

Institutional Opening and Urban Energy Transition: Technological Paths and Spatial Squeeze of China's Belt and Road Initiative

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Abstract: Urban energy transitions depend on recombining cross-boundary technologies, a process fundamentally catalyzed by institutional opening. Treating the 2013 Belt and Road Initiative (BRI) node designation as a quasi-experiment across 282 Chinese cities (2006 – 2022), this study evaluates the causal effects, technological paths, and spatial boundaries of institutional opening on energy-transition efficiency (ETE). We identify three core dynamics. First, BRI-induced opening robustly improves urban ETE, yielding pronounced dividends in Central Western regions, Silk Road nodes, and cities exhibiting strong green-development willingness but lower talent-attraction intensity. Second, opening drives efficiency leaps primarily by expanding technological innovation capacity and fostering technological diversification, rather than deepening technological specialization. Externally, robust intellectual property protection mitigates the policy-induced contraction of technological specialization, while escalating geopolitical risks paradoxically reinforce the transmission efficacy of technological diversification. Third, despite positive overall ETE co-movement, local BRI exposure triggers significant “near-neighbor siphoning.” This spatial displacement is network-bounded: under trade-gravity weights, siphoning attenuates within a 400 – 600 km radius, whereas transportation corridors induce “long-arm polarization,” squeezing peripheral cities across extended distances. Ultimately, this study clarifies the structural tension between localized green dividends and spatial siphoning, providing vital micro-level evidence for cross-regional collaborative governance.

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1 Introduction

The global sustainability agenda has positioned urban green transitions at the center of strategic policy. The UN 2030 Sustainable Development Goals jointly target clean energy (SDG 7), sustainable cities (SDG 11), and climate action (SDG 13), establishing a unified benchmark for urban low-carbon development (Wiedmann and Allen, 2021). As hubs of energy consumption and emissions, cities are the crucial spatial units where demand-side abatement, electrification, and green infrastructure are implemented. Their mitigation potential relies heavily on land use, developmental stages, and governance efficacy (Creutzig et al., 2022; Seto et al., 2021; IPCC, 2022). Therefore, decoupling energy consumption and pollution from economic growth represents both a critical urban governance challenge and a fundamental efficiency imperative for open national strategies.

Driven by the global sustainability agenda and China’s dual-carbon targets, urban green transitions now occupy the center of macroeconomic policy. Chinese cities, as the primary hubs of energy use and emissions, are actively shifting from extensive spatial expansion to efficiency-driven structural upgrading (UN-Habitat, 2022; Khiali-Miab et al., 2024). Urban energy-transition efficiency (ETE) dictates local pollution control and energy security, ultimately determining the compatibility of open national strategies with binding low-carbon constraints (Sharifi, 2021; IEA, 2023; Yan, 2026). In this context, the Belt and Road Initiative (BRI)—introduced in 2013 through cross-border infrastructure, enhanced market access, and multilateral rule alignment—serves as an identifiable quasi-experiment to evaluate how institutional opening reshapes urban green development and the energy economy.

The existing literature supplies essential theoretical foundations while revealing critical gaps that this study addresses. First, on openness and energy efficiency, trade and technology diffusion raise productivity by enlarging markets and transmitting knowledge, though actual gains depend heavily on local absorptive capacity and factor allocation (Melitz, 2003; Keller, 2004). While evidence shows the BRI supports green productivity in connected cities (Wang and Cheng, 2024), this dividend is not strictly linear: infrastructure and trade expansion can induce short-run energy rebounds and spatial reallocations, skewing green gains across regions (Durrani et al., 2025; Sautner et al., 2023; Xie and Li, 2024; Caldara and Iacoviello, 2022). Second, regarding technological evolution and spatial networks, theories of directed technical change

indicate that energy prices, regulations, and knowledge recombination shape the search for energy-saving technologies (Popp, 2002; Acemoglu et al., 2012). However, applied studies largely treat green innovation as a single aggregate output, bypassing the structural decomposition of technological evolution and rarely identifying the spatial boundaries of opening-induced spillovers. Third, advancing causal identification, the modern difference-in-differences literature requires researchers to explicitly separate average treatment effects from event-time dynamics when facing treatment heterogeneity (Callaway and Sant'Anna, 2021; Borusyak et al., 2024; Arkhangelsky et al., 2021; Rambachan and Roth, 2023).

In light of this, based on a panel of 282 Chinese cities (2006–2022), we combine mathematical modeling and causal inference to systematically examine the treatment effects, technological paths, moderating mechanisms, and spatial spillover boundaries of the BRI on pollution-constrained urban ETE.

Our core findings verify that the BRI-induced institutional opening significantly and robustly enhances urban ETE, while also revealing that the efficiency dividends of such macroeconomic strategies face clear boundary constraints and significant spatial unevenness. Meanwhile, this dividend relies heavily on expanded technological search and cross-boundary knowledge recombination, actualized via technological innovation capacity (TIC) and technological diversification (TCD), whereas technological specialization (TCS) offers no effective transmission. Within this process, sound intellectual property protection (IPP) effectively buffers the opening-induced decline in specialization, while escalating geopolitical risks (GPR) positively reinforce the efficacy of diversification. More importantly, the local surge in energy efficiency does not occur in a vacuum; it inevitably coexists with negative spatial reallocation across trade spheres and transportation corridors, triggering significant and dynamically evolving "near-neighbor siphoning" and "network squeezing" effects on surrounding cities.

This study makes four contributions to the literature.

(1) it provides a theoretical framework that captures both local gains and spatial reallocation. By integrating technological innovation, cross-domain diversification, and specialization into urban decision-making, and accounting for neighbor interactions via diffusion and competition,

the resulting threshold conditions explain the coexistence of local efficiency improvements and negative spillovers.

(2) it tightens causal identification under complex policy shocks. Energy transition is measured using an environmental-constrained SBM-DEA model. Empirically, TWFE DID, and imputation DID, honest DID, and synthetic DID are reported concurrently. Night-time lights serve as an alternative energy input, and overlapping green or open-door policies are rigorously isolated.

(3) it opens the technological mechanism beyond simple innovation counts by decomposing knowledge recombination into scale, breadth, and depth. We demonstrate that cross-domain recombination is the central channel for urban energy transition, with external shocks and local institutions moderating the three paths asymmetrically.

(4) it identifies spatial associations and their boundaries across four networks rather than a single contiguity matrix. Using a spatial DID design based on geographic distance, economic gravity, trade gravity, and railway connectivity, we find that local ETE gains coexist with a near-neighbor squeeze. Negative trade spillovers converge between 400 and 600 km, whereas railway-corridor spillovers strengthen as the radius expands.

The remainder of this paper is structured as follows: Section 2 reviews the related literature. Section 3 constructs the theoretical framework, and proposes testable hypotheses. Section 4 describes the data and variable measurements. Section 5 details the model specifications and identification strategies. Section 6 reports the baseline estimates, mechanism tests, heterogeneity, and spatial spillover analyses. Section 7 concludes the study and discusses future research directions.

2 Literature Review

2.1 The BRI and green efficiency

On Open-economy theory characterizes connectivity as a catalyst for market expansion and the reallocation of intermediate goods and knowledge (Keller, 2004). While macro-level evidence indicates that the BRI generally improves green TFP and energy efficiency, these gains

are heavily moderated by local industrial structures, financial development, and investment modes (Yang and Ni, 2022).

At the city and firm levels, node status has been shown to support green development, corporate low-carbon transitions, and emissions reduction (Wang and Cheng, 2024). However, trade and infrastructure expansion can also induce energy rebounds and spatial resource reallocations, resulting in uneven green returns across regions (Durrani et al., 2025). Furthermore, spatial expansion along BRI corridors reshapes industrial and commercial agglomeration, carrying long-term consequences for environmental sustainability (Wei et al., 2023). The extended construction cycles of cross-border infrastructure can lock in future energy trajectories (Adshead et al., 2021), meaning that local energy transitions rely on aligning sectoral coupling with broader climate targets (Gupta et al., 2026).

Despite this growing literature, research on green efficiency remains concentrated on provincial or national aggregates. Few studies place a precisely defined prefecture-level node status and a pollution-constrained ETE measure into the same causal design.

2.2 Technological innovation, knowledge recombination, and ETE

Classical innovation and trade theories hold that while openness expands access to external knowledge, actual productivity gains remain constrained by local absorptive capacity and factor allocation (Cohen and Levinthal, 1990; Melitz, 2003). Correspondingly, the directed technical change framework demonstrates that environmental regulations and energy prices actively redirect search trajectories toward energy-saving technologies (Popp, 2002; Acemoglu et al., 2012).

At the urban scale, innovation is not merely a linear function of aggregate R&D stock. Pioneering new technological paths requires integrating both related and unrelated knowledge, with dynamic recombinant relatedness predicting regional innovation more accurately than static industrial proximity (Boschma et al., 2023).

Finally, the distributional consequences of these technological trajectories are profound. While urban innovation policies leverage green finance and talent to improve carbon productivity and generate spatial spillovers (Ren et al., 2024), related variety alone cannot fully bridge regional low-carbon gaps, despite shaping entry into green sectors (Pinheiro et al., 2022).

As falling renewable and storage costs widen the feasible set for cross-domain recombination (Way et al., 2022), the spatial incidence of the energy transition ultimately depends on which cities possess the capability to design and deploy these recombinant green technologies (Romero-Lankao et al., 2023).

2.3 Policy conditions, external frictions, and city types

Macroeconomic policy conditions and urban heterogeneity critically shape the green returns to opening. Because low-carbon city pilots and green-finance reform zones overlap spatially and temporally with BRI node designations, leaving these instruments uncontrolled conflates their effects with institutional opening (Chen et al., 2022; Du et al., 2022). Additionally, as green bonds expand alongside urban climate agendas (Flammer, 2021), evaluating these staggered adoptions using standard two-way fixed-effects (TWFE) models can yield biased estimates that depart from the target parameter when treatment effects are heterogeneous (Baker et al., 2022).

External frictions and local institutions further direct the absorption of technological change. Intellectual property protection lowers transaction costs for proprietary knowledge and encourages innovation (Neves et al., 2021), while a robust industrial-upgrading base enables the absorption of energy-saving equipment and cross-industry knowledge. Notably, while geopolitical risk raises the costs of cross-border cooperation, it simultaneously strengthens the motive to search for secure, diversified technologies (Blondeel et al., 2021; Sautner et al., 2023; Xie and Li, 2024). Although local climate agendas embed mitigation targets into policy texts and establish observable grouping conditions, the actual implementation of these subnational actions must be evaluated separately (Salvia et al., 2021; Hale et al., 2021).

Lastly, while smart-city investments and urban data analytics reshape the information base of energy governance, the types, priorities, and distributional impacts of these digital transitions are far from uniform (Kandt and Batty, 2021; Caragliu and Del Bo, 2022; Zhu et al., 2024). The ongoing intersection of low-carbon transitions with financial and geopolitical risks continues to shift the frontiers of technological search and project implementation within open networks (Semieniuk et al., 2021; Kuzemko et al., 2022).

2.4 Synthesis

Despite extensive literature on macroeconomic green returns, three critical gaps remain. First, focusing on aggregate green TFP obscures the tension between economic expansion and pollution-constrained energy transitions at the prefecture level. Second, treating green innovation merely as aggregate output fails to capture how opening shocks reorient technological search through knowledge recombination. Third, empirical designs rarely examine how external frictions moderate this trajectory, nor do they leverage physical networks to delineate the spatial boundaries of policy spillovers.

3 Theoretical Analysis and Formal Modelling

This section embeds the BRI shock, the scale–breadth–depth dimensions of the urban knowledge base, and the moderating roles of intellectual property, industrial foundations, and geopolitical risk within a single equilibrium framework. The model yields four testable propositions regarding local efficiency improvements, technological paths, conditional heterogeneity, and the spatial division of gains. Finally, Figure 1 schematically summarizes the direct policy effects, mediating channels, moderating conditions, and spatial spillovers.

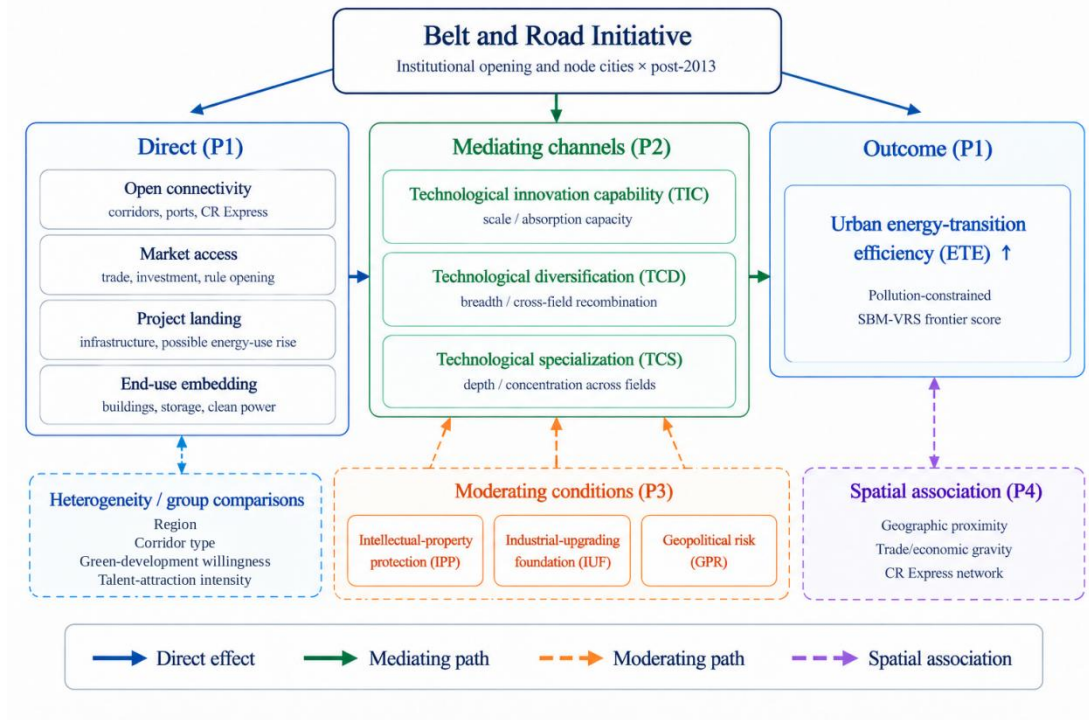


Figure 1. Theoretical framework

3.1 Theoretical analysis

3.1.1 The BRI and the structural tension in urban ETE

As the primary catalyst for high-standard institutional opening, the BRI embeds cross-border corridors, deeper market access, and international rules into local production, fundamentally reshaping pollution-constrained ETE. Node status improves spatial accessibility and the efficiency of intermediate-input allocation, while the associated foreign investment and environmental standards support green development and carbon abatement along the corridors (Wang and Cheng, 2024).

