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Beyond Digital Infrastructure: Telecommunications Service-Market Development and Energy Carbon Intensity in Chinese Cities

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Abstract

As digitalisation reshapes economic coordination and governance, the role of telecommunications services extends beyond network construction and ICT access. However, the environmental relevance of the activity of the telecommunications service market is not understood sufficiently. Drawing on panel data for 269 cities at the Chinese prefecture level from 2006 to 2022, this study estimates fixed-effect models and conducts a series of robustness tests to alleviate potential endogeneity and specification concerns. The results show that telecommunications service-market development (TMD) is significantly negatively associated with urban energy carbon intensity. Specifically, the baseline estimate indicates that a one-unit increase in logged TMD is associated with approximately a 0.835-unit reduction in carbon intensity. However, it is positively associated with per-capita CO₂ emissions, while its association with total CO₂ emissions is statistically insignificant. This relationship is robust to alternative measurements, model specifications, and endogeneity treatment. Moreover, both carbon intensity and TMD exhibit significant spatial dependence, and the main Spatial Durbin Model yields direct and indirect effects of −0.483 and −8.842, respectively, indicating negative spatial spillovers across cities. The moderation results further show that higher levels of digital economy development and fiscal decentralization significantly attenuate the negative association between TMD and energy carbon intensity in the interaction models. These results extend research on ICT development, digital infrastructure, digital economy, and low-carbon development by shifting attention from telecommunications infrastructure to TMD as a market-based information-service condition.

Keywords: telecommunications service-market development (TMD); energy carbon intensity; spatial spillovers; digital economy; fiscal decentralization



Academic Editor: Maria Malvoni

Received: 18 August 2026

Revised: 10 October 2026

Accepted: 14 October 2026

Published: 16 October 2026

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1. Introduction

Urban Energy carbon intensity is a key indicator for measuring a city's low-carbon transition [1]. It reflects the level of carbon emissions per unit of economic output—that is, the carbon emission cost a city incurs when converting energy inputs into economic output [2]. In China, this issue is particularly important, as cities are central to achieving carbon peaking and carbon neutrality goals but differ substantially in their energy systems, industrial structures, and transition capacity [3]. Most existing studies explain the decline

in carbon intensity from the perspectives of energy structure adjustment, environmental regulations, technological progress, and industrial upgrading [4–6]. While these explanations are certainly important, the existing literature has paid relatively insufficient attention to the service-oriented conditions within urban economic systems that support information transmission, production coordination, resource allocation, and energy-use management.

Telecommunications services are closely connected to these service-side conditions. In recent years, an increasing number of studies have begun to focus on the environmental impacts of digital infrastructure, information and communication technologies, and the digital economy [7,8]. Some scholars have pointed out that digital transformation and network externalities alter the ways in which services are used, the patterns of interaction among market participants, and the organizational mechanisms governing the flow and interconnection of information [9,10]. However, much of the existing research still understands the telecommunications industry mainly from an infrastructure or technology-input perspective, focusing on hardware-related indicators such as base-station network construction, internet access penetration, and digital terminal use [11,12]. This infrastructure-oriented perspective pays insufficient attention to the role that telecommunications, as a market-based information-service activity, plays in the overall functioning of the regional economy.

This study focuses on telecommunications service-market development (TMD), rather than merely examining the availability of communication networks. Telecommunications service-market development refers to the scale and development of market-oriented telecommunications service activities within the regional economic system. This study examines whether higher levels of TMD are associated with lower urban energy carbon intensity. More active telecommunications services may reduce communication costs, improve information services for suppliers and consumers, and accelerate knowledge sharing among firms, governments, and other economic actors [11]. This perspective helps move the analysis beyond infrastructure construction and highlights the service-side role of telecommunications in urban low-carbon transition and carbon-intensity management.

Although there is already considerable academic understanding of the relationship between digital development and carbon reduction, three issues remain insufficiently addressed [9,10]. First, the environmental role of TMD has been relatively overlooked from the perspective of the telecommunications service market. Existing studies tend to emphasize the availability of communication networks and digital infrastructure, while paying less attention to whether telecommunications services are actively embedded in market communication, production coordination, and resource allocation. Second, the spatial spillover effects of TMD on carbon intensity have not been fully examined. Existing research mainly focuses on the local effects of digital development within individual regions, while paying less attention to whether telecommunications services, as network-based infrastructure, may generate cross-regional effects through information diffusion, technology exchange, and economic linkages. Whether the carbon-reduction effect of TMD extends beyond individual cities and produces spatial spillover effects remains an empirical question. Third, the conditions under which TMD affects carbon intensity remain insufficiently understood. Although existing studies have emphasized the importance of regional economic and institutional environments, limited attention has been paid to whether factors such as digital economy and fiscal decentralization may influence the effectiveness of TMD in promoting low-carbon development.

To address these issues, this study uses panel data from 269 Chinese prefecture-level cities from 2006 to 2022 to examine whether TMD is associated with lower urban energy carbon intensity. This study uses a fixed-effects model as the baseline specification and employs robustness tests and policy-based IV-2SLS estimation to alleviate potential endogeneity concerns. Next, it compares differences across China's three major regions and

the Hu Line. Third, it further examines the spatial spillover effects of TMD by employing spatial econometric models. Finally, it analyzes the moderating effects of the digital economy and fiscal decentralization.

This study makes three contributions. First, it extends research on digitalization and low-carbon transition by shifting the analytical focus from telecommunications infrastructure and ICT access to telecommunications service-market activity. Rather than treating telecommunications only as a technological input or network condition, this study conceptualizes TMD as a market-based information-service condition that shapes information exchange, resource matching, production coordination, and energy-use management within regional economic systems. This perspective is closely related to the policy, governance, management, innovation, and use dimensions of digitalization. Second, this study extends the analysis by examining the spatial spillover effects of TMD. By incorporating spatial interactions into the empirical framework, this study provides evidence on whether the carbon-reduction effects of telecommunications service-market activity extend beyond individual cities. Third, this study shows that the TMD–energy carbon intensity relationship is conditional on local digital, institutional, and spatial contexts. By considering digital economy development, fiscal decentralization, regional development differences, and the Hu Huanyong Line, this study provides a more differentiated understanding of how telecommunications service-market activity is associated with urban carbon-intensity management across regional settings.

The remainder of this paper is organized as follows: Section 2 develops the theoretical mechanisms and research hypotheses. Section 3 describes the methodology, variables, and data. Section 4 reports the baseline regression, robustness and endogeneity tests, heterogeneity analysis, spatial Durbin model estimation and spillover effect analysis, and moderation analysis. Section 5 discusses the empirical findings and policy implications. Section 6 concludes the paper.

2. Literature Review and Hypotheses

2.1. TMD and Energy Carbon Intensity

Energy carbon intensity refers to carbon emissions per unit of economic output [1]. In urban production systems, a reduction in carbon intensity stems not only from the use of clean energy and technological upgrades but also from the efficiency of coordination among information flows, resource allocation, production activities, and energy decision-making [4–6]. In the era of the digital economy, telecommunications services have become an important information-service infrastructure for factor allocation and coordination across entities [13]. Different from studies that mainly emphasize digital infrastructure construction or internet penetration, this study focuses on the market activity of telecommunications services and its role in reducing information frictions within urban economic systems. Disruptions in information flow can increase firms' search costs, reduce supply chain matching efficiency, and lead to deviations in production planning, which in turn result in transportation waste, excess inventory, resource misallocation, and higher energy consumption per unit of output [14].

