192*** (0.030)	0.198*** (0.030)	0.183*** (0.030)	0.181*** (0.030)	0.173*** (0.030)
InED	0.586*** (0.037)	0.244*** (0.046)	0.568*** (0.038)	0.321*** (0.047)	0.450*** (0.039)	0.216*** (0.048)	0.233*** (0.046)
InCS	0.111*** (0.027)	0.091*** (0.027)	0.129*** (0.027)	0.091*** (0.027)	0.133*** (0.026)	0.095*** (0.027)	0.093*** (0.027)
InIS	0.087** (0.035)	0.091*** (0.035)	0.123*** (0.035)	0.087** (0.036)	0.105*** (0.035)	0.090** (0.035)	0.093*** (0.035)
InFS	0.044** (0.021)	0.038* (0.021)	0.051** (0.021)	0.042* (0.021)	0.036* (0.021)	0.041* (0.021)	0.039* (0.021)
promotion	0.006 (0.006)	0.004 (0.006)	0.006 (0.006)	0.005 (0.006)	0.005 (0.006)	0.004 (0.006)	0.004 (0.006)
City	YES						
Year	YES						
N	2580	2580	2580	2580	2580	2580	2580
R ²	0.276	0.469	0.406	0.458	0.365	0.478	0.465
Log-likelihood	1079.687	1105.847	1080.164	1074.677	1111.521	1099.873	1108.628

*, **, *** denote significant levels at 10%, 5%, and 1%, respectively. Robust standard errors are reported in parentheses. City and Year represents city fixed effects and year fixed effects, respectively.

Table 5 The robustness test.

	SEM	SDM	Replace the dependent variable	Lagged dependent variable	Intra-province geographical matrix	Extra-province geographical matrix
ρ		0.663*** (0.038)	0.438*** (0.048)	0.562*** (0.039)	0.427*** (0.021)	0.258*** (0.049)
λ	0.673*** (0.036)					
g_{-1}				0.156*** (0.019)		
Control variables	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	2580	2580	2580	2580	2580	2580
R ²	0.404	0.413	0.226		0.375	0.487
Log-likelihood	1072.770	1089.147	-1727.461		1118.197	959.118
F-value				798.75***		

*, **, *** denote significant levels at 10%, 5%, and 1%. Robust standard errors are reported in parentheses. Control variables are consistent with those used in the baseline regression.

- (1) *Model substitution.* The spatial error model (SEM) and spatial Durbin model (SDM) are employed as alternatives to the benchmark model. In these models, ρ represents the coefficient of the lagged dependent variable $W_{\text{InNII}_{it}}$, while λ represents the coefficient of the lagged error term $W\mu$. The results indicate that the peer effect remains significantly positive across both alternative specifications. This finding reinforces the conclusion of the benchmark model and provides strong evidence of the robustness of the observed peer effects in NII decision-making.
- (2) *Replacing the dependent variable.* To test the robustness of the dependent variable specification, the dependent variable in the benchmark regression model is replaced with an alternative, more restrictive indicator. Specifically, fixed asset investment in the 'information transmission, computer services and software industry' is used to represent NII in a more restricted sense. The results indicate that the peer effects coefficient remains significantly positive after the substitution, with both the direction and significance levels

consistent with those in the benchmark model. This finding indicates that the observed peer effects are robust to changes in the measurement of the dependent variable.

- (3) *Inclusion of the lagged dependent variable.* To account for potential lag effects and the influence of unobserved historical factors, the model incorporates the lagged term of the dependent variable. Here, g_{-1} represents the coefficient of the lagged term. The results demonstrate that even after including the lagged term, the peer effects coefficient remains significantly positive and maintains the same direction as in the benchmark model. This finding further supports the robustness of the empirical findings.
- (4) *Alternative spatial weight matrix.* To assess the sensitivity of peer effects to different spatial relationship structures, this study constructs intra-provincial and extra-provincial geographical distance matrices as alternative spatial weight matrices. The results indicate that the peer effects coefficients of the core variables remain positive and statistically significant across these alternative

Table 6 Counterfactual test - 'pseudo-neighbourhood'.