However, this transmission mechanism is not uniformly linear. Although connectivity lowers transaction costs and pushes the local production possibility frontier outward, initial construction and short-run surges in heavy-industry trade can induce energy rebounds (Durrani et al., 2025). Whether the local energy transition actually materializes depends on successfully embedding clean power, storage, and energy-saving technologies into the built environment and end-use systems (Bilardo et al., 2024; Mussawar et al., 2024; Khiali-Miab et al., 2024). The net effect on ETE is thus a balance between the technological dividend and scale-driven energy expansion: efficiency rises when technical upgrading dominates, but short-term green performance falters when high-carbon capacity expands.

3.1.2 The tripartite mechanism of technological recombination

Under an opening shock, urban technology does not accumulate along a single margin. Instead, it involves Technological Innovation Capacity (TIC) as the scale of knowledge stock, Technological Diversification (TCD) as the breadth of cross-domain recombination, and Technological Specialization (TCS) as the depth of concentration in existing fields (Zhao et al., 2022). While related combinations favor incremental gains, entering a new green trajectory requires both related and unrelated knowledge (Boschma et al., 2023; Hidalgo, 2021). Cross-links among technology, design, and markets also spawn new specializations (Castaldi and Drivas, 2023). Institutional opening alters the marginal return to each dimension, transmitting these changes to ETE.

First, formal opening widens markets and knowledge flows, raising exposure to frontier energy-saving processes and stricter standards. Internalizing this knowledge depends on

absorptive capacity—existing stocks, routines, and R&D (Cohen and Levinthal, 1990). Green technologies specifically rely on complementarities between green and non-green knowledge (Barbieri et al., 2023), with urban invention patent value serving as the observable scale measure (Kou and Liu, 2017). Because knowledge is nonrival, larger markets raise expected returns to green innovation (Romer, 1990) and the marginal return to TIC. Thus, when TIC complements local efforts, the unit cost of installing energy-saving processes falls, boosting ETE.

Second, knowledge diffusion is cognitively local: external knowledge is best absorbed when related to the local base. Dynamic recombinant relatedness predicts this cross-domain recombination better than static industrial proximity (Boschma et al., 2023). The entry of green technologies into new domains depends on recombinant novelty and local combinatorial capabilities (Orsatti et al., 2024). Opening lowers barriers to cross-city R&D and equipment trade, reshaping the feasible energy system through green technology interdependencies (Barbieri et al., 2023). Ultimately, cross-domain recombination, TCD, functions as the indispensable breadth channel facilitating the energy transition.

Third, moderate concentration supports scaled application and cost reduction, but deep specialization creates path dependence, preventing clean processes from displacing long-lived high-carbon infrastructure (Zhao et al., 2022; Seto et al., 2021). For example, district heating locked into coal-fired cogeneration reinforces a high-carbon path (Liu, S. et al., 2024). Under new carbon constraints, excessive specialization narrows the technological search. Ultimately, its impact on ETE is entirely context-dependent: it acts as a positive catalyst when synergizing with clean energy, but risks severe negative lock-in when confined to carbon-intensive infrastructure.

3.1.3 Asymmetric moderation by institutions and external shocks

The policy dividends of institutional opening are strictly bounded by local institutions and macroeconomic shocks (Du et al., 2022). Intellectual property protection (IPP), the industrial-upgrading foundation (IUF), and geopolitical risk (GPR) correspond to distinct, non-interchangeable mechanisms: appropriability and transaction frictions, structural absorptive capacity, and search motives under external uncertainty, respectively.

First, IPP governs appropriability and transaction costs, thereby conditioning the TCS path. Stronger protection lowers imitation risks, internalizes returns on specialized energy-saving designs, and facilitates low-carbon capital trade (Neves et al., 2021; Dussaux et al., 2022). However, green technology faces an innovation–diffusion paradox: protection has a threshold above which followers’ adoption costs surge, and below which leaders’ R&D incentives weaken (Du, W. et al., 2025). IPP can thus deepen clean specialization or hinder diffusion, with the net effect depending on whether protection falls near the optimal incentive threshold or enters the range of excessive monopoly.

Second, IUF reflects absorptive capacity embedded in the industrial structure, determining whether advanced equipment and cross-industry knowledge can be localized. International linkages and cross-links among technology, design, and markets support related green diversification (Castaldi and Drivas, 2023; Corrocher et al., 2024). Although industrial structure evolves slowly and is largely absorbed by city fixed effects, related variety and complexity can freeze the spatial division of labor and widen regional gaps (Pinheiro et al., 2022). Moreover, long-lived infrastructure locked into coal cogeneration impedes the absorption of clean technologies (Liu, S. et al., 2024). Consequently, IUF may strengthen transmission from TIC, TCD, and TCS to ETE, or offset it through high-carbon lock-in. The net effect balances absorptive gains against path-dependent costs.

Third, the low-carbon transition is inherently geopolitical. GPR reshapes technological search under external uncertainty: higher risks raise the costs of cross-border cooperation and equipment imports, yet paradoxically force cities to broaden their search to secure energy and technology supplies (Blondeel et al., 2021; Caldara and Iacoviello, 2022). Similarly, firm-level climate exposure alters search and disclosure incentives (Sautner et al., 2023). Energy crises force a trade-off between short-run security and long-run transition, accelerating domestic clean supply but interrupting fossil-fuel exits (Kuzemko et al., 2022). Thus, GPR may strengthen the BRI’s effect on TCD through security motives, or weaken TIC and TCS by disrupting cooperation and freezing specialized investments. Which force dominates remains an empirical question.

3.1.4 Spatial association and the boundary of network spillovers

Although node status is administratively bounded, knowledge, trade, and labor flow dynamically across city networks. Because increasing returns pull economic activity toward node cities, neighbors face a structural trade-off between diffusion gains and competition costs (Krugman, 1991). While human-capital spillovers boost learning and entrepreneurship, urban frictions—like commuting and housing costs—eventually limit expansion and reallocate growth spatially (Duranton and Puga, 2023). Co-agglomeration raises firm energy efficiency through knowledge spillovers and input reallocation (Du and Hao, 2025). Consequently, neighbors might receive technological spillovers or lose capital, talent, and projects to the node (Chen et al., 2022). The net neighbor effect is diffusion minus competition.

When neighboring cities jointly pursue energy transitions, diffusion and competition reshape local marginal returns. Strategic complementarity feeds neighbors' policy efforts back into the local city, allowing ETE to display both positive co-movement and negative displacement (Cui and Cao, 2024; Wang and Shao, 2025). Diversified agglomeration yields a positive, distance-decaying spillover when innovation thresholds are high, whereas specialized agglomeration transmits more weakly and relies heavily on local conditions (Wen et al., 2024). The net spatial sign reflects the relative dominance of diffusion over competition.

Spillover reach depends on interactions encoded by spatial weights, as transmission carriers decay differently (Debary and Le Gallo, 2025). Geographic proximity channels tacit knowledge and decays rapidly, whereas trade gravity extends market access and competition much farther. Corridor networks compress spatial frictions, either diffusing resources to hinterlands or empowering core cities to siphon activity (Baum-Snow et al., 2020; Yang, Y. et al., 2024). Because corridors lengthen both diffusion and competition arms, spillover boundaries and signs must be explicitly identified across distinct geographic, trade, and transport weights.

3.2 Formal modelling

Building on Section 3.1, the model places treatment status, the institution–structure–shock conditions, and the three technology states inside the ETE function, and derives testable implications for the local net effect, the technology paths, and association with neighboring treatment. The objects are the direct return to opening, mediation through technology states, moderation along those paths, and spatial association as the sum of diffusion and competition.

3.2.1 Equilibrium of policy, technology, and energy transition

The unit of analysis is a representative city. Let d_i denote city i 's treatment status and z_i the condition vector ordered as IPP, IUF, and GPR. The technology state is $M_i = (M_{i,tc}, M_{i,td}, M_{i,ts})'$, corresponding to TIC, TCD, and TCS. Eff_i is effort to improve energy efficiency. The city chooses the three technology states and efficiency effort under the initiative and the conditions:

$$\Pi_i(M_i, Eff_i | d_i, z_i) = \varphi_M(d_i, z_i)'M_i + \varphi_e(d_i, z_i) Eff_i + \rho'M_i Eff_i - \frac{1}{2}M_i' C_M M_i - c_e Eff_i^2/2 \quad (T1)$$

Here, φ_M is the vector of marginal returns to the three technology states, C_M is a positive definite cost matrix, ρ governs complementarity between technology and efficiency effort, and c_e is the marginal cost of that effort. Strict concavity requires $c_e - \rho'C_M^{-1}\rho > 0$. Policy and conditions enter through the marginal returns to innovation and to efficiency effort:

$$\varphi_M(d_i, z_i) = \varphi_{M0} + \varphi_{Md}d_i + B_M z_i + \Gamma_M(d_i z_i); \quad \varphi_e(d_i, z_i) = \varphi_{e0} + \varphi_{ed}d_i + b_e' z_i \quad (T2)$$

Here, φ_{M0} and φ_{Md} are three-dimensional vectors; B_M and Γ_M are 3×3 coefficient matrices; φ_{e0} and φ_{ed} are scalars; and b_e is a three-dimensional vector. The entries $\gamma_{ts,ipp}$ and $\gamma_{td,gpr}$ in Γ_M represent interactions between IPP and TCS and between GPR and TCD, respectively. The IUF column allows industrial-upgrading conditions to affect absorption and conversion along all three technology paths. These relationships yield the joint first-order conditions for the technology states and efficiency effort:

$$C_M M_i - \rho Eff_i = \varphi_M(d_i, z_i); \quad c_e Eff_i - \rho'M_i = \varphi_e(d_i, z_i) \quad (T3)$$

On the parameter region that supports an interior solution, strict concavity yields a unique equilibrium. The closed form shows that policy can shift the three technology states directly and, through complementarity, feed back onto efficiency effort:

$$M_i^* = C_M^{-1}[\varphi_M(d_i, z_i) + \rho Eff_i^*]; \quad Eff_i^* = [\varphi_e(d_i, z_i) + \rho'C_M^{-1}\varphi_M(d_i, z_i)]/[c_e - \rho'C_M^{-1}\rho] \quad (T4)$$

Substituting the equilibrium values into the ETE function and specifying $\kappa d_i^2/2$ as the short-run efficiency loss associated with project implementation, construction, and resource reallocation (as discussed in Section 3.1.1) gives equation:

$$Yete_i^*(d_i, z_i) = y_0 + \omega_d d_i + \omega_M' M_i^* + \omega_e Eff_i^* - \kappa d_i^2/2 \quad (T5)$$

Equation (T5) states that the initiative affects ETE through the direct return to opening, the three technology states, and efficiency effort. Let $\omega_M = (\omega_{tc}, \omega_{td}, \omega_{ts})'$. The theoretical

benchmark takes $\omega_{tc} \geq 0$ and $\omega_{td} \geq 0$: capacity accumulation and cross-domain recombination can both raise efficiency. The sign of ω_{ts} depends on whether specialization points toward energy-saving technology.

3.2.2 Comparative statics for policy, conditions, and spatial association

Since the marginal return is linear in the binary treatment d_i , we define $M_{i,d}(z_i)$ and $E_{i,d}(z_i)$ as the treatment-induced discrete differences in the technological state and efficiency effort, respectively:

$$M_{i,d}(z_i) \equiv M_i^*(1, z_i) - M_i^*(0, z_i); \quad E_{i,d}(z_i) \equiv E_{eff_i}^*(1, z_i) - E_{eff_i}^*(0, z_i) \quad (T6)$$

$$\Delta Yete_i(z_i) \equiv Yete_i^*(1, z_i) - Yete_i^*(0, z_i) = \omega_d + \omega_M' M_{i,d}(z_i) + \omega_e E_{i,d}(z_i) - \kappa/2 \quad (T7)$$

Comparative static analyses embed these local conditions directly into the technological responses. IPP primarily operates through the cross-partial derivative $\partial M_{i,d,ts} / \partial z_{i,ipp}$, while GPR maps to $\partial M_{i,d,td} / \partial z_{i,gpr}$. Furthermore, IUF moderates knowledge absorption and conversion across all three technological margins. Since these three mediators jointly reflect incentives, external frictions, and structural lock-in, their net directional impacts remain theoretically indeterminate and are therefore left for empirical determination.

To operationalize the spatial allocation of gains, let $Wnbr_{it}$ represent the neighboring treatment intensity for city i in year t , defined as the spatially weighted sum of other cities' treatment statuses $Dbri_{jt}$. Following Section 3.1.4, this spatial exposure captures both diffusion dividends and competition penalties:

$$Wnbr_{it} = \sum_{j \neq i} w_{ijt} Dbri_{jt}; \quad \partial Yete_{it}^* / \partial Wnbr_{it} = \omega_{diff} - \omega_{comp} \quad (T8)$$

If $\omega_{diff} > \omega_{comp}$, neighboring treatment positively correlates with local ETE. If $\omega_{comp} > \omega_{diff}$, the competition for capital and talent dominates, generating a negative spatial association. Crucially, while trade-network competition generally decays with distance, cross-border corridor networks can simultaneously extend both the diffusion and competition arms.