TMD may be associated with energy carbon intensity through the information-sharing capabilities of telecommunications services. More active telecommunications services facilitate the flow of information regarding markets, production, logistics, and energy use among enterprises, suppliers, customers, platforms, and local governments [15]. By improving communication quality and digital connectivity, telecommunications services reduce information frictions, improve transaction coordination, enhance resource matching, and support more efficient energy-use management [16]. These functions can help firms adjust production plans, coordinate supply and demand, and reduce unnecessary resource

and energy inputs. From this perspective, TMD is not simply a matter of network expansion, but a service-side condition that may improve the coordination efficiency of production and energy-use decisions.

The environmental effects of TMD are not necessarily unidirectional [17]. On the one hand, the expansion of telecommunications services increases electricity demand through network operations, data transmission, and growth in digital services [18,19]. On the other hand, more active telecommunications services may support energy-saving practices within and beyond the telecommunications sector, including more efficient facility operation, data-based energy management, and improved coordination of energy-use decisions [20]. Therefore, whether improvements in organizational efficiency can offset the additional energy consumption resulting from telecommunications activities remains to be empirically tested [12,21]. If the efficiency gains prevail, TMD will be associated with lower urban energy carbon intensity. Accordingly, this study proposes the following hypothesis:

H1. *TMD is negatively associated with energy carbon intensity.*

2.2. Spatial Spillover Effects of TMD

Telecommunications services are characterized by strong network connectivity and externality effects. Unlike traditional production factors that are mainly confined within administrative boundaries, telecommunications services facilitate information exchange, knowledge diffusion, and economic interactions across regions [22]. Therefore, improvements in TMD in one city may not only affect its own carbon intensity but also influence neighboring cities through spatial linkages.

Existing studies on digital development and carbon reduction have increasingly recognized that environmental effects may extend beyond local regions due to technology diffusion, information sharing, and regional economic connections [18,23–25]. Spatial econometric approaches, particularly the Spatial Durbin Model, have therefore been applied to identify both local and cross-regional effects of digital development on carbon-related outcomes.

Given the network characteristics of telecommunications services, this study expects that the carbon-reduction effect of TMD may generate spatial spillovers. Specifically, cities with higher levels of TMD may facilitate the diffusion of low-carbon technologies, management practices, and resource allocation efficiency to geographically connected cities, thereby contributing to reductions in carbon intensity beyond their own boundaries. Accordingly, we propose:

H2. *TMD is associated with negative spatial spillover effects on urban energy carbon intensity.*

2.3. Moderating Effects

2.3.1. Digital Economy

The digital economy moderates the relationship between TMD and energy carbon intensity [26]. Telecommunications services provide connectivity, while the digital economy embodies the broader capacity of cities to process data, coordinate platforms, and apply digital tools in production and resource management [27]. In cities with more developed digital economies, telecommunications services are more likely to be embedded in production management, supply chain coordination, resource allocation, and energy use monitoring [15]. This can strengthen the service-side role of telecommunications by improving data processing, platform coordination, and digital energy-management capacity [11].

However, the digital economy also increases energy demand through the expansion of digital infrastructure and platform-based activities. Data centers, platform-based ser-

vices, digital devices, and high-frequency online transactions may generate additional electricity consumption, creating a potential energy rebound effect [28]. Therefore, its role should be understood as a conditioning factor rather than a uniformly strengthening force. Accordingly, this study proposes the following hypothesis:

H3a. *The digital economy moderates the relationship between TMD and urban energy carbon intensity.*

2.3.2. Fiscal Decentralization

Fiscal decentralization also moderates the relationship between TMD and energy carbon intensity. By granting local governments greater autonomy in revenue and expenditure, fiscal decentralization influences their capacity to allocate resources, support digital service systems, and implement low-carbon governance [29]. A higher level of fiscal decentralization may create better institutional conditions for telecommunications services to play a role in energy management, resource recycling, and production coordination [30]. For example, local fiscal autonomy helps governments coordinate the development of digital infrastructure, the provision of industrial services, and environmental governance arrangements based on local development foundations and industrial characteristics. At the same time, fiscal pressures and economic growth-oriented incentives may weaken environmental regulation or even drive the expansion of energy-intensive industries [31]. Therefore, fiscal decentralization may influence the environmental effects of TMD, but this impact is not unidirectional [32]; rather, it depends on local fiscal capacity and governance incentives. Based on the above analysis, this study proposes the following hypotheses:

H3b. *Fiscal decentralization moderates the relationship between TMD and urban energy carbon intensity.*

The conceptual framework derived from the above theoretical reasoning and hypotheses is presented in Figure 1.

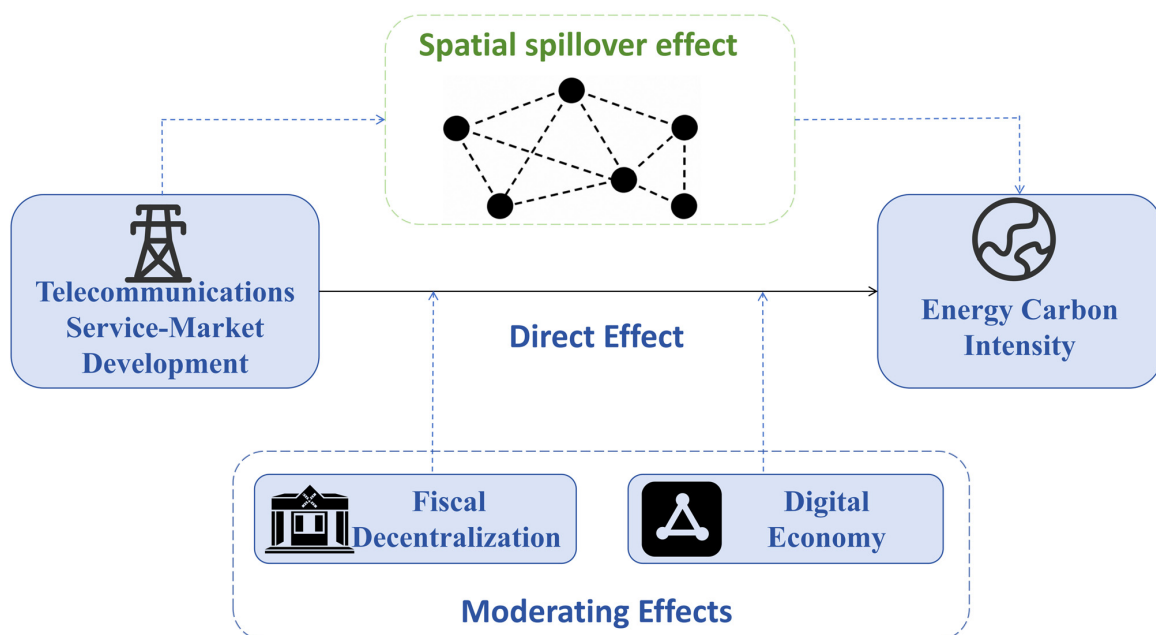


Figure 1. Research Framework.

3. Materials and Methods

3.1. Methodology

3.1.1. Basic Regression Model

The baseline empirical regression model is as follows:

$$CI_{it} = \alpha_0 + \alpha_1 TMD_{it} + \sum_{j=1}^N \beta_j X_{jit} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where CI_{it} is energy carbon intensity in city i in year t ; TMD_{it} is telecommunications service-market development; X_{jit} are control variables; μ_i and η_t are city and year fixed effects, respectively; ε_{it} is the error term.

