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From Openness to Competitive Advantage: Mechanisms, Heterogeneity, and Tiered Opening-up Strategies in China's Urban Global Competition

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Abstract

Amidst increasingly globalised urban competition, this study investigates how comprehensive openness shapes urban competitiveness in emerging economies. Building on panel data from 288 Chinese prefecture-level cities (2008–2023), we construct multidimensional indices for comprehensive openness and urban competitiveness and employ dynamic panel, moderating effect, and spatial econometric models to examine the mechanisms, heterogeneity, and spatial spillovers of comprehensive openness. Results show the following. First, comprehensive openness significantly enhances urban competitiveness in the short ($\hat{\alpha}_s = 0.05$) and long ($\hat{\alpha}_L = 0.17$) terms, with the long-term effect amplified by the accumulation of factor endowments, business environment quality, and global position. Second, this positive impact is channeled through improved green innovation efficiency and increased global connectivity, enhanced by high-quality institutional environments and FinTech development. Third, aligning with the dynamic adaptation theory in new structural economics, the effectiveness of comprehensive openness is contingent upon a city's inherent global structural position—specifically, its embeddedness in global networks and maturity of its innovation ecosystem. Fourth, we identify a 'local gain, neighbour loss' pattern in spatial spillovers, highlighting the need for regional coordination policies to mitigate resource misallocation. Finally, we benchmark results against global city rankings and propose a tiered opening-up strategy, suggesting differentiated goals for cities based on their developmental tiers, such as contesting global rule-making authority, forging specialised functional platforms, achieving breakthrough through specialised niches, or enhancing regional connectivity. This study offers empirical insights for cities in emerging economies seeking to ascend the global urban hierarchy through strategic openness.

Keywords: *comprehensive openness, urban competitiveness, global structural position, spatial spillover effects, tiered opening-up strategy*

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1 INTRODUCTION

The world economic landscape is undergoing a profound transformation, with a resurgence of trade protectionism, escalation of geopolitical tensions, and restructuring of global supply chains. The United Nations World Economic Situation and Prospects 2026 report indicates a projected continued slowdown in global economic growth, with the global trade growth rate potentially falling to 2.2% in 2026, marking a decade low (United Nations, 2026). This new international economic environment presents unprecedented challenges for global urban development. Urban competition is shifting from its traditional reliance on resource endowments towards the capacity to acquire, allocate, and innovatively utilise high-end international factors within global networks (Sgambati & Gargiulo, 2022). In this

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transformative context, China's steadily advancing Comprehensive Openness (CO) strategy holds significant theoretical and practical relevance.

China's distinctive CO strategy encompasses three key dimensions: (i) advancing institutional opening concerning rules, regulations, management, and standards; (ii) progressively relaxing market access restrictions for foreign investment; and (iii) deepening international cooperation through the Belt and Road Initiative. This mode of openness is reshaping the position of Chinese cities within the global urban network. Data from The World According to GaWC 2024 show that the number of Chinese cities ranked Beta or higher increased from 19 in 2018 to 23 in 2024, while the United States witnessed a decrease from 16 to 13 (GaWC, 2024). Nevertheless, data from the Global Innovation Index 2023 reveal a stark contrast in high-end knowledge production and innovation control: The United States hosts 118 cities at the NODE level or above, more than four times that of China's 28 (WIPO, 2023). This juxtaposition highlights a critical issue: while Chinese cities have made remarkable strides in global connectivity networks, their control of high-level nodes within global innovation networks shows a significant gap. This phenomenon raises a pivotal academic question: how does CO affect the competitiveness of Chinese cities within global networks and innovation systems under the new international environment? Addressing this question carries substantial theoretical and policy implications.

The literature on urban competitiveness (UC) has evolved from static comparative advantage to dynamic capacity building. Traditional theories focused on static factors such as resource endowments and locational advantages, whereas contemporary research underscores a city's nodal position in global networks and its dynamic capabilities to attract and configure innovative elements (Taylor, 2004; Kresl & Ietri, 2014). In the Chinese context, the effects of CO are multidimensional. It can significantly enhance a city's competitive position by improving global connectivity through infrastructure interconnectivity or upgrading the business environment via institutional innovations such as Pilot Free Trade Zones (Wang et al., 2020; Ni et al., 2022). However, it may exacerbate regional development disparities and create 'agglomeration shadow' effects (Tan et al., 2022; Liu et al., 2023). Existing research points to two notable limitations: a lack of granular analysis of the mechanisms through which CO influences UC and a neglect of the heterogeneous nature of its spatial spillover effects.

This study investigates 288 Chinese prefecture-level-and-above cities from 2008 to 2023 to examine how CO affects UC. It addresses three research questions. First, does the impact of CO on UC exhibit time-varying characteristics, and how do its short-term shocks differ from its long-term effects? Second, through which specific channels does CO influence UC? Third, what variations exist in the effects of CO among cities with different inherent global structural positions, and what characterises its spatial spillover effects? We argue that our findings will deepen the understanding of the relationship between CO and urban development and provide a scientific basis for formulating differentiated regional opening policies.

The marginal contributions of this study are threefold. First, it employs a dynamic panel model to capture the distinct short- and long-term effects of CO. Second, it clarifies the transmission pathways and moderating mechanisms through which CO affects UC, addressing the insufficient mechanistic analysis in prior studies. Third, it deepens the inquiry into the spatial spillover effects of CO by revealing a 'local gain, neighbour loss' dual structure and proposes a tiered urban opening-up strategy based on Globalization and World Cities Study Group and Network (GaWC) and Global Innovation Index (GII) benchmarks. The findings will offer novel

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insights for Chinese cities aiming for functional ascension in global competition and provide a reference for cities in other emerging economies navigating new globalisation challenges.

The remainder of this paper is structured as follows. Section 2 reviews the literature and develops theoretical hypotheses. Section 3 details the research design, including data sources, variable measurements, and model specifications. Subsequently, Section 4 presents and discusses the empirical results. Section 5 concludes with findings and policy recommendations.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Comprehensive Openness and Urban Competitiveness

2.1.1 Comprehensive Openness

As a pivotal concept in contemporary international economics, CO signifies a paradigm shift in open economies from a 'factor flow' model to an 'institutional innovation' model (Wang, 2021). Its essential characteristics are twofold: (1) factor integration, which optimises resource allocation through the cross-border flow of goods, services, capital, technology, and data; and (2) institutional coupling, which involves proactive alignment with international rules and governance reforms within domestic economic institutional reforms (Zhang & Li, 2023). This concept transcends traditional openness metrics based on trade or investment alone. Through the institutional design of special functional zones such as pilot free trade zones and cross-border data flow pilots, CO constructs a complete chain aimed at reducing institutional transaction costs, agglomerating high-end production factors, and securing governance nodes within global value chains (Wang, 2025). Showing that the essence of competition among modern open economies lies in the quality of their institutional environments, CO establishes a dynamic coupling mechanism between factor flows and institutional innovation, proposing a pathway for institutional leapfrogging during global value chain restructuring (Bi & Li, 2018). This study constructs a two-dimensional measurement framework encompassing 'factor flow-oriented' and 'institution-oriented' openness to identify Chinese cities' capacity to participate in global economic governance (see Table 2).

2.1.2 Urban Competitiveness

UC refers to a city's systemic capability to acquire, configure, and transform strategic resources—capital, information, talent, and data—within global urban networks to gain value dominance (Ni, 2003; Taylor, 2004). Its essence is embodied in three unifications: factor allocation efficiency and institutional innovation capacity (Su & Tu, 2018); economic value creation and social welfare enhancement (Yang & Ni, 2017); and regional competitive advantage and global network power (Wang et al., 2019; Ni et al., 2021). The theoretical evolution of UC demonstrates three paradigm shifts. First, the benchmark has moved from static comparative advantage to dynamic competitive advantage. Second, the analytical dimension has expanded from singular economic indicators to a synergistic 'economic–social–ecological' system. Third, the spatial scale has extended from regional market dominance to global value chain governance (Ni, 2003; Taylor, 2004).

Existing research employs two primary methodological systems for measuring UC. First, the process-oriented approach focuses on the formation mechanisms of competitiveness, using explanatory indicators such as production factors and institutional environment to delineate the transmission path from 'factor input' to 'capacity transformation' (Ni et al., 2021).

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Representative methods include the 'Gong-Xian-Jian' (Bow-String-Arrow) model (Ni, 2003), which systematically measures the synergistic effects of hard (e.g. labour, capital) and soft (e.g. institutions, culture) factors. Second, the outcome-oriented approach directly measures the results of competitiveness, emphasising a city's value-capture ability within global value chains. Core methods include using explicit indicators such as economic density and international air routes to map a city's network control power, helping to synthesise a global urban competitiveness index (Taylor, 2004) or integrating economic density and economic growth to depict the scale and speed of value creation, culminating in a composite UC index (Wang et al., 2019). The key distinction is that process-oriented indicators (e.g. R&D investment, institutional variables) are prone to endogeneity due to potential reverse causality with explanatory variables. Conversely, outcome-oriented indicators maintain clearer conceptual boundaries with explanatory variables, facilitating more robust causal identification (Ni et al., 2021). Accordingly, this study adopts the outcome-oriented approach, constructing a four-dimensional measurement framework—'value creation, high-end factors, industrial function, quality of life'—to identify a city's structural power within the global division of labour (see Table 1). This method mitigates endogeneity concerns and allows for uncovering the pathways through which CO enhances UC via mediation and moderation effect models.

2.2 Effect of Comprehensive Openness on Enhancing Urban Competitiveness

From the perspectives of regional development and global interconnectedness, CO's direct effect on enhancing UC is primarily realised through optimising local factor allocation, aligning with advanced international institutional rules, and deeply embedding into global division of labour networks. Research has identified the efficiency of production factor allocation, the international compatibility of the institutional environment, and a city's nodal position within global networks as crucial determinants of UC (Ni et al., 2021; Wang et al., 2019). First, dismantling barriers to factor mobility promotes the agglomeration and recombination of high-end factors such as capital, technology, and talent within cities, directly boosting productivity and growth potential. Second, aligning institutional rules with high international standards can significantly reduce institutional transaction costs, fostering a transparent and predictable business environment and enhancing a city's appeal to global resources. Finally, deep integration into global markets and production networks enables cities to transcend local market limitations, accessing economies of scale and opportunities for functional upgrading within a broader division of labour system.

CO significantly impacts these three aspects. Through the dual channels of 'bringing in' and 'going global', CO facilitates the free flow and optimal recombination of production factors within and beyond cities. This attracts external high-quality factors and upgrades the quality of local factors, improving overall allocation efficiency (Cao & Ni, 2020). Simultaneously, CO exerts pressure for and accelerates institutional reforms—for instance, aligning with international trade and investment rules via platforms such as pilot free trade zones, leading to improvements in areas such as the business environment and intellectual property protection, which reduces uncertainty for businesses (Zheng & Duan, 2022). Furthermore, CO transforms cities from local economies into nodes within global networks. By participating in global industrial and value chains, cities expand their market reach, deepen their specialisation, and potentially climb to higher value-added segments (Li & Ni, 2013; Shi & Sun, 2025). Collectively, these mechanisms underpin the positive direct effect of CO on UC, and the following hypothesis is proposed:

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H1a: Comprehensive openness exerts a significant positive effect on urban competitiveness.

However, CO's role in promoting UC is not statically dependent on a city's initial endowments. Instead, it is achieved dynamically through the cumulative effects triggered by the CO process itself—factor upgrading, institutional evolution, and network strengthening. In the long run, CO can catalyse and accelerate a virtuous cycle: the continuous inflow and optimal recombination of factors elevate the quality of a city's factor endowments; deep alignment with international rules drives the iterative improvement of the institutional environment; and deep embedding and functional ascension within global networks consolidate and enhance the city's strategic position (Zhou & Gao, 2024). This dynamic, self-reinforcing cumulative process is consistent with path dependency theory (Martin & Sunley, 2006), which emphasises that initial conditions and historical sequences shape long-term development trajectories. Moreover, absorptive capacity theory (Cohen & Levinthal, 1990) suggests that the ability to recognise, assimilate, and apply external knowledge—enhanced through sustained openness—creates increasing returns to learning-by-doing and knowledge spillovers over time. Consequently, competitiveness gains from openness exhibit a significantly increasing long-term effect. Therefore, we propose the following:

H1b: The cumulative effects of factor endowment upgrade, institutional environment optimisation, and global network position enhancement, induced by comprehensive openness, strengthen over time, leading to a pronounced long-term promotional effect on urban competitiveness.

2.3 Mechanisms by which Comprehensive Openness Affects Urban Competitiveness

The pathway through which CO enhances UC is a complex, multi-stage, and multi-layered transmission process. Its impact is realised by driving structural transformations in a city's internal key capacities and depends profoundly on the city's local enabling systems and its global structural position. Accordingly, this study focuses on three mediating variables—green innovation efficiency, public environmental concern, and global connectivity—treating them as proxies for the three theoretical mechanisms of 'optimising local factor allocation', 'aligning with advanced international institutional rules', and 'deeply embedding into the global division of labour network', respectively. Concurrently, it introduces local enabling systems (business environment, FinTech, AI) and global structural positions (global network embeddedness, innovation ecosystem maturity) as moderating variables to analyze their conditional roles in these pathways.

2.3.1 Factor Allocation Optimisation Path via Green Innovation Efficiency

Green innovation efficiency refers to the comprehensive efficacy of reallocating and transforming production factors, such as capital, technology, and talent, towards green production under dual resource and environmental constraints (Feng et al., 2023). CO drives the leap in green innovation efficiency through a dual force. On the one hand, external pressures from international market competition and compliance with increasingly stringent global environmental regulations compel local governments and firms to shift factors from traditional high-energy-consuming models towards clean technologies and green industries (Acemoglu et al., 2012). On the other hand, CO facilitates the cross-border flow of green technologies, knowledge, and management expertise, enabling cities to integrate global cutting-edge green elements with local resources at lower cost and higher efficiency, achieving 'import–digestion–re-innovation' and enhancing green total factor productivity (Changalima et al., 2025).

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Enhanced green innovation efficiency profoundly impacts UC. Higher efficiency implies lower resource and environmental costs per unit of economic growth, directly strengthening a city's sustainability and resilience. This aligns with global sustainable development goals and low-carbon transition trends, elevating the city's long-term value and attractiveness in the eyes of global capital and talent (Zhao et al., 2022). Simultaneously, leading green industries and technologies can help a city secure advantageous position within emerging global green value chains, forming a unique green competitive advantage. Therefore, we propose the following:

H2a: Comprehensive openness exerts a significant positive effect on urban competitiveness by enhancing green innovation efficiency.

The strength of the pathway through which CO enhances UC via green innovation efficiency depends critically on a city's local enabling systems. First, a superior business environment reduces the institutional transaction costs associated with green technology transfer, intellectual property transactions, and regulatory compliance, accelerating factor recombination (Lin, 2011; Amin et al., 2023). This aligns with the institutional complementarity perspective (Hall & Soskice, 2001)—the effectiveness of market-based policies is enhanced when supported by high-quality institutional frameworks. Second, FinTech development alleviates financing constraints for green innovation by providing precise and efficient tools for green credit, green bond issuance, and risk management, directing capital towards high-efficiency green projects (Sheng, 2020). This resonates with the financial development literature (Goldfarb & Tucker, 2019), which emphasises that advanced financial systems improve resource allocation and facilitate the translation of openness into tangible investment outcomes. Third, high-level application of AI can optimise energy systems and enhance the intelligence of resource recycling, directly improving the efficiency of green production processes and spurring new green business models (Wang et al., 2022). Collectively, these local enabling systems act as amplifiers, strengthening the indirect effect of CO on UC via green innovation efficiency. Therefore, we propose the following:

H2b: In achieving comprehensive openness, the positive effect on urban competitiveness via enhanced green innovation efficiency is more pronounced for cities with stronger local enabling systems (business environment, FinTech, AI).

A city's global structural position further conditions the effectiveness of this pathway. Cities with high global network embeddedness (e.g. Alpha-level global hubs in GaWC ratings) are primary destinations for global green capital and technology and more likely to participate in setting international green standards and rules, occupying high-value segments in green factor allocation. This aligns with world city network theory (Taylor, 2004), which argues that a city's nodal position in global flows determines its capacity to command and control strategic resources. Similarly, cities with mature innovation ecosystems (e.g. rated NEXUS or HUB-level by GII) possess more robust industry–university–research collaboration networks and greater knowledge absorptive capacity, enabling them to translate external green knowledge spillovers into substantive local innovation more efficiently, fostering sustainable green competitiveness (Spigel, 2017; Du et al., 2019). According to new structural economics (Lin, 2011), the effectiveness of openness policies is contingent upon a city's factor endowments and structural capabilities. Cities with higher structural positions are better equipped to leverage openness for sustainable development. Therefore, we propose the following:

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H2c: In achieving comprehensive openness, the positive effect on UC via enhanced green innovation efficiency is more pronounced for cities with an advanced global structural position (higher global network embeddedness, greater innovation ecosystem maturity).