3.2.3 Two-city strategic interaction and the spatial allocation of gains

To establish a microfoundation for the spatial sign, consider neighboring cities i and j choosing efficiency efforts g_i and g_j . Their net marginal returns are $A_i = \varphi_i(d_i, z_i) + (\tau - \chi) d_j$,

where τ denotes the diffusion of knowledge and projects, and χ denotes competition costs. Neighboring treatment therefore shifts local returns and induces strategic feedback:

$$\Pi_i = A_i g_i - c_i g_i^2/2 + \sigma g_i g_j; \quad \Pi_j = A_j g_j - c_j g_j^2/2 + \sigma g_i g_j \quad (\text{T9})$$

Here, $\tau > \chi$ implies diffusion exceeds competition, while $\tau < \chi$ means competition dominates. Moving simultaneously, the cities reach a Nash equilibrium defined by the first-order conditions:

$$c_i g_i - \sigma g_j = A_i; \quad c_j g_j - \sigma g_i = A_j \quad (\text{T10})$$

If $c_i, c_j > 0$, and $\Delta_N = c_i c_j - \sigma^2 > 0$, the best responses intersect uniquely. Solving (T10) yields city i 's equilibrium effort:

$$\Delta_N = c_i c_j - \sigma^2 > 0, \quad g_i^{NE} = [c_j A_i + \sigma A_j] / \Delta_N \quad (\text{T11})$$

Substituting g_i^{NE} into $Yete_i^* = y_i + \omega_d d_i + \omega_g g_i^{NE}$, and assuming $\omega_g > 0$, the discrete difference with respect to the neighbor's binary treatment is:

$$\Delta_{dj} Yete_i^* = \omega_g [c_j(\tau - \chi) + \sigma \varphi_{j,d}] / \Delta_N \quad (\text{T12})$$

where $\varphi_{j,d} \equiv \varphi_j(1, z_j) - \varphi_j(0, z_j)$ is the change in the neighbor's marginal return when its treatment switches to 1. The numerator's first term is the direct diffusion–competition effect, and the second is the strategic feedback from the neighbor's policy-induced effort. Assuming $\Delta_N > 0$, the net spatial effect is positive if $c_j(\tau - \chi) + \sigma \varphi_{j,d} > 0$, and negative if competition costs dominate the interaction.

3.2.4 Testable propositions

Proposition 1 (P1): If $\Delta Yete_i(z_i) = \omega_d + \omega_M' M_{i,d}(z_i) + \omega_e E_{i,d}(z_i) - \kappa/2 > 0$, the theoretical ETE in a treated node city exceeds its counterfactual. This implies that direct returns, technology transmission, and efficiency efforts must collectively surpass implementation costs.

Proposition 2 (P2): If $M_{i,d,tc}(z_i) > 0$ and $M_{i,d,td}(z_i) > 0$, the policy effectively promotes TIC scale and TCD recombination. The direction of $M_{i,d,ts}(z_i)$, however, is unsigned. Assuming $\omega_{tc}, \omega_{td} \geq 0$, the first two states contribute non-negatively to EFE. The sign of ω_{ts} depends conditionally on whether specialization matches clean-energy demand.

Proposition 3 (P3): IPP, IUF, and GPR condition the policy-induced technology response via z_i . The parameter $\gamma_{ts,ipp}$ captures the IPP $\rightarrow$ TCS path, and $\gamma_{td,gpr}$ the GPR $\rightarrow$ TCD path.

Similarly, $\gamma_{tc,iuf}$, $\gamma_{td,iuf}$, and $\gamma_{ts,iuf}$ delineate how IUF shapes absorption and conversion across the three paths. Their ultimate directions remain empirical, determined by the balance of incentives, frictions, and structural lock-in.

Proposition 4 (P4): The spatial association with neighboring treatment reflects the net balance of diffusion and competition. Linearly, $\partial Yete_{it}^* / \partial Wnbr_{it} = \omega_{diff} - \omega_{comp}$. In the two-city game, given $\omega_g > 0$ and $\Delta_N > 0$, the sign evaluates to $sgn(\Delta_{dj} \cdot Yete_i^*) = sgn[c_j(\tau - \chi) + \sigma\phi_{j,d}]$. While trade-network competition generally decays with distance, corridor networks can simultaneously extend both diffusion and competition radii.

4. Data and Measurement

4.1 Data and sample construction

Our empirical analysis relies on a panel dataset of 282 Chinese cities at the prefecture level and above from 2006 to 2022, providing 4794 observations for the core causal and spatial estimations. Data on energy efficiency, macroeconomic conditions, and environmental constraints are primarily compiled from the *China City Statistical Yearbook*, the *EPS database*, and the *Chinese Research Data Services (CNRDS)*. To prevent empirical estimates from being driven by severe outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

4.2 Dependent variable

The dependent variable in our baseline model is ETE, denoted $Yete$ and measured via Data Envelopment Analysis (DEA). The standard CCR model assumes constant returns to scale and uses a radial measure to find the maximum proportional contraction in inputs, holding desirable outputs steady and keeping undesirable outputs at or below observed levels. Its benchmark formulation is:

$$\theta_{CCR,it} = \min \theta, \text{ s.t. } X_t \lambda \leq \theta x_{it}; Y_t \lambda \geq y_{it}; B_t \lambda \leq b_{it}; \lambda \geq 0$$

Where X_t , Y_t , and B_t are reference matrices for inputs, desirable outputs, and undesirable outputs in year t ; λ is the intensity vector; and θ_{CCR} is the radial efficiency score. Because actual production inputs and outputs rarely change in identical proportions, the radial CCR model fails to identify non-proportional slacks (excess inputs or output shortfalls). To address this, Tone (2001) developed the non-radial, non-oriented SBM-DEA model. By incorporating slacks directly into the objective function, it allows independent adjustments. Its undesirable-output

extension treats pollution explicitly, jointly modeling resource use, economic output, and environmental externalities.

We treat each city-year observation as a decision-making unit (DMU). The input vector x includes labor input (L) measured by registered population of cities, capital input (K) calculated via the perpetual inventory method, and energy input (E) measured by energy consumption in hundreds of tons of standard coal. Desirable output y is GDP, and undesirable outputs b are PM2.5 and PM10. For city i in year t , let m , q_g , and q_b index the dimensions of inputs, desirable outputs, and undesirable outputs, with corresponding slacks s^- , s^+ , and s^b .

$$\rho_{SBM,it} = \frac{1 - \frac{1}{m} \sum_{r=1}^m \frac{s_{rit}^-}{x_{rit}}}{1 + \frac{1}{(q_g + q_b)} \left(\sum_{l=1}^{q_g} \frac{s_{lit}^+}{y_{lit}} + \sum_{h=1}^{q_b} \frac{s_{hit}^b}{b_{hit}} \right)}$$

The efficiency score $\rho_{SBM,it}$ evaluates input slacks, desirable output shortfalls, and excess pollution simultaneously. Fewer input slacks, larger desirable outputs, and smaller undesirable slacks imply a higher ETE.

As Figure 2 illustrates, mean urban ETE declined from 0.513 in 2006 to a sample low of 0.328 in 2019, before a modest recovery to 0.345 in 2022. Spatially, high ETE areas fragmented from contiguous clusters into isolated pockets—primarily in the Northeast and West—while North and Central China downgraded. Distributionally, cities scoring above 0.500 plummeted from 125 in 2006 to 34 in 2022, whereas those below 0.300 surged from 28 to 136. Crucially, this downward trajectory reflects a lagging position relative to the contemporaneous SBM-VRS frontier—driven by frontier shifts and rapid input expansion—rather than an absolute deterioration in efficiency.

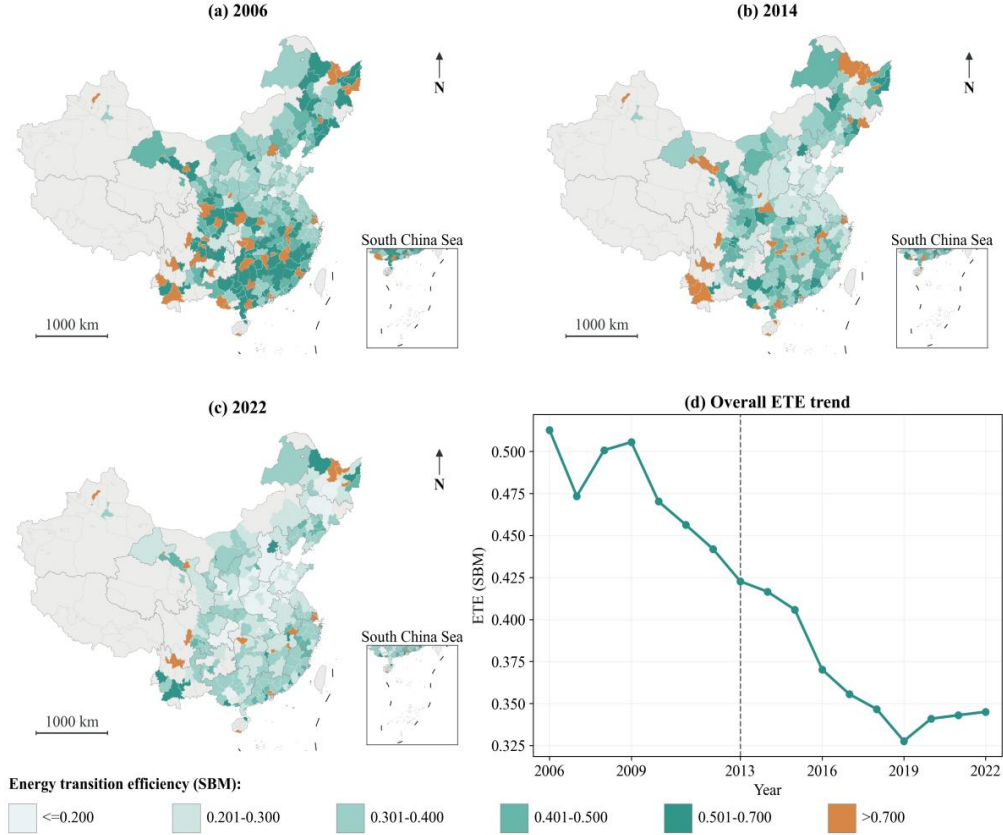


Figure 2. Spatial Distribution and Overall Trend of ETE: 2006, 2014, and 2022

4.3 Treatment variable

The treatment variable, $Dbri$, is the interaction of spatial policy exposure ($Dnod$) and a common post-2013 time shock ($Dpst$). The BRI's distinct sequence of proposal and institutionalization provides a clear temporal boundary for identifying quasi-natural shocks. Proposed sequentially in late 2013 and officially integrated into the Central Committee's major reform agenda by November 2013, the Initiative establishes 2013 as the universal treatment onset. Filtering out Hong Kong, Macao, and Lhasa due to severe data limitations, our final sample retains 282 cities: 38 treated nodes (19 Belt and 19 Road cities) and 244 controls.

Figure 3(a) maps this spatial distribution: Belt nodes are concentrated along inland corridors and border hubs, while Road nodes cluster around coastal maritime networks. The node indicator $Dnod_i$ equals 1 for treated cities, and the post-shock indicator $Dpst_t$ equals 1 from 2013 onward. The interaction $Dbri_{it} = Dnod_i \times Dpst_t$ therefore equals 1 only for node cities in the post-implementation period.

Figure 3(b) plots the annual ETE group means. Before the BRI, treated node cities exhibited persistently lower efficiency than controls (e.g., 0.469 and 0.520 in 2006). Over the 2006–2012 pre-treatment window, the treated and control means averaged 0.441 and 0.486, declining by 11.1% and 14.2% respectively. However, post-2013, this trajectory shifts structurally. The control group’s efficiency deteriorates more rapidly, dropping to 0.340 by 2022, whereas the treated group sustains a relatively higher mean of 0.379. This post-shock relative improvement in the treated group provides early descriptive evidence of the BRI's efficiency dividend.

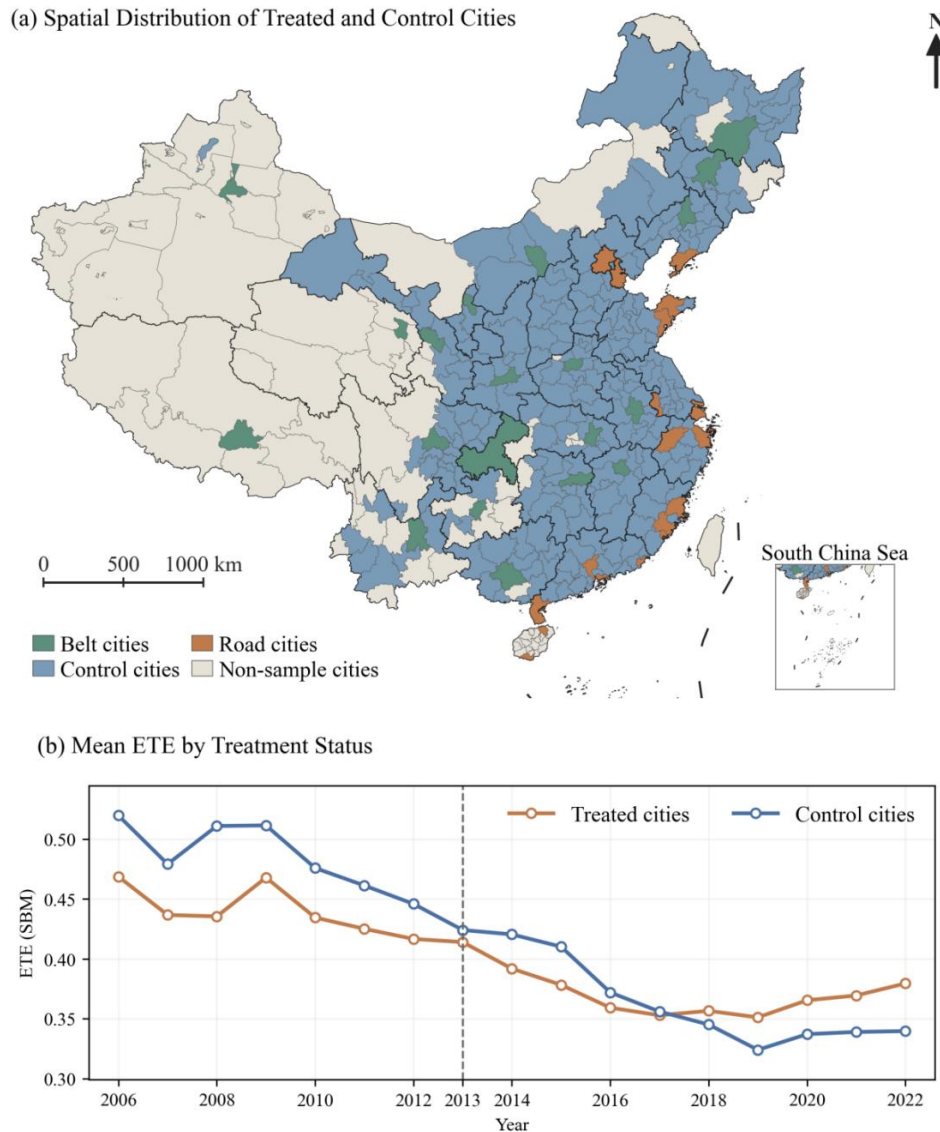


Figure 3. Spatial Distribution and ETE of Treated and Control Cities

4.4 Mediating and moderating variables

4.4.1 Mediating variables

To characterize the technological pathways bridging the BRI and urban energy transition, we specify a three-dimensional mediation framework: scale, breadth, and depth. The mediators—technological innovation capacity (TIC, Mtc), technological diversification (TCD, Mtd), and technological specialization (TCS, Mts)—capture three structural margins: quantitative capacity accumulation, cognitive expansion across fields, and concentration along specific technological trajectories.