3.1.2. IV-2SLS

To mitigate potential endogeneity, the main IV-2SLS analysis uses a policy-exposure instrument constructed by interacting each city's baseline (2006) TMD with the post-4G period. A supplementary specification jointly uses baseline TMD interacted with the post-3G and post-4G periods.

China issued 4G operating licenses nationwide in December 2013, providing a common telecommunications-sector policy change. Baseline TMD captures pre-existing cross-city differences in telecommunications-market exposure before 4G commercialization. The identifying assumption is that, conditional on the fixed effects and controls, this policy-exposure instrument affects carbon intensity only through its effect on current TMD rather than through other city-specific channels. As concurrent industrial upgrading, digital development, and energy restructuring may also affect carbon intensity independently of TMD, we additionally include province-by-year fixed effects in a robustness specification to control for province-specific annual shocks, although city-specific trends may remain. The first-stage and second-stage regressions are specified as follows:

$$TMD_{it} = \pi_0 + \pi_1 IV_{it} + \sum_{j=1}^N \delta_j X_{jit} + \mu_i + \eta_t + u_{it} \quad (2)$$

$$CI_{it} = \rho_0 + \rho_1 TMD_{it} + \sum_{j=1}^N \theta_j X_{jit} + \mu_i + \eta_t + v_{it} \quad (3)$$

where the policy-exposure variables instrument for current TMD. Instrument relevance is evaluated using the Kleibergen–Paap rk Wald F statistic.

3.1.3. Examination of Regional Heterogeneity Effects

To examine regional heterogeneity, this study first estimates the baseline model separately for different regional subsamples:

$$CI_{it} = \alpha_{0g} + \alpha_{1g} TMD_{it} + \sum_{j=1}^N \beta_{jg} X_{jit} + \mu_i + \eta_t + \varepsilon_{it}, i \in g \quad (4)$$

where g denotes the regional group, including eastern, central, and western regions, as well as cities southeast and northwest of the Hu Line. The coefficient α_{1g} captures the estimated association between TMD and energy carbon intensity within each regional group.

To further test whether the TMD coefficients differ significantly across regions, this study also estimates interaction-term models:

$$CI_{it} = \alpha_0 + \alpha_1 TMD_{it} + \alpha_2 (TMD_{it} \times Central_i) + \alpha_3 (TMD_{it} \times West_i) + \sum_{j=1}^N \beta_j X_{jit} + \mu_i + \eta_t + \varepsilon_{it} \quad (5)$$

$$CI_{it} = \theta_0 + \theta_1 TMD_{it} + \theta_2 (TMD_{it} \times Northwest_i) + \sum_{j=1}^N \delta_j X_{jit} + \mu_i + \eta_t + \varepsilon_{it} \quad (6)$$

In Equation (5), the eastern region is the reference group. In Equation (6), the southeast side of the Hu Line is the reference group. The interaction terms are used to test whether the TMD coefficient differs across regional groups.

3.1.4. Spatial Autocorrelation Test

Annual global Moran's I statistics are computed for TMD and energy carbon intensity, using an inverse-distance spatial weight matrix W . In the baseline specification, city pairs within 1000 km are weighted by the inverse of geographic distance, whereas pairs beyond 1000 km receive zero weight. For variable x in year t , Moran's I is defined as:

$$I_t = \frac{N \sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_{it} - \bar{x}_t)(x_{jt} - \bar{x}_t)}{(\sum_{i=1}^N \sum_{j=1}^N w_{ij}) \sum_{i=1}^N (x_{it} - \bar{x}_t)^2} \quad (7)$$

where N is the number of cities, W_{ij} is the inverse-distance weight between city i and city j , and $\bar{x}_t$ is the annual mean. Positive and statistically significant values indicate positive spatial autocorrelation.

3.1.5. Spatial Durbin Model

To account for spatial dependence, we estimate a spatial Durbin model (SDM):

$$CI_{it} = \rho \sum_{j=1}^N W_{ij} CI_{jt} + \beta TMD_{it} + \gamma \sum_{j=1}^N W_{ij} TMD_{jt} + \sum_{k=1}^K \theta_k X_{k,it} + \sum_{k=1}^K \phi_k \sum_{j=1}^N W_{ij} X_{k,jt} + u_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where CI_{it} is energy carbon intensity, TMD_{it} is telecommunications service-market development, $X_{k,it}$ denotes the k -th control variable, μ_i and λ_t are city and year fixed effects, and ε_{it} is the error term. W is the spectrally normalized inverse-distance spatial weight matrix. Spectral normalization rescales the matrix without altering the relative ordering of geographic proximity, and robustness is assessed using an 800-km inverse-distance matrix, a row-normalized 1000-km inverse-distance matrix, and a 1000-km binary distance-band matrix. The SDM nests the spatial autoregressive (SAR) and spatial error (SEM) models and is estimated by quasi-maximum likelihood. Model selection is guided by the Hausman test for fixed versus random effects and by likelihood-ratio tests comparing the SDM with the SAR and SEM specifications.

3.1.6. Moderating Effect Model

The moderating effect is examined by introducing interaction terms between TMD and the moderating variables:

$$CI_{it} = \beta_0 + \beta_1 TMD_{it} + \beta_2 Mod_{it} + \beta_3 (TMD_{it} \times Mod_{it}) + \sum_{j=1}^N \beta_j X_{jit} + \mu_i + \eta_t + \varepsilon_{it} \quad (9)$$

where Mod_{it} denotes the moderating variable, including the digital economy ($Dige_{it}$) and fiscal decentralization ($Fisc_{it}$). The coefficient β_3 captures the moderating effect.

3.2. Sources of Data

This study selected 269 prefecture-level cities in China from 2006 to 2022 as its sample. The data were primarily drawn from the China Statistical Yearbook, the Urban Statistical Yearbook, the China Energy Statistical Yearbook, and the China Environmental Statistical Yearbook.

3.3. Variables

3.3.1. The Dependent Variable

Energy carbon intensity: Following the research methods of Shen, Shi, Zhao, Sun and Shan [1], energy carbon intensity is defined as total carbon emissions divided by gross domestic product. This indicator is a key measure for assessing the quality of green and low-carbon development. The baseline regressions use this ratio in levels, expressed as tonnes of CO₂ per RMB 10,000 of GDP. Its natural logarithm, total CO₂ emissions, per-capita CO₂ emissions, and GDP are also examined as alternative outcomes.

3.3.2. The Independent Variable

Telecommunications service-market development (TMD): TMD is measured using the natural logarithm of per-capita telecommunications business revenue. Per-capita revenue is calculated by dividing telecommunications business revenue by resident population, which reduces the direct influence of population scale. This revenue-based indicator reflects the scale of telecommunications service-market activity but does not directly capture competition intensity, market concentration, entry and exit, or pricing dynamics. To examine the robustness of the measurement, the logarithm of total telecommunications revenue, revenue growth, log revenue growth, and telecommunications revenue scaled by GDP are also used as alternative measures.

3.3.3. The Moderator Variables

Digital Economy: Based on Wang, Dong, Dong and Taghizadeh-Hesary [27], we use the entropy method to measure a digital economy index. This indicator covers the internet popularization rate, relevant practitioners and outputs, mobile web users, and digital inclusive finance development. In the moderation analysis, the one-period lagged natural logarithm of the digital economy index is used and mean-centered before constructing the interaction term with TMD.