2.3.2 Institutional Rule Alignment Path via Public Environmental Concern

Public environmental concern, reflecting the intensity of social actors' awareness and demands regarding environmental issues, serves as a fundamental social force driving the evolution of formal and informal environmental institutions towards advanced international standards (Wu et al., 2022; Li et al., 2025). It acts as a 'social sensor' and 'pressure transmitter' for the mechanism of 'aligning with advanced international institutional rules'.

CO significantly elevates local public environmental awareness and expectations through the flow of information and ideas. The influx of international environmental agendas, governance concepts, and civic action modes, amplified by media and networks, generates bottom-up social pressure (Singh et al., 2020). This social pressure converges with the top-down pressure from international rules introduced by CO, jointly compelling local governments to accelerate the modernisation of environmental governance systems—for example, by strengthening environmental information disclosure, broadening public participation channels, and strictly enforcing environmental regulations—and substantively advancing the alignment of local institutions with international norms. The institutional optimisation driven by public environmental concern is key to upgrading the 'soft environment' of UC. A city that is responsive to public demands and possesses transparent and efficient environmental governance significantly reduces uncertainty and risk for firms regarding environmental compliance. This helps retain businesses and attracts high-end domestic and foreign investment and talent that value social responsibility and long-term reputation (Bye & Fæhn, 2022). Furthermore, good environmental governance performance itself becomes a vital component of a city's brand and liveability, directly enhancing its appeal to human capital.

H3a: Comprehensive openness exerts a significant positive effect on urban competitiveness by raising public concern about the environment.

The process through which public concern translates into effective institutional change and ultimately enhances competitiveness is significantly moderated by a city's local enabling systems. First, the translation of public concern into institutional change depends highly on the local institutional foundation. A transparent, efficient, and responsive business environment implies that the government possesses better governance capacity and willingness to respond to and incorporate public demands, swiftly turning social pressure into policy action (Lin, 2011). Second, the development of FinTech can empower green consumption and environmental behaviour, ensuring that public choices are expressed through residential mobility and consumption patterns generate more direct economic signals, strengthening incentives for firms and government. Third, AI technology can be used for environmental monitoring and Big Data analysis, enhancing the transparency and accessibility of environmental information and making public oversight more precise and potent (Acemoglu & Restrepo, 2020a). Collectively, these local enabling systems enhance the efficacy of the institutional rule alignment pathway. Therefore, we propose the following:

H3b: In achieving comprehensive openness, the positive effect on urban competitiveness via increased public concern for the environment is more pronounced for cities with stronger local enabling systems (business environment, FinTech, AI).

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A city's global structural position determines the breadth and depth of the institutional changes triggered by public environmental concern. Cities with high global network embeddedness are under the spotlight of international public opinion and transnational NGOs; their environmental issues are more likely to escalate into international concern, creating a stronger mechanism to force an 'institutional alignment' (Acemoglu et al., 2012). This reflects the logic of world city network theory (Taylor, 2004): globally connected cities face greater external scrutiny and are more responsive to international norms. Moreover, mature innovation ecosystems encompass technological innovation and social and governance innovation, capable of providing more diverse and cutting-edge institutional solutions to address public environmental demands (Spigel, 2017). Such ecosystems enable cities to translate public pressure into effective governance reforms more efficiently. Therefore, we propose the following:

H3c: In achieving comprehensive openness, the positive effect on urban competitiveness via increased public concern for the environment is more pronounced for cities with a more advanced global structural position (higher global network embeddedness, greater innovation ecosystem maturity).

2.3.3 Division of Labour Network Embedding Path via Global Connectivity Capacity

Global connectivity capacity, measured by the density and intensity of tangible and intangible channels such as air passenger flow, logistics, and information flow, is the most direct and fundamental physical manifestation of a city's 'deep embedding into the global division of labour network' (Wang et al., 2020).

First, CO policies are directly manifested in leaps in infrastructure interconnectivity. Measures such as increasing international flight routes, expanding hub airports, and operating China–Europe freight trains drastically compress the temporal, spatial, and economic distance between a city and other global nodes (Jorfi & Winkler, 2025). Second, enhanced global connectivity transforms a city from a relatively isolated economy into a critical node within global flow networks (of people, goods, capital, and information), enabling easier access to global supply chains, attraction of transnational talent, and acquisition and diffusion of cutting-edge knowledge and technology. Third, strong global connectivity capacity acts as a 'multiplier' for UC. It directly expands a city's economic hinterland, allowing it to serve global markets and achieve economies of scale and scope. As a key network node, the city's capacity to configure global strategic resources (e.g. high-end capital, corporate headquarters, international organisations) is strengthened, creating opportunities to ascend to governance positions within global value chains. This enhancement of position embodies a city's core competitiveness. Therefore, we propose the following:

H4a: Comprehensive openness exerts a significant positive effect on urban competitiveness by strengthening global connectivity capacity.

Building global connectivity requires massive investment, and the realisation of its benefits is significantly moderated by a city's local enabling systems. First, an efficient business environment ensures the smooth clearance of personnel and goods, reducing the institutional costs of cross-border flows and transforming physical connectivity into efficient economic connectivity. Second, developed FinTech secures the efficiency and security of cross-border capital flows, serving as the 'circulatory system' underpinning global trade and investment. Third, AI technology can optimise the operational efficiency of ports, airports, and logistics centres, enhancing the intelligent management of the connectivity network (Acemoglu &

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Restrepo, 2020b；Enri-Peiró et al., 2025). These local enabling systems ensure that physical connectivity translates into economic gains. Therefore, we propose the following:

H4b: In achieving comprehensive openness, the positive effect on urban competitiveness via strengthened global connectivity capacity is pronounced for cities with stronger local enabling systems (business environment, FinTech, AI).

The value of global connectivity exhibits significant network externalities and threshold effects. For cities already possessing high global network embeddedness, additional connectivity yields stronger network synergy and agglomeration effects, consolidating and elevating their 'command and control' functions as global or regional hubs (Taylor, 2004). This reflects the core insight of world city network theory that network positions generate increasing returns to connectivity. For cities with mature innovation ecosystems, strong global connectivity means more efficient channels for knowledge absorption, enabling faster translation into local innovative capacity, securing advantages in knowledge-intensive global divisions of labour. According to new structural economics (Lin, 2011), the marginal returns to openness policies depend on a city's structural capabilities, and those with higher structural positions are better positioned to capitalise on increased global connectivity. Therefore, we propose the following:

H4c: In achieving comprehensive openness, the positive effect on urban competitiveness via strengthened global connectivity capacity is more pronounced for cities with a more advanced global structural position (higher global network embeddedness, greater innovation ecosystem maturity).

2.3.4 Regional Coordinated Development Path Based on Spatial Externalities

The influence of CO on UC exhibits significant spatial externalities. This influence is not confined to the administrative boundaries of the opening city but generates complex diffusion and feedback effects across space through mechanisms such as factor flows, industrial linkages, and market agglomeration. Under certain conditions, this spillover effect can manifest negatively, whereby the competitiveness gains of a local city inhibit the developmental momentum of neighbouring cities, creating an imbalanced regional dynamic (Zhou & Gao, 2024).

From a theoretical mechanism perspective, the factor siphon effect occurs first. By optimising the institutional environment, reducing transaction costs, and deepening market access, CO significantly strengthens the factor agglomeration power of core cities (Ning et al., 2016), leading to a net outflow of capital, high-skilled labour, and corporate headquarters from peripheral to core cities. The second is the competition crowding-out effect. Core cities hold advantages in the industrial division of labour, knowledge spillovers, and market efficiency, weakening the industrial upgrading capacity of neighbouring cities (Kerr & Robert-Nicoud, 2020; Cristache et al.,2025). Third, the market restructuring effect—the spatial restructuring of market demand induced by openness—intensifies the spatial polarisation of economic activity, causing neighbouring cities to experience constrained growth owing to disadvantages in market access.

From an empirical support perspective, Li et al. (2025) reveal that core cities in central and western China absorb consumer resources from surrounding areas through openness, creating a consumption siphon effect. Liu et al. (2023) verify the 'agglomeration shadow' effect, where core cities inhibit the development of neighbouring cities through network linkages. Tan et al.

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(2022) find that geographic proximity exacerbates zero-sum resource competition between cities. Ding et al. (2021) show that the siphon effect of core cities within national-level urban agglomerations on neighbouring regions intensifies as distance decreases.

Within the CO process, the enhancement of a local city's competitiveness is accompanied by a negative spatial spillover effect on geographically adjacent cities. The underlying mechanism is that CO's institutional dividends and market advantages reinforce the core city's ability to attract high-end factors (e.g. capital, talent) while squeezing the industrial upgrading space and market share of neighbouring cities, leading to their relative developmental lag. Therefore, we propose the following:

H5: While enhancing the competitiveness of the local city, comprehensive openness generates a negative spatial spillover effect on geographically adjacent cities.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Model Specification

3.1.1 Two-Way Fixed Effects Panel Model

To test H1a, which posits a positive direct effect of CO on UC in the short term, a two-way fixed effects panel model is constructed:

$$UCI_{it} = \alpha_0 + \alpha_1 COI_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \qquad (1)$$

Where UCI_{it} denotes the competitiveness index for urban i in period t, and COI_{it} represents the comprehensive openness index. $Controls_{kit}$ denotes the k-th control variable for urban i in period t, included to account for confounding factors. μ_i captures city-specific fixed effects, controlling for time-invariant city characteristics (e.g. geographic location, resource endowment). δ_t denotes time fixed effects, controlling for common macro shocks (e.g. nationwide policy shifts). ε_{it} is the idiosyncratic error term. A statistically significant positive estimate for the core coefficient α_1 would provide support for H1a, indicating a positive effect of CO on UC after controlling for other factors.

Notably, this static specification captures the contemporaneous association between CO and UC but does not account for dynamic adjustment processes or long-term cumulative effects. Therefore, H1b, which concerns the long-term promotional effect driven by the accumulation of factor endowments, institutional quality, and global position, is tested separately using a dynamic panel model (System GMM) in Subsection 4.3.2.

3.1.2 Mediation and Moderation Effect Models

Building on a significant α_1 in the baseline model (1), a three-step procedure (Hayes, 2022) is employed, combined with bias-corrected bootstrap sampling (500 repetitions), to test the mediation hypotheses H2a, H3a, and H4a.7

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3.1.2.1 Mediation Effect

$$Medvar_{it} = \beta_0 + \beta_1 COI_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$UCI_{it} = \theta_0 + \theta_1 COI_{it} + \theta_2 Medvar_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

The mediating variables ($Medvar_{it}$) are green innovation efficiency (GIE_{it}), public environmental awareness (PEA_{it}), and global connectivity capacity (GCC_{it}). A significant indirect effect ($\hat{\beta}_1\hat{\theta}_2$), indicated by a bias-corrected bootstrap confidence interval excluding zero, confirms statistical significance of the mediation effect. Its contribution ratio to the total effect is calculated as $|\hat{\beta}_1\hat{\theta}_2|/(|\hat{\beta}_1\hat{\theta}_2| + |\hat{\theta}_1|)$. Effects with a contribution ratio below 5% are considered economically insignificant.

3.1.2.2 Moderation Effect and Heterogeneity Analysis

To test H2b, H2c, H3b, H3c, H4b, and H4c—which respectively examine the moderating roles of local enabling systems and global structural position in the three mediating pathways—the following moderation model is specified:

$$UCI_{it} = \eta_0 + \eta_1 COI_{it} + \eta_2 Adjvar_{it} + \eta_3 COI_{it} \times Adjvar_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

Moderators ($Adjvar_{it}$) are categorised into two distinct groups, each corresponding to the theoretical mechanisms elaborated in Subsection 2.3:

(i) Urban **Local Enabling Systems**. This category includes the Business Environment Health Index ($BEHI_{it}$), the FinTech Index (FTI_{it}), and the Artificial Intelligence Index (AI_{it}). These variables are employed to test whether a city's domestic institutional and technological infrastructure amplifies the mediated effects of CO on UC through green innovation efficiency (H2b), public environmental concern (H3b), and global connectivity capacity (H4b).

(ii) **Global Structural Position**. This category includes Global Network Embeddedness (GNE_{it}) and Innovation Ecosystem Maturity (IEM_{it}), both quantified based on international GaWC and GII ratings. These variables reflect a city's pre-existing hierarchical position within the global urban system and its innovation landscape and are used to test whether such structural advantages condition the effectiveness of the three mediating pathways—green innovation efficiency (H2c), public environmental concern (H3c), and global connectivity capacity (H4c)—consistent with the dynamic adaptation thesis of new structural economics (Lin, 2011).

3.1.3 Spatial Econometric Model

To test H5 regarding spatial spillovers, a spatial panel model is employed:

$$UCI_{it} = \rho \sum_{j=1}^{n} w_{ij} UCI_{jt} + \pi\, COI_{it} + \theta \sum_{j=1}^{n} w_{ij} COI_{jt} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \sum_{k=1}^{K} \tau_k \sum_{j=1}^{n} w_{ij}\, Controls_{kjt} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{n} w_{ij}\, \varepsilon_{jt} + v_{it} \quad v_{it} \sim N(0, \sigma_v^2), \quad (6)$$

where w_{ij} is the spatial weight matrix, and terms such as $\sum_{j=1}^{n} w_{ij} UCI_{jt}$ denote spatial lags capturing spillover effects from neighbouring cities j. ρ, θ, τ_k, λ are spatial coefficients. This general specification nests common models such as SAR, SEM, SDM, and SAC. Multiple spatial weight matrices are considered (contiguity, inverse-distance, exponential decay, Gaussian decay, threshold distance, and economic-geographic nested); formulas are provided

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in Appendix A (A1–A7). The primary estimation uses the row-standardised economic-geographic nested matrix (w_{ij}^{nested}).

3.2 Variable Definition and Measurement

3.2.1 Urban Competitiveness Index (UCI_{it})

To mitigate potential endogeneity arising from conceptual overlap with the COI_{it}, an outcome-oriented measurement approach is adopted. The index system focuses on 'value creation and wealth growth', 'high-end factors and high-value outputs', and 'industrial structure and functional hierarchy' (see Table 1). The entropy method is primarily used to construct UCI_{it} (baseline). Following common practice in the composite index literature, we employ the entropy method as our primary weighting scheme due to its data-driven, non-subjective nature. However, entropy weights reflect the statistical dispersion of indicators rather than theoretically derived importance weights. Therefore, we conduct robustness checks using PCA-based weights. For robustness, a Principal Component Analysis (PCA)-based index ($UCI_{PCA_{it}}$) is also constructed (cumulative variance explained ≥85%). Both indices are normalised to [0,1]; higher values indicate greater competitiveness.

The measurement framework for the High-Quality Development Index ($HQDI_{it}$) and the Urban Competitiveness Index (UC_{it}) is detailed in Appendix A Tables A1 and A2, respectively, for reference and comparison purposes. The former focuses on a city's comprehensive development status, while the latter emphasises the process of urban competition.

Table 1 – Urban Competitiveness Index Measurement Framework. Source: own search

Objective	Dimension	Indicator	Weight	Property
UCI	Value Creation and Wealth Growth	GDP per capita	0.0236	Positive
		GDP per unit of built-up area	0.1171	Positive
		Ratio of urban disposable income per capita to national average	0.0143	Positive
	High-End Factors and High-Value Outputs	Inflow rate of high-level talent	0.1051	Positive
		Share of listed companies among industrial enterprises above designated size	0.1190	Positive
		City's share of national actual utilised foreign direct investment (FDI)	0.1451	Positive
		City's share of national invention patent grants	0.1986	Positive
	Industrial Structure and Functional Hierarchy	Industrial structure advancement index	0.0179	Negative
		Agglomeration degree of foreign-funded enterprises	0.0622	Positive
		Employment share in information transmission, computer services, and software industries	0.0428	Positive
	Ecological Environment and Quality of Life	Annual average PM 2.5 concentration	0.0231	Negative
		Green coverage rate in built-up areas	0.0027	Positive
		Harmless treatment rate of municipal solid waste	0.0042	Positive
		Number of public buses per 10,000 people	0.0255	Positive
		Share of social security expenditure in general public budget expenditure	0.0080	Positive
		Ratio of average commercial housing price to average wage of employed staff	0.0148	Negative
		Gas penetration rate	0.0018	Positive

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		Tap water penetration rate	0.0012	Positive
		Number of hospital beds per 10,000 people	0.0182	Positive
		Public library books per 100 people	0.0545	Positive

Note: The construction of the Urban Competitiveness Index (UCI) draws on multiple theoretical and methodological sources. The outcome-oriented approach and the focus on value creation, high-end factors, and industrial structure follow Ni (2003) and Ni et al. (2021). The inclusion of global network-related indicators is informed by Taylor (2004) and Wang et al. (2019). The industrial structure advancement index is calculated following Gan et al. (2011). The selection of liveability and quality-of-life indicators are based on Ni et al. (2022) and the OECD Better Life Index framework. Subsection 3.3.1 presents the data sources.