	SAR	SEM	SDM
<i>p</i>	−0.041 (0.042)		0.048 (0.052)
λ		0.054 (0.051)	
<i>Control variables</i>	YES	YES	YES
<i>City</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES
<i>N</i>	2580	2580	2580
<i>R</i> ²	0.444	0.453	0.374
<i>Log-likelihood</i>	945.714	945.771	962.130

^{*}, ^{**}, ^{***} denote significant levels at 10%, 5%, and 1%, respectively. Robust standard errors are reported in parentheses. Control variables are consistent with those used in the baseline regression

Table 7 Counterfactual test - 'pure pseudo-neighbourhood'.

	SAR	SEM	SDM
<i>p</i>	−0.017 (0.018)		0.023 (0.020)
λ		0.017 (0.020)	
<i>Control variables</i>	YES	YES	YES
<i>City</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES
<i>N</i>	2580	2580	2580
<i>R</i> ²	0.450	0.454	0.436
<i>Log-likelihood</i>	945.686	945.601	970.020

^{*}, ^{**}, ^{***} denote significant levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses. Control variables are identical to those used in the baseline regression.

specifications. This demonstrates the robustness of peer effects in NII decision-making under different spatial configurations.

Counterfactual inference. To further assess the validity of the identified peer effects in NII decision-making, this study employs counterfactual inference by constructing two types of counterfactual spatial matrices: the 'pseudo-neighbourhood' matrix and the 'pure pseudo-neighbourhood' matrix. The aim is to examine whether cities without actual spatial, administrative, or economic proximity exert any significant influence on local investment decision-making. If true peer effects exist, the investment behaviour of non-adjacent cities or artificially linked cities should only exert a weak or statistically insignificant effects.

In the 'pseudo-neighbourhood' spatial matrix, each city is randomly assigned $m - 1$ prefecture-level cities from across the country as its 'neighbours', without regard to provincial boundaries or actual spatial relationships. As shown in Table 6, the estimation results from the SAR, SEM, and SDM models show that the coefficients for the spatial lag terms are statistically insignificant. This finding indicates that when spatial relationships are artificially constructed, rather than grounded in real-world geographical or administrative proximity, the NII behaviours of these 'pseudo-neighbouring' cities does not meaningfully influence on local investment decision-making.

For the 'pure pseudo-neighbourhood' matrix, cities within the same province are excluded, and each city is randomly assigned 'neighbouring' cities from other provinces only. The results of the 'pure pseudo-neighbourhood' test, shown in Table 7, indicate that the peer effects coefficients remain insignificant across the SAR, SEM, and SDM models. This finding further supports the conclusion that cities randomly selected from outside the province exert no meaningful influence on local NII decision-making. It reinforces the interpretation that peer effects are primarily driven by cities with geographic or administrative proximity, rather than by arbitrary or random associations. Overall, these results provide additional confirmation of the robustness and reliability of the empirical conclusions drawn in this study.

Complementarity test. The results indicate that significant peer effects exist in NII decision-making across cities regardless of economic development level (Table 8). However, notable heterogeneity emerges between groups: underdeveloped cities exhibit much stronger peer effects (coefficient = 0.716) compared to developed cities (coefficient = 0.148). This suggests that underdeveloped cities are more prone to imitation, with their

Table 8 The complementarity test of peer effects.