Fiscal Decentralization: This study uses the ratio of government general budget revenue to general budget expenditure as a measure of fiscal decentralization, drawing on the research by Zhang, Li, Xu and Xiong [30]. In the moderation analysis, the one-period lagged natural logarithm of fiscal decentralization is used and mean-centered before constructing the interaction term with TMD.

3.3.4. Control Variables

To mitigate omitted-variable bias, the model includes a set of city-level controls covering economic development, human capital, urbanization, infrastructure, public services, innovation, openness, and environmental governance. Table 1 reports the definitions and descriptive statistics of all variables.

Table 1. Variable definitions and descriptive statistics.

Variable Type	Variables	Symbol	Indicators	Mean	SD	Min	Max
Dependent Variable	Energy carbon intensity	CI	Ratio of total carbon emissions to GDP (tonnes CO ₂ per RMB 10,000 GDP); ln(CI) used as an alternative outcome	4.128	5.124	0.035	89.658
Independent Variable	Telecommunications service-market development	TMD	Per-capita telecommunications business revenue (yuan/person); ln(per-capita revenue) used in regressions	880.717	884.836	34.097	16,003.066

Table 1. Cont.

Variable Type	Variables	Symbol	Indicators	Mean	SD	Min	Max
Moderating Variable	Digital economy	Dige	Composite digital economy index constructed using the entropy method based on internet penetration, internet-related employment and output, mobile internet use, and digital financial inclusion.	0.054	0.076	0.000	0.940
	Fiscal decentralization	Fisc	Ratio of government general budget revenue to general budget expenditure; lagged ln form used in moderation	0.466	0.226	0.054	1.541
Robustness variable	Carbon emissions	CO ₂	Natural logarithm of total energy-related carbon emissions, used as an alternative carbon outcome for robustness checks	8.006	0.561	6.314	11.643
Control variable	Financial development level	Fin	Ratio of financial institution deposits and loans to GDP	2.383	1.187	0.504	21.297
	Human capital level	Capt	Number of students in ordinary colleges divided by total population at the end of the year	0.019	0.024	0.000	0.147
	Urbanization level	Urban	Ratio of urban population to total population	0.534	0.166	0.115	1.007
	Urban infrastructure investment	Moder	Fixed-asset investment in municipal public utilities	11.778	1.570	2.996	16.219
	Infrastructure level	infr	Natural logarithm of road area	7.014	0.985	1.946	10.017
	Ecological environment quality	eco	Green coverage rate of built-up areas	39.116	6.372	0.970	64.780
	Social welfare level	Welf	Natural logarithm of number of hospital beds	9.538	0.716	6.846	11.848
	Innovation investment	Inno	Innovation input of RD personnel	8.683	1.687	2.303	13.851
	Environmental governance capacity	Envi	Harmless treatment rate of domestic garbage	87.859	21.929	0.000	101.000
	Opening-up level	Ope	Natural logarithm of actual utilized FDI	9.713	2.007	0.000	14.561
	People's livelihood service level	Liv	Gas penetration rate	91.024	14.108	0.010	141.333

4. Results

4.1. Baseline Regression

Table 2 presents the results of the baseline regression. The coefficient remains negative and statistically significant as controls are added. In the full specification with city and year fixed effects, the coefficient is -0.835 . A 10% increase in per-capita telecommunications revenue is associated with an approximately 0.0796-tonne decline in CO₂ per RMB 10,000 of GDP. This indicates a consistent negative relationship between TMD and urban energy

carbon intensity. It should be noted that this result merely confirms the correlation between the two variables and does not constitute rigorous evidence of causality.

Table 2. Baseline regression test results.

Variables	(1) CI	(2) CI	(3) CI	(4) CI
TMD	−1.015 *** (0.233)	−0.946 *** (0.217)	−0.935 *** (0.213)	−0.835 *** (0.201)
Fin		0.349 ** (0.155)	0.336 ** (0.155)	0.307 ** (0.151)
Capt		−0.142 (33.505)	−0.517 (33.531)	−1.000 (32.489)
Urban		−3.598 * (1.918)	−3.705 * (1.899)	−3.319 * (1.812)
Moder			0.127 (0.091)	0.110 (0.091)
infr			−0.083 (0.280)	−0.120 (0.296)
Welf			0.748 (0.646)	0.617 (0.623)
eco				0.031 (0.025)
Envi				0.011 ** (0.005)
Liv				−0.017 (0.014)
Ope				−0.015 (0.073)
Inno				0.146 (0.141)
Control variables	N	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	4573	4573	4569	4533
Within R-squared	0.024	0.033	0.036	0.038

Note: City-clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Robustness Test and Treatment of Endogeneity Problems

4.2.1. Robustness Tests

To examine the robustness of the baseline results, this study conducts a series of additional tests, including alternative outcome measures, alternative model specifications, and outlier treatment. The results are shown in Table 3.

Table 3. Robustness results.

Variables	(1) ln(CI)	(2) ln(Total CO ₂)	(3) ln(Per-Capita CO ₂)	(4) ln(GDP)	(5) CI	(6) CI
	Alternative outcome			Economic outcome	Province × year FE	Trim 1–99%
TMD	−0.0491 *** (0.0145)	0.0083 (0.0064)	0.0510 *** (0.0094)	0.0574 *** (0.0141)	−0.3644 ** (0.1646)	−0.6631 *** (0.1515)
Control variables	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Absorbed	Y
Province × year FE	N	N	N	N	Y	N
N	4533	4533	4533	4533	4431	4361

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

The results remain consistent across different specifications. Specifically, TMD is significantly negatively associated with $\ln(\text{CI})$, but positively associated with $\ln(\text{per-capita CO}_2)$ and $\ln(\text{GDP})$. Its association with $\ln(\text{total CO}_2 \text{ emissions})$ is statistically insignificant. The effect remains negative and significant when province-by-year fixed effects are adopted. Furthermore, after excluding observations outside the 1st–99th percentiles, the estimated coefficient of TMD remains negative and significant, confirming that the baseline finding is not driven by extreme observations. Overall, these robustness checks support a robust negative association between TMD and urban energy carbon intensity.

4.2.2. Endogeneity Treatment

Although the baseline fixed-effects model controls for time-invariant city characteristics and common time shocks, endogeneity concerns may remain due to reverse causality and omitted time-varying factors. To address these concerns, we construct a policy-exposure instrumental variable using baseline (2006) TMD interacted with the post-4G policy period. As a supplementary specification, we further employ baseline TMD interacted with both post-3G and post-4G periods as joint instruments. The results are shown in Table 4.

Table 4. Policy-Exposure IV-2SLS Estimates and Robustness Checks.

Variables	(1) First Stage: TMD	(2) Second Stage: CI	(3) First Stage: TMD	(4) Second Stage: CI	(5) First Stage: TMD	(6) Second Stage: CI
	4G exposure	4G exposure	3G + 4G exposure	3G + 4G exposure	4G exposure + Province × Year FE	4G exposure + Province × Year FE
TMD		−3.9215 *** (0.9108)		−3.7946 *** (1.0224)		−3.7051 *** (0.9531)
Baseline TMD × Post-4G	−0.3603 *** (0.0381)		−0.2409 *** (0.0410)		−0.3202 *** (0.0458)	
Baseline TMD × Post-3G			−0.3491 *** (0.0306)			
Control variables	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Absorbed	Absorbed
Province × Year FE	N	N	N	N	Y	Y
Observations	4533	4533	4533	4533	4533	4533
Kleibergen– Paap rk Wald F	89.38		136.25		48.96	

Note: City-clustered standard errors are in parentheses; *** $p < 0.01$.