3.2.2 Comprehensive Openness Index (COI_{it})

Table 2 presents the index system, theoretically encompassing trade, investment, and institutional openness. The entropy method is used to construct COI_{it} (baseline), with a PCA-based version ($COI_{PCA_{it}}$) for robustness. Sub-indices for factor flow-based openness ($FFBO_{it}$) and institution-based openness (IBO_{it}) are also constructed (entropy method) to examine their distinct effects. Following Zhang et al.'s (2023) methodology, the policy intensity of special functional zones (e.g. national-level airport economic zones) is calculated based on establishment status ($Estab_i$) and operational duration (T).

Table 2 – Comprehensive Openness Index Measurement Framework. Source: own search

Objective	Dimension	Indicator	Weight	Property
COI	Factor Flow-Based Openness	Foreign trade dependence (Total trade / GDP)	0.0373	Positive
		FDI dependence (Actual utilised FDI / GDP)	0.0237	Positive
	Institution-Based Openness	Policy intensity of National Airport Economic Demonstration Zones	0.1921	Positive
		Policy intensity of National Pilot Free Trade Zones	0.1613	Positive
		Policy intensity of National Comprehensive Bonded Zones	0.0956	Positive
		Policy intensity of National New Areas	0.1578	Positive
		Policy intensity of National Cross-Border E-Commerce Pilot Zones	0.1159	Positive
		Policy intensity of National High-Tech Industrial Development Zones	0.0567	Positive
		Policy intensity of National Economic and Technological Development Zones	0.0571	Positive
		Policy intensity of National Data Opening Pilot Cities	0.1025	Positive

Note: The construction of the Comprehensive Openness Index (COI) distinguishes between factor flow-based openness and institution-based openness, following the conceptual framework of Bi and Li (2018) and Wang (2021). The calculation of policy intensity for special functional zones (establishment status × operational duration) follows the methodology of Zhang et al. (2023). The selection of specific policy types is based on the national-level pilot zone catalogue maintained by the State Council and the Ministry of Commerce of China, as systematically compiled by Wang (2025). Subsection 3.3.1 presents the data sources.

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3.2.3 Mediating and Moderating Variables

3.2.3.1 Mediating Variables

In line with H2a, H3a, and H4a, three variables are selected as mediating mechanisms: green innovation efficiency (GIE_{it}), public environmental awareness (PEA_{it}), and global connectivity capacity (GCC_{it}). First, following Feng et al. (2023), GIE_{it} is measured using the super-efficiency Slack-Based Measure model, integrating energy use, environmental costs, and outputs. Second, drawing on Wu et al. (2022) and Li et al. (2025), PEA_{it} is constructed via the entropy method using Baidu search index data for environmental pollution-related keywords. Third, following Wang et al. (2020), GCC_{it} is measured via entropy method using indicators such as passenger/cargo throughput, flight movements, and China–Europe rail service status.

3.2.3.2 Moderating Variables

H2b, H2c, H3b, H3c, H4b, and H4c examine the moderating roles of local enabling systems (H2b, H3b, H4b) and global structural position (H2c, H3c, H4c) across the three mediating pathways of green innovation efficiency, public environmental concern, and global connectivity capacity. Thus, the moderating variables are categorised into two types as follows:

(i) City local enabling systems: Based on New Structural Economics (Lin, 2011) and Innovation Diffusion Theory (Rogers, 2003), the Business Environment Health Index ($BEHI_{it}$), FinTech Index (FTI_{it}), and Artificial Intelligence Index (AI_{it}) are selected to examine whether they amplify the mediated effects of CO on UC through the three pathways (H2b, H3b, H4b). $BEHI_{it}$ is sourced from the Report on the Evaluation of Government-Business Relations in Chinese Cities (2017–2023) published by the Center for Enterprise and Organization Studies at Renmin University of China. Following Sheng(2020), FTI_{it} is constructed via the entropy method using Baidu search index data for FinTech keywords. Third, drawing on Wang et al. (2022), AI_{it} is measured as the natural logarithm of the number of AI firms in city i during period t.

(ii) A city's global structural position: First, grounded in World City Network theory (Taylor, 2004), higher-level nodal cities function as 'command and control' centres for global capital and information—their network effects from CO are stronger. Accordingly, based on GaWC 2024 ratings, 'Alpha'-level cities are defined as 'Global Hubs', 'Beta' and lower-rated cities as 'Regional Nodes', and the remainder as 'Local Cities'. A continuous score is generated from this classification to quantify a city's Global Network Embeddedness (GNE_{it}). Second, according to Innovation Ecosystem theory (Spigel, 2017), mature urban innovation ecosystems can more efficiently absorb and transform the knowledge spillovers generated by CO. Therefore, based on the GII 2023, cities at the 'NEXUS or HUB' level are defined as 'Global Innovators', those at the 'NODE or UPSTART' level as 'Regional Innovators', and the rest as 'Innovation Followers'. A continuous score is generated to measure a city's Innovation Ecosystem Maturity (IEM_{it}). These variables are employed to test whether a city's pre-existing structural position within the global hierarchy and innovation landscape conditions the effectiveness of the three mediating pathways (H2c, H3c, H4c).

The inclusion of these moderators enables a comprehensive test of whether the impact of CO on UC varies systematically depending on a city's local enabling capabilities and its pre-existing position within the global urban network and innovation ecosystem.

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3.2.4 Control Variables

To isolate confounding factors, following Ni et al. (2022), controls comprise gross fixed capital formation share of GDP ($GFCF_{it}$), log of college students per 10,000 people (HC_{it}), log of per capita budgetary expenditure (PRE_{it}), share of S&T expenditure in total budgetary outlay (TI_{it}), physicians (assistant) per 10,000 people (PD_{it}), and industrial value-added share of GDP (IR_{it}). All regressions employ two-way (city and year) fixed effects with clustered standard errors.

3.3 Sample Data and Descriptive Statistics

3.3.1 Sample Selection and Data Sources

A balanced panel dataset comprising 288 prefecture-level-and-above cities in China over the period 2008–2023 is constructed, yielding 4,608 observations. Following the sample selection criteria, we exclude cities with severe data gaps—specifically, those with a single variable missing more than 50% of observations or multiple variables missing more than 30%—and autonomous prefectures with their distinct policy environments and potential heterogeneity that could bias the estimates.

The primary data sources are the China City Statistical Yearbooks (2009–2024), patent databases from the National Intellectual Property Administration, local statistical bulletins, the Wind Economic Database, corporate annual reports, and Qichacha. To maximise sample coverage while maintaining data integrity, missing values are addressed through linear interpolation. This method is applied only to gaps of no more than three consecutive periods to avoid introducing artificial trend smoothing. Variables with missing rates exceeding the predefined thresholds (30% for multiple variables or 50% for a single variable) result in the exclusion of the corresponding city from the sample, as described above.

Table A3 provides detailed descriptive statistics and a comprehensive account of missing data patterns. Most variables are fully observed. Among the mediating variables, public environmental awareness (PEA_{it}) has the highest missing rate (14.3%), primarily due to the limited availability of Baidu Search Index data for certain cities in the early years of the sample period; missing values for this variable are imputed using linear interpolation with a maximum gap of three consecutive periods. All control variables exhibit low missing rates (ranging from 0.9% to 4.7%) and are similarly imputed. The Business Environment Health Index ($BEHI_{it}$) is an exception: it is available only for the 2017–2023 period, resulting in a structurally unbalanced panel with 2,308 missing observations (50.1%). Therefore, $BEHI_{it}$ is not imputed. All regressions involving this variable are based on the available 2,300 observations, and appropriate caveats are noted in the relevant analyses. Finally, to mitigate the influence of outliers, all continuous variables are winsorised at the 1st and 99th percentiles.

3.3.3 Descriptive Statistics

Appendix A Table A4 shows that the mean of UCI_{it} is 0.05 (SD=0.04), with a maximum of 0.44 (e.g. Shenzhen, Shanghai) and minimum of 0.01. The standard deviation (SD) is 0.80 times the mean, indicating substantial heterogeneity across cities. COI_{it} exhibits a similar pattern of 'low mean, high dispersion'. Other variables align with expectations from prior literature.

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4. RESULTS AND DISCUSSION

4.1 Baseline Regression Results

Based on the Hausman test result ($\chi^2 = 525.86$, $p < 0.01$), the panel fixed-effects model was selected. Table 3 employs a progressive regression approach to identify the impact of the *COI* on the *UCI*. Column (1) includes no control variables or fixed effects. Column (2) incorporates city and year fixed effects to account for individual heterogeneity and temporal trends. Column (3) adds the full set of control variables to mitigate omitted variable bias. Columns (4) and (5) report results using *HQDI* and the process-oriented *UC*, respectively, as alternative dependent variables while including controls and two-way fixed effects.

The regression results reveal three key findings. The first concerns the significance of the effect. Statistically, the coefficient for *COI* is 0.34 ($p < 0.01$) without controls and fixed effects (Column 1). After adding two-way fixed effects (Column 2), the coefficient drops to 0.05 ($p < 0.01$), while the R^2 jumps to 0.97. Incorporating control variables (Column 3) leads to a slight coefficient adjustment to 0.05 ($p < 0.01$) with a further improved R^2—*COI* significantly enhances UC at the 1% level. Economically, the coefficient of 0.05 (Column 3) implies that a one-SD increase in *COI* (*SD* = 0.08) raises *UCI* by approximately 0.01 units (within its [0,1] range), equivalent to 8.26% of *UCI's* SD[①]—a modest economic magnitude. The high R^2 values in Columns (2)–(3) are expected, given the inclusion of city and year fixed effects, which absorb a substantial portion of time-invariant and common macro-level variation. This high explanatory power should not be interpreted as suggesting that *COI* alone accounts for nearly all variation in *UCI*; rather, it reflects the joint explanatory power of the fixed effects and the full set of controls.

Second, regarding the heterogeneity of effects, the *COI* coefficient in Column (4) is 0.07 ($p < 0.01$). However, the R^2 is lower than in Column (3), likely because *HQDI* includes an 'open development' dimension that overlaps with *COI*, introducing endogeneity that reduces estimation precision (Wooldridge, 2010). The *COI* coefficient in Column (5) is 0.36 ($p < 0.01$), significantly higher than in Columns (3) and (4), but again with a lower R^2. This inflation likely stems from conceptual nesting, as the process-oriented *UC* index includes dimensions such as 'international connectivity' and 'institutional quality', which are integral to the openness process itself, creating reverse causality and more pronounced endogeneity bias.

The third finding concerns the robustness of the effect. Regardless of whether the outcome-oriented *UCI*, the process-oriented *UC*, or the comprehensive-development-focused *HQDI* is used as the dependent variable, *COI* consistently shows a statistically significant positive effect at the 1% level, confirming the robustness of the core finding.

In summary, while the estimated positive association between CO and UC is statistically significant, its economic magnitude is modest. These findings are directionally consistent with the prediction of H1a. However, the static fixed-effects model captures contemporaneous correlations rather than causal relationships. Causal identification is addressed separately in Subsections 4.3 and 4.4 using instrumental variables, system GMM, and staggered difference-

① $\Delta UCI_{it} = \hat{\alpha}_1 \times SD(CUO_{it}) = 0.0458 \times 0.0768 \approx 0.0035; \frac{\Delta UCI_{it}}{SD(UCI_{it})} \times 100\% = \frac{0.0035}{0.0426} \times 100\% \approx 8.26\%$

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in-differences (DID) designs.

Table 3 – Benchmark Regression Results. Source: own search

Variable	(1)	(2)	(3)	(4)	(5)
	UCI	*UCI*	*UCI*	*HQDI*	*UC*
COI	0.3372*** (51.9880)	0.0464*** (2.9953)	0.0458*** (3.1270)	0.0748*** (5.8057)	0.3588*** (11.4662)
Controls	No	No	Yes	Yes	Yes
Two-Way FE	No	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608
R^2	0.3698	0.9737	0.9745	0.8887	0.8368

Note: t-statistics based on robust standard errors are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively; this convention applies to all subsequent tables.

4.2 Robustness Tests

To ensure the reliability of the baseline results, a battery of robustness checks was conducted, including variable replacement, methodological adjustments, model extensions, and placebo tests. These tests, detailed in Appendix A Table A5, aimed to rule out potential biases from measurement error, sample outliers, and model misspecification. The positive effect of *COI* on *UCI* remains consistent across all these alternative specifications, confirming the robustness of the finding and supporting H1a.

To ensure the reliability of the baseline results, a battery of robustness checks was conducted, including variable replacement, methodological adjustments, model extensions, and placebo tests. These tests, detailed in Appendix A Table A5, aimed to rule out potential biases from measurement error, sample outliers, and model misspecification. The estimated positive association between *COI* and *UCI* remains consistent across all these alternative specifications—the baseline finding is not an artifact of particular measurement choices or model specifications. This consistency provides additional support for H1a, although causal interpretation relies on the identification strategies presented in Subsections 4.3 and 4.4.

4.3 Endogeneity and Identification

Potential endogeneity in the *COI* variable (the Hausman test confirmed this endogeneity),[①] arising from bidirectional causality, omitted variables, and historical path dependency, was addressed using two-stage least squares (2SLS) and system generalised method of moments (GMM) estimations to verify the causal effect of *COI* on *UCI*.

4.3.1 2SLS Estimation

4.3.1.1 Instrumental Variable (IV) Construction

The 2SLS estimation aims to correct for contemporaneous endogeneity. Following the rationale of Nunn and Qian (2014) and Angrist and Pischke (2014), three IVs were constructed to leverage exogenous historical and external variation:

[①] The Hausman test results ($\chi^2 = 119.21$, $p < 0.01$) reject the null hypothesis at the 1% significance level—the COI variable is endogenous.

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IV_1 (Information Access Cost): Minimum distance from the city to a national optical fibre backbone hub, interacted with a linear time trend. The historical placement of backbone hubs is exogenous, and geographic distance influences openness via information-age access costs, independent of other growth channels.

IV_2 (Exogenous Demand Shock): A Bartik-style instrument (Yu et al., 2025) interacting national foreign trade growth with a dummy for historically open cities.[①] The national trend is an exogenous macro shock, and the historical city status creates a quasi-experimental group with differential sensitivity to this shock.

IV_3 (Historical Transport Cost): River density interacted with a linear time trend. This captures the path dependency of trade traditions shaped by geography, influencing openness primarily through a historically declining trade cost channel.

While our IVs are grounded in the literature and pass standard diagnostic tests, we acknowledge that no instrument is perfectly exogenous and do not rely on IV alone. We triangulate across three conceptually distinct identification strategies (2SLS, GMM, and staggered DID). The consistency of results across these considerably different identifying assumptions substantially strengthens confidence in a causal interpretation.

4.3.2.2 2SLS Results

Table 4, Columns (1)–(2) present results using IV_1 and IV_2. The Kleibergen-Paap LM statistic (644.472, $p<0.01$) rejects under-identification. The Cragg-Donald Wald F statistic (349.35) exceeds critical values, rejecting weak instruments. The Sargan test ($p=0.99$) does not reject the over-identification restrictions. Results using IV_1 and IV_3 (Columns (3)–(4)) are similar and serve as a robustness check. The second-stage coefficient for COI is 0.08 ($p<0.01$), larger than the baseline FE estimate—the latter may have been downward biased.

4.3.2 System GMM Estimation

System GMM addresses path dependency and dynamic endogeneity. Grounded in the path-dependency theory from evolutionary economics (Wziatek-Kubiak, 2023), a dynamic panel model is specified (Equation 7), including the one-period lag of UCI.

$$UCI_{it} = \alpha_0 + \alpha_1 UCI_{i,t-1} + \alpha_2 COI_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \qquad (7)$$

Column (5) of Table 4 shows that the Arellano-Bond test yields $z=-3.33$, $p<0.01$ for AR (1) and $z=0.49$, $p=0.62>0.10$ for AR (2). These results satisfy the requirements for the error term in System GMM estimation. The Hansen test of over-identifying restrictions under robust standard errors ($\chi^2=8.96$, $p=0.11>0.10$), along with the detailed Hansen tests for subsets of instruments in the level and difference equations, jointly validate that the instrument set (including IV_1, IV_2, and the internal instruments) satisfies the exogeneity and exclusion conditions. Similarly, the instrument set in Column (6) of Table 4 (including IV_1, IV_3, and the internal instruments) also meets the requirements for exogeneity and exclusion, serving as a robustness check for the results in Column (5).

[①] Open cities refer to those designated under China's pre-1992 policies, including Special Economic Zones, Coastal Open Cities, Border Open Cities, and Inland Open Cities.