	L-L	L-H	H-H	H-L
<i>p</i>	0.716*** (0.052)	0.119* (0.063)	0.148** (0.062)	0.185*** (0.051)
<i>Control variables</i>	YES	YES	YES	YES
<i>N</i>	1419	1419	1419	1419
<i>R</i> ²	0.714	0.672	0.629	0.631
<i>F-value</i>	456.470	375.387	308.884	311.644

^{*}, ^{**}, ^{***} denote significant levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses. Control variables are consistent with those included in the baseline regression.

investment decision-making more heavily influenced by peer behaviour. Such mimicry is likely driven by a desire to maintain regional competitiveness and narrow the development gap with more advanced regions. Conversely, developed cities appear to demonstrate greater autonomy and strategic discretion in their NII decision-making, relying more on local conditions, fiscal capacity, and existing infrastructure foundations.

Further directional analysis uncovers the asymmetry pattern of imitation: underdeveloped cities exhibit significant imitation of developed cities (coefficient = 0.185, significant at the 1% level), whereas the imitation of underdeveloped cities by developed cities is notably weaker (coefficient = 0.119, significant at the 10% level). This asymmetry provides direct empirical support for Hypothesis 2, which posits that developed cities are more likely to be imitated by underdeveloped counterparts. Moreover, this finding is consistent with the peer effects identified by Yuan et al. (2023) in the context of high-speed rail construction, suggesting that such imitation tendencies might be a generalizable phenomenon across different infrastructure domains.

From a behavioural economics perspective, the stronger imitation behaviour observed in underdeveloped cities reflects a form of social learning, whereby mimicking peers is a rational strategy to reduce decision-making risk under high uncertainty. This behaviour is emblematic of a widespread 'catch-up' mentality in China. However, such imitation can also lead to overinvestment in similar projects, leading to resource misallocation and reduced efficiency. In contrast, the lower imitation coefficient and greater decision-making independence found in developed cities highlight their enhanced ability to better leverage infrastructure investments. As noted in empirical studies by Wang et al. (2025) and Zhou et al. (2021), infrastructure investments in developed regions—especially coastal cities—tend to yield more significant economic benefits, including improved

Table 9 The regression results of the learning mechanism.

	All	Eastern	Central	Western
Internal	0.102*** (0.016)	0.134*** (0.022)	0.112*** (0.029)	0.080*** (0.027)
R ²	0.268	0.327	0.348	0.119
F-value	134.577***	66.923***	72.522***	12.394***
External	0.015*** (0.001)	0.003 (0.002)	0.027*** (0.003)	0.022*** (0.002)
R ²	0.327	0.344	0.413	0.288
F-value	196.705***	79.475***	105.439***	40.768***
Control variables	YES	YES	YES	YES
N	2838	1067	1056	715

*; **; *** denote significant levels at 10%, 5%, and 1%, respectively. Standard errors are in parentheses. Control variables are consistent with those in the baseline regression.

investment efficiency and higher-quality economic growth. These cities are also more capable of avoiding the pitfalls of indiscriminate imitation and homogenised competition.

Mechanism test and exogenous shocks of the peer effects

Learning mechanism. Mechanism testing confirms both internal learning and external demonstration significantly contribute to peer effects in NII decision-making, thereby providing strong support for Hypothesis 3. On the internal dimension, regression results indicate that local governments reinforce existing investment patterns based on accumulated experience instead of correcting for previous irrational decision-making (see Table 9). The coefficient for internal learning is significantly positive both nationally as well as within eastern, central, and western regions. This pattern reflects a path-dependent tendency in decision-making: local governments stick to established investment trajectories, even when earlier decision-making has proven sub-optimal (Liu et al., 2023b). Such behaviour aligns with the concept of path dependence in behavioural economics, wherein past decisions exert a disproportionate influence on current strategies. For example, indiscriminate infrastructure investment-like in underutilised data centres or an oversupply of EV charging stations – illustrates how repeating past approaches without critical reflection can lead to resource waste (Yi et al., 2020). Crucially, this behaviour entrenches inefficiencies (Yi et al., 2020)—experience justifies sustaining irrational investments rather than correcting them, thereby exacerbating infrastructure misallocation and deepening regional imbalances. These findings align with observed temporal path dependence in local development behaviour (Liu et al., 2023b).