The first-stage results indicate strong instrument relevance. The Kleibergen–Paap rk Wald F statistics are 89.38 for the post-4G exposure instrument and 136.25 for the joint 3G–4G specification, both exceeding conventional thresholds. The second-stage estimates show that TMD remains negatively associated with carbon intensity, with coefficients of −3.9215 and −3.7946, respectively. Compared with the baseline fixed-effects coefficient of −0.835, the IV estimates of −3.9215 and −3.7946 are approximately 4.5–4.7 times larger in absolute magnitude.

This difference may be related to the distinct sources of variation underlying the two estimators. The fixed-effects estimate reflects the within-city association between observed TMD and carbon intensity, whereas the IV estimates rely on changes in TMD associated with differences in pre-policy telecommunications-market exposure following the introduction of 4G. If the relationship between TMD and carbon intensity varies across these sources of variation, the two estimators may yield different coefficient magnitudes. Notably, the IV estimates remain similar under the 4G-only and joint 3G–4G specifications, and the coefficient remains relatively stable at -3.7051 after introducing province-by-year fixed effects. This consistency suggests that the larger IV estimates are not specific to a single instrument specification or fixed-effects setting.

To further account for concurrent regional changes following the introduction of 4G, we additionally estimate the IV model with province-by-year fixed effects. This specification absorbs province-specific annual shocks that may be associated with industrial upgrading, digital development, innovation policies, energy restructuring, and other regional changes. The first-stage relationship remains strong, with a Kleibergen–Paap rk Wald F statistic of 48.96, while the second-stage coefficient of TMD remains significantly negative at -3.7051 .

Overall, the IV estimates remain consistent with the negative association identified in the baseline model and provide supplementary evidence that helps alleviate concerns regarding potential endogeneity. Because the exclusion restriction cannot be directly tested, these IV results are interpreted cautiously and are not treated as definitive causal estimates.

4.3. Heterogeneity Analysis

Due to differences in economic development levels, environmental regulation intensity, digital infrastructure conditions, and policy implementation capacity, the relationship between TMD and energy carbon intensity may vary across regions. To examine spatial heterogeneity, this study conducts subgroup regressions based on China's three major regions (Eastern, Central, and Western China) and the Hu Huanyong Line, and further employs pooled interaction tests to examine whether the estimated TMD coefficients differ significantly across groups. The results are reported in Table 5.

Table 5. Regional heterogeneity analysis results.

Variables	(1) East	(2) Central	(3) West	(4) Hu Huanyong Line Southeast	(5) Hu Huanyong Line Northwest
TMD	−0.234 (0.216)	−0.050 (0.167)	−0.831 ** (0.362)	−0.371 ** (0.150)	−1.433 * (0.783)
Controls	Y	Y	Y	Y	Y
Joint cross-group <i>p</i> -value	0.000	0.000	0.000	0.001	0.001
Observations	1664	1581	1288	4126	407
Within R-squared	0.142	0.069	0.062	0.043	0.198

Note: City-clustered standard errors are in parentheses; ** $p < 0.05$, * $p < 0.1$.

The subgroup regression results show that the coefficients of TMD are -0.234 , -0.050 , and -0.831 in Eastern, Central, and Western China, respectively. The pooled interaction test confirms significant differences in the TMD coefficients across the three regions. These results indicate significant regional heterogeneity, with the strongest negative association observed in the western subsample.

The Hu Huanyong Line analysis further shows that the coefficient of TMD is -0.371 for cities southeast of the line and -1.433 for cities northwest of the line. The pooled cross-group test indicates significant differences between the two groups. Given the relatively smaller sample size of the northwest subsample, the larger coefficient should

be interpreted as evidence of heterogeneous effects rather than as a precise ranking of regional impacts.

4.4. Spatial Dependence and Spillover Effects

4.4.1. Spatial Autocorrelation Analysis

Although the baseline fixed-effects model controls for time-invariant city characteristics and common temporal shocks, TMD and carbon intensity may exhibit spatial dependence due to geographic proximity, regional economic linkages, and technology diffusion. Ignoring such spatial interactions may lead to an incomplete understanding of the relationship between TMD and carbon intensity. Therefore, we first examine the spatial autocorrelation of the key variables using Global Moran's I statistics.

Table 6 reports the annual Moran's I values for carbon intensity and TMD based on the 1000-km inverse-distance spatial weight matrix with spectral normalization. The results show that carbon intensity exhibits significant positive spatial autocorrelation throughout the sample period from 2006 to 2022. The Moran's I values range from 0.1202 to 0.1647 and are statistically significant at the 1% level in all years, indicating that cities with similar carbon intensity levels tend to cluster geographically. Similarly, TMD also demonstrates significant positive spatial dependence. The Moran's I statistics remain positive and statistically significant throughout the sample period, ranging from 0.0443 to 0.2026. Although the strength of spatial clustering varies over time, the persistent significance suggests that TMD is not randomly distributed across cities but is associated with spatial diffusion and regional linkages. These findings indicate that both carbon intensity and TMD exhibit substantial spatial dependence, providing empirical support for further estimating spatial econometric models.

Table 6. Global Moran's I.

Year	Carbon Intensity Moran's I	<i>p</i> -Value	TMD Moran's I	<i>p</i> -Value
2006	0.1202	0.0000	0.2016	0.0000
2007	0.1361	0.0000	0.2026	0.0000
2008	0.1581	0.0000	0.1871	0.0000
2009	0.1504	0.0000	0.1597	0.0000
2010	0.1458	0.0000	0.1409	0.0000
2011	0.1647	0.0000	0.1732	0.0000
2012	0.1535	0.0000	0.1127	0.0000
2013	0.1366	0.0000	0.1366	0.0000
2014	0.1362	0.0000	0.0960	0.0000
2015	0.1279	0.0000	0.0954	0.0000
2016	0.1338	0.0000	0.0858	0.0000
2017	0.1355	0.0000	0.0965	0.0000
2018	0.1340	0.0000	0.0732	0.0000
2019	0.1599	0.0000	0.0443	0.0001
2020	0.1570	0.0000	0.0512	0.0000
2021	0.1605	0.0000	0.0707	0.0000
2022	0.1628	0.0000	0.1215	0.0000

Notes: Moran's I is calculated using the 1000-km inverse-distance spatial-weight matrix with spectral normalization. The sample is identical to that used in the spatial panel analysis.

4.4.2. Spatial Spillover Analysis

Given the significant spatial autocorrelation identified above, we further employ the Spatial Durbin Model (SDM) to examine whether TMD exhibits spatial spillover effects. Table 7 reports the results under four spatial-weight specifications. The baseline specification uses a 1000-km inverse-distance matrix with spectral normalization. As robustness checks, we additionally use an 800-km inverse-distance matrix with spectral normaliza-

tion, a 1000-km inverse-distance matrix with row normalization, and a 1000-km binary distance-band matrix with spectral normalization.

Table 7. Spatial Durbin model estimates and spatial spillover effects of TMD.