(1)Technological innovation capacity (Mtc). We measure Mtc using Fudan University's City Innovation Index (Kou and Liu, 2017). By utilizing patent legal-status histories and age-specific renewal fees, this index estimates the monetary value of CNIPA-granted patents to reflect the true innovation stock. To correct for right-skewness and extreme outliers, the raw index Mti_{it} is winsorized at the 1st and 99th percentiles and log-transformed: $Mtc_{it} = \ln(1 + Mti_{it})$.

(2)Technological diversification (Mtd). To measure structural breadth, we classify patents at the four-digit IPC level and calculate Revealed Technological Comparative Advantage ($RTCA$): $RTCA_{ikt} = \frac{P_{ikt}/P_{kt}}{P_{it}/P_t}$, where P_{ikt} is the patent count for city i in technology class k in year t . The baseline breadth count is $Diver_{it} = \sum_k 1(RTCA_{ikt} \geq 1)$. Our continuous diversification measure uses technological-space distance: $Mtd_{it} = 1 - Sim_{it}$, where Sim_{it} represents portfolio similarity in the technology space. Higher values indicate broader capacity for cross-field recombination.

(3)Technological specialization (Mts). We measure structural concentration using the coefficient of variation across 35 WIPO technology fields. We first calculate Relative Technological Advantage (RTA) and transform it into a bounded index to ensure symmetry: $Ad_RTA_{ikt} = \frac{RTA_{ikt} - 1}{RTA_{ikt} + 1} + 1$. The Mts_{it} is the ratio of the standard deviation to the mean across k fields: $Mts_{it} = \frac{\sigma_k(Ad_RTA_{ikt})}{\mu_k(Ad_RTA_{ikt})}_{it}$. A higher value signifies that a city's technological advantage is highly concentrated within a narrow subset of specialized fields.

4.4.2 Moderating variables

The moderating variables map to three specific conditions: institutional friction, structural absorption, and external shocks. The baseline intellectual property protection (IPP, $Zipp$) and

industrial-upgrading foundation (IUF, $Zind$) are measured as city-level cross-sections from 2006 to 2012, reflecting pre-BRI knowledge appropriability and industrial receptiveness. Meanwhile, geopolitical risk (GPR, $Zgpr$) enters the model as a national time-varying shock, illustrating how external uncertainty shifts the boundaries of technological search.

(1) Intellectual-property protection ($Zipp$). We formally construct the city-year intellectual-property enforcement location quotient as: $ipp_{it} = \frac{J_{it}/GDP_{it}}{J_t^{\text{CN}}/GDP_t^{\text{CN}}}$, where J_{it} denotes the volume of intellectual-property enforcement actions in city i during year t , and the denominator represents the corresponding national benchmark. We apply a logarithmic transformation, $LIPP_{it} = \ln(1 + ipp_{it})$, and derive its pre-treatment baseline mean as $LIPP_i^{\text{pre}} = \frac{1}{7} \sum_{t=2006}^{2012} LIPP_{it}$. To mitigate the influence of outliers, this pre-policy mean is strictly winsorized at the 1st and 99th percentiles (denoted by prefix $W_$) and subsequently standardized across all cities: $Zipp_i = \frac{W_LIPP_i^{\text{pre}} - \mu_{W_LIPP}}{\sigma_{W_LIPP}}$. A higher $Zipp_i$ signifies a more robust pre-BRI baseline of IPP, which theoretically reduces transaction frictions in cross-border technology transfers, green-project contracting, and the appropriation of innovation returns.

(2) Industrial upgrading foundation ($Zind$). Let $\omega_{m,it}$ denote the GDP share of sector m (primary, secondary, or tertiary) in city i in year t . The index monotonically assigns greater weights to higher-order sectors: $IU_{it} = \sum_{m=1}^3 m \times \omega_{m,it}$. We define its pre-policy cross-sectional baseline as $IU_i^{\text{pre}} = \frac{1}{7} \sum_{t=2006}^{2012} IU_{it}$. Following winsorization, we standardize this index across the sample: $Zind_i = \frac{W_IU_i^{\text{pre}} - \mu_{W_IU}}{\sigma_{W_IU}}$. A higher $Zind$ reflects a structural pivot from primary activities toward services and technology-intensive sectors. Thus, it serves as a robust proxy for the pre-treatment industrial structural foundation, dictating the city's absorptive capacity for energy-saving processes, green projects, and factor reallocation.

(3) Geopolitical risk ($Zgpr$). Let GPR_m^{CHN} denote the monthly geopolitical risk index for China. We calculate the annual aggregate as $GPR_t = \frac{1}{12} \sum_{m=1}^{12} GPR_m^{\text{CHN}}$ and standardize the annual time series over the 2006–2022 sample period: $Zgpr_t = (GPR_t - \mu_{GPR}) / \sigma_{GPR}$. This index relies on the text-based algorithmic measure developed by Caldara and Iacoviello (2022), which quantifies the proportion of articles in major international newspapers

discussing geopolitical events and threats. Consequently, $Zgpr$ captures the macroeconomic uncertainty induced by global geopolitical frictions. Because it captures a common national macro-shock, it enters the empirical specification as a purely time-varying, spatially invariant aggregate variable.

4.5 Control variables

Our baseline regressions include five economic and four environmental controls to absorb time-varying differences in the urban economic base and climate conditions, addressing unobservables not fully captured by city fixed effects.

4.5.1 Economic controls

(1) Population density ($Xepd$): Log of year-end resident population per administrative area. It controls for energy-demand density and urban scale economies. (2) Economic-activity density ($Xead$): Log of GDP per administrative area. It measures the spatial intensity of economic output rather than mere aggregate scale. (3) Financial development ($Xefd$): Log of the ratio of total year-end deposits and loans to GDP. Financial depth affects energy-project investment and capital turnover. (4) Openness ($Xeop$): The trade-to-GDP ratio, transformed via $\ln(1+x)$ to accommodate zeros. This is also a key selection feature of BRI node cities. (5) Urbanization ($Xeur$): Log of the resident urban population share, which shifts the energy mix, infrastructure load, and public service concentration.

4.5.2 Environmental controls

(1) Annual precipitation ($Xnra$): Log-transformed. It affects water constraints, thermal-plant cooling, and pollutant washout. (2) Annual mean temperature ($Xnte$): Measured in degrees Celsius and entered without log-transformation to allow for negative values. It captures heating and cooling loads. (3) Annual sunshine hours ($Xnsu$): Log-transformed. It relates to both solar-resource endowments and heating demand. (4) Annual mean wind speed ($Xnwi$): Log-transformed. It affects atmospheric dispersion and wind resources, influencing pollution concentrations and clean electricity supply.

4.6 Descriptive statistics

Table 1 and Figure 4 summarize the descriptive statistics for 4,794 observations across 282 cities from 2006 to 2022. The mean of the dependent variable, urban EFE ($Yete$), is 0.414. Its

distinctly right-skewed kernel density suggests that most cities operate strictly within the relative efficiency frontier. The BRI treatment indicator (*Dbri*) averages 0.079. For the mediating variables, technological innovation capacity (*Mtc*) shows the highest dispersion (1.505 ± 1.401), while technological diversification (*Mtd*) s and specialization (*Mts*) s are more concentrated. The moderators—intellectual property protection (*Zipp*), industrial-upgrading foundation (*Zind*), and geopolitical risk (*Zgpr*)—are standardized to 0 means.

Standardized boxplots of Figure 4 (b) display pronounced right tails for *Mtc* and *Zipp*, pulled by a few high-value outliers, and the correlation heatmap of Figure 4 (a) shows a preliminary correlation of -0.32 between *Mtc* and *Yete*. Kernel density plots of Figure 4 (c) further reveal that node cities consistently have a larger innovation stock but narrower diversification. The lack of complete overlap in the density distributions of core variables highlights observable baseline differences between the treated and control groups.

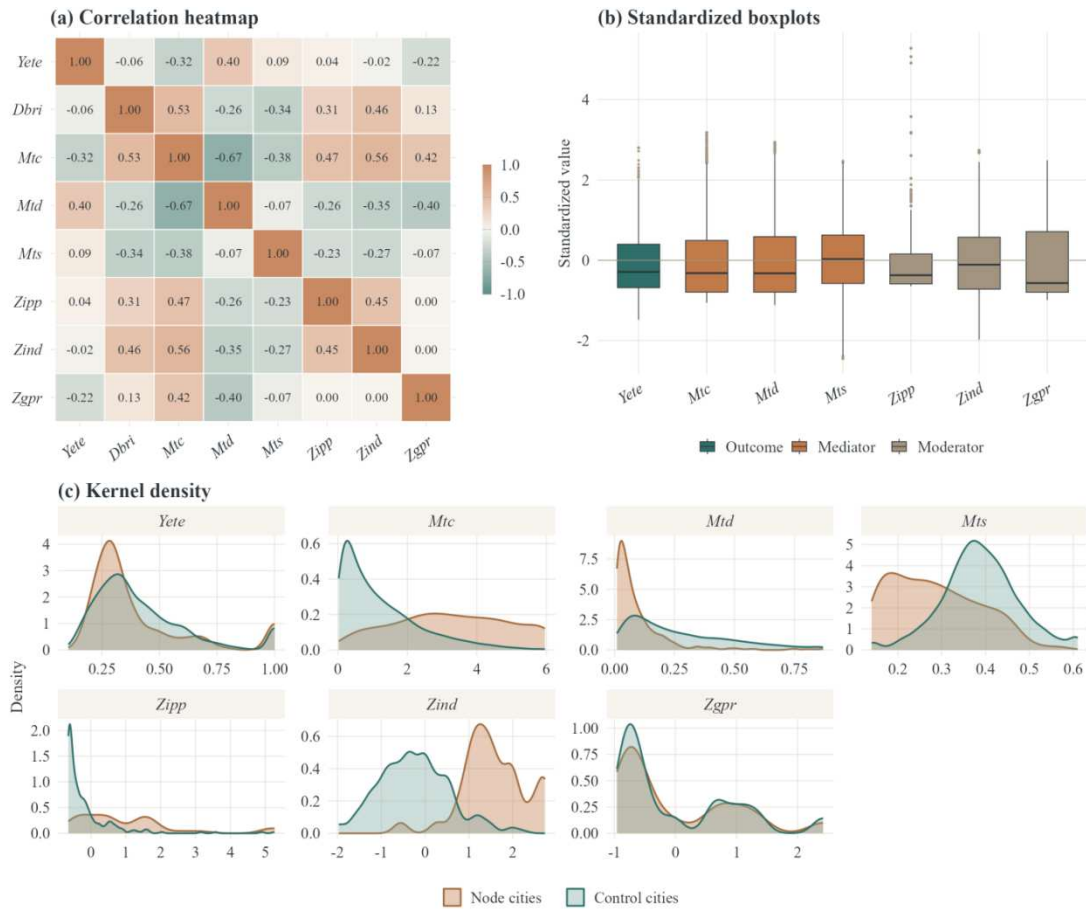


Figure 4. Descriptive Diagnostics

Table 1. Descriptive Statistics of Main Variables

Type	Variable	Symbol	N	Mean	SD	Min	Max
Outcome	ETE	<i>Yete</i>	4794	0.414	0.209	0.104	1.000
Treatment	BRI node city	<i>Dnod</i>	4794	0.135	0.341	0.000	1.000
	BRI treatment	<i>Dbri</i>	4794	0.079	0.270	0.000	1.000
Mediator	Technological innovation capacity	<i>Mtc</i>	4794	1.505	1.401	0.025	5.956
	Technological diversification	<i>Mtd</i>	4794	0.246	0.212	0.010	0.869
	Technology specialization	<i>Mts</i>	4794	0.374	0.096	0.140	0.610
Moderator	Intellectual property protection	<i>Zipp</i>	4794	0.000	1.000	-0.645	5.268
	Industrial upgrading foundation	<i>Zind</i>	4794	0.000	1.000	-1.972	2.732
	Geopolitical risk	<i>Zgpr</i>	4794	0.000	0.970	-0.959	2.415
Economic control	Population density	<i>Xepd</i>	4794	1.734	0.171	1.079	1.989
	Economic density	<i>Xead</i>	4794	1.934	0.196	1.346	2.330
	Financial development	<i>Xefd</i>	4794	0.767	0.423	-0.114	1.873
Environmental control	Openness	<i>Xeop</i>	4794	0.003	0.003	0.000	0.012
	Urbanization	<i>Xeur</i>	4794	-1.098	0.527	-2.235	-0.023
	Precipitation	<i>Xnra</i>	4794	6.784	0.591	4.972	7.759
	Temperature	<i>Xnte</i>	4794	14.919	5.186	2.606	24.018
	Sunshine hours	<i>Xnsu</i>	4794	7.564	0.258	6.917	8.052
	Wind speed	<i>Xnwi</i>	4794	0.736	0.226	0.130	1.254

5. Specifications and Identification

5.1 TWFE DID

To estimate the average treatment effect (ATT) of the BRI on urban ETE, we initially employ a standard two-way fixed effects difference-in-differences (TWFE-DID) model. This approach is explicitly chosen because it rigorously controls for both city-specific unobservables and aggregate time trends, ensuring a cleaner causal identification of the policy shock. The baseline model is specified as:

$$Yete_{it} = \beta Dbri_{it} + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where $Yete_{it}$ represents the ETE of city i in year t . The key explanatory variable, $Dbri_{it} = Dnod_i \times Dpst_t$, is the interaction between the node-city indicator and the post-policy indicator. Its

coefficient, β , measures the net policy effect: the relative post-BRI change in ETE for treated node cities versus the control group. The vector X_{it} comprises five economic and four environmental covariates to reduce omitted-variable bias arising from differing developmental stages and natural conditions. The terms μ_i and λ_t denote city and year fixed effects, respectively. Specifically, μ_i controls for time-invariant local attributes, such as resource endowments and baseline geography, while λ_t absorbs common time-varying macroeconomic shocks. ε_{it} is the idiosyncratic error term.