On the external dimension, a significantly positive national demonstration effect indicates local governments tend to imitate perceived successful infrastructure investments undertaken by peer cities. Particularly under conditions of uncertainty, they reference neighbouring outcomes to guide their decision-making, thereby reducing perceived risk by adopting seemingly effective approaches (Yuan et al., 2023). Crucially, this imitation exhibits clear regional heterogeneity. The effect is strongest in central and western regions, where cities are more likely to engage in horizontal learning from peers to navigate policy ambiguity and compensate for limited administrative or financial capacity. Conversely, the effect is notably weaker in more developed eastern region, likely due to its greater fiscal resources and policy autonomy, which reduce the need to rely on external reference points. This regional heterogeneity in peer influence aligns with existing evidence that inter-city imitation varies by development level (Zhou and Zhong, 2024), further supporting

Table 10 The regression results of the competition mechanism.

	All	Eastern	Central	Western
Fiscal	0.018*** (0.001)	0.017*** (0.002)	0.024*** (0.003)	0.024*** (0.002)
R ²	0.332	0.373	0.413	0.240
F-value	200.688***	89.809***	105.228***	31.851***
Talent	0.011*** (0.001)	0.006*** (0.002)	0.016*** (0.002)	0.017*** (0.002)
R ²	0.310	0.348	0.393	0.196
F-value	181.939***	80.869***	96.887***	24.607***
Industrial	0.025*** (0.001)	0.018*** (0.002)	0.042*** (0.002)	0.029*** (0.003)
R ²	0.369	0.388	0.513	0.271
F-value	236.613***	95.906***	157.744***	37.545***
Control variables	YES	YES	YES	YES
N	2838	1067	1056	715

*; **; *** denote significant levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses. Control variables are the same as those used in the baseline regression.

the notion that peer effects are conditioned by local institutional and economic environments.

Competition mechanism. The mechanism test model examines how competition mechanisms drive peer effects in NII decision-making. Regression results show that fiscal, talent, and industrial competition all have significantly positive coefficients at the national level (Table 10). This suggests that cities strategically emulate the NII decision-making of their peers in response to multifaceted competitive pressures. Notably, these effects exhibit clear regional heterogeneity. Fiscal and talent competition effects are more pronounced in central and western China than in the resource-rich eastern region. Eastern cities prioritise endogenous growth due to greater resources, while central and western areas face intense competition for financial resources and skilled human capital, making them more sensitive to the investment behaviours of neighbouring cities. These findings echo those of Ma et al. (2024), who find that the effect of fiscal competition is insignificant in eastern China but very strong in central and western regions.

Industrial competition emerges as one of the most compelling findings, particularly its strong driving effect in central China. This reflects the region's pressing need for industrial transformation, where local governments prioritise monitoring and replicating peers' NII investments to secure advantages in emerging sectors like artificial intelligence and big data. Such imitation serves as a strategic response to uncertainty, helping cities avoid falling behind and pursue leapfrog development. This form of risk-averse imitation mirrors behaviour observed in corporate sector, where firms emulate peers under uncertainty—such as in the adoption of green innovation (Wang et al., 2022b). However, such policy replication risks homogenised competition and systemic inefficiencies. Empirical research confirms local authorities engage in significant policy benchmarking, but in the absence of effective regional coordination, which can lead to industrial convergence, reduced diversity, and significant efficiency losses (Yu et al., 2017).

Exogenous shocks. Mechanism tests confirm that national policies (NBDP, BCS, SCP) act as exogenous shocks amplifying peer effects in China's NII investments, thereby supporting Hypothesis 4 (Table 11). These effects, however, exhibit clear regional heterogeneity, shaped by differences in development levels and

Table 11 The regression results of exogenous shocks.