	(1) 1000 km Spectral	(2) 800 km Spectral	(3) 1000 km Row	(4) Binary 1000 km
Panel A. SDM coefficient estimates				
TMD	−0.426 *** (0.094)	−0.414 *** (0.094)	−0.401 *** (0.092)	−0.562 *** (0.093)
W × TMD	−2.032 *** (0.652)	−1.829 *** (0.585)	−0.940 ** (0.452)	−5.895 *** (1.029)
Spatial autoregressive coefficient (rho)	0.800 *** (0.042)	0.788 *** (0.042)	0.791 *** (0.035)	0.661 *** (0.070)
Panel B. Average spatial impacts of TMD				
Direct effect	−0.483 *** (0.094)	−0.470 *** (0.094)	−0.447 *** (0.092)	−0.621 *** (0.094)
Indirect effect	−8.842 *** (2.737)	−6.861 *** (2.028)	−5.933 *** (2.058)	−15.343 *** (3.637)
Total effect	−9.325 *** (2.747)	−7.331 *** (2.038)	−6.379 *** (2.069)	−15.964 *** (3.651)
Controls	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	4454	4454	4454	4454

Notes: Standard errors are reported in parentheses. ** $p < 0.05$, *** $p < 0.01$. Columns (1)–(4) use 1000-km spectral, 800-km spectral, 1000-km row-normalized, and 1000-km binary spatial weight matrices, respectively.

The results in Panel A show that the coefficient of TMD remains significantly negative across all four specifications, ranging from −0.401 to −0.562. The spatial autoregressive coefficient is also positive and statistically significant in all specifications, ranging from 0.661 to 0.800, indicating substantial spatial dependence in urban energy carbon intensity. Since the coefficients of an SDM cannot be directly interpreted as marginal effects because of spatial feedback, we rely on the decomposed direct, indirect, and total effects reported in Panel B. The estimated direct effects range from −0.447 to −0.621, while the indirect effects range from −5.933 to −15.343. All direct, indirect, and total effects remain statistically significant and negative across the four spatial-weight specifications.

The substantially larger indirect effects should not be interpreted as implying that the effect of TMD on any single neighboring city is several times larger than its local effect. In the SDM, the indirect effect represents the average cumulative effect transmitted to all other cities through the spatial network. A change in TMD in one city can affect connected cities and subsequently propagate further through repeated spatial feedback. Because the indirect effect aggregates these cross-city transmission paths, its magnitude may be substantially larger than the direct effect, particularly when spatial dependence is strong.

At the same time, the magnitude of the indirect effect varies across alternative spatial-weight specifications. For example, the indirect effect declines from −8.842 under the baseline 1000-km spectral-normalized matrix to −5.933 under row normalization, while it increases to −15.343 under the binary distance-band matrix. These differences indicate that the estimated magnitude of spatial spillovers is sensitive to how inter-city spatial linkages are defined, even though the direction and statistical significance of the spillover effect remain robust. Accordingly, the results provide consistent evidence of negative spatial spillovers, but the numerical magnitude of the indirect effect should be interpreted cautiously rather than as a fixed per-city marginal effect.

Overall, the SDM results indicate that the relationship between TMD and energy carbon intensity involves both local and cross-city spatial effects. The robustness of the negative direct and indirect effects across alternative distance thresholds, normalization methods, and weight structures strengthens the evidence that spatial dependence should be taken into account when evaluating the environmental implications of TMD.

4.5. Moderation Analyses

Section 2 suggests that the digital economy and fiscal decentralization condition the association between TMD and energy carbon intensity. This study develops an interaction-term model to test these moderating effects; Table 8 presents the regression results. To mitigate potential simultaneity concerns and reduce scale-related skewness, the moderating variables are measured using their one-year lagged logarithmic values. The lagged moderators are mean-centered before constructing interaction terms with TMD.

Table 8. Moderation analysis results.

	(1)	(2)	(3)	(4)
TMD	−0.723 *** (0.165)	−0.642 *** (0.147)	−0.719 *** (0.158)	−0.315 ** (0.149)
Dige	−0.106 (0.086)	−2.631 *** (0.705)		
TMD × Dige		0.373 *** (0.107)		
Fisc			−0.727 * (0.406)	−14.405 *** (2.934)
TMD × Fisc				2.177 *** (0.450)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4266	4266	4266	4266
Within R-squared	0.057	0.084	0.060	0.144

Note: Moderators are one-year-lagged logarithms and are mean-centered; city-clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5.1. Moderating Effect of the Digital Economy

Table 8 columns (1) and (2) report the moderating effect of the digital economy. Column (1) shows that the coefficient of the digital economy is −0.106 and statistically insignificant, while the coefficient of TMD remains negative and significant. Column (2) introduces the interaction term between TMD and the digital economy, with a coefficient of 0.373, which is significantly positive at the 1% level. Since the dependent variable is energy carbon intensity and the coefficient of TMD is negative, the positive interaction term indicates that digital economy development weakens the negative association between TMD and energy carbon intensity. Specifically, although TMD is associated with lower carbon intensity, this association becomes weaker in cities with higher levels of digital economy development.

This finding suggests that the digital economy does not necessarily amplify the carbon-reduction effect of TMD. One possible explanation is that while digitalization may improve resource allocation efficiency and promote technological applications, it may also increase energy demand through digital infrastructure construction, data processing activities, and related electricity consumption, partially offsetting the energy-efficiency gains associated with TMD.

4.5.2. Moderating Effect of Fiscal Decentralization

Table 8 columns (3) and (4) present the moderating effect of fiscal decentralization. Column (3) shows that the coefficient of fiscal decentralization is −0.727 and statistically

significant at the 10% level. Column (4) reports that the interaction term between TMD and fiscal decentralization is 2.177, which is significantly positive at the 1% level.

Because the coefficient of TMD is negative, the positive interaction term indicates that fiscal decentralization weakens the negative association between TMD and energy carbon intensity. In other words, the carbon-intensity-reducing relationship associated with TMD is smaller in cities with higher levels of fiscal decentralization.

This result suggests that greater fiscal autonomy does not automatically strengthen the low-carbon effects of TMD. A possible explanation is that although fiscal decentralization may enhance local governments' capacity to allocate resources and support infrastructure development, it may also increase local discretion in promoting economic expansion and investment activities, which could offset part of the carbon-efficiency improvements brought by TMD.

5. Discussion and Policy Implications

This study shows that TMD is negatively associated with urban energy carbon intensity. This finding moves beyond the traditional focus of academic research on telecommunications infrastructure and shifts the attention to its role in serving the urban economy [11]. Active telecommunications services reshape information flows, transaction coordination, resource matching, and energy decision-making. Therefore, TMD is a market-based condition for information services, rather than a change in institutional or competitive structures. More importantly, the result suggests that the environmental value of telecommunications services may arise primarily from their capacity to reduce information frictions and improve the coordination efficiency of urban production and energy use.

The relationship between TMD and carbon outcomes is primarily reflected in carbon intensity rather than absolute emission reduction. In the alternative outcome tests, TMD remains negatively associated with $\ln(CI)$, while its coefficient on total carbon emissions is statistically insignificant. Meanwhile, TMD is positively associated with per-capita carbon emissions and economic output, suggesting that TMD may accompany economic expansion and increased production activity. These results indicate that absolute emissions are strongly influenced by factors such as city size, industrial scale, and overall economic growth [33]. Therefore, the baseline result should be understood as evidence that TMD is more closely associated with carbon-efficiency improvement, rather than as direct evidence of absolute emission reduction. This distinction highlights the importance of differentiating relative efficiency improvements from reductions in total emissions when evaluating the environmental implications of TMD.