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The results in Column (5) of Table 4 show the following. First, the short-term effect: The coefficient for contemporaneous *COI* is 0.02 (p<0.05), smaller than the baseline, potentially indicating policy implementation lags or initial market adaptation costs (Rodrik, 2018). Second, path dependency: The lagged *UCI* coefficient is 0.90 (p<0.01), confirming strong historical inertia in competitiveness (Martin & Sunley, 2006). Third, the long-run effect: The calculated long-run effect of COI is 0.17 (p<0.05),[①] substantially larger than the short-term effect, highlighting the cumulative impact of CO through factor endowments, business environments, and global positioning over time. The results in Column (6), using an alternative IV set, are highly consistent, supporting the robustness of the GMM estimates. Diagnostic tests (Arellano-Bond tests for AR (1) and AR (2), Hansen tests for over-identification) are satisfactory.

In summary, the 2SLS and System GMM analyses jointly provide evidence consistent with a causal interpretation of the *COI* and *UCI* relationship. While the short-term estimated effect is modest, the long-term estimated effect is substantially stronger. These findings support H1b—the cumulative effects of factor endowment upgrading, institutional environment optimisation, and global network position enhancement induced by CO strengthen over time, leading to a more pronounced long-term promotional effect on UC.

Table 4 – 2SLS and System GMM Estimates. Source: own search

Variable	(1) First Stage	(2) Second Stage	(3) First Stage	(4) Second Stage	(5) System GMM	(6) System GMM
	COI	*UCI*	*COI*	*UCI*	*UCI*	*UCI*
COI		0.0809*** (11.3242)		0.0844*** (13.6109)	0.0167** (2.4505)	0.0213*** (3.1018)
L.UCI					0.8991*** (5.5174)	0.8936*** (7.5346)
IV_1	-0.00003*** (-25.8824)		-0.00003*** (-23.5074)			
IV_2	0.0005*** (3.4358)					
IV_3			0.0139*** (16.1914)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608	4608
F	349.35***	45.50***	494.48***	53.42***	1450.91***	2140.66***
Identification Tests						
K-P LM χ^2		644.472***		862.115***		
C-D Wald F		349.348***		494.477***		
Sargan/Hansen *J* [*p*-val]		0.003 [0.9854]		0.935 [0.3335]	8.96 [0.111]	7.70 [0.173]

[①] The long-run effect of CUO_{it} =$\hat{\alpha}_2/(1-\hat{\alpha}_1)$=0.0167/（1-0.8991）≈0.1651

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A-B Test: AR(1)[*p*]					-3.33 [0.000]	-3.89 [0.000]
A-B Test: AR(2)[*p*]					0.49 [0.624]	0.33 [0.739]
Long-Run Effect of *COI*					0.1651**	0.2000**

Note: IV_1, Min distance to fibrze-optic hub × time trend. IV_2, National trade growth × historical open city dummy. IV_3, River density × time trend. Robust t/z-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Columns (5) and (6), System GMM uses indicated external IVs and internal instruments (lagged levels for differenced eq., lagged differences for level eq.)

4.4 Exogenous Shock Test

While the 2SLS and System GMM methods mitigate endogeneity and dynamic bias, both rely on model assumptions and the exogeneity of instruments. Conversely, an exogenous shock test leverages exogenous spatio-temporal variation in policy implementation—such as differential approval times for Comprehensive Bonded Zones—to capture the Local Average Treatment Effect (LATE) more directly, providing more robust causal support for the baseline results (Angrist & Pischke, 2014).

4.4.1 Staggered Difference-in-Differences Model

To further address potential endogeneity and strengthen causal inference, this study introduces an exogenous shock test using the establishment of 105 national Comprehensive Bonded Zones (CBZs) from 2006 to 2023 as a quasi-natural experiment. The staggered DID estimator (Callaway & Sant'Anna, 2021) is employed to identify the net policy effect.

$$UCI_{it} = \alpha + \beta IBZ_{it} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it}, \qquad (8)$$

where CBZ_{it} is the policy treatment indicator ($Treat_i \times Post_t$). $Treat_i$ equals 1 if city i was approved for a CBZ and 0 otherwise. $Post_t$ equals 1 for the approval year and all subsequent years. Other variables are as defined in Equation (1).

Columns (1)–(3) of Table 5 show that the coefficient for *CBZ* is positive and statistically significant at the 1% level across all model specifications, indicating a significant enhancing effect on *UCI*.

Table 5 – Staggered DID and PSM-DID Regression Results. Source: own search

Variable	(1)	(2)	(3)	(4) Cross-sectional PSM-DID	(5) Year-by-year PSM-DID
	UCI	*UCI*	*UCI*	*UCI*	*UCI*
IBZ	0.0505*** (35.2921)	0.0038*** (3.1135)	0.0031*** (2.7342)	0.0033*** (3.1553)	0.0032*** (3.5383)
Controls	No	No	Yes	Yes	Yes
Two-Way FE	No	Yes	Yes	Yes	Yes
N	4608	4608	4608	4533	3977
R^2	0.2129	0.9720	0.9730	0.9733	0.9680

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4.4.2 Robustness Checks

4.4.2.1 Parallel Trends Test

Given the heterogeneous timing of policy shocks, an event study model (Jacobson et al., 2005) is used to test the parallel trends assumption.

$$UCI_{it} = \alpha + \sum_{j=-5}^{5} \beta_j D_{i,t+j} + \sum_{k=1}^{K} \gamma_k Controls_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (9)$$

where $D_{i,t+j}$ is an event dummy equal to 1 when city i is $|j|$ years before or after policy implementation. Periods five years or more before/after are grouped into $|j|=5$, and the year immediately before the policy ($j=-1$) is omitted as the reference.

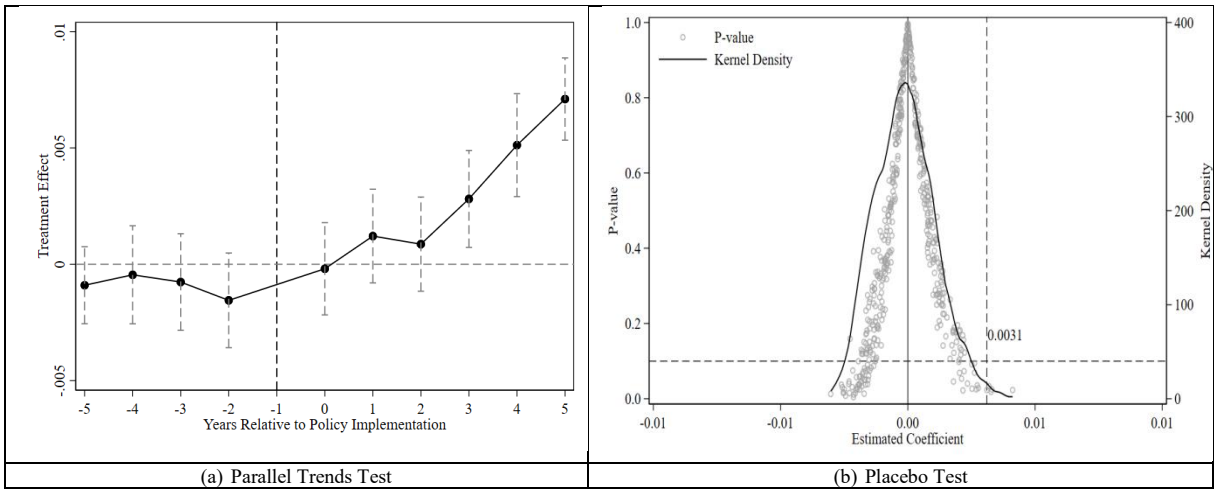
As shown in Figure 1(a), the estimated coefficients $\hat{\beta}_j$ for the five pre-treatment periods are statistically insignificant at the 5% level, and their 95% confidence intervals contain zero. This strictly satisfies the parallel trends assumption, ruling out pre-existing differential trends. The dynamic treatment effects reveal the following: (i) Policy lag: The effect becomes statistically significant only in the third year of CBZ establishment, consistent with theories of adjustment costs in policy implementation (Atkin et al., 2017); (ii) Accumulating effect: The effect grows over time, supporting the existence of cumulative learning effects—the institutional dividends of CBZs are gradually released through industrial chain synergies and technology spillovers, forming a self-reinforcing mechanism (Aghion et al., 2016).

This result underscores the non-linear nature of urban opening policies. Short-term frictions in administrative coordination and market adaptation can lead to delayed effects, whereas in the long run, economies of scale in institutional innovation and knowledge diffusion substantially enhance UC (Helpman, 2018).

4.4.2.2 Placebo Test

Following the counterfactual design of Abadie et al. (2010), 500 random pseudo-treatment groups were generated by randomly assigning the CBZ status to 105 cities each time, along with pseudo-implementation dates. The kernel density distribution of the resulting placebo coefficients (Figure 1(b)) is centred around zero, with over 95% of the estimates being statistically insignificant ($p > 0.10$). This distribution is clearly distinct from the baseline estimate of 0.0031, effectively ruling out spurious correlations from random noise.

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(a) Parallel Trends Test (b) Placebo Test

Figure 1 – Parallel Trends and Placebo Tests. Source: own search

Note: Figure 1(a) plots the dynamic treatment effects with 95% confidence intervals. The vertical dashed line at event year -1 indicates the omitted reference period. Figure 1(b) shows the kernel density distribution of 500 placebo coefficients alongside the baseline estimate. The vertical dashed line at 0.0031 on the horizontal axis indicates the baseline estimated effect of the CBZs policy.

4.4.2.3 PSM-DID Test

A calliper (1:2) nearest-neighbour matching was performed on the control variables, cross-sectionally and for each period. Post-matching, the vast majority of standardised biases were below 20%, with a mean below 25%. The PSM-DID regressions (Table 5, Columns (4)–(5)) show that the coefficient for the treatment effect remains statistically significant at the 1% level, consistent with the baseline results.

In summary, the series of tests—staggered DID, parallel trends, placebo, and PSM-DID—provide robust evidence consistent with a causal interpretation of the *COI* and *UCI* relationship, and further supporting H1a and H1b. Specifically, the significant and sustained policy effect documented in the staggered DID analysis aligns with H1a's prediction of a positive direct effect, while the cumulative strengthening of the effect over time (as shown in the event study) is consistent with H1b's expectation of long-term cumulative returns.

4.5 Mechanism Analysis

Having established the causal effect of *COI* on *UCI* through endogeneity controls and quasi-natural experiments, this section investigates the underlying transmission channels—specifically, whether green innovation efficiency (*GIE*), public environmental awareness (*PEA*), and global connectivity capacity (*GCC*) serve as the core mediating mechanisms.

4.5.1 Green Innovation Efficiency

Estimation results based on Equations (2)–(3) (Columns (1)–(2) of Table 6) confirm the significant mediating role of *GIE*. First, the impact of *COI* on *GIE* is positive and significant ($\hat{\beta}_1 = 0.55$, $p < 0.01$). After including *GIE* in the model, the direct effect of *COI* on *UCI* decreases from the baseline 0.05 to 0.04—*GIE* partially absorbs the policy benefits of CO. Second, the path coefficients ($\hat{\theta}_2 = 0.01$, $p < 0.10$; $\hat{\theta}_1 = 0.04$, $p < 0.01$) suggest that *COI*

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enhances *UCI* indirectly by improving *GIE*. Bootstrap testing (500 replications) confirms the robustness of this mediating effect. The indirect effect ($\hat{\beta}_1\hat{\theta}_2$) is 0.00 with a 95% confidence interval of [0.00, 0.01],[①] contributing 8.09% to the total effect. This finding supports the Porter hypothesis—CO fosters cleaner production and green technological progress through knowledge spillovers, enhancing UC (Acemoglu et al., 2016).

4.5.2 Public Environmental Awareness

The results in Columns (3)-(4) of Table 6 show that *PEA* is a significant mediator. First, *COI* significantly increases *PEA* ($\hat{\beta}_1$= 27.54, $p < 0.01$). Controlling for *PEA* reduces the direct effect of *COI* on *UCI* from 0.05 to 0.03—*PEA* partially absorbs and transmits the positive effect of openness (Hayes, 2022). Second, the mediating path ($\hat{\theta}_2$= 0.00, $p < 0.01$; $\hat{\theta}_1$ = 0.03, $p < 0.01$) indicates that *COI* boosts *UCI* indirectly by raising *PEA*. Bootstrap tests confirm a significant indirect effect ($\hat{\beta}_1\hat{\theta}_2$= 0.01, 95% CI [0.00, 0.01],[②] accounting for 14.28% of the total effect. This aligns with the social monitoring hypothesis (Szkudlarek, 2014), whereby CO increases public scrutiny on environmental issues (e.g. via media and participation), pressuring local governments to improve environmental governance and ultimately strengthening sustainable UC. Notably, *PEA's* mediation contribution (14.28%) exceeds that of *GIE* (8.09%), underscoring the pivotal role of social capital in institutional change.

4.5.3 Global Connectivity Capacity

The results in Columns (5)–(6) of Table 6 validate the significant mediating effect of *GCC*. First, *COI* exerts a strong positive impact on *GCC* ($\hat{\beta}_1$= 0.13, $p < 0.01$). After controlling for *GCC*, the direct effect of *COI* on *UCI* decreases from 0.05 to 0.04—*GCC* partially channels the benefits of CO. Second, the path estimates ($\hat{\theta}_2$= 0.06, $p < 0.10$; $\hat{\theta}_1$ = 0.04, $p < 0.05$) suggest that *COI* enhances *UCI* indirectly by strengthening *GCC*. Bootstrap analysis confirms a significant indirect effect ($\hat{\beta}_1\hat{\theta}_2$= 0.01, 95% CI [0.00, 0.02]),[③] contributing 17.27% to the total effect. This finding supports global value chain embeddedness theory (Gereffi et al., 2005)—CO enhances a city's hub status in the global division of labour by improving logistics efficiency, attracting foreign investment, and fostering technical cooperation, boosting its overall competitiveness.

In summary, the evidence suggests that the three mechanisms together form a 'technology–society–network' transmission pathway: *GIE* drives technological upgrading, *PEA* pressures governance improvements, and *GCC* embeds cities into global value chains. These findings collectively support H2a, H3a, and H4a.

Table 6 – Mediation Mechanism Analysis. Source: own search

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GIE	*UCI*	*PEA*	*UCI*	*GCC*	*UCI*
COI	0.5499*** (5.0930)	0.0438*** (3.0528)	27.5384*** (6.4789)	0.0323*** (3.3019)	0.1282*** (4.4245)	0.0379** (2.3121)
GIE		0.0070* (1.9135)				

[①] The indirect effect $\hat{\beta}_1\hat{\theta}_2 \approx 0.0038$, with a bias offset of -0.00008, yields a 95% confidence interval of [0.0016, 0.0064].
[②] The indirect effect $\hat{\beta}_1\hat{\theta}_2 \approx 0.0054$, with a bias offset of 0.00005, yields a 95% confidence interval of [0.0032, 0.0079].
[③] The indirect effect $\hat{\beta}_1\hat{\theta}_2 \approx 0.0079$, with a bias offset of 0.0002, yields a 95% confidence interval of [0.0018, 0.0165].

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PEA				0.0002*** (3.4325)		
GCC						0.0616* (1.9222)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608	4608
R^2	0.7039	0.9751	0.9324	0.9723	0.9446	0.9753

4.6 Moderating Effects and Heterogeneity Analysis

Having identified the three transmission channels—*GIE*, *PEA* and *GCC*—this subsection investigates whether these mechanisms are conditionally amplified or systematically differentiated based on variations in cities' enabling systems (e.g. business environment, FinTech, and AI) and their global structural positions (e.g. global network embeddedness and innovation ecosystem maturity).

4.6.1 Moderating Effects of Local Enabling Systems

4.6.1.1 Business Environment: Non-linear Moderating Effect of Institutional Dividends

Column (1) of Table 7 shows that while the coefficient for the Business Environment Health Index (*BEHI*) is insignificant ($\hat{\eta}_2$ = -0.00, $p > 0.10$), its interaction term with *COI* (*BEHI* × *COI*) is significantly positive ($\hat{\eta}_3$= 0.00, $p < 0.05$). The main effect of *COI* is negative when *BEHI* is not considered ($\hat{\eta}_1$= -0.02, $p > 0.10$); however, this negative impact is significantly mitigated in cities with higher *BEHI* scores. This suggests that *BEHI*, as a proxy for institutional quality, strengthens the marginal returns to openness by reducing uncertainty in contract enforcement and attracting foreign investment and technology diffusion (Acemoglu et al., 2005). This aligns with the theory of institutional complementarity (Hall & Soskice, 2001)—CO exerts a more positive effect within high-quality institutional environments. Although the *BEHI* data cover only part of the sample (*N*=2,300), potentially introducing some bias, its significant moderating effect ($p < 0.05$) supports the strengthening role of institutional quality. Therefore, optimising the business environment (e.g. through one-stop government services) is a prerequisite for unleashing the dividends of openness.