	All	Eastern	Central	Western
NBDP	0.119*** (0.017)	0.088*** (0.023)	0.188*** (0.027)	0.120*** (0.038)
R ²	0.302	0.352	0.396	0.147
F-value	174.881***	82.271***	98.355***	17.425***
BCS	0.034** (0.013)	0.028 (0.020)	0.101*** (0.023)	-0.033 (0.021)
R ²	0.291	0.344	0.380	0.138
F-value	166.297***	79.365***	91.804***	16.176***
SCP	0.010 (0.011)	0.060*** (0.019)	0.037** (0.018)	-0.024 (0.019)
R ²	0.290	0.349	0.371	0.137
F-value	165.148***	81.192***	88.426***	16.032***
Control variables	YES	YES	YES	YES
N	2838	1067	1056	715

*; **; *** denote significant levels at 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses. Control variables are consistent with those in the baseline regression.

institutional capacity. The impact of NBDP effect is more pronounced in central and western China, where higher levels of uncertainty prompt local authorities to emulate the behaviour of successful pilot cities. This pattern aligns with institutional theory, which suggests that under uncertainty, organisations tend to copy practices that are perceived as successful elsewhere (Zhang et al., 2020). Conversely, the wealthier eastern region, with its greater resources and autonomy, shows minimal imitation, as investment decisions are more closely tailored to local industrial needs.

Similarly, the BCS increases peer effects at the nation level, but with substantial regional variation. Eastern cities generally draw on their own prior experience and development plans, resulting in limited imitation. In Western cities, the BCS does not significantly drive peer effects, possibly due to structural or capacity constraints. However, in the central region, the peer effect is particularly strong. Local governments actively emulate broadband investments made by pilot cities to stay competitive in emerging technology sectors. Yet such behaviour can backfire—competition to outdo neighbours may cause overinvestment and waste as cities replicate each other's projects without regard for local needs (Zhang et al., 2020). These findings suggest the need for region-sensitive, coordinated planning and caution against one-size-fits-all national broadband policies.

The SCP shows a clear east–west divide in its impact. At the national level, its overall effect on peer imitation is relatively weak. However, in central and eastern regions, the SCP significantly boosts imitation, as local governments mimic pilot-city smart initiatives to reduce decision-making risks. In contrast, in the western region shows little response to the SCP, primarily due to economic and technical constraints. This disparity reflects China's digital divide: wherein western cities lack the infrastructure, financial resources, and technical expertise necessary to replicate the more advanced models developed in the east.

Conclusions and policy implications

To identify and validate the strategic interaction mechanisms in NII decision-making, this study constructs a multi-dimensional spatial econometric model to examine peer effects and their underlying mechanisms. Specifically, we construct multi-dimensional spatial weight matrices—incorporating economic, administrative, geographic, economic-geographic, transportation, and industrial linkages—to identify peer effects across seven spatial correlation contexts. We further conduct complementarity

tests to explore asymmetric interactions between developed and underdeveloped cities, and quantify the roles of learning mechanisms, competition mechanisms, and exogenous policy shocks in shaping peer effects. The key findings are as follows: (1) Significant peer effects exist across all seven spatial correlation contexts, with transportation and industrial linkages exhibiting the strongest intercity influences. These results remain robust across alternative estimation methods, dependent variable specifications, and spatial weight matrices, demonstrating high result reliability. (2) Significant asymmetry characterizes peer effects between cities at varying development levels. Underdeveloped cities demonstrate substantial imitation of developed counterparts in NII decision-making, whereas developed cities primarily function as imitated referents. This pattern reflects how resource-constrained localities mitigate decision-making risks by emulating pioneers. (3) Learning and competition mechanisms constitute core drivers, reinforced by exogenous policy shocks. For learning mechanisms, internal experience accumulation strengthens imitation more than corrective adjustments. Regarding competitive mechanisms, industrial competition dominates as the primary driver, particularly in central China where industrial upgrading pressures are acute. Fiscal and talent competition exert greater imitation pressure on central-western governments compared to eastern regions, compelling policy alignment to maintain competitiveness. Moreover, National-level pilot programs, such as National Big Data Comprehensive Pilot Zones, provide key decision-making references, enhancing mutual imitation among cities in NII decision-making.