5.2 Imputation DID

The standard TWFE specification relies on a linear projection that may fail to recover the true ATT under heterogeneous treatment effects. While our simultaneous 2013 treatment onset avoids the negative-weighting bias typical of staggered designs, TWFE inherently leaves untreated potential outcomes embedded within the residual. To address this, we employ the Imputation DID estimator (Borusyak et al., 2024), which explicitly models the untreated counterfactuals before computing the post-ATT of the BRI on urban ETE. The imputation DID model is specified as:

$$E[Yete_{it}(0) | X_{it}, \mu_i, \lambda_t] = \alpha + X_{it}'\gamma + \mu_i + \lambda_t \quad (2a)$$

$$ATT_{imp} = (1/N_I) \sum_{i \in G, t \geq 2013} [Yete_{it} - \hat{Yete}_{it}(0)] \quad (2b)$$

Equation (2a) specifies the imputed counterfactual ETE for city i in year t had the initiative not occurred. In Equation (2b), G is the set of 38 node cities, N_I is their number of post-2013 observations, and ATT_{imp} measures the mean gap between the observed and counterfactual ETE after implementation. Other variables correspond identically to Equation (1).

5.3 Event study

While both the baseline TWFE and the imputation estimators capture the average post-2013 treatment effect of the BRI on urban ETE, they inherently obscure the temporal dynamics driving this mean and fail to formally evaluate potential deviations from parallel trends. To illuminate the precise temporal trajectory of the BRI policy shock, we specify the following event-study framework:

$$Yete_{it} = \sum_{k \neq -1} \beta_k Erel_{it}^k + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Here, $Erel_{it}^k$ is the event-time indicator for a node city i in year t , with k tracking periods relative to the 2013 BRI onset. The year 2012 ($k = -1$) is the omitted reference period. The pre-

policy coefficients (β_k for $k < -1$) test for differential urban ETE trends prior to the Initiative; estimates statistically indistinguishable from 0 confirm the parallel-trends assumption. The post-policy coefficients (β_k for $k \geq 0$) map the dynamic evolution and persistence of the BRI-induced urban ETE effect over time. The remaining variables match Equation (1).

5.4 Mediation models

Institutional opening drives the urban ETE not merely through a simple arithmetic accumulation of green patents, but by structurally transforming the innovation stock, the mode of knowledge recombination, and the technological specialization landscape (Imai et al., 2010). To formally identify these transmission pathways, we specify the following mediation framework:

$$M_{it} = \theta Dbri_{it} + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (4a)$$

$$Yete_{it} = \beta' Dbri_{it} + \eta M_{it} + X_{it}'\gamma + \mu_i + \lambda_t + u_{it} \quad (4b)$$

In Equation (4a), the mediator M is technological innovation capacity (Mtc), diversification (Mtd), or specialization (Mts). The coefficient θ captures the BRI's average effect on each technology state. Equation (4b) adds the mediator back into the baseline ETE model; η isolates the mediator's conditional association with urban ETE. The indirect effect ($\theta \times \eta$) is evaluated using city-cluster bootstrapped standard errors.

Because local institutions and external shocks can amplify or constrain these technological paths, we further interact the BRI treatment with our pre-defined conditions:

$$M_{it} = \theta Dbri_{it} + \psi (Dbri_{it} \times Z_{it}) + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (4c)$$

In Equation (4c), the moderator Z denotes three moderators IPP ($Zipp$), IUF ($Zind$), or GPR ($Zgpr$). The interaction coefficient ψ reveals how these specific institutional and macroeconomic conditions change the technological response to the Initiative.

5.5 Spatial DID models

Because BRI node cities are deeply embedded in cross-regional transport, trade, and railway networks, the institutional opening shock likely extends beyond the treated focal city to affect neighboring or network-connected cities. This spatial transmission operates through the strategic siting of major projects, cross-city factor reallocations, and technological spillovers. To formally isolate these spatial interactions and evaluate their impact on urban ETE, we specify a Spatial DID framework:

$$Yete_{it} = \rho \sum_{j \neq i} w_{ij} Yete_{jt} + \beta Dbri_{it} + \varphi \sum_{j \neq i} w_{ij} Dbri_{jt} + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (5a)$$

Here, w_{ij} represents an element of the spatial-weight matrix. All matrices are row-standardized, such that $w_{ij}^* = w_{ij}/\sum_k w_{ik}$, with a zero diagonal ($w_{ii} = 0$). The spatial autoregressive coefficient ρ captures the endogenous spatial dependence of ETE between neighboring and focal cities. The coefficient ϕ on the spatial lag of the treatment explicitly measures the exogenous spatial association between node-city designations in surrounding areas and local ETE. All other covariates match Equation (1).

Because spatial feedback mechanisms imply that point estimates do not directly equate to marginal effects, we systematically decompose the estimates into direct, indirect (spillover), and total effects. The direct effect quantifies the net impact of a city's own BRI node designation on its ETE. The indirect effect captures the spatial spillover—how a city's node designation alters the ETE in other cities connected via the relevant network. The total effect is their sum.

To robustly capture multi-dimensional connectivity, we construct four distinct spatial-weight matrices: ① Inverse geographic distance (W^G): Sets the weight to $1/d_{ij}$, where d_{ij} is the great-circle spatial distance between cities i and j . ② Economic gravity (W^E): Utilizes the product of population and economic activity in city j during year t , strictly scaled by geographic distance, to capture the spatial decay of economic mass. ③ Trade gravity (W^T): Employs a composite product of trade openness and economic quality, scaled by distance, to trace cross-city commercial linkages. ④ Express network (W^N) Introduces a time-varying indicator equal to 1 if city j had launched a China–Europe railway service by year t , scaled by distance, effectively capturing connectivity along international rail corridors.

To further identify the attenuation threshold and precise spatial boundaries of these spillovers, we truncate each baseline spatial-weight matrix at a specified radius d , set weights beyond d , to 0, and iteratively row-standardize the truncated matrices. This procedure yields distance-specific spatial weights and neighboring-treatment exposures:

$$w_{ij}(d) = w_{ij} \cdot 1(d_{ij} \leq d), \quad Wnbri_{it}(d) = \sum_{j \neq i} w_{ij}(d) Dbri_{jt} \quad (5b)$$

The indicator function $1(d_{ij} \leq d)$ equals 1 when the great-circle distance between cities i and j does not exceed d , and 0 otherwise. We incrementally set the distance threshold d to 200, 400, 600, 800, and 1000 km. For each structural cutoff, we recompute the truncated weights $w_{ij}(d)$ and the corresponding exposure $Wnbri_{it}(d)$, and subsequently re-estimate Equation (5a). This yields distance-specific point estimates for $\rho(d)$ and the spatial spillover effect. A specific cutoff is interpreted as an effective physical boundary when the magnitude of $\rho(d)$ or the indirect

spillover estimate materially decays, loses statistical significance, or stabilizes beyond that distance band.

6. Empirical Results

6.1 Baseline estimates

Table 2 presents the baseline estimates of the BRI's impact on urban ETE. Column (1), controlling solely for two-way fixed effects, yields a highly significant *Dbri* coefficient (β) of 0.051. Columns (2) —(3) incrementally add the economic and environmental covariates. With the full set of controls, β stabilizes at 0.024–0.025 and remains statistically significant, demonstrating that the positive effect is not confounded by observable baseline differences in economic development or local climate. Columns (4)—(5) further verify inferential robustness by employing city-clustered and heteroskedasticity-robust standard errors, respectively; the coefficient remains consistently significant at 0.024. Column (6) of Table 2 and Figure 5 reports the DID-imputation ATT. In the first stage, the model is fitted using only control-group observations and pre-policy node-city observations, preventing post-treatment outcomes from contaminating the untreated counterfactual path. The estimated ATT is 0.023 (significant at the 5% level), closely matching the conventional TWFE estimate. This confirms that the positive BRI effect does not rely solely on the linear weighting structure of standard TWFE. Among the controls, economic density, financial development, and openness negatively correlate with urban ETE, while urbanization and temperature show positive associations. Overall, the BRI institutional opening robustly improves urban ETE in node cities.

Table 2. Baseline Results

Variable	No-controls TWFE DID (1)	Economic-Control TWFE DID (2)	Full Control TWFE DID (3)	City cluster TWFE DID (4)	Robust TWFE DID (5)	Imputation DID (6)
<i>Dbri</i>	0.051*** (0.006)	0.025*** (0.006)	0.024*** (0.006)	0.024** (0.011)	0.024*** (0.005)	0.023** (0.009)
<i>Xepd</i>		0.447*** (0.132)	0.390*** (0.133)	0.390 (0.322)	0.390** (0.161)	0.278 (0.360)
<i>Xead</i>		-0.347*** (0.044)	-0.332*** (0.044)	-0.332*** (0.123)	-0.332*** (0.060)	-0.325** (0.132)
<i>Xefd</i>		-0.093***	-0.091***	-0.091***	-0.091***	-0.090***

		(0.009)	(0.009)	(0.018)	(0.010)	(0.020)
<i>Xeop</i>		-4.071***	-3.734***	-3.734***	-3.734***	-4.497***
		(0.720)	(0.720)	(1.143)	(0.606)	(1.292)
<i>Xeur</i>		0.058***	0.060***	0.060**	0.060***	0.064**
		(0.010)	(0.010)	(0.026)	(0.010)	(0.027)
<i>Xnra</i>			0.011	0.011	0.011	0.009
			(0.007)	(0.009)	(0.007)	(0.009)
<i>Xnte</i>			0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
<i>Xnsu</i>			0.008	0.008	0.008	0.014
			(0.018)	(0.026)	(0.019)	(0.029)
<i>Xnwi</i>			-0.084***	-0.084**	-0.084***	-0.097**
			(0.015)	(0.042)	(0.017)	(0.046)
<i>Cons</i>	0.765***	0.846	0.804	0.804	0.804	0.947
	(0.007)	(0.648)	(0.677)	(0.677)	(0.677)	(0.746)
N	4794	4794	4794	4794	4794	4794
R ²	0.015	0.056	0.064	0.064	0.064	0.051

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Standard errors are in parentheses. Columns (1)–(5) are TWFE DID; Column (1) has no controls; (2) adds economic controls; (3) adds environmental controls; (4) uses city-clustered standard errors; (5) uses robust standard errors. Column (6) reports the DID-imputation post-treatment ATT. Control coefficients in (6) come from the first-stage untreated-potential-outcome regression (never-treated cities plus node cities before 2013), with city-clustered standard errors.

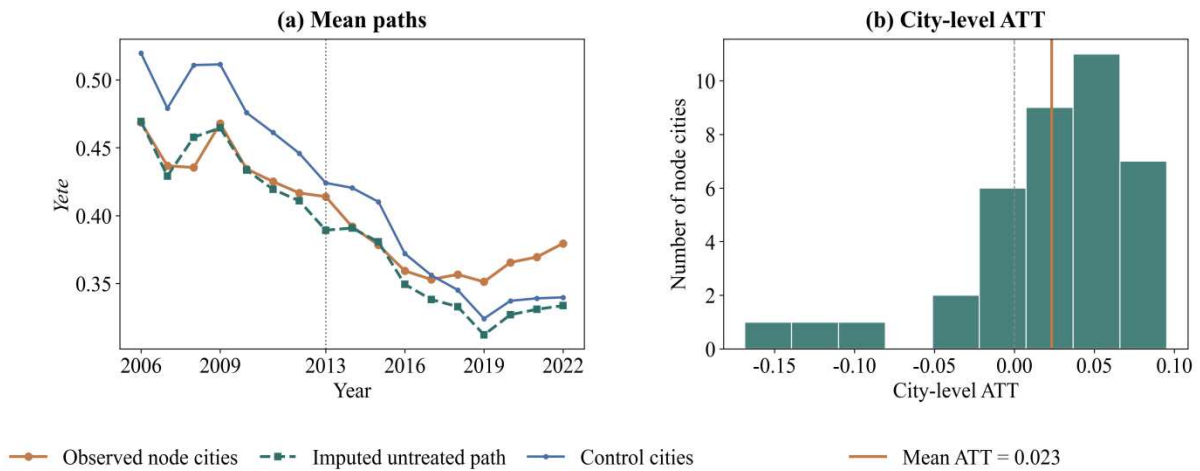


Figure 5. DID-imputation: Actual vs. Counterfactual ETE in Node Cities

Note: Panel (a) compares the observed urban ETE in node cities with the Equation (2a) counterfactual path. The 2013 vertical line marks the policy start; the post-2013 gap represents the annual net contribution defined in Equation (2b). Panel (b) displays the distribution of city-level ATTs for the 38 node cities, marking the mean (0.023) with a vertical line.