4.6.1.2 FinTech: Positive Moderating Effect on Resource Allocation Efficiency

Column (2) of Table 7 indicates that the FinTech Index (*FTI*) has a significant positive coefficient ($\hat{\eta}_2$ = 0.01, $p < 0.05$), and its interaction with *COI* (*FTI* × *COI*) is positive and significant ($\hat{\eta}_3$ = 0.04, $p < 0.05$). The main effect of *COI* remains significantly negative after controlling for *FTI* ($\hat{\eta}_1$ = -0.15, $p < 0.05$). Nevertheless, the moderating effect of *FTI* significantly enhances the marginal contribution of *COI* to *UCI*. This implies that the development of *FTI* (e.g. blockchain-based credit reporting, robo-advisors) alleviates information asymmetry and credit rationing, optimising capital allocation efficiency and enabling openness to be more effectively translated into investment growth and technology spillovers (Goldfarb & Tucker, 2019). City governments must promote regulatory sandboxes for FinTech to prevent potential financial risks from offsetting technology spillovers, amplifying the benefits of CO.

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4.6.1.3 Artificial Intelligence: The Dual-Edged Sword Effect of Technology Substitution

Column (3) of Table 7 reveals that the Artificial Intelligence Index (*AI*) has a significant negative coefficient ($\hat{\eta}_2$= -0.00, $p < 0.05$), but its interaction with *COI* (*AI* × *COI*) is significantly positive ($\hat{\eta}_3$= 0.01, $p < 0.05$). The main effect of *COI* remains significantly negative after controlling for AI ($\hat{\eta}_1$= -0.08, $p < 0.05$), but *AI's* moderating effect partially counteracts this negative impact. The negative main effect of *AI* may reflect its short-term automation substitution potentially squeezing the competitive advantage of traditional labour-intensive industries (Frank et al., 2019), offsetting the efficiency gains from openness and inhibiting *UCI*. However, the positive interaction term (*AI* × *COI*) suggests that technology introduction in an open environment can promote complementary applications of *AI*, enhancing labour productivity (Brynjolfsson & McAfee, 2014) and improving *UCI*. The coexistence of *AI's* negative main effect and positive interaction effect necessitates that city governments balance short-term labour adjustments with long-term technological progress, implementing workforce reskilling programs to mitigate *AI's* substitution shocks.

In summary, the evidence indicates that local enabling systems—*BEHI*, *FTI,* and *AI*—significantly moderate the CO and UC relationship. The positive interaction terms suggest that these systems amplify the benefits of openness. These findings support H2b, H3b, and H4b—the positive effect of CO on UC via the three mediating pathways is more pronounced for cities with stronger local enabling systems.

Table 7 – Moderating Mechanism Analysis. Source: own search

Variable	*UCI*		
	(1)	(2)	(3)
COI	-0.0229 (-1.2591)	-0.1451** (-2.0711)	-0.0804* (-1.9667)
BEHI	-0.0000 (-1.3960)		
FTI		0.0053** (2.3398)	
AI			-0.0023** (-2.3513)
*BEHI*COI*	0.0006** (2.3401)		
*FTI*COI*		0.0353** (2.4543)	
*AI*COI*			0.0119** (2.5781)
Controls	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes
N	2300	4608	4608
R^2	0.9878	0.9785	0.9752

Note: The Business Environment Health Index (*BEHI*) is available only for 2017–2023, resulting in 2,300 observations; this limited sample may introduce bias.

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4.6.2 Heterogeneous Boundaries of Global Structural Position

Given the observed structural feature of Chinese cities, where top-tier global networks and innovation hubs largely overlap, this study employs a dual-track strategy to ensure robustness. The primary analysis transforms theoretical groupings based on GaWC and GII into continuous variables: Global Network Embeddedness (*GNE*) and Innovation Ecosystem Maturity (*IEM*). A continuous interaction model is used to estimate their gradient moderating effects, avoiding potential sample bias from categorical classification. Robustness checks, presented in Appendix A Tables A6–A7 and Figure A2, provide auxiliary analyses based on multi-dimensional classifications (including various grouping schemes and categorical interaction models). These exploratory results are consistent with the main findings, offering multi-angle validation.

4.6.2.1 Global Network Embeddedness

Column (1) of Table 8 shows that while the coefficient for *COI* is insignificant ($\hat{\eta}_1$= -0.01, p > 0.10), its interaction with GNE is significantly positive ($\hat{\eta}_3$= 0.02, p < 0.01, remaining significant at the 1% level after Bonferroni correction). This indicates a significant positive moderating effect of global network embeddedness—for each level increase in a city's *GNE*, the marginal effect of *COI* on *UCI* increases by an average of 0.02 units. This finding confirms the network externality advantages of global hub cities in the opening process: a high degree of global network embeddedness significantly amplifies the positive impact of CO by enhancing the allocation efficiency of capital, technology, and data.

4.6.2.2 Innovation Ecosystem Maturity

Column (2) of Table 8 shows that while the coefficient for *COI* is insignificant ($\hat{\eta}_1$= -0.00, p > 0.10), its interaction with IEM is significantly positive ($\hat{\eta}_3$= 0.03, p < 0.01, remaining significant at the 1% level after Bonferroni correction). This indicates a significant positive moderating effect of innovation ecosystem maturity—for each level increase in *IEM*, the marginal effect of *COI* on *UCI* increases by an average of 0.03 units. This verifies that the technological absorptive and transformative capacity of a mature innovation ecosystem can effectively convert external knowledge spillovers induced by openness into local competitiveness.

4.6.2.3 Synergy between Global Network Embeddedness and Innovation Ecosystem

Further analysis based on combined classifications of GaWC and GII (Column (3) of Table 8) reveals systematic differences in the moderating effects across city types. The interaction effect is most pronounced for 'global dual-high hubs'—cities with high GNE and IEM, where the coefficient for *GC_rank*1 × *COI* is 0.04 (p < 0.05). Conversely, cities possessing an advantage in only a single dimension (network-specialised or innovation-specialised) exhibit weaker or statistically insignificant moderating effects. This pattern suggests that the synergistic complementarity between deep global connectivity and strong innovative capacity is a defining characteristic of China's top-tier cities in maximising the dividends of openness. A one-dimensional advantage is insufficient to fully harness the benefits of CO.

In summary, the evidence indicates that the marginal effect of CO on UC is not uniform but systematically depends on a city's pre-existing structural position within the global hierarchy and innovation landscape. The significant positive interaction terms for *GNE* and *IEM* suggest that cities with higher global structural positions reap disproportionately larger gains from

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openness. These findings align with the core tenet of New Structural Economics (Lin, 2011) and support H2c, H3c, and H4c—the positive effect of CO on UC via the three mediating pathways is more pronounced for cities with a more advanced global structural position.

Table 8 – Heterogeneity Analysis. Source: own search

Variable	*UCI*		
	(1) GaWC	(2) GII	(3) GaWC-GII Combined Classification
COI	-0.0116 (-0.9684)	-0.0010 (-0.0860)	0.0094 (0.7735)
*GNE*COI*	0.0219*** (3.6349)		
*IEM*COI*		0.0252*** (4.2760)	
*GC_rank*1**COI*			0.0425** (2.1846)
*GC_rank*2**COI*			0.0320** (2.0884)
*GC_rank*3**COI*			0.0040 (0.1380)
Controls	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes
N	4608	4608	4608
R^2	0.9758	0.9760	0.9749

Note: In Columns (1)–(2), the significance of GNE×COI and IEM×COI holds after Bonferroni correction for multiple hypothesis testing ($p = 0.0010$ and $p = 0.0001$, respectively, both < 0.01). In Column (3), an F-test for the joint significance of the interaction terms GC rank1×COI, GC rank2×COI, and GC rank3×COI yields $p = 0.0662$ (< 0.10), with a Bonferroni-corrected p-value of 0.1986 (see Appendix A Table A6).

4.7 Further Discussion: Spatial Spillover Effects

Having validated the moderating effects and heterogeneous boundaries, we further examine the spatial externalities. If significant knowledge diffusion or resource siphoning exists between cities, the opening strategy of a single city may reshape the regional competitive landscape through spatial spillover effects.

4.7.1 Spatial Correlation Test

The global Moran's I index from 2008 to 2023 (see Appendix A Table A8) shows significant positive values ($p < 0.01$) across all six spatial weight matrices (contiguity, inverse distance, etc.), with values stably ranging between 0.05 and 0.30. This indicates that urban development is not isolated but influenced by neighbouring cities, demonstrating stable spatial interaction. Furthermore, Moran's I show a slight decline after 2017, possibly due to the expansion of high-speed rail networks and the diffusion of digital technologies weakening traditional geographic constraints (Saeed et al., 2025). This spatial correlation suggests that UC may generate cross-regional spillovers (e.g. knowledge diffusion or resource siphoning), necessitating further quantification through spatial econometric models (Shao et al., 2022).

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4.7.2 Selection of Spatial Econometric Models

Based on the test results in Table 9, the Spatial Durbin Model with Fixed Effects (SDM_FE) is selected for the following reasons: (i) Model suitability tests: The Hausman test comparing SDM_FE and SDM_RE yields $\chi^2 = 63.46$ ($p < 0.01$), rejecting the random effects specification in favour of SDM_FE. Subsequent likelihood ratio tests comparing SDM_FE with SAR_FE, SEM_FE, and SAC_FE yield χ^2 statistics of 30.34, 23.04, and 22.99 respectively (all $p < 0.01$). SDM_FE also exhibits the lowest Akaike Information Criterion (AIC). The spatial autoregressive coefficient ($\rho = 0.24$, $p < 0.01$) is significant, confirming SDM_FE as the optimal model (Shao et al., 2022). (ii) Interpretation of SDM_FE results: The coefficient for *COI* is 0.05 ($p < 0.01$), confirming its significant positive direct effect on *UCI*. Conversely, the spatially lagged term ($W \times COI$) has a coefficient of -0.05 ($p < 0.01$). This indicates a potential competitive resource-siphoning effect induced by *COI*, where global hub cities may leverage network advantages to absorb innovative resources from surrounding areas, potentially increasing regional disparities.

4.7.3 Robustness Checks for the Spatial Durbin Model

Robustness checks using six different spatial weight matrices (see Appendix A Table A9) confirm the stability of the findings. The spatial autoregressive coefficients remain significantly positive across all matrices. The direct effect of *COI* on *UCI* is consistently stable at approximately 0.05 ($p < 0.01$), confirming the universal positive impact of *COI*. The significant negative coefficient for the spatially lagged *COI* term ($W \times COI$) across matrices robustly confirms the existence of inter-city competitive resource-siphoning.

4.7.4 Decomposition of Spatial Effects

The decomposition of spatial effects (Appendix A Table A9) reveals significant spatial heterogeneity in the impact of *COI* on *UCI*. (i) Direct effects - Local growth engine: The direct effects of COI are highly significant across all six weight matrices (coefficients ranging from 0.047 to 0.049, $p < 0.01$)—*COI* acts as a core mechanism for enhancing *UCI* through local factor agglomeration and industrial upgrading. (ii) Indirect effects: Evidence of competitive siphoning: The indirect effect is strongest under the inverse distance matrix (-0.08, $p < 0.01$), indicating significant resource siphoning in geographically proximate regions. It is weaker under the threshold distance matrix (-0.02, $p < 0.05$), which may partially offset the negative spillover. This result aligns with the dynamic interplay of 'polarisation' and 'trickle-down' effects described in core-periphery theory. (iii) Total effects - Evidence of factor misallocation: The total effect is insignificant or negative under most matrices (e.g. -0.03, $p > 0.10$ under the inverse distance matrix), highlighting the unequal spatial distribution of the benefits of openness and points to factor misallocation between cities, requiring correction through regional coordination policies.

In summary, the 'local gain, neighbour loss' dual structure characterising the estimated impact of *COI* on *UCI* suggests patterns consistent with resource polarisation and what may be interpreted as competitive siphoning effects within the spatial spillovers of UC. This finding supports H5—while enhancing the competitiveness of the local city, CO generates a negative spatial spillover effect on geographically adjacent cities.

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Table 9 – Selection of Spatial Econometric Models. Source: own search

Variable	*UCI*				
	(1) SAR_FE	(2) SDM_FE	(3) SDM_RE	(4) SEM_FE	(5) SAC_FE
COI	0.0455*** (18.0193)	0.0489*** (18.3794)	0.0525*** (19.1590)	0.0466*** (18.1641)	0.0467*** (18.0586)
W×COI		-0.0452*** (-3.2467)	-0.0763*** (-9.1958)		
ρ (Spatial AR)	0.1888*** (3.0172)	0.2387*** (3.7289)	0.4650*** (8.8135)		-0.0222 (-0.2110)
λ (Spatial Error)				0.2619*** (4.1292)	0.2779*** (2.8651)
Controls	Yes	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608
R^2	0.4420	0.5715	0.5065	0.4858	0.4899
AIC	-32922.0755	-32938.4203	-30879.2166	-32929.3762	-32927.4318
BIC	-32864.1555	-32835.4515	-30763.3767	-32871.4563	-32863.0763

5. Research Conclusions and Policy Recommendations

5.1 Research Conclusions

This study systematically investigates how CO shapes UC in emerging economies, drawing on panel data from 288 Chinese prefecture-level cities (2008–2023). By constructing multidimensional indices for CO and UC and employing dynamic panel models, mediation and moderation analyses, and spatial econometric models, we uncover a nuanced picture of the mechanisms, heterogeneity, and spatial spillovers through which openness translates into competitive advantage.

The empirical analysis yields six core findings, each linked to specific hypotheses. First, *COI* significantly enhances *UCI* in the short term ($\hat{\alpha}_S = 0.05, p < 0.01$) and the long term ($\hat{\alpha}_L = 0.17$, $p < 0.05$), with the long-term effect amplified by the cumulative upgrading of factor endowments, business environment quality, and global position. This finding supports H1a (positive direct effect) and H1b (stronger long-term cumulative effect). Second, this positive association operates through a 'technology–society–network' transmission pathway: *GIE* (technology), *PEA* (society), and *GCC* (network) serve as significant mediating mechanisms, supporting H2a, H3a, and H4a, respectively. Third, the effectiveness of these mediating pathways is significantly amplified by cities' local enabling systems—specifically, *BEHI*, *FTI*, and *AI*. The positive interaction terms indicate that stronger local enabling systems enhance the translation of openness into competitive advantage through all three pathways. These findings support H2b, H3b, and H4b—the positive effects of CO on UC via green innovation efficiency, public environmental concern, and global connectivity are more pronounced for cities with stronger local enabling systems. Fourth, the effectiveness of *COI* is also highly contingent on a city's inherent global structural position—specifically, its embeddedness in global networks (*GNE*) and maturity of its innovation ecosystem (*IEM*). The significant positive interaction terms indicate that cities with higher structural positions reap larger gains from openness. These findings support H2c, H3c, and H4c—the mediating pathways are more effective for cities with

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more advanced global structural positions. Fifth, the spatial effect of CO exhibits a 'local gain, neighbour loss' dual structure, suggesting resource polarisation and negative spillovers. This finding supports H5—CO generates negative spatial spillovers on geographically adjacent cities. Sixth, by benchmarking results against global city rankings (GaWC, GII), we propose a tiered opening strategy with differentiated goals for cities at different developmental tiers. This policy translation is directly informed by the conditioning roles of local enabling systems (H2b, H3b, H4b) and global structural position (H2c, H3c, H4c), as well as the long-term cumulative effect documented in H1b.

These findings address three notable gaps in the existing literature. First, prior research on city openness has predominantly focused on trade and investment flows, often overlooking the institutional dimension of openness and its interaction with cities' pre-existing structural positions within global networks (Kresl & Ietri, 2014; Ni et al., 2021). By distinguishing between factor flow-based and institution-based openness, and by explicitly incorporating global structural position as a moderating condition, this study moves beyond the conventional trade-centric view. Second, while agglomeration shadow effects have been theorised (Kerr & Robert-Nicoud, 2020), empirical evidence on the spatial spillovers of openness policies, particularly the 'local gain–neighbour loss' pattern, remains scarce. Our spatial econometric analysis provides direct evidence of such competitive resource siphoning, contributing to the urban spatial economics literature. Third, existing work has often treated the mechanisms linking openness to urban outcomes as a black box, with limited attention to the distinct roles of technological, social, and network pathways. This study opens the black box by identifying three parallel mediating mechanisms and demonstrating how local enabling systems and global structural position condition their effectiveness.