Based on the above conclusions, the following policy recommendations are proposed:

- (1) Optimize planning coordination and adopt differentiated investment strategies
Regional coordination mechanisms should be established to enhance resource sharing, such as co-developing data centres, and to avoid redundant infrastructure. Developed cities ought to prioritize cutting-edge technologies with high innovation potential (e.g. AI, 6G). Meanwhile, underdeveloped cities should prioritize projects rigorously aligned with local needs, cost-effectiveness, and public welfare contributions. Implementing a differentiated performance evaluation framework remains essential; developed cities must be assessed on technological sophistication, standard-setting capabilities, and industrial influence, whereas their underdeveloped counterparts require evaluation metrics emphasizing coverage scope, service accessibility, industrial relevance, and cost efficiency. Developing countries should leverage core growth poles to guide demand-driven investment strategies in lagging regions and reduce regional disparities
- (2) Innovate financing mechanisms and strengthen risk management
Private investment require expansion through standardized PPPs with clear risk-sharing protocols. And innovative instruments such as infrastructure Real Estate Investment Trusts. Concurrently, robust lifecycle oversight and risk assessment frameworks are essential to ensure capital efficiency and debt sustainability. Given the global prevalence of new infrastructure financing constraints—particularly in fiscally constrained developing economies—diversified financing approaches (e.g. PPPs) and effective risk mitigation practices are critical. Crucially, mechanisms attracting private capital through balanced risk-return profiles, supported by independent regulatory oversight, can safeguard long-term fiscal viability and protect public interests.

(3) Institutionalize knowledge-sharing and foster localized innovation

Structured regional learning platforms (e.g. national case repositories, technical forums) should facilitate policy experience exchange while curbing indiscriminate imitation. Developed cities are encouraged to systematically share best practices, whereas underdeveloped counterparts ought to critically assess transferability and innovate contextually by leveraging indigenous assets (e.g. industrial clusters, cultural resources) to cultivate competitive advantages. The central government may accelerate such specialization through pilot programs and fiscal incentives. Developing countries should establish cross-jurisdictional learning networks to diffuse proven methodologies, emphasizing locally tailored digital industries anchored in comparative advantages to foster regionally complementary development.

This study has certain limitations that warrant further research. First, the measurement of NII relies on industry-level proxy variables due to the absence of official statistics. Future research could aim for greater precision by using more granular data as it becomes available. Second, while this study focuses on three exogenous shocks affecting peer effects in NII decision-making, many other policy interventions and external factors in China may similarly influence these spatial dynamics. Future research could explore a broader range of exogenous shocks, including sector-specific policies, regulatory reforms, and macroeconomic interventions, to develop a more comprehensive understanding of how external factors shape peer effects in NII decision-making.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Received: 10 March 2025; Accepted: 28 October 2025;

Published online: 09 December 2025

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Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 72471081 and 72134002), Humanities and Social Science Fund of Ministry of Education of China (Grant No. 23YJAZH053), and Hebei Province Yanzhao Golden Platform Talent Plan project (Grant No. HJYB202529).

Author contributions

T.H. and S.L. designed the study, developed the research framework, and collected the preliminary data. T.H., S.L., and Y.Q. contributed to the development and implementation of the methodology, as well as the execution of the empirical analysis. T.H. and Y.Q. wrote the original draft, including the formulation of key arguments and data interpretation. Y.Z. and B.L. reviewed and critically revised the manuscript for intellectual content, providing suggestions for improving the analysis and presentation. All authors actively participated in the manuscript revisions, ensuring the accuracy and clarity of the final version, and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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