6.2 Dynamics and window sensitivity

Considering that TWFE DID can assign negative weights under heterogeneous and dynamic treatment effects, we incorporate group-time average treatment effects, event-study dynamics, and bounds on parallel-trend deviations (Callaway and Sant'Anna, 2021; Roth, 2022; Schmidheiny and Siegloch, 2023; Sun and Abraham, 2021). Figure 6(a) plots the dynamic event-study estimates from Equation (3). Prior to the BRI, aside from a significantly negative coefficient at $k=-5$ (-0.029), all other pre-treatment estimates fluctuate near 0. This confirms the absence of a systematic long-run divergence in urban ETE, though the $k=-5$ anomaly requires caution. Post-treatment, the early coefficients are small and insignificant. However, the effects later magnify, with coefficients at $k=6, 7, 8$, and 9 rising to $0.038, 0.037, 0.037$, and 0.044 (all statistically significant). This nonlinear pattern reflects a lagged, cumulative urban ETE response to the BRI, rather than an immediate structural break.

Figure 6(b) tests the sensitivity of these results by shortening the event window. The estimates for the $[-3, 5]$, $[-4, 6]$, and $[-5, 8]$ intervals are $0.015, 0.017$, and 0.025 , respectively. The two narrower windows remain marginally significant at the 10% level. While the positive direction confirms the baseline ATT, precision mechanically drops within shorter time horizons.

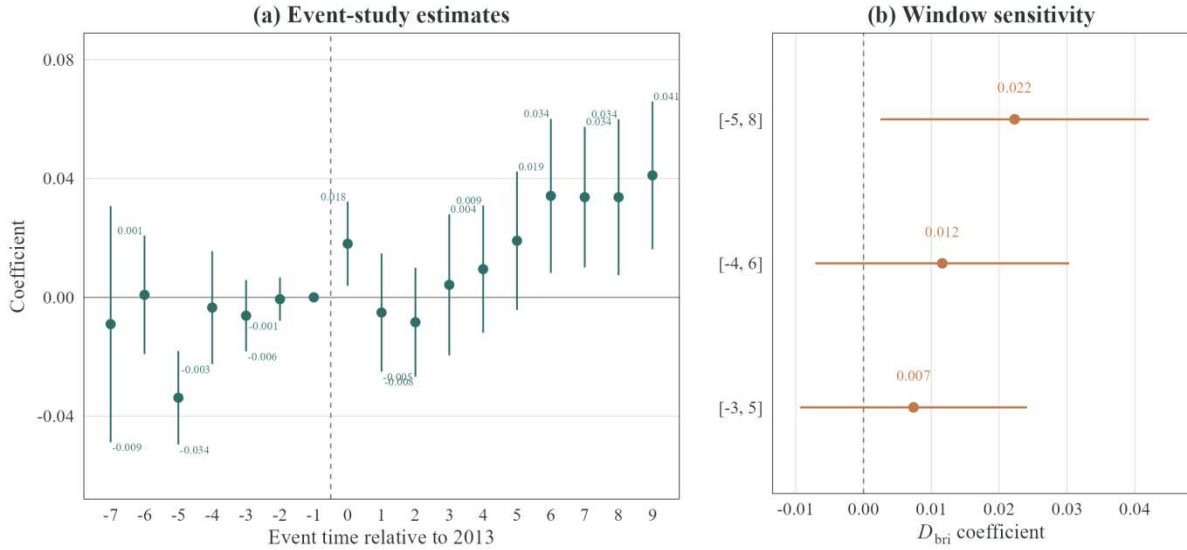


Figure 6. Event-study Estimates and Window Sensitivity

6.3 Robustness checks

6.3.1 Placebos tests

To verify that the urban ETE improvement is not driven by random assignments or idiosyncratic year shocks, we perform spatial and temporal placebos. Fixing the 2013 BRI onset, we randomly draw 38 pseudo-node cities 1,000 times. Figure 7(a) shows that the resulting pseudo-coefficients center around a mean of 0.000 with a standard deviation of 0.016. Compared to our true TWFE benchmark of 0.024, only 14.7% of these random draws yield an absolute value as large. Although random labels do not systematically reproduce the positive BRI effect on urban ETE, the non-zero tail share indicates that this spatial design does not perfectly partial out institutional selection into node status. Our second exercise applies a temporal placebo by shifting the BRI treatment to earlier pre-policy years.

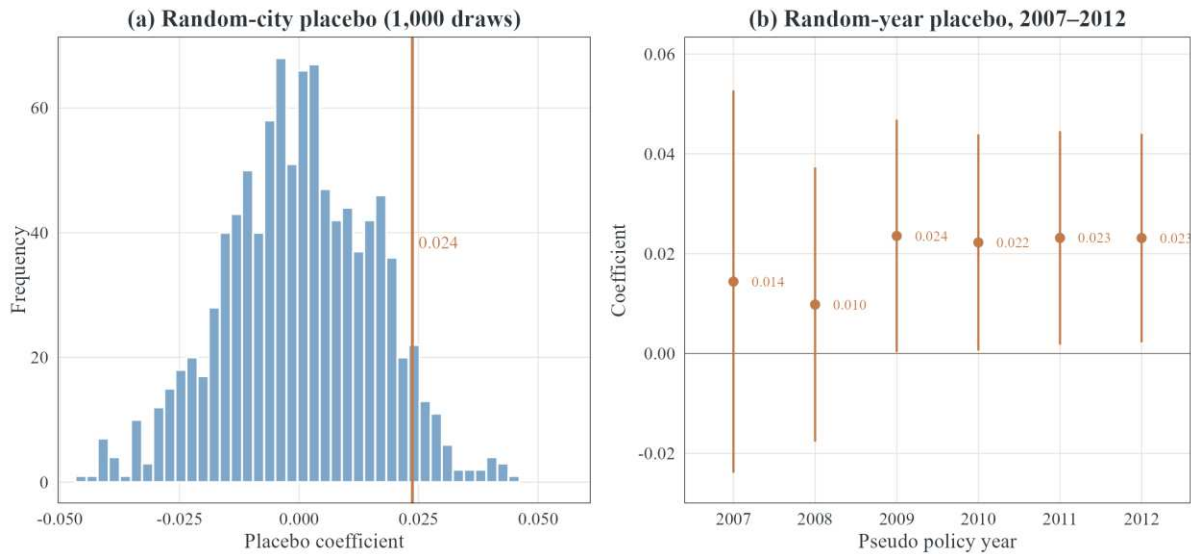


Figure 7. Random-city and Random-year Placebos

6.3.2 Bacon decomposition and Honest DID

Because all node cities entered the BRI treatment simultaneously in 2013, our design avoids staggered adoption. We therefore use the Goodman-Bacon (2021) decomposition mainly to confirm the TWFE weighting structure: the 2×2 comparison between treated and never-treated groups carries a weight of 1, and treated-to-treated comparisons carry a weight of 0, effectively ruling out negative weights. Without controls, this 2×2 DID is 0.051, matching Column (1) of Table 2; with full controls, the TWFE estimate for urban ETE falls to 0.024.

Given the statistically significant pre-policy coefficient at $k = -5$ observed in Figure 6, we further apply the Honest DID framework with relative magnitude restrictions (Rambachan and Roth, 2023) to evaluate the sensitivity of the average post-treatment effect on urban ETE to potential parallel-trend violations. Using the mean of the post-policy event-study coefficients and city-clustered standard errors, the 95% confidence interval is roughly $[0.000, 0.043]$ when no extra deviation is allowed ($M = 0$), barely excluding zero. However, allowing for trend deviations equal to 0.25 and 0.50 times the maximum pre-treatment deviation widens the intervals to $[-0.007, 0.051]$ and $[-0.014, 0.058]$, respectively, both including zero. Figure 8 suggests that our baseline findings regarding the BRI's effect on urban ETE are somewhat fragile to small-to-moderate deviations from parallel trends.

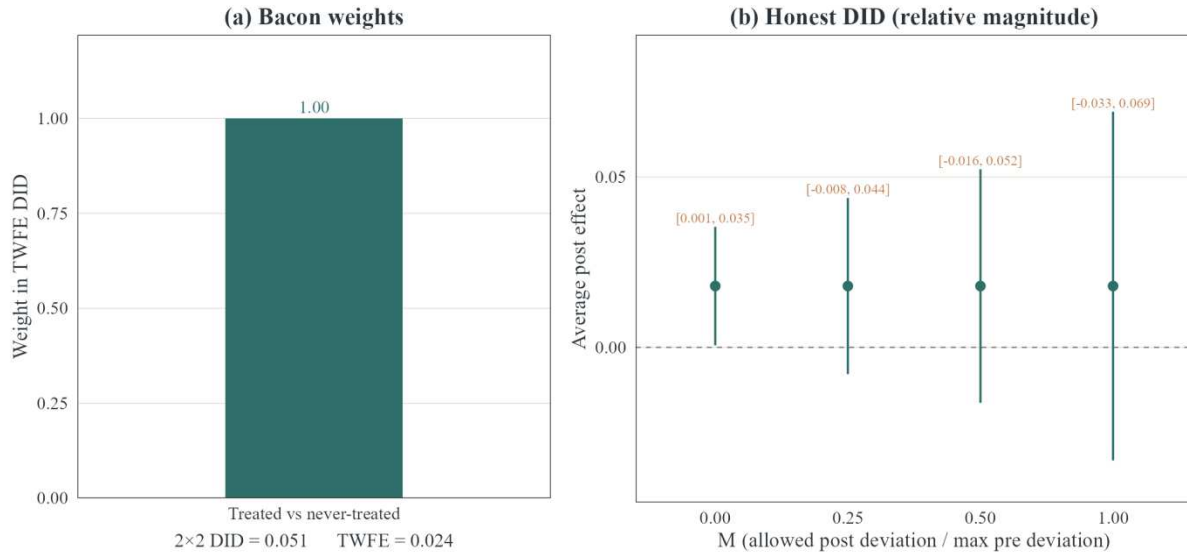


Figure 8. Bacon Decomposition and Honest DID Sensitivity

6.3.3 Controlling for overlapping policies

The BRI node-city designation coincides with various domestic green-development and institutional-opening pilots. Without controlling for these overlapping policies, the *Dbri* coefficient might mistakenly capture their effects. To isolate the BRI's true impact on urban ETE, we add policy indicators (PT) to our baseline TWFE model. Each indicator equals 1 from the year a city is approved for the relevant pilot or zone, and 0 otherwise. We control for four specific policies: the Low-Carbon City Pilot (LCP), the Carbon Emissions Trading Pilot (CTP), the Green Finance Reform and Innovation Pilot Zone (GFR), and the Free Trade Zone (FTZ). LCP and CTP are based on city-level approval cohorts; GFR combines provincial zones and designated city cohorts; and FTZ approvals are mapped from provinces to prefecture-level cities

to proxy for zone exposure. Table 3 reports the results with these overlapping policy controls. Columns (1)–(4) add the LCP, CTP, GFR, and FTZ indicators one at a time. The coefficient remains between 0.022 and 0.026 and is consistently significant. Column (5) includes all four policies simultaneously, yielding a coefficient of 0.023. These findings confirm that the BRI significantly improves urban ETE even after partialing out concurrent policy effects.

Table 3. Overlapping-policy Controls

Variable	Control of LCP (1)	Control of CTP (2)	Control of GFR (3)	Control of FTZ (4)	Control of all policies (5)
<i>Dbri</i>	0.022*	0.026**	0.024**	0.024**	0.023**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
<i>PT</i>	0.010	-0.029**	-0.022	0.001	—
	(0.008)	(0.014)	(0.015)	(0.008)	—
<i>Cons</i>	0.791	0.769	0.712	0.803	0.659
	(0.679)	(0.677)	(0.673)	(0.677)	(0.678)
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794	4794
R ²	0.346	0.379	0.372	0.357	0.366

Note: * p<0.10, ** p<0.05, *** p<0.01. City-clustered standard errors are in parentheses.

6.3.4 Bartik shift-share IV estimates

To further mitigate endogeneity concerns arising from the potentially non-random selection of BRI node cities, Table 4 employs a Bartik shift-share instrumental variable (IV) approach. This strategy isolates exogenous variation in policy exposure by interacting an aggregate national shift (the leave-one-out national mean of *Dbri*) with predetermined local exposure shares (2006–2012 standardized city-level averages of openness, financial development, and urbanization). By relying on historical cross-sectional exposure rather than contemporaneous local unobservables, this method provides a robust identification of the causal effect (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

Columns (1) — (3) report the two-stage least squares (2SLS) estimates using these three respective instruments. All specifications include the full control set and two-way fixed effects.

The first-stage F-statistics are 17.39, 94.16, and 40.41, respectively, all comfortably exceeding the conventional weak-instrument threshold of 10. Because the post-2013 national shift averages roughly 0.135, a one-standard-deviation increase in initial openness, financial development, or urbanization exogenously raises the probability of node treatment by approximately 10, 21, and 14 percentage points.

Crucially, the second-stage coefficients for *Dbri* are 0.177, 0.083, and 0.119, all remaining positive and statistically significant at the 1% level. While these local ATE are larger in magnitude than the baseline TWFE estimate—capturing efficiency gains specifically among complier cities whose node designation was driven by their initial endowments—their consistent positive signs strongly corroborate the structural direction of the BRI's positive impact on urban energy transition.

Table 4. Bartik IV estimates results

Variable	Openness Bartik (1)	Finance Bartik (2)	Urbanization Bartik (3)
<i>Dbri</i>	0.177*** (0.062)	0.083*** (0.023)	0.119*** (0.044)
<i>Cons</i>	1.252* (0.685)	0.975 (0.671)	1.081 (0.709)
Bartik, first stage	0.757*** (0.182)	1.548*** (0.160)	1.040*** (0.164)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered first-stage F	17.39	94.16	40.41
N	4794	4794	4794
R ²	0.898	0.898	0.897

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. City-clustered standard errors are in parentheses. The first-stage F statistic is cluster-robust. The intercept is the reference-city intercept from the second-stage dummy regression, and its standard error is clustered by city at that stage. The standard error on *Dbri* is the two-stage least squares standard error.

6.3.5 Other robustness checks

To address the limitations of conventional DID weighting, we apply Synthetic DID (SDID), which jointly optimizes unit and time weights to better match the pre-treatment trajectories of node cities (Arkhangelsky et al., 2021; Athey and Imbens, 2022). In Column (1) of Table 5, the

estimated ATT is 0.042 and highly significant. This confirms that the positive BRI effect on urban ETE holds after reweighting.