The theoretical contributions of this study are threefold. The first is mechanism contribution. By identifying the 'technology–society–network' transmission pathway, we move beyond technological determinism to reveal that social capital (*PEA*) and network position (*GCC*) play equally critical and, in some cases, larger mediating roles than technological innovation per se. This multi-channel perspective offers a more comprehensive account of how openness translates into competitive advantage. The second is local conditionality contribution**.** The significant moderating effects of *BEHI*, *FTI*, and *AI* demonstrate that investments in institutional quality, financial technology, and artificial intelligence can substantially amplify the returns to openness. This finding provides policy-relevant evidence that local enabling systems are not merely complementary but essential for unlocking the full potential of openness. The third is the global conditionality contribution. The significant moderating effects of GNE and IEM provide robust empirical support for the dynamic adaptation thesis of new structural economics (Lin, 2011). The finding that cities with higher structural positions reap disproportionately larger gains from openness underscores that openness policies must be dynamically aligned with a city's factor endowments and structural capabilities. The final contribution is spatial. The identification of a 'local gain, neighbour loss' dual structure contributes to the spatial economics literature by empirically documenting patterns consistent with polarisation—trickle-down dynamics in the context of openness policies. This finding challenges the assumption that openness benefits diffuse evenly across space and highlights the importance of regional coordination mechanisms.

From a policy perspective, the findings carry clear implications for cities in emerging economies seeking to ascend the global urban hierarchy. The strong long-term effect of CO (H1b) suggests that openness should be pursued as a sustained, cumulative strategy rather than

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a series of short-term experiments. The three mediating pathways imply that openness policies must be complemented by targeted investments in green innovation, institutional transparency, and physical infrastructure connectivity. The moderating roles of local enabling systems (H2b, H3b, H4b) indicate that investments in institutional quality, FinTech, and AI capabilities can significantly amplify the benefits of openness, particularly for lower-tier cities seeking to build foundational capacity. The conditioning role of global structural position (H2c, H3c, H4c) indicates that a one-size-fits-all openness strategy is unlikely to succeed; instead, cities must calibrate their openness pathways to their pre-existing positions in global networks and innovation ecosystems. The tiered opening-up strategy elaborated next translates these theoretical insights into actionable policy pathways for cities at different developmental tiers, while the spatial spillover findings (H5) underscore the necessity of regional coordination mechanisms to transform negative externalities into shared gains.

5.2 Policy Implications

The significant dependence of CO's effects on a city's 'global structural position' suggests that China's urban opening-up model must shift from one centred on traditional factor flows to one focused on functional specialisation. International experience shows that the core competitiveness of top global cities stems from their ability to configure capital, information, and innovative elements worldwide, enabling them to dominate high-value segments of global value chains and the formulation of international rules. Therefore, Chinese cities should redesign their CO strategies based on their functional roles within the global urban network.

Grounding the tiered strategy in empirical evidence. Our policy recommendations are grounded in five key empirical findings. First, the significant long-run effect of *COI* on *UCI* ($\hat{\alpha}_L = 0.17$, $p < 0.05$) underscores the importance of sustained, cumulative openness strategies rather than short-term policy experiments. Second, the three mediating pathways—*GIE*, *PEA*, and *GCC*—suggest that openness policies should be complemented by targeted investments in technology, institutions, and infrastructure. Third, the moderating role of local enabling systems (*BEHI, FTI, AI*) indicates that investments in institutional quality, FinTech infrastructure, and AI capabilities can significantly amplify the benefits of openness. Fourth, the moderating role of global structural position (*GNE*, *IEM*) implies that openness strategies must be calibrated to a city's pre-existing position in global networks and innovation ecosystems. Fifth, the 'local gain, neighbour loss' spatial spillover pattern calls for regional coordination mechanisms to mitigate negative externalities. The tiered opening-up strategy that follows translates these empirical insights into actionable policy pathways for cities at different developmental stages.

5.2.1 Tiered Pathways for Functional Ascension

Leveraging GaWC and GII ratings, Chinese cities can be strategically divided into four tiers, each with a distinct development path.

5.2.1.1 Tier 1: Global Rule-Setters (e.g. Beijing, Shanghai)

Benchmarking against New York and London, the goal is for one city to reach GaWC's Alpha++ status and another to break into the GII top 5 by 2030, transitioning from 'flow hubs' to 'rule sources'. The primary gap lies in hosting international organisation headquarters, top-tier arbitration institutions, and cultural influence. The development pathways are as follows. First, establish international standard-setting taskforces in fields such as AI ethics and digital trade in Beijing or Shanghai. Second, create top-tier resource hubs through initiatives such as a 'Nobel

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Laureate Lab Cluster Plan' and bidding for major global science summits post-2030. Finally, the empirical grounding tier directly leverages the long-run cumulative effect (H1b) and the strong moderating role of *GNE* and *IEM* (H2c, H3c, H4c), as these cities already possess the highest global structural positions.

5.2.1.2 Tier 2: Regional Function-Shapers (e.g. Guangzhou, Shenzhen)

Benchmarking against Alpha+ cities like Singapore and Tokyo, the goal is for these Chinese cities to ascend on GaWC or GII rankings by 2030, transforming from 'domestic centres' into 'global functional platforms'. The gap is transitioning from 'scale centres' to 'standard and pricing centres' in their specialties (e.g. commerce in Guangzhou, innovation in Shenzhen). The development pathways are as follows: First, build global headquarters in specialised fields (e.g. an 'International Cross-Border Data Flow Management Pilot Zone' in Shenzhen). Second, construct international talent magnets with comprehensive visa, tax, and cultural amenities. Third, the empirical grounding tier builds on the global connectivity pathway (H4a) and the moderating role of institutional quality (*BEHI*, H2b, H3b, H4b) to consolidate functional specialisation.

5.2.1.3 Tier 3: Specialised Niche-Breakers (e.g. Tianjin, Chengdu, Hangzhou)

Benchmarking against Alpha-level cities like Munich and Houston, the goal for these Chinese cities is to rise 1–2 levels in GaWC and have 5–10 enter the GII emerging clusters top 100 by 2030, shifting from 'comprehensive development' to 'single-point breakthroughs'. The gap is a lack of specialised clusters with global industrial chain control. The development pathways are as follows: First, cultivate world-class specialised clusters (e.g. electronics in Chengdu, optoelectronics in Wuhan) targeting over 30% global market share in niches. Second, establish open R&D outposts ('overseas innovation incubators') in leading innovation countries. Finally, the empirical grounding tier capitalises on the green innovation efficiency pathway (H2a) and the moderating role of innovation ecosystem maturity (*IEM*, H2c, H3c, H4c) to build distinctive technological capabilities.

5.2.1.4 Tier 4: Foundational Capacity-Builders (e.g. Zhengzhou, Shenyang, Haikou).

Benchmarking against Beta-level global cities like Atlanta and Seattle, the goal for these Chinese cities is to consolidate their roles as core nodes within domestic industrial chains, establish themselves as national hubs, and proactively integrate into global networks. This needs a strategic shift from passively receiving functional spillovers to actively forging external linkages. A key challenge is their vulnerability to the siphon effects from higher-tier cities and the risk of falling into homogenised competition. The development pathways are as follows: First, build regional factor allocation platforms based on local advantages (e.g. specialised commodity or technology markets). Second, establish coordinated regional mechanisms, such as co-building 'enclave industrial parks' with higher-tier cities featuring tax-sharing agreements to convert 'polarisation' into 'trickle-down' effects. Finally, the empirical grounding tier directly addresses the spatial spillover findings (H5) by embedding cities in regional coordination mechanisms, while leveraging local enabling systems (*FTI*, *AI*; H2b, H3b, H4b) to build foundational capacity.

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5.2.2 Strengthening Systemic Synergistic Support

5.2.2.1 Reinforce the 'Technology- Society -Network' transmission mechanism

We recommend that technology-wise, launch a 'Global City Innovation Partnership Program'; institution-wise, pilot 'International Commercial Dispute Resolution Special Zones' in Beijing or Shanghai and establish overseas IP protection centres; and network-wise, incorporate metrics such as international flight routes into 'global connectivity' assessments.

5.2.2.2 Address the spatial 'local gain-neighbours loss' dilemma

Drawing on international models (e.g. the New York-New Jersey–Connecticut metropolitan governance) and domestic pilots (e.g. the Yangtze River Delta Green and Integrated Development Demonstration Zone), China should try out mechanisms for sharing GDP and tax revenues across municipal boundaries within its major city clusters. Furthermore, national authorities ought to formulate 'Global Functional Layout Plans for Key Urban Agglomerations' to clarify the distinct roles of cities within each cluster and prevent duplicative or overlapping competition.

5.2.3 Establishing a Dynamic Evaluation Framework

First, incorporate global rankings into performance evaluation, making progress in GaWC, GII, and similar rankings part of the assessment for local leadership and urban development plans. Second, leverage think tank support. National high-end think tanks should publish annual reports (e.g. Diagnostic Report on the Global Position of Chinese Cities) to provide precise benchmarking and early warnings.

Overall, China's urban opening-up strategy should pivot towards precise, tiered benchmarking. Tier 1 cities should contest global rule-making authority, Tier 2 should shape specialised functional platforms, Tier 3 should achieve breakthrough in specialised niches, and Tier 4 should enhance regional connectivity. This must be accompanied by a dynamic evaluation mechanism and strengthened systemic support to transform CO advantages into sustainable global competitiveness.

5.3 Limitations and Future Research

This study has some limitations. First, its focus on Chinese cities may limit the generalisability of findings to other emerging economies with different institutional contexts and development stages. Second, the empirical analysis based on 2008–2023 data may not fully capture potential non-linear threshold effects of CO on UC. Third, the mechanism analysis focuses on macro-level pathways, lacking micro-level evidence from firm behaviour.

Researchers should look at the following areas. First, incorporate samples from cities in Belt and Road Initiative partner countries or BRICS nations to explore heterogeneity under different institutional and cultural contexts. Second, employ models such as the Panel Smooth Transition Regression to identify potential non-linear evolutionary patterns, or machine learning methods (e.g. random forests, causal forests) to identify heterogeneous treatment effects without strong parametric assumptions. Third, integrate firm-level data to dissect the micro-level transmission path of 'CO-firm-UC'. Fourth, future research should systematically integrate theoretical insights from the agglomeration economies and urban spatial structure literature to enrich the

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analysis of how openness interacts with urban density and specialisation.

References

1. Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's Tobacco Control Program. *Journal of the American Statistical Association,* 105(490), 493–505.
2. Acemoglu, D., Johnson, S., & Robinson, J. A. (2005). The rise of Europe: Atlantic trade, institutional change, and economic growth. *American Economic Review,* 95(3), 546–579.
3. Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review,* 102(1), 131–166. https://doi.org/10.1257/aer.102.1.131
4. Acemoglu, D., Akcigit, U., Hanley, D., & Kerr, W. (2016). Transition to clean technology. *Journal of Political Economy,* 124(1), 52–104.
5. Acemoglu, D., & Restrepo, P. (2020a). Robots and Jobs: Evidence from US Labour Markets. *Journal of Political Economy,* 128(6), 2188-2244. https://doi.org/10.1086/705716
6. Acemoglu, D., & Restrepo, P. (2020b). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions Economy and Society*, 13(1), 25-35. https://doi.org/10.1093/cjres/rsz022
7. Aghion, P., Akcigit, U., Deaton, A., & Roulet, A. (2016). Creative destruction and subjective well-being. *American Economic Review,* 106(12), 3869–3897.
8. Amin, N., Shabbir, M. S., Song, H., Farrukh, M. U., Iqbal, S., & Abbass, K. (2023). A step towards environmental mitigation: Do green technological innovation and institutional quality make a difference? *Technological Forecasting and Social Change,* 190, 122413.
9. Angrist, J. D., & Pischke, J. S. (2014). *Mastering 'metrics: The path from cause to effect*. Princeton University Press.
10. Atkin, D., Khandelwal, A. K., & Osman, A. (2017). Exporting and firm performance: Evidence from a randomized experiment. *The Quarterly Journal of Economics,* 132(2), 551–615. https://doi.org/10.1093/qje/qjx002
11. Bi, J. Y., & Li, W. (2018). Innovating and perfecting China's all-round opening-up pattern. *Studies on Socialism with Chinese Characteristics,* 1, 42–49.
12. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
13. Bye, B., & Fæhn, T. (2022). The role of human capital in structural change and growth in an open economy: Innovative and absorptive capacity effects. *World Economy,* 45(4), 1021–1049.
14. Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics,* 225(2), 200–230.
15. Cao, Q. F., & Ni, P. F. (2020). The hierarchical structure of China's urban system and the development of urban agglomerations: An analysis based on cities' global competitiveness, global connectivity, and radiation capacity. *West Forum,* 30(2), 45–56.
16. Changalima, I. A., Ismail, I. J., & Amani, D. (2025). Driving SME performance through

technological absorptive capacity and e-business innovation. *Sustainable Technology and Entrepreneurship*, 4(1), 100089. https://doi.org/10.1016/j.stae.2024.100089

17. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128–152.
18. Cristache, N., Croitoru, G., & Florea, N. V. (2025). The influence of knowledge management on innovation and organizational performance. *Journal of Innovation & Knowledge*, 10(5), 100793. https://10.1016/j.jik.2025.100793
19. Ding, R. Z., Xu, B. Y., & Zhang, H. (2021). Can urban agglomerations drive regional economic growth? An empirical analysis based on 7 national-level urban agglomerations. *Economic Geography,* 41(5), 37–45.
20. Du, L. Z., Zhao, Y. H., Tao, K. T., & Lin, W. F. (2019). The compound effect of environmental regulation and governance transition on enhancing green competitiveness: Evidence from Chinese industry. *Economic Research Journal,* 54(10), 106–120.
21. Enri-Peiró, S., González-Arroyo, G., & Guijarro-García, M. (2025). The role of digital transformation as a key driver of competitiveness in small and medium-sized enterprises. *ESIC Market*, 56(3), e423. https://doi.org/10.7200/esicm.56.423
22. Feng, Y. D., Liu, Y. B., & Cheng, F. Y. (2023). Regional differences and spatial convergence of green total-factor energy efficiency in Chinese cities. *Geographical Research,* 42(9), 2343–2368.
23. Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., ... & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labour. *Proceedings of the National Academy of Sciences of the United States of America,* 116(14), 6531–6539.
24. Gan, C. H., Zheng, R. G., & Yu, D. F. (2011). The impact of industrial structure change on economic growth and volatility in China. Economic Research Journal, 46 (5), 4-16+31.
25. Gereffi, G., Humphrey, J., & Sturgeon, T. (2005). The governance of global value chains. *Review of International Political Economy,* 12(1), 78–104. https://doi.org/10.1080/09692290500049805
26. Globalization and World Cities Research Network. (2024). *The world according to GaWC 2024*. Loughborough University. https://www.lboro.ac.uk/microsites/geography/gawc/
27. Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature,* 57(1), 3–43. https://doi.org/10.1257/jel.20171452
28. Hall, P. A., & Soskice, D. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage*. Oxford University Press.
29. Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press.
30. Helpman, E. (2018). *Globalization and inequality*. Harvard University Press.
31. Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (2005). Estimating the returns to community college schooling for displaced workers. *Journal of Econometrics, 125*(1–2), 271–304. https://doi.org/10.1016/j.jeconom.2004.04.010
32. Jorfi, S., & Winkler, T. J. (2025). Translating IT capabilities: Linking enabling infrastructure to digital transformation in hospitals—Sustainable digital enablement

framework. *Sustainable Technology and Entrepreneurship*, 100117. https://doi.org/10.1016/j.stae.2025.100117

33. Kerr, W. R., & Robert-Nicoud, F. (2020). Tech clusters. *Journal of Economic Perspectives,* 34(3), 50–76. https://doi.org/10.1257/jep.34.3.50
34. Kresl, P., & Ietri, D. (2014). *Urban competitiveness: Theory and practice*. Routledge.
35. Li, J., & Cheng, M. R. (2025). The mechanism and pathways of economic policy uncertainty inducing social anxiety: Evidence from city-level Baidu search index and corporate annual report text analysis. *East China Economic Management,* 39(6), 89–98.
36. Li, K. X., Ye, X., & Mao, Z. G. (2025). Spatial pattern and influencing factors of urban consumption competitiveness in China. *Economic Geography,* 45(3), 87–97.
37. Li, S. B., & Sun, H. (2023). Agglomeration externalities, network externalities and urban economic development. *Journal of Arid Land Resources and Environment,* 37(6), 38–45.
38. Li, Y. W., & Ni, P. F. (2013). Externalities, transportation networks, and economic growth in urban agglomerations. *Social Sciences in China,* 3, 22–42+203–204.
39. Lin, J. Y. (2011). New structural economics: A framework for rethinking development. *The World Bank Research Observer,* 26(2), 193–221. https://doi.org/10.1093/wbro/lkr007
40. Liu, H., Li, X. M., Tian, S. Z., Li, S. B., & Sun, H. (2023). Agglomeration externalities, network externalities and urban economic development. *Journal of Arid Land Resources and Environment,* 37(6), 38–45.
41. Ning, L.T., Wang, F., & Li, J. (2016). Urban innovation, regional externalities of foreign direct investment and industrial agglomeration: Evidence from Chinese cities. *Research Policy,* 45(4), 830–843. https://doi.org/10.1016/j.respol.2016.01.014
42. Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography,* 6(4), 395–437.
43. Ni, P. F. (Ed.). (2003). *Report on Chinese urban competitiveness No. 1*. Social Sciences Academic Press.
44. Ni, P. F., Li, Q. H., Li, B., & Liu, X. N. (2022). Technological progress, institutional environment, and the efficiency of urban competitiveness: An analysis based on data from 1007 global cities. *Urban and Environmental Studies,* 3, 70–87.
45. Ni, P. F., Wang, H. B., Xu, H. D., & Gong, W. J. (2021). Global urban competitiveness: Structure, hierarchy, and typology—A cluster analysis based on 1007 global cities. *Jianghai Academic Journal,* 1, 104–111.
46. Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *American Economic Review,* 104(6), 1630–1666.
47. Rodrik, D. (2018). Populism and the economics of globalization. *Journal of International Business Policy,* 1(1–2), 12–33. https://doi.org/10.1057/s42214-018-0001-4
48. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
49. Saeed, K. A., Green, A. W., & Hedrick, A. B. (2025). Unpacking digital transformation - Constructing a framework based on industry use cases. *Journal of Innovation & Knowledge*, 10(5), 100759. https://10.1016/j.jik.2025.100759
50. Shao, S., Fan, M. T., & Yang, L. L. (2022). Economic structural adjustment, green

technological progress, and China's low-carbon transition development: An empirical investigation from the perspective of overall technology frontier and spatial spillover effects. *Management World,* 38(2), 46–69+4–10. https://doi.org/10.19744/j.cnki.11-1235/f.2022.0031