Existing studies on the environmental consequences of digital infrastructure have largely focused on local effects, assuming that the impacts of technological development are primarily realized within administrative boundaries. The findings of this study challenge this localized perspective by showing that the environmental implications of TMD are spatially differentiated and geographically interconnected. The heterogeneous effects across regions suggest that the benefits of TMD depend on local development conditions rather than following a uniform pattern. In particular, the stronger association observed in western regions may reflect differences in local development conditions and the scope for efficiency improvements. However, the regional regressions do not directly identify the reasons for this difference.

More importantly, the spatial analysis reveals that TMD should be understood as a regional network process rather than an isolated city-level phenomenon. The significant spatial dependence and negative spillover effects suggest that the environmental consequences of TMD may extend beyond the locations where telecommunications service-market activity occurs [34,35]. This finding complements existing research that emphasizes

the direct effects of digital technologies by highlighting the role of inter-city connections, technology diffusion, and regional linkages in shaping environmental outcomes. Therefore, the environmental value of TMD depends not only on the level of development within individual cities but also on their position within broader spatial networks.

The moderating results show that the environmental relevance of TMD is conditional on local digital and institutional environments. The interaction between TMD and the digital economy suggests that digital economy development attenuates the negative association between TMD and energy carbon intensity. This reflects the dual role of digital economy development. On the one hand, digital technologies can optimize resource coordination and energy management [11]. On the other hand, the expansion of digital infrastructure and platform-based activities may increase electricity demand, partially offsetting the energy savings achieved through efficiency improvements [21]. Fiscal decentralization weakens this negative correlation. This finding suggests that greater local fiscal autonomy does not necessarily enhance the environmental benefits associated with TMD. Although fiscal decentralization may improve local governments' resource allocation capacity, it may also strengthen incentives for economic expansion and investment-oriented development, thereby partially offsetting the carbon-intensity reduction associated with TMD.

6. Conclusions

Based on panel data from 269 prefecture-level cities in China from 2006 to 2022, this study examines the relationship between TMD and urban energy carbon intensity. In this paper, TMD is defined as the scale and development of market-oriented telecommunications service activities within the regional economic system. The study finds that TMD is significantly and negatively associated with urban energy carbon intensity, suggesting that TMD is related to improvements in carbon efficiency.

The study's findings offer three main insights. First, the relationship between TMD and carbon outcomes is more evident for carbon intensity than for absolute emissions. Specifically, TMD is significantly negatively associated with $\ln(CI)$, while its relationship with $\ln(\text{total CO}_2 \text{ emissions})$ is insignificant and its relationship with $\ln(\text{per-capita CO}_2 \text{ emissions})$ is positive. These results suggest that TMD is more closely related to improvements in carbon efficiency rather than direct reductions in absolute emissions. Second, the environmental effects of TMD vary across regional and spatial contexts. The heterogeneity analysis shows that the negative association is stronger in western China, while the spatial analysis indicates significant spatial dependence and negative spillover effects of TMD across connected cities. Third, the effects of TMD are also conditioned by the broader institutional and digital environment. The moderation analysis shows that both digital economy development and fiscal decentralization significantly attenuate the negative association between TMD and carbon intensity, indicating that the TMD–carbon-efficiency relationship varies with local digital development and fiscal arrangements.

The absence of a statistically significant association with total CO₂ emissions, together with the positive association with per-capita CO₂ emissions, means that carbon-efficiency improvements should not be interpreted as equivalent to absolute emission reductions. TMD should therefore be combined with policies directly targeting emission control. The research findings also suggest that urban low-carbon policies should not view telecommunications services merely as a matter of network infrastructure development. From the perspectives of digital governance and carbon intensity management, potential applications include integrating telecommunications services with information exchange, production coordination, resource allocation, and energy management. These applications warrant policy attention, although their effectiveness as channels for reducing carbon intensity requires further evaluation.

The findings also provide implications for regional policy design. The heterogeneous effects across regions suggest that policies supporting telecommunications services should take account of local economic conditions, infrastructure foundations, and implementation capacity. Western cities, which exhibit a statistically significant negative association between TMD and carbon intensity, could consider improving digital application capacity and strengthening the integration between telecommunications services and low-carbon governance. The regional estimates do not, however, establish that telecommunications investment yields higher returns or greater emission reductions in western cities. At the same time, the significant spatial spillover effects under the specified geographical weight matrices support consideration of cross-city coordination in telecommunications service development and application.

Furthermore, attention should be paid to the potential energy consequences of digital expansion. Although telecommunications services may improve information efficiency and energy management, the expansion of digital infrastructure and data-intensive activities may increase electricity demand. This is a possible explanation for the digital economy interaction result, rather than a directly verified energy rebound mechanism. Therefore, future digital development strategies should focus not only on expanding telecommunications services but also on improving the energy efficiency of digital infrastructure and related activities. The fiscal decentralization interaction result also suggests that greater fiscal autonomy does not automatically strengthen the negative association between TMD and carbon intensity. Local fiscal support for telecommunications service applications could therefore incorporate assessments of energy use and emissions outcomes alongside economic and service-development objectives. This finding does not in itself justify reducing fiscal decentralization. This study has three main limitations. First, although per-capita telecommunications revenue reduces the influence of population scale, this revenue-based measure cannot fully capture other dimensions of TMD, such as service quality, competition intensity, pricing mechanisms, and operator behavior. It should therefore be interpreted primarily as a scale-oriented measure of telecommunications service-market activity. Second, city-level data cannot fully reveal the micro mechanisms through which telecommunications services influence firms' production decisions and energy practices; firm- or project-level data would enable more direct mechanism tests. Third, although the spatial analysis identifies significant spatial dependence and spillover patterns, future research can further combine policy shocks, quasi-natural experiments, and micro-level energy data to better identify the causal mechanisms underlying these spatial effects.

Author Contributions: Conceptualization, H.Z.; methodology, H.Z.; writing—original draft preparation, H.Z.; funding acquisition, H.Z.; data curation, X.S.; software, X.S.; formal analysis, X.S.; writing—review and editing, D.Z.; supervision, D.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Natural Science Basic Research Program of Shaanxi Province (No. 2025JC-YBQN-1015). The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Institutional Review Board Statement: Not applicable. This study utilized secondary data obtained from publicly available statistical sources, including the China Statistical Yearbook, the China Urban Statistical Yearbook, the China Energy Statistical Yearbook, and the National Bureau of Statistics of China. The study did not involve direct interaction with human participants, the collection of personal information, or experimental procedures involving humans or animals. Therefore, formal ethical approval from an institutional review board was not required. All data were handled in accordance with applicable research ethics standards.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the publicly cited statistical yearbooks and the official databases of the National Bureau of Statistics of China. The data are available from the corresponding author upon reasonable request.