To reduce omitted-variable bias from functional misspecification, Column (2) estimates a partially linear double machine learning (DML-PLR) model using Lasso. After cross-fitting, the *Dbri* coefficient is 0.045. Although its sign matches the baseline, it lacks conventional statistical significance, likely because this high-dimensional nonlinear structure demands greater statistical precision.

Columns (3) and (4) of Table 5 remeasure urban ETE by replacing the conventional energy input with a night-time-lights inversion in the CCR DEA model. Because night-time luminosity is a well-established, high-resolution proxy for local economic and energy footprints (Henderson et al., 2012; Shi et al., 2021), it effectively mitigates measurement error. The light-based TWFE and imputation DID estimates for the BRI shock are 0.056 and 0.058, respectively, both significant at the 1% level.

Additionally, because the treatment group contains only 38 city clusters, conventional standard errors may over-reject the null hypothesis. Guided by small-cluster inference literature (Cameron and Miller, 2015), Column (5) applies CR2 cluster-robust standard errors with a Satterthwaite degrees-of-freedom correction. The coefficient remains statistically significant at 0.024. This confirms that our baseline findings on urban ETE are robust to small-cluster adjustments.

Taken together, the extensive battery of empirical tests and robustness checks presented above provides compelling and definitive support for *P1*.

Table 5. Other Robustness Results

Variable	Synthetic DID (1)	DML-PLR (2)	Night-time-light TWFE (3)	Night-time-light imputation (4)	CR2 cluster-robust (5)
<i>Dbri</i>	0.042** (0.020)	0.045 (0.035)	0.056*** (0.018)	0.058*** (0.018)	0.024** (0.011)
<i>Cons</i>	— —	— —	-0.809 (0.522)	-0.648 (0.536)	0.804 (0.677)
City FE	Weighted	Yes	Yes	No	Yes
Year FE	Weighted	Yes	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	4794	4794	4515	4515	4794

R ²	0.112	0.154	0.117	0.120	0.358
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Note: * p<0.10, ** p<0.05, *** p<0.01. City-clustered standard errors are in parentheses.

6.4 Technological pathways tests

6.4.1 Mediating paths tests

Guided by the theoretical mechanisms and the formal framework developed in the preceding sections, we conceptually decompose the technological state along three dimensions—scale, breadth, and depth—to empirically investigate three complementary transmission channels between institutional opening and urban ETE: technological innovation capacity (TIC), technological diversification (TCD), and technological specialization (TCS). Table 6 reports the BRI's effect on the mediators (Path a) and their conditional relationship with urban ETE (Path b). Table 7 reports the indirect effects based on 1000 bootstrap replications.

① **Pathway of TIC (BRI → TIC → ETE).** In Column (1) of Table 6, based on Equation (4a) —(4b), the variable *Dbri* coefficient (θ) is 0.364 and significant, showing that the BRI significantly boosts the TIC of node cities. Column (2) shows that, conditional on *Dbri*, the effect of the mediator *Mtc* on *Yete* (η) is 0.014 with significant at the 10% level. Moreover, the Table 7 bootstrap test reveals an indirect effect of 0.005, explaining about 20.8% of the total effect. This indicates that BRI-induced institutional opening improves urban ETE partially by invigorating TIC.

② **Pathway of TCD (BRI → TCD → ETE).** In column (3) of Table 6, the coefficient θ is 0.096 and significant at the 1% level, indicating that the BRI increases TCD. In column (4), the coefficient η on *Mtd* is 0.036 and significant at the 5% level. Table 7 reports an indirect effect of 0.003, equivalent to 14.5% of the total effect. This pattern supports TCD as a relatively robust transmission channel: institutional opening broadens cities' technological search and cross-field recombination, which is associated with higher ETE.

③ **Pathway of TCS (BRI → TCS → ETE).** In column (5) of Table 6, the coefficient θ is −0.043 and significant, indicating that the BRI reduces TCS. In column (6), however, the coefficient η on *Mts* is −0.001 and statistically insignificant. Table 7 reports an indirect effect of only 0.0005, about 0.2% of the total effect, which is also statistically insignificant. Thus, while the BRI alters urban technology portfolios, the subsequent decline in specialization fails to significantly mediate the institutional opening –urban ETE relationship. A broader opportunity

set reduces concentration but does not guarantee efficiency. This net-zero outcome likely reflects offsetting forces: de-specialization can break high-carbon lock-ins, yet it may also dilute a city's green-core advantages. Simply lowering concentration has little transformative impact unless it drives cross-field knowledge recombination, a process explicitly captured by technological diversification.

Overall, TIC serves as the most consistent mechanism driving the BRI's impact on urban ETE, followed by TCD, whereas TCS does not constitute an effective transmission path.

Table 6. Mediation Tests of the Technological pathways

Mediation path Variable	BRI→TIC→ETE		BRI→TCD→ETE		BRI→TCS→ETE	
	<i>Mtc</i> (1)	<i>Yete</i> (2)	<i>Mtd</i> (3)	<i>Yete</i> (4)	<i>Mts</i> (5)	<i>Yete</i> (6)
<i>Dbri</i>	0.364*** (0.100)	0.019* (0.011)	0.096*** (0.016)	0.020* (0.011)	-0.043*** (0.013)	0.024** (0.011)
<i>Mtc</i>		0.014* (0.007)				
<i>Mtd</i>				0.036** (0.015)		
<i>Mts</i>						-0.001 (0.031)
<i>Cons</i>	1.591 (4.673)	0.373 (0.611)	2.074*** (0.782)	0.320 (0.615)	-1.000* (0.584)	0.393 (0.623)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794	4794	4794
R ²	0.207	0.235	0.557	0.365	0.122	0.358
Indirect effect	0.005* (0.003)		0.003** (0.002)		0.0005 (0.001)	
Direct effect	0.019* (0.011)		0.020* (0.011)		0.024** (0.011)	
Total effect			0.024** (0.011)			

Note:*** p<0.01, ** p<0.05, * p<0.10. Standard errors are in parentheses. Odd-numbered columns capture the BRI's effect on the mediating variables (Path a), whereas even-numbered columns report the corresponding mediators' impact on urban ETE conditional on the BRI indicator (Path b).

Table 7. Bootstrap Tests of Mediation-path

Mediator	Path a (BRI→M)	SE (a)	Path b (M→ETE)	SE (b)	Direct effect	Indirect effect	Total effect	Mediation share
TIC	0.364***	(0.100)	0.014* (0.007)		0.019*	0.005*	0.024**	20.8%
TCD	0.096***	(0.016)	0.036** (0.015)		0.020*	0.003**	0.024**	14.5%

Mediator	Path a (BRI→M)	SE (a)	Path b (M→ETE)	SE (b)	Direct effect	Indirect effect	Total effect	Mediation share
TCS	-0.043***	(0.013)	-0.001	(0.031)	0.024**	0.0005	0.024**	0.2%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Path a is BRI→mediator (M); path b is the mediator coefficient in the ETE equation conditional on BRI. Indirect effects are $a \times b$ with city-cluster bootstrap inference (1,000 draws).

6.4.2 Moderating roles tests

Institutional environments and external risk exposures can fundamentally alter the direction and magnitude of the BRI's impact on urban technological trajectories. Table 8 and Figure 9 present the formal moderating effects of intellectual property protection (IPP), industrial upgrading foundation (IUF), and geopolitical risk (GPR).

Moderation of IPP. Based on Equation (4c), Panel A of Table 8 reveals that IPP significantly cushions the BRI-induced decline in TCS. In the *Mts* equation, the $Dbri \times Zipp$ interaction is 0.015 (significant at the 5% level). Stronger IPP limits the spillover of core specialized technologies, partly offsetting the de-specialization driven by institutional opening. However, IPP does not significantly moderate the TIC and TCD paths. This likely occurs because IPP protects existing proprietary knowledge, whereas innovation capacity and cross-domain recombination depend more on external resource flows than on local protection margins.

② **Moderation of IUF.** Panel B of Table 8 shows that none of the three $Dbri \times Zind$ interactions is statistically significant. This suggests that node cities' responses in innovation and technological restructuring do not depend strongly on their initial IUF; the estimated BRI response is relatively similar across cities with different industrial structures. A possible explanation is that access to external markets and opportunities for cross-domain resource recombination provide a strong impetus that can partly overcome local endowment thresholds, allowing cities with different industrial bases to match opening opportunities to their own technology and efficiency needs.

③ **Moderation of GPR.** Panel C of Table 8 shows that the $Dbri \times Zgpr$ interaction in the TCD equation is 0.020 and highly significant, indicating that GPR positively moderates the TCD-path. Node cities facing greater geopolitical uncertainty may use the opening opportunity more actively to broaden technological search in response to potential technology restrictions or supply-chain disruption. The interactions of GPR with TIC and TCS are not statistically significant. External geopolitical pressure may therefore encourage horizontal diversification as a

risk-management strategy without quickly displacing path-dependent specialization or substituting for the long-term accumulation of internal R&D needed to raise core innovation capacity directly.

Taken together, IPP significantly buffers the BRI-induced contraction in TCS, while GPR positively moderates the TCD path. These results provide evidence for the *P3*.

Table 8. Moderating Effects Regressions

Variable	<i>Mtc</i> (1)	<i>Mtd</i> (2)	<i>Mts</i> (3)
Panel A: Intellectual property protection base (<i>Zipp</i>)			
<i>Dbri</i>	0.420*** (0.109)	0.094*** (0.017)	−0.057*** (0.014)
<i>Dbri</i> × <i>Zipp</i>	−0.056 (0.072)	0.002 (0.005)	0.015** (0.006)
Cons	1.641 (4.670)	2.072*** (0.782)	−1.013* (0.582)
R ²	0.209	0.556	0.126
Panel B: Industrial upgrading foundation (<i>Zind</i>)			
<i>Dbri</i>	0.687** (0.278)	0.082*** (0.029)	−0.063*** (0.024)
<i>Dbri</i> × <i>Zind</i>	−0.210 (0.160)	0.009 (0.013)	0.014 (0.016)
Cons	1.165 (4.703)	2.093*** (0.783)	−0.972* (0.586)
R ²	0.212	0.557	0.123
Panel C: Geopolitical risk (<i>Zgpr</i>)			
<i>Dbri</i>	0.373*** (0.091)	0.090*** (0.015)	−0.043*** (0.013)
<i>Dbri</i> × <i>Zgpr</i>	−0.028 (0.033)	0.020*** (0.006)	0.003 (0.004)
Cons	1.438 (4.685)	2.180*** (0.777)	−0.984* (0.585)
R ²	0.207	0.553	0.122
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4794	4794	4794

Note: * p<0.10, ** p<0.05, and *** p<0.01. Standard errors are in parentheses.

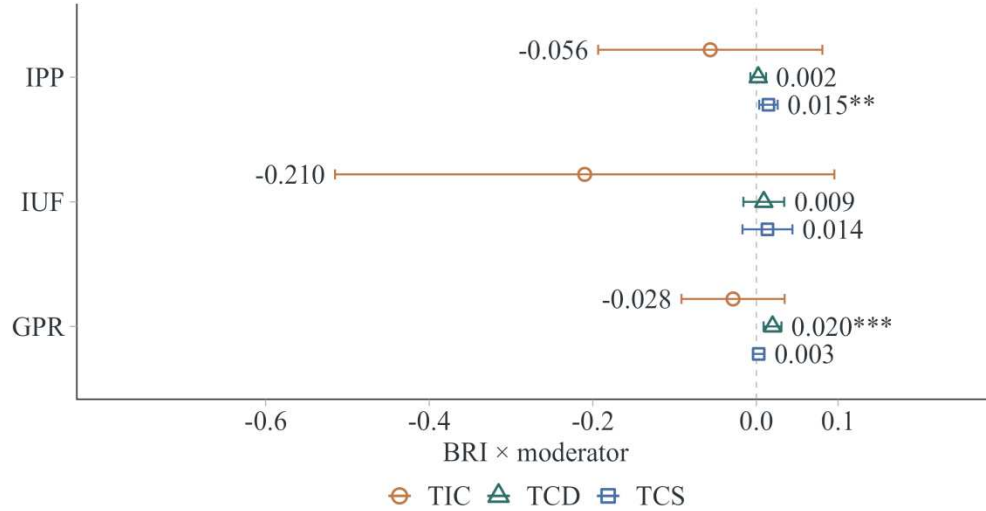


Figure 9. Moderating Effects across Three Technological Paths

6.5 Heterogeneity Analysis

The response of urban ETE to the BRI shock may vary systematically with local macroeconomic environments and baseline endowments. Table 9 and Figure 10 report heterogeneity across geographic economic regions, corridor types, green-development willingness, and talent-attraction intensity.

6.5.1 Heterogeneity by economic region

Columns (1)–(3) of Table 9 reveal a distinct geographic catch-up convergence. The *Dbri* coefficient is 0.041 for Central China and 0.060 for Western China, both significant at the 1% level, whereas the estimate for Eastern China is 0.005 and statistically insignificant. Eastern coastal cities, possessing a more advanced transition baseline, exhibit limited room for marginal efficiency gains. Consequently, the energy-transition dividends generated by institutional opening are predominantly captured by inland node cities in the Central and Western regions through BRI-facilitated factor reallocation and energy-structure optimization.

6.5.2 Heterogeneity by corridor type

Columns (4) and (5) of Table 9 differentiate land-based nodes along the Silk Road Economic Belt (the Belt) from maritime nodes along the 21st Century Maritime Silk Road (the Road). The *Dbri* coefficient for Belt cities is 0.043 and highly significant, while the Road estimate is -0.003 and insignificant. This divergence reflects the Initiative's internal spatial division of labor. Maritime nodes already benefit from mature external-opening frameworks,

yielding smaller marginal gains. In contrast, inland Belt nodes rely heavily on the newly established international-corridor connectivity and hinterland resource reallocation, resulting in substantially larger local ETE improvements.