51. Sgambati, S., & Gargiulo, C. (2022). The evolution of urban competitiveness studies over the past 30 years: A bibliometric analysis. *Cities,* 128, 103811.
52. Sheng, T. X. (2020). FinTech, optimal banking market structure, and credit supply to micro and small enterprises. *Journal of Financial Research,* 6, 114–132.
53. Shi, M. J., & Sun, Y. W. (2025). The effect of urban network externalities on urban economic performance: Concurrently discussing the dynamic mechanism of urban network formation. *Social Science Front,* 3, 72–83.
54. Singh, S. K., Del Giudice, M., Chierici, R., & Graziano, D. (2020). Green innovation and environmental performance: The role of green transformational leadership and green human resource management. *Technological Forecasting and Social Change,* 150, 13–24. https://doi.org/10.1016/j.techfore.2019.119762
55. Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice,* 41(1), 49–72. https://doi.org/10.1111/etap.12167
56. Su, N., & Tu, Q. Y. (2018). The connotation and interactive characteristics of global city attraction, competitiveness, and creativity. *Journal of Tongji University (Social Science Edition),* 29(5), 115–124.
57. Szkudlarek, P. (2014). Telecommunications services market in the light of the Agency Theory and the Transaction Cost Theory under New Institutional Economics: Case for Poland. *Journal of International Studies,* 7(3), 70–80. https://doi.org/10.14254/2071-8330.2014/7-3/6
58. Tan, S., Wei, Y., Li, X. L., & Sun, X. (2022). The impact of urban network externalities and agglomeration externalities on urban economy from different proximity perspectives: A case study of the urban network in Liaoning Province. *Geographical Research,* 41(9), 2404–2417.
59. Taylor, P. J. (2004). *World city network: A global urban analysis*. Routledge.
60. United Nations. (2026). *World economic situation and prospects* 2026. https://www.un.org/development/desa/dpad/publication/world-economic-situation-and-prospects-2026/
61. Wang, C. J., Chen, P. R., Wang, J. E., & Li, N. (2020). Assessment methodology and pattern of infrastructure connectivity between China and Silk Road countries. *Geographical Research,* 39(12), 2685–2704.
62. Wang, H. B. (2021). Re-exploration of the connotation and objective inevitability of the concept of opening up. *Journal of Capital University of Economics and Business,* 23(5), 3–16.
63. Wang, H. B., Ni, P. F., Gong, W. J., & Xu, H. D. (2019). Chinese urban patterns, hierarchy, and types from a global perspective: A study based on global urban competitiveness data. *Journal of Beijing University of Technology (Social Sciences Edition),* 19(1), 60–68.
64. Wang, L. H. (2022). Artificial intelligence technology, task attributes, and occupational

substitution risk: Micro-level empirical evidence. *Management World,* 38(7), 60–79.

65. Wang, Z. (2025). Place-based policies, financial friction, and city size: Evidence from China's institutional opening-up. *Economic Analysis and Policy,* 87, 1522–1556. https://doi.org/10.1016/j.eap.2025.07.016
66. World Intellectual Property Organization. (2023). *Global Innovation Index 2023: Innovation in the face of uncertainty* (16th ed.). WIPO. https://doi.org/10.34667/tind.48220
67. Wu, L. B., Yang, M. M., & Sun, K. G. (2022). The impact of public environmental concern on corporate and government environmental governance. *China Population, Resources and Environment,* 32(2), 1–14.
68. Wziątek-Kubiak, A. T. (2023). Development in modern evolutionary economics perspective. *Ekonomista,* 4, 368–386. https://doi.org/10.52335/ekon/174758
69. Yang, X. L., & Ni, P. F. (2017). Review on the origin and development of urban sustainable competitiveness. *Economic Perspectives,* 9, 96–110.
70. Yu, Z., Li, M., & Zhuang, E. J. (2025). Application and testing of the Bartik instrumental variable method in causal identification. *The Journal of Quantitative & Technical Economics,* 42(1), 200–220. https://doi.org/10.13653/j.cnki.jqte.20241125.001
71. Zhang, H. S., Xie, Y. X., & Yang, G. J. (2023). Institutional opening-up and consumer welfare improvement: Evidence from cross-border e-commerce comprehensive pilot zones. *Economic Research Journal,* 58(8), 155–173.
72. Zhang, Z. R., & Li, W. (2023). Comprehensively optimizing the regional opening-up layout. *Red Flag Manuscript,* 16, 37–40.
73. Zhao, X., Ma, X., Shang, Y., Yang, Z., & Shahzad, U. (2022). Green economic growth and its inherent driving factors in Chinese cities: Based on the Metafrontier-global-SBM super-efficiency DEA model. *Gondwana Research,* 106, 315–328. https://doi.org/10.1016/j.gr.2022.01.013
74. Zheng, Y., & Duan, Y. B. (2022). 'Fang Guan Fu' reform, regional business environment, and urban competitiveness: An empirical analysis based on panel data of Chinese cities. *Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition),* 35(4), 63–74.
75. Zhou, Z. H., & Gao, P. (2024). Research on urban competition and cooperation relationships based on the global city network. *Shanghai Journal of Economics,* 2, 41–53.

Appendix A

Appendix A present the detailed results corresponding to the extended analysis discussed in the main text.

A1. Formulas for Spatial Weight Matrices

Let d_{ij} be the geographic distance between city i and city j. The geographic distance refers to the straight-line distance calculated from latitude and longitude coordinates.

A1.1 Contiguity (w_{ij}^{cont})

$$w_{ij}^{cont} = \begin{cases} 1, & \text{if city } j \text{ is one of the three geographically nearest neighbors to city } i \text{ and } i \neq j \\ 0, & \text{otherwise} \end{cases} \quad \text{(A1)}$$

A1.2 Inverse Distance (w_{ij}^{inv})

$$w_{ij}^{inv} = \begin{cases} \frac{1}{d_{ij}}, & \text{if } 0 < d_{ij} \leq D_{\max}(i \neq j)(\text{with} D_{\max} = 1500\text{km}) \\ 0, & \text{otherwise}\left(d_{ij} = 0 \text{ or } d_{ij} > D_{\max}\right) \end{cases} \quad \text{(A2)}$$

A1.3 Exponential Decay (w_{ij}^{exp})

$$w_{ij}^{exp} = \begin{cases} \exp\left(-\frac{d_{ij}}{\rho}\right), & \text{if } d_{ij} > 0 (i \neq j) (\text{with decay radius } \rho = 300 \text{ km}) \\ 0, & \text{if } d_{ij} = 0 (i = j) \end{cases} \quad \text{(A3)}$$

Where ρ is the bandwidth parameter, which determines the rate of decay. A smaller value of ρ leads to faster distance decay in weights, resulting in a more geographically concentrated range of spatial association.

A1.4 Gaussian Decay (w_{ij}^{gauss})

$$w_{ij}^{gauss} = \begin{cases} \exp\left(-\frac{d_{ij}^2}{2\rho^2}\right), & \text{if } d_{ij} > 0 (i \neq j) \\ 0, & \text{if } d_{ij} = 0 (i = j) \end{cases} \quad \text{(A4)}$$

Gaussian decay is characterized by slower decay for proximity weights and more rapid decay for distant weights.

A1.5 Threshold Distance (w_{ij}^{thres})

$$w_{ij}^{thres} = \begin{cases} 1, & \text{if } 0 < d_{ij} \leq D_{thres} \text{ (with } Dthres = 300 \text{ km)} \\ 0, & \text{otherwise}\left(d_{ij} = 0 \ (i = j) \text{ or } \ d_{ij} > D_{thres}\right) \end{cases} \quad \text{(A5)}$$

A1.6 Economic Distance (w_{ij}^{econ})

$$w_{ij}^{econ} = \begin{cases} \frac{1}{1+\frac{\left|\overline{pgdp}_i - \overline{pgdp}_j\right|}{\overline{PGDP}}}, & \text{if } d_{ij} > 0 (i \neq j) \\ 0, & \text{if } d_{ij} = 0 (i = j) \end{cases} \quad \text{(A6)}$$

Where $\overline{pgdp}_i$,$\overline{pgdp}_j$ are average per capita GDPs for cities *i* and *j* over 2008–2023; $\overline{PGDP}$ is the national average. Following Shao et al. (2016), α=0.5.

A1.7 Economic-Geographic Nested (w_{ij}^{nested})

$$w_{ij}^{nested} = \begin{cases} \alpha \cdot w_{ij}^{exp} + (1-\alpha) \cdot w_{ij}^{econ}, & \text{if } d_{ij} > 0 (i \neq j) \\ 0, & \text{if } d_{ij} = 0 (i = j) \end{cases} \quad \text{(A7)}$$

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A2. High-Quality Development Index (*HQDI*)

Appendix Table A1 presents the measurement framework for the High-Quality Development Index (*HQDI*), which assesses a city's comprehensive development status. This index is designed to provide a robustness test for the Urban Competitiveness Index (*UCI*).

Table A1 – High-Quality Development Index Measurement Framework. Source: own search

Objective	Dimension	Category	Indicator	Weight	Property
HDQI	Innovative Development	Innovation Input	Share of Science and Technology expenditure in local fiscal expenditure	0.0147	Positive
			Share of education expenditure in local fiscal expenditure	0.0013	Positive
			Number of full-time university teachers per 10,000 people	0.0186	Positive
			Employment in strategic emerging industries	0.0623	Positive
		Innovation Output	Number of patents granted per 10,000 people	0.0298	Positive
			Number of FinTech firms per 10,000 people	0.0655	Positive
			Number of AI firms per 10,000 people	0.0526	Positive
	Coordinated Development	Economic Level	Retail sales of consumer goods per capita	0.0087	Positive
			Fixed asset investment per capita	0.0084	Positive
			GDP per capita	0.0077	Positive
		Economic Structure	Urbanization rate	0.0033	Positive
			Industrialization rate (Industrial value-added / GDP)	0.0023	Positive
			Industrial structure advancement index	0.0061	Positive
			Industrial structure rationalization index	0.0762	Positive
	Open Development	FDI Attraction	Number of FDI contracted projects	0.0724	Negative
			Amount of actually utilized FDI	0.0465	Positive
			Share of foreign-funded enterprises	0.0193	Positive
		Foreign Trade	Export value	0.0652	Positive
			Import value	0.1491	Positive
	Green Development	Eco-Environment	Air quality compliance rate	0.0106	Positive
			Green coverage rate in built-up areas	0.0068	Positive
		Environmental Load	Industrial wastewater discharge	0.0226	Negative
			Industrial SO_2 emissions	0.0851	Negative
			Industrial soot and dust emissions	0.0745	Negative
		Environmental Governance	Comprehensive utilization rate of general industrial solid waste	0.0021	Positive
			Centralized treatment rate of sewage treatment plants	0.0011	Positive
			Harmless treatment rate of municipal solid waste	0.0010	Positive
		Social Security	Average wage of employees	0.0066	Positive

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	Shared Development		Share of social security expenditure	0.0026	Positive
			Number of hospital beds per 10,000 people	0.0059	Positive
		Public Services	Internet broadband access ports per capita	0.0423	Positive
			Urban road area per capita	0.0047	Positive
			Daily domestic water consumption per capita	0.0041	Positive
			Per capita public green area	0.0026	Positive
			Public library books per 100 people	0.0177	Positive

Note: The construction of the High-Quality Development Index (HQDI) follows the conceptual framework of the 'five development concepts' (innovation, coordination, openness, green, and sharing) as articulated in Chinese policy discourse and operationalized in the academic literature. The selection of innovation indicators draws on Ni (2003) and Ni et al. (2021), which emphasize the role of knowledge creation and technological capabilities in urban development. The coordinated development dimension incorporates the industrial structure advancement index calculated following Gan et al. (2011). The open development indicators are informed by Bi & Li (2018) and Wang (2025), who distinguish between factor flow-based and institution-based openness. The green development indicators reference the environmental performance framework of Feng et al. (2023) and Zhao et al. (2022). The shared development dimension, particularly the public service indicators, builds on the quality-of-life measures discussed in Ni et al. (2022) and the OECD Better Life Index framework. All data sources are detailed in Section 3.3.1.

A3. Urban Competitiveness Index (*UC*)

Appendix Table A2 presents the measurement framework for the process-oriented Urban Competitiveness Index (*UC*), which is designed to serve as a robustness check for the outcome-oriented Urban Competitiveness Index (*UCI*).

Table A2– Urban Competitiveness Index Measurement Framework. Source: own search

Objective	Dimension	Indicator	Weight	Property
UC	Economic Control	Share of financial institution loan balance in GDP	0.0153	Positive
		Share of listed companies among industrial enterprises above designated size	0.0811	Positive
		Share of high-tech enterprise revenue (in High-Tech Zones) in GDP	0.0862	Positive
	International Connectivity	Aviation workload	0.1578	Positive
		China-Europe Railway Express operation status (DID variable)	0.1819	Positive
		Agglomeration degree of foreign-funded enterprises	0.0424	Positive
	Talent Attractiveness	College students per 10,000 people	0.0375	Positive
		Inflow intensity of high-level talent	0.0717	Positive
		Full-time university teachers per 10,000 people	0.0391	Positive
	Institutional Quality	Market integration index	0.0073	Positive
		Fiscal transparency	0.0325	Positive
		Business Environment Health Index	0.0659	Positive
		Entrepreneurial activity	0.0284	Positive
		Digital Inclusive Finance Index	0.0218	Positive
	Livability	Air quality compliance rate	0.0223	Positive
		Green coverage rate in built-up areas	0.0019	Positive
		Harmless treatment rate of municipal solid waste	0.0028	Positive
		Number of public buses per 10,000 people	0.0174	Positive
		Share of social security expenditure in general public budget expenditure	0.0055	Positive

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		Ratio of average commercial housing price to average wage of employed staff	0.0101	Negative
		Gas penetration rate	0.0012	Positive
		Tap water penetration rate	0.0008	Positive
		Number of hospital beds per 10,000 people	0.0124	Positive
		Internet broadband subscribers per 100 people	0.0196	Positive
		Public library books per 100 people	0.0371	Positive

Note: The construction of the process-oriented Urban Competitiveness Index (UC) draws on multiple theoretical and methodological sources. The economic control dimension follows the 'Bow–String–Arrow' model of urban competitiveness (Ni, 2003) and the global urban competitiveness framework (Ni et al., 2021). The international connectivity indicators are informed by world city network theory (Taylor, 2004) and empirical applications in the Chinese context (Wang et al., 2019; Wang et al., 2020). The talent attractiveness dimension reflects the human capital perspective in urban competitiveness research (Kresl & Ietri, 2014). The institutional quality indicators incorporate the business environment framework (Zheng & Duan, 2022) and the digital inclusive finance index developed by the Digital Finance Research Center of Peking University. The livability dimension is based on quality-of-life indicators commonly used in urban studies (Ni et al., 2022) and draws on the OECD Better Life Index framework. All data sources are detailed in Section 3.3.1.