6.5.3 Heterogeneity by green-development willingness

To capture pre-policy local green-development orientation, we calculate the proportion of city government work reports dedicated to terms such as “energy consumption,” “emissions reduction,” and “low carbon,” partitioning the sample at the median. In Columns (6) and (7) of Table 9, the *Dbri* coefficient is 0.037 (significant at the 1% level) for high-orientation cities, compared to an insignificant 0.012 for low-orientation cities. Cities that proactively integrated energy conservation into their policy agendas before the shock are better equipped to implement complementary measures, effectively translating opening opportunities into tangible ETE gains.

6.5.4 Heterogeneity by talent-attraction intensity

We construct a talent-attraction index using semantic analysis of city government work reports, categorizing keywords into policy orientation, recruited talent types, services, and recruitment methods. We assign semantic weights of 1.5 to emphatic modifiers (e.g., “deepen,” “ensure”) and 1.2 to continuity terms (e.g., “further,” “sustain”), calculating the weighted keyword share and splitting the sample at the median. Columns (8) and (9) of Table 9 show a significant *Dbri* coefficient of 0.034 for the low-intensity group and an insignificant -0.010 for the high-intensity cohort. Similar to the regional results, this catch-up pattern suggests that cities with mature talent-attraction frameworks face diminishing marginal returns. Conversely, cities with weaker initial recruitment capabilities leverage BRI market access and external talent inflows to systematically bridge the efficiency gap and boost their ETE.

Table 9. Heterogeneity Tests Results

Variable	East (1)	Central (2)	West (3)	Belt node (4)	Road Node (5)	High green willingness (6)	Low green willingness (7)	High talent intensity (8)	Low talent intensity (9)
<i>Dbri</i>	0.005 (0.017)	0.041*** (0.011)	0.060*** (0.017)	0.043*** (0.008)	-0.003 (0.018)	0.037*** (0.011)	0.012 (0.019)	-0.010 (0.015)	0.034** (0.016)
Cons	0.676 (0.994)	-0.050 (0.891)	1.798 (1.313)	0.857 (0.675)	0.734 (0.678)	0.104 (0.909)	0.980 (1.014)	0.277 (1.143)	0.452 (0.799)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1700	1683	1411	4794	4794	1938	2737	1054	3570
R ²	0.117	0.236	0.427	0.373	0.387	0.412	0.332	0.122	0.372
Diff.	0.036* (0.021)	0.055** (0.025)		0.041** (0.018)		0.025 (0.022)		-0.044** (0.022)	

Note: * p<0.10, ** p<0.05, *** p<0.01. City-clustered standard errors are in parentheses.

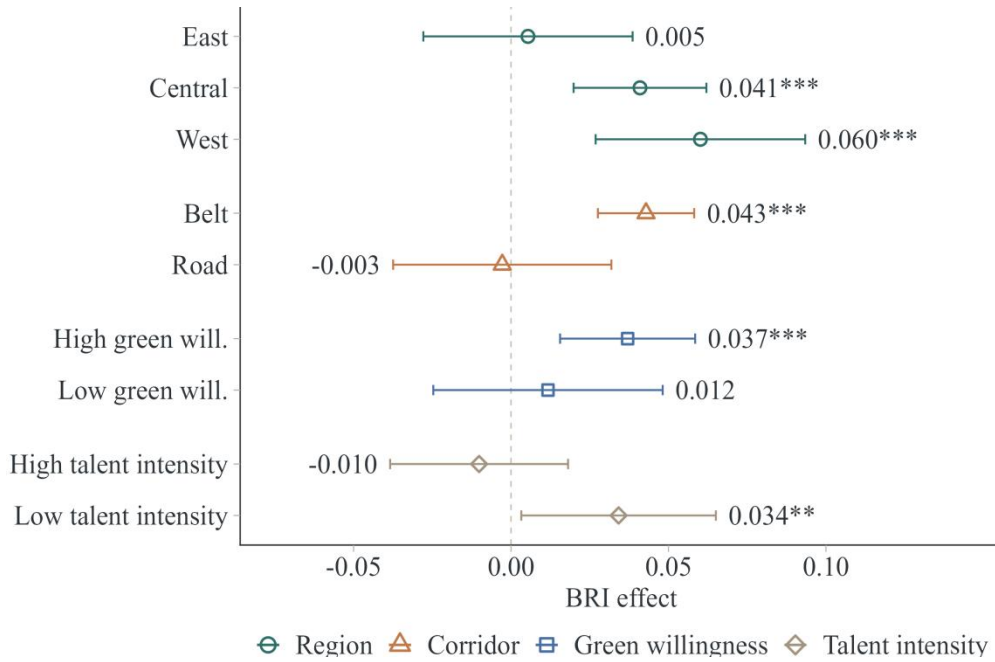


Figure 10. Heterogeneity tests

6.6 Spatial Associations and Spillover Boundaries

6.6.1 Multidimensional spatial association

Theoretical frameworks in spatial economics suggest that the net impact of neighboring cities' treatment status on local urban ETE depends on the interplay between positive technological diffusion and negative factor competition. Columns (1) through (4) of Table 10 present the Spatial DID estimates utilizing four distinct spatial weighting matrices: geographic inverse-distance (W^G), economic-gravity (W^E), trade-gravity (W^T), and express-network (W^N). Across all specifications, the direct effect of the BRI on ETE remains positive and statistically significant, ranging from 0.012 to 0.024. The spatial autoregressive coefficients ρ for the $W \times Yete$ are estimated at 0.885, 0.616, 0.434, and 0.429, respectively, all achieving significance at the 1% level. This confirms a robust positive spatial dependence in urban ETE across multidimensional configurations.

Conversely, the coefficient ϕ for the spatially lagged treatment ($W \times Dbri$) is negative and highly significant across all four matrices. This negative spatial spillover is most pronounced under the geographic inverse-distance matrix (-0.501), capturing direct competition for green resources among geographically proximate and industrially analogous cities. The express-network estimate follows in magnitude (-0.372), implying that major logistics corridors facilitate the rapid concentration of developmental resources into hub cities. The negative spillovers are comparatively moderated under the economic-gravity (-0.102) and trade-gravity (-0.144) matrices, where supply-chain integration and market-driven technology diffusion likely counterbalance some reallocation pressures. This pattern indicates that negative spatial reallocation operates primarily through physical proximity and transport corridors, whereas deepening economic and trade cooperation helps mitigate this exclusionary squeeze.

Figure 11(a) and the Table 10 spatial-effects decomposition confirm these dynamics, yielding consistently negative and significant total effects (-0.478, -0.078, -0.124, and -0.360) across all four matrices. These results indicate that corridor-based opening remains spatially exclusive, failing to generate regional Pareto improvements. Instead, the BRI induces a “siphon effect” where local urban ETE gains come at the expense of neighboring jurisdictions through negative spatial reallocation. Two possible reasons drive this asymmetry. First, enhanced connectivity allows node cities to disproportionately attract high-quality green factors and

monopolize technological recombination, structurally disadvantaging the periphery. Second, interregional competition incentivizes node cities to upgrade their industrial cores while relocating energy-intensive production to the hinterland, effectively externalizing their environmental and efficiency costs to surrounding areas.

Table 10. Spatial DID Estimation Results

Variable	Geographic Matrices- W^G (1)	Economic Matrices- W^E (2)	Trade Matrices- W^T (3)	Express Matrices- W^N (4)
<i>Dbri</i>	0.023*** (0.006)	0.024*** (0.006)	0.020*** (0.006)	0.012** (0.006)
$W \times Dbri$	-0.501*** (0.095)	-0.102*** (0.018)	-0.144*** (0.015)	-0.372*** (0.026)
$W \times Yete$	0.885*** (0.019)	0.616*** (0.026)	0.434*** (0.030)	0.429*** (0.047)
Direct effect	0.023*** (0.006)	0.024*** (0.006)	0.020*** (0.006)	0.012** (0.006)
Indirect effect	-0.501*** (0.095)	-0.102*** (0.018)	-0.144*** (0.015)	-0.372*** (0.026)
Total effect	-0.478*** (0.096)	-0.078*** (0.020)	-0.124*** (0.017)	-0.360*** (0.028)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794
Log likelihood	6283.6	6295.2	6217.0	6235.2
R ²	0.524	0.531	0.508	0.509

Note: * p<0.10, ** p<0.05, *** p<0.01. ML standard errors are in parentheses.

6.6.2 Spatial spillover boundary

Regional policies can accelerate local urban energy transition while generating spatial siphoning (Wang and Shao, 2025). To identify the radius of this negative reallocation driven by the BRI, we apply the distance-threshold function in Equation (5b), truncating the four spatial weights at 200, 400, 600, 800, and 1,000 km intervals. As plotted in Figure 11(b), the direct effect remains positive and significant across all cutoffs, showing that local urban energy transition gains coexist with negative spillovers. The attenuation patterns, however, vary by network:

① Convergence within an effective trade-network range. Under trade gravity, negative spillovers deepen rapidly from 200 km (-0.044) to 600 km (-0.089) before stabilizing around -0.084 at 800–1,000 km. The 400–600 km range serves as an effective boundary for supply-chain cooperation under institutional opening. Beyond this, market segmentation causes the siphoning pressure to level off.

② Long-range polarization along the railway network. Under the transport network, negative spillovers grow monotonically with distance, reaching -0.083 at 1,000 km. By reducing geographic friction, the BRI's railway connectivity allows hub cities to attract resources and relocate energy-intensive production over vast distances, driving long-range regional polarization.

③ Limited role of physical proximity alone. Spillovers under economic gravity are only marginally significant at 200 km (-0.039), while inverse-geographic-distance estimates remain insignificant at all cutoffs. This indicates that negative reallocation relies on tangible interaction channels—trade links and rail corridors—rather than mere physical proximity.

Overall, these results strongly support **P4**, clarifying how institutional opening spatially reshapes the urban energy transition.

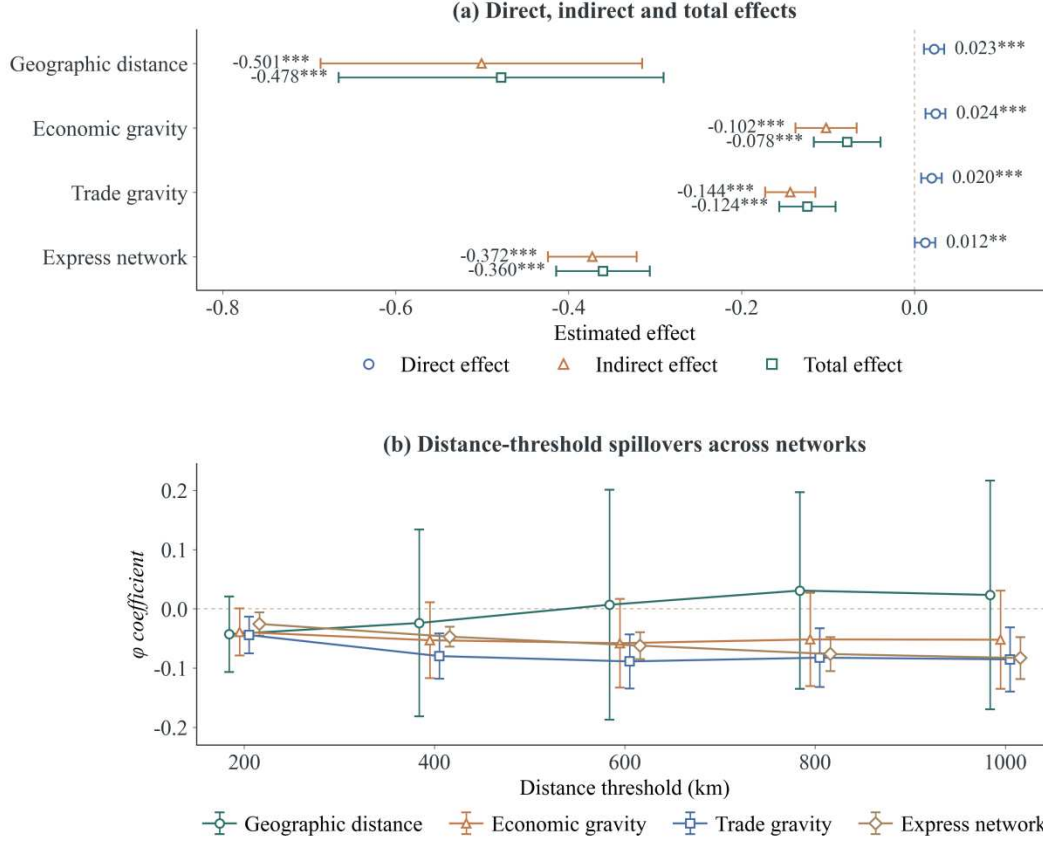


Figure 11. Treatment Effects and Distance-threshold Spillovers

7. Conclusions and Outlooks

This study constructs a formal framework to evaluate the impact of institutional opening on urban ETE, utilizing the BRI node designation as a quasi-natural experiment across 282 Chinese cities (2006–2022). By decomposing the technology channel and employing multidimensional spatial matrices, we document the following core findings:

First, the BRI significantly drives local urban energy transition, though dynamic trajectories indicate a necessary long-term gestation period. These gains follow a structural “catch-up” convergence, predominantly benefiting Central and Western inland corridors and cities with strong green-governance willingness but initially weak talent-attraction bases.

Second, mediation tests confirm that TIC and TCD act as the primary transmission channels, capturing 20.8% and 14.5% of the total effect, respectively, while TCS does not provide an effective mediation path. This indicates that the EFE dividends stem from broad technological search and cross-domain recombination rather than path-dependent specialization. Crucially, this

restructuring process is context-dependent: strict IPP effectively buffers the decline in TCS, and external GPR significantly accelerates TCD, whereas the initial IUF does not constrain these dynamic responses.

Third, institutional opening generates a spatially exclusive “siphon effect.” Local ETE gains coincide with negative spillovers on neighboring cities' resource access. This negative reallocation stabilizes at a 400–600 km radius within trade networks, but generates long-range spatial polarization along railway express corridors, extending up to a 1000 km radius..

Subsequent research could capture time-varying opening intensity using micro-level cooperation projects, patent text, and equipment investment data, identifying the exact timelines when technological recombination translates into production efficiency. Furthermore, integrating richer network data into spatial models will help to more precisely isolate the boundary between positive technological diffusion and negative spatial competition..

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