A4. Missing Data Statistics and Imputation Methods

Table A3 – Descriptive Statistics of Variables. Source: own search

Variable Category	Variable	Observations (N)	Missing Observations	Missing (%)	Imputation Method
Dependent Variable	UCI_{it}	4608	0	0	None
Core Independent Variable	COI_{it}	4608	0	0	None
Mediating Variables	GIE_{it}	4608	0	0	None
	PEA_{it}	4031	577	14.3	Linear interpolation (max 3 consecutive gaps)
	GCC_{it}	4608	0	0	None
Moderating Variables	$BEHI_{it}$	2300	2308	50.1	Not imputed
	FTI_{it}	4608	0	0	None
	AI_{it}	4608	0	0	None
	GNE_{it}	4608	0	0	None
	IEM_{it}	4608	0	0	None
Control Variables	$GFCF_{it}$	4608	128	2.8	Linear interpolation (max 3 consecutive gaps)
	HC_{it}	4608	86	1.9	Linear interpolation (max 3 consecutive gaps)
	PRE_{it}	4608	42	0.9	Linear interpolation (max 3 consecutive gaps)
	TI_{it}	4608	215	4.7	Linear interpolation (max 3 consecutive gaps)
	PD_{it}	4608	94	2	Linear interpolation (max 3 consecutive gaps)
	IR_{it}	4608	73	1.6	Linear interpolation (max 3 consecutive gaps)

Note: Linear interpolation was applied only to gaps of no more than three consecutive periods to avoid artificial trend smoothing. Variables with missing rates exceeding 30% (or >50% for single variables) led to city exclusion as per sample selection criteria described in Section 3.3.1. $BEHI_{it}$ is reported for transparency

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but was not imputed due to its structurally unbalanced panel nature; regressions using $BEHI_{it}$ is based on the available 2300 observations with appropriate caveats.

A5. Descriptive Statistics

Table A4 shows that the mean of UCI_{it} is 0.05 (SD=0.04), with a maximum of 0.44 (e.g. Shenzhen, Shanghai) and minimum of 0.01. The standard deviation is 0.80 times the mean, indicating substantial heterogeneity across cities. COI_{it} exhibits a similar pattern of 'low mean, high dispersion'. Other variables align with expectations from prior literature.

Table A4 – Descriptive Statistics of Variables. Source: own search

Variable		Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	UCI_{it}	4608	0.0500	0.0426	0.0062	0.4394
Core Independent Variable	COI_{it}	4608	0.0393	0.0768	0.0000	0.8498
Mediating Variables	GIE_{it}	4608	0.3381	0.1395	0.1026	1.1928
	PEA_{it}	4031	21.3645	23.2927	0.0000	140.3644
	GCC_{it}	4608	0.0271	0.0862	0.0000	0.8920
Moderating Variables	$BEHI_{it}$	2300	37.1769	19.1559	0.0000	100.0000
	FTI_{it}	4608	165.8649	100.2638	0.0000	359.6825
	AI_{it}	4608	4.8640	2.0051	0.0000	11.5395
	GNE_{it}	4608	0.3299	0.8892	0.0000	4.0000
	IEM_{it}	4608	0.2431	0.6796	0.0000	4.0000
Control Variables	$GFCF_{it}$	4608	0.7814	0.3060	0.2045	1.7643
	HC_{it}	4608	4.7032	1.0032	1.9940	6.8895
	PRE_{it}	4608	8.9383	0.6020	7.4198	10.3481
	TI_{it}	4608	0.0164	0.0156	0.0012	0.0818
	PD_{it}	4608	23.8200	8.9934	7.3986	55.7532
	IR_{it}	4608	0.3918	0.1230	0.1015	0.7073

A6. Robustness Tests

To ensure the reliability of the baseline regression results, a series of robustness checks were conducted, including variable substitution, methodological adjustments, model extensions, and placebo tests. These aimed to rule out interference from measurement bias, sample outliers, and model misspecification. The results are summarized in Table A5.

A6.1 Variable Substitution

To verify that conclusions are not affected by measurement bias.

A6.1.1 Substituting the Dependent Variable

Table A5 column (1) replaces the entropy-method *UCI* with the PCA-method *UCI_PCA*. The coefficient for *COI* remains significantly positive at 0.08 ($p < 0.01$).

A6.1.2 Substituting the Core Independent Variable

Table A5 column (2)–(4) replace *COI* with *COI_PCA* (PCA-based), Institution-Based Openness (*IBO*), and Factor Flow-Based Openness (*FFBO*), respectively. The coefficients

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(0.05, 0.04, 0.25) are all significant at the 1% level, confirming the positive effect of openness on *UCI* is robust to measurement.

A6.2 Adjusting Estimation Methods

To verify results are not constrained by data distribution characteristics.

A6.2.1 Bootstrap Stratified Sampling

Table A5 column (5) performs 500 repetitions of stratified sampling by Eastern, Central, and Western China. The *COI* coefficient is 0.05 ($p < 0.01$).

A6.2.2 Winsorization

Table A5 column (6) winsorizes all continuous variables at the 1st and 99th percentiles. The *COI* coefficient is 0.03 ($p < 0.01$), indicating results are not driven by outliers.

A6.2.3 Excluding Municipalities

Table A5 column (7) excludes Beijing, Shanghai, etc. The *COI* coefficient is 0.04 ($p < 0.01$).

A6.3 Model Extensions

To verify the robustness of the model specification.

A6.3.1 Panel Tobit Estimation

As *UCI* has a lower bound near zero, a Tobit model is used in Table A5 column (8). The *COI* coefficient is 0.05 ($p < 0.01$).

A6.3.2 Driscoll-Kraay Standard Errors

Table A5 column (9) accounts for heteroskedasticity, cross-sectional correlation, and autocorrelation using xtscc. The *COI* coefficient is 0.05 ($p < 0.01$).

A6.4 Placebo Test

A random walk process generated 500 pseudo-*COI* variables to simulate random shocks. The kernel density distribution of the placebo coefficients is tightly centered around zero (μ = -0.0003, σ = 0.0101), while the true coefficient ($\hat{\beta}$= 0.0458) lies in the right tail (see Figure A1). Only 0.20% of the randomization results were more significant than the true effect ($p < 0.01$), ruling out spurious correlations and confirming statistical robustness.

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In summary, the positive effect of *COI* on *UCI* holds across this comprehensive battery of robustness checks, supporting H1.

Table A5 – Robustness Tests. Source: own search

Variable	(1)	(2)	(3)	(4)	(5)
	Substitute Dep. Var.	Substitute Indep. Var.	Substitute Indep. Var.	Substitute Indep. Var.	bootstrap (500 replications)
	UCI_PCA	*UCI*	*UCI*	*UCI*	*UCI*
COI	0.0807*** (2.9714)				0.0458*** (7.3452)
COI_PCA		0.0450*** (2.8279)			
IBO			0.0421*** (3.0391)		
FFBO				0.2513*** (3.0454)	
Controls	Yes	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608
R^2	0.9524	0.9740	0.9745	0.9735	0.3219

Continued Table A5:

Variable	(6)	(7)	(8)	(9)
	Winsorized (1%, 99%)	Excl. Municipalities	Tobit	D-K Errors
	UCI	*UCI*	*UCI*	*UCI*
COI	0.0255** (2.0055)	0.0425*** (3.6382)	0.0458*** (18.1149)	0.0458*** (8.1728)
Controls	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes
N	4608	4544	4608	4173
R^2	0.9730	0.9676	-1.0561	0.3219

Note: Column (8) reports panel Tobit results (Log likelihood = 16465.617). Column (9) uses Driscoll-Kraay standard errors. Robust t-statistics in parentheses; ***, **, *denote significance at 1%, 5%, 10%.

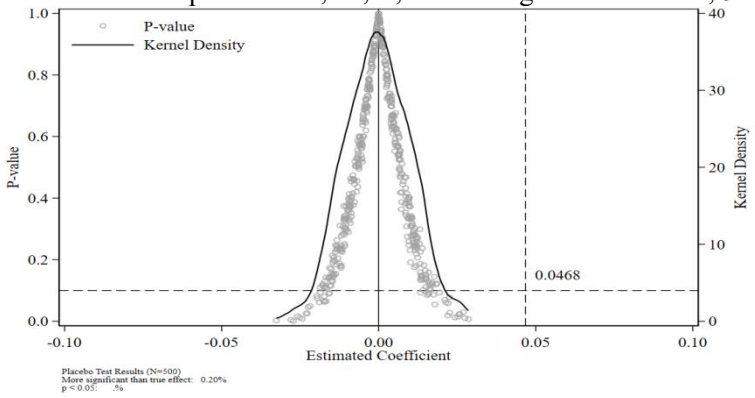


Figure A1 – Placebo Test

Note: The figure presents the results of 500 randomization placebo tests for the fixed effects model. The blue curve is the kernel density estimate of the placebo coefficients. Grey circles represent the p-value for each randomization. The red dashed line indicates the true estimated coefficient (0.0458). Only 0.20% of the

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randomizations yielded results more significant than the true effect.

A7. Robustness Checks for Heterogeneity Analysis

Table A6 reports statistical tests employing the Bonferroni correction for the core heterogeneity findings to account for the family-wise error rate. Following correction, the moderating effects of Global Network Embeddedness (*GNE*) and Innovation Ecosystem Maturity (*IEM*) remain highly significant at the 1% level ($p = 0.0010$ and $p = 0.0001$), providing robust confirmation of the main findings. In contrast, the exploratory test based on the combined classification does not achieve conventional significance levels after correction ($p = 0.1986$), which appropriately reflects its auxiliary and indicative nature and does not detract from the core conclusions derived from the continuous variable models.

Table A6 – Bonferroni Correction for Multiple Hypothesis Testing. Source: own search

Test	Raw_Pvalue	Bonferroni_Pvalue
*GNE*COI*	0.0003	0.0010
*IEM*COI*	0.0000	0.0001
*GC_rank*COI* (Combined Test)	0.0662	0.1986

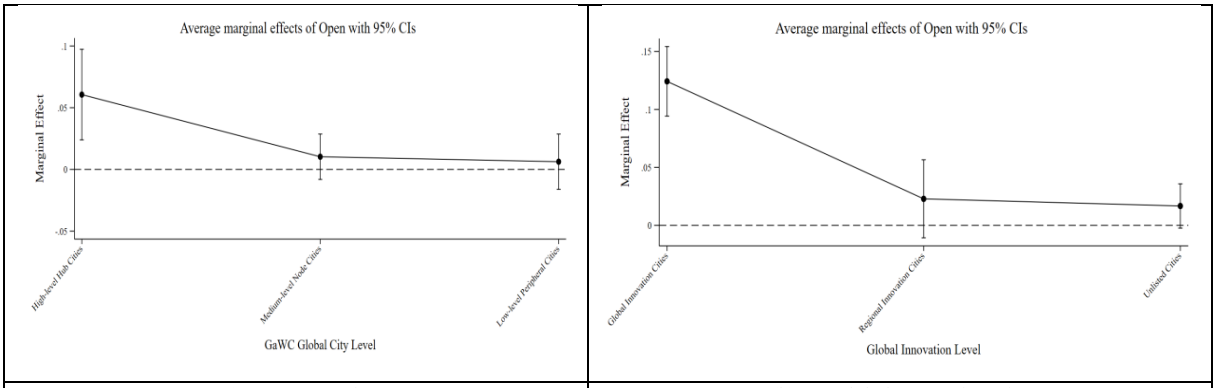
Table A7 and Figure A2 present exploratory interaction model results based on early theoretical groupings (three-category and combined classifications). These are placed in the appendix as their categorical schemes are relatively simplified and the results are not corrected for multiple testing, requiring cautious interpretation. Nonetheless, they show a clear, consistent pattern: interaction terms are significantly negative compared to the 'high-capability' or 'dual-high' baseline groups. This suggests the positive effect of *COI* on *UCI* is relatively stronger in higher-tier cities, echoing the main text's conclusion that cities with higher structural positions gain greater marginal benefits from openness, thereby supporting the main finding.

Table A7 – Robustness Tests for Heterogeneity Analysis. Source: own search

Variable	*UCI*		
	(1) GaWC	(2) GII	(3) GaWC-GII Combined Classification
COI	0.0606*** (3.2377)	0.1243*** (8.1135)	0.1244*** (8.1298)
*GaWC_rank2*COI*	-0.0503** (-2.3970)		
*GaWC_rank3*COI*	-0.0544** (-2.5824)		
*GII_rank2*COI*		-0.1014*** (-4.3683)	
*GII_rank3*COI*		-0.1076*** (-6.0154)	
*Dual_rank2*COI*			-0.1325*** (-7.9569)
*Dual_rank3*COI*			-0.0989*** (-4.7011)
Controls	Yes	Yes	Yes

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Two-Way FE	Yes	Yes	Yes
N	4608	4608	4608
R^2	0.9754	0.9769	0.9769



(a) By GaWC Tier (b) By Global Innovation Tier

Figure A2 – Diminishing Marginal Effects of Comprehensive Openness. Source: own search

A8. Spatial Spillover Effects

Table A8 showing yearly Moran's I value for the six spatial weight matrices, all statistically significant at conventional levels, demonstrating stable positive spatial autocorrelation in urban development.

Table A8 – Moran's I Index (2008-2023). Source: own search

Year	Moran's I					
	(1) Contiguity	(2) Inverse Distance	(3) Exponential Decay	(4) Gaussian Decay	(5) Threshold Distance	(6) Economic-Geographic Nested
2008	0.3052***	0.0833***	0.0929***	0.1116***	0.1874***	0.1624***
2009	0.2995***	0.0814***	0.0906***	0.1085***	0.1847***	0.1592***
2010	0.2836***	0.0773***	0.0866***	0.1043***	0.1836***	0.1545***
2011	0.2775***	0.0753***	0.0846***	0.1026***	0.1867***	0.1536***
2012	0.2840***	0.0778***	0.0877***	0.1064***	0.1887***	0.1591***
2013	0.2739***	0.0717***	0.0792***	0.0955***	0.1703***	0.1512***
2014	0.2608***	0.0677***	0.0761***	0.0919***	0.1719***	0.1442***
2015	0.2622***	0.0665***	0.0735***	0.0884***	0.1691***	0.1418***
2016	0.2393***	0.0654***	0.0725***	0.0871***	0.1578***	0.1396***
2017	0.2230***	0.0573***	0.0623***	0.0748***	0.1445***	0.1264***
2018	0.1945***	0.0539***	0.0598***	0.0716***	0.1392***	0.1196***
2019	0.1810***	0.0486***	0.0545***	0.0653***	0.1309	0.1110***
2020	0.1727***	0.0472***	0.0535***	0.0642***	0.1246***	0.1092***
2021	0.1855***	0.0504***	0.0561***	0.0671***	0.1295***	0.1151***
2022	0.1956***	0.0527***	0.0585***	0.0706***	0.1292***	0.1196***
2023	0.1994***	0.0536***	0.0590***	0.0710***	0.1290***	0.1218***

Table A9 presenting SDM estimation results using the six different spatial weight matrices. The direct effect of *COI* on *UCI* is consistently positive and significant (0.047~0.049, p<0.01). The spatially lagged effect ($W \times COI$) is consistently negative and significant, confirming the competitive resource-siphoning effect. The decomposition shows positive direct effects,

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negative indirect effects, and mostly insignificant total effects, robust across matrices.

Table A9 – Robustness Tests for the Spatial Durbin Model. Source: own search

Variable	*UCI*					
	(1) Contiguity	(2) Inverse Distance	(3) Exponential Decay	(4) Gaussian Decay	(5) Threshold Distance	(6) Economic-Geographic Nested
COI	0.0470*** (18.2772)	0.0476*** (18.6376)	0.0472*** (18.3879)	0.0472*** (18.3611)	0.0473*** (18.2955)	0.0491*** (18.5051)
W×COI	-0.0099** (-2.4320)	-0.0746*** (-4.0290)	-0.0480*** (-2.9186)	-0.0405*** (-3.2566)	-0.0254*** (-3.7551)	-0.0527*** (-4.1678)
ρ (Spatial AR)	0.0394** (2.0216)	0.1529* (1.7296)	0.2598*** (3.6292)	0.2676*** (4.9844)	0.2572*** (7.9527)	0.2339*** (3.6551)
Direct_COI	0.0470*** (17.8777)	0.0475*** (18.1703)	0.0471*** (17.9727)	0.0470*** (17.9478)	0.0471*** (17.9125)	0.0490*** (18.1317)
Indirect_COI	-0.0084** (-2.1411)	-0.0807*** (-3.6679)	-0.0490** (-2.2844)	-0.0383** (-2.3822)	-0.0176** (-2.1157)	-0.0543*** (-3.4319)
Total_COI	0.0386*** (8.9726)	-0.0332 (-1.5250)	-0.0019 (-0.0894)	0.0087 (0.5453)	0.0295*** (3.5356)	-0.0053 (-0.3490)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Two-Way FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4608	4608	4608	4608	4608	4608
R^2	0.4806	0.4494	0.3539	0.3661	0.4861	0.5452
AIC	-32886.6646	-32912.3385	-32914.0522	-32924.3523	-32960.3603	-32910.2672
BIC	-32712.9048	-32738.5787	-32740.2924	-32750.5925	-32786.6005	-32736.5074

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