Acknowledgments: Declaration of generative AI and AI-assisted technologies in the manuscript preparation process: In preparing this work, the authors used ChatGPT 6, an AI-powered language tool developed by OpenAI, solely to improve the clarity, readability, grammar, and academic style of the manuscript. The tool was not used to generate research ideas, design empirical strategies, collect or analyze data, interpret results, or draw conclusions. Following the use of this tool, the authors reviewed, edited, and verified all content as necessary and assume full responsibility for the final content of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Shen, Y.; Shi, X.; Zhao, Z.; Sun, Y.; Shan, Y. Measuring the low-carbon energy transition in Chinese cities. *Iscience* **2023**, *26*, 105803. [\[CrossRef\]](#)
- Ramaswami, A.; Chavez, A. What metrics best reflect the energy and carbon intensity of cities? Insights from theory and modeling of 20 US cities. *Environ. Res. Lett.* **2013**, *8*, 035011. [\[CrossRef\]](#)
- Liu, Z.; Deng, Z.; He, G.; Wang, H.; Zhang, X.; Lin, J.; Qi, Y.; Liang, X. Challenges and opportunities for carbon neutrality in China. *Nat. Rev. Earth Environ.* **2022**, *3*, 141–155. [\[CrossRef\]](#)
- Feng, Y.; Gao, Y.; Meng, X.; Shi, J.; Shi, K.; Hu, S.; Jia, F. The impacts of casual environmental regulation on carbon intensity in China: Dual mediating pathways of energy low-carbon reconstitution and industrial structure upgrading. *Environ. Res.* **2023**, *238*, 117289. [\[CrossRef\]](#)
- Ke, N.; Chen, J.; Cheng, T. The drivers of carbon intensity and emission reduction strategies in heavy industry: Evidence from nonlinear and spatial perspectives. *Ecol. Indic.* **2024**, *160*, 111764. [\[CrossRef\]](#)
- Yin, J.; Ibrahim, S.; Mohd, N.N.A.; Zhong, C.; Mao, X. Unpacking multidimensional effects of economic restructuring and technological progress on carbon emission performance: The moderating role of environmental regulation. *Sci. Rep.* **2025**, *15*, 1267. [\[CrossRef\]](#)
- Li, Y.; Xu, Y.; Wen, C. Digital pathways to sustainability: The impact of digital infrastructure in the coordinated development of environment, economy and society. *Environ. Dev. Sustain.* **2024**, *28*, 22475–22508. [\[CrossRef\]](#)
- Ma, R.; Lin, B. Digital infrastructure construction drives green economic transformation: Evidence from Chinese cities. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 460. [\[CrossRef\]](#)
- Mei, B.; Khan, A.A.; Khan, S.U.; Ali, M.A.S.; Luo, J. Variation of digital economy's effect on carbon emissions: Improving energy efficiency and structure for energy conservation and emission reduction. *Environ. Sci. Pollut. Res.* **2023**, *30*, 87300–87313. [\[CrossRef\]](#)
- Huang, J.; Chen, X.; Zhao, X. How digital technology reduces carbon emissions: From the perspective of green innovation, industry upgrading, and energy transition. *J. Knowl. Econ.* **2024**, *15*, 19294–19326. [\[CrossRef\]](#)
- Liao, K.; Liu, J. Digital infrastructure empowerment and urban carbon emissions: Evidence from China. *Telecommun. Policy* **2024**, *48*, 102764. [\[CrossRef\]](#)
- Ren, S.; Hao, Y.; Xu, L.; Wu, H.; Ba, N. Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* **2021**, *98*, 105220. [\[CrossRef\]](#)
- Zhu, C.; Guo, X.; Zou, S. Impact of information and communications technology alignment on supply chain performance in the Industry 4.0 era: Mediation effect of supply chain integration. *J. Ind. Prod. Eng.* **2022**, *39*, 505–520. [\[CrossRef\]](#)
- Wang, X.; Liu, Z.; Lei, X. How digital orientation promotes digital process innovation from the perspectives of knowledge and capability: Evidence from China. *J. Knowl. Manag.* **2025**, *29*, 259–280. [\[CrossRef\]](#)
- Xue, R.; Ong, T.S.; Di Vaio, A. Environmentally Sustainable Development: The Role of Supply Chain Digitalization in Firms' Green Productivity. *Sustain. Dev.* **2025**, *33*, 7807–7825. [\[CrossRef\]](#)
- Yang, Z.; Zhang, J. Digital infrastructure construction and the development of new-quality productive forces in enterprises. *Sci. Rep.* **2025**, *15*, 24671. [\[CrossRef\]](#)
- Wang, J.; Dong, X.; Dong, K. How does ICT agglomeration affect carbon emissions? The case of Yangtze River Delta urban agglomeration in China. *Energy Econ.* **2022**, *111*, 106107. [\[CrossRef\]](#)
- Peng, H.-R.; Ling, K.; Zhang, Y.-J. The carbon emission reduction effect of digital infrastructure development: Evidence from the broadband China policy. *J. Clean. Prod.* **2024**, *434*, 140060. [\[CrossRef\]](#)

19. Tang, K.; Yang, G. Does digital infrastructure cut carbon emissions in Chinese cities? *Sustain. Prod. Consum.* **2023**, *35*, 431–443. [[CrossRef](#)]
20. Dekeyrel, S.; Fessler, M. Digitalisation: An enabler for the clean energy transition. *J. Energy Nat. Resour. Law* **2024**, *42*, 185–209. [[CrossRef](#)]
21. Zhu, Y.; Lan, M. Digital economy and carbon rebound effect: Evidence from Chinese cities. *Energy Econ.* **2023**, *126*, 106957. [[CrossRef](#)]
22. Yilmaz, S.; Haynes, K.E.; Dinc, M. Geographic and Network Neighbors: Spillover Effects of Telecommunications Infrastructure. *J. Reg. Sci.* **2002**, *42*, 339–360. [[CrossRef](#)]
23. Cheng, Y.; Zhang, Y.; Wang, J.; Jiang, J. The impact of the urban digital economy on China's carbon intensity: Spatial spillover and mediating effect. *Resour. Conserv. Recycl.* **2023**, *189*, 106762. [[CrossRef](#)]
24. Bai, L.; Guo, T.; Xu, W.; Liu, Y.; Kuang, M.; Jiang, L. Effects of digital economy on carbon emission intensity in Chinese cities: A life-cycle theory and the application of non-linear spatial panel smooth transition threshold model. *Energy Policy* **2023**, *183*, 113792. [[CrossRef](#)]
25. Zhang, W.; Fan, H.; Zhao, Q. Seeing green: How does digital infrastructure affect carbon emission intensity? *Energy Econ.* **2023**, *127*, 107085. [[CrossRef](#)]
26. Zhang, W.; Liu, X.; Wang, D.; Zhou, J. Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* **2022**, *165*, 112927. [[CrossRef](#)]
27. Wang, J.; Dong, K.; Dong, X.; Taghizadeh-Hesary, F. Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Econ.* **2022**, *113*, 106198. [[CrossRef](#)]
28. Peng, H.-R.; Zhang, Y.-J.; Liu, J.-Y. The energy rebound effect of digital development: Evidence from 285 cities in China. *Energy* **2023**, *270*, 126837. [[CrossRef](#)]
29. He, Q.; Wei, F.; Zhang, K.; Zhong, R.; Kong, F.; Qi, Y. Fiscal decentralization, leader localization, and reduction of pollution and carbon emissions—Empirical evidence from China's fiscal “province-managing-county” reform. *J. Environ. Manag.* **2024**, *360*, 121175. [[CrossRef](#)]
30. Zhang, S.; Li, Y.; Xu, C.; Xiong, Z. Does fiscal decentralization reduce environmental degradation through mitigating resource mismatch and digital transformation? Evidence from China's resource-based cities. *Resour. Policy* **2024**, *95*, 105155. [[CrossRef](#)]
31. Yang, J.; Yu, D.; Guan, Z. Fiscal decentralization, local government behavior and environmental pollution: Evidence from “Province-Managing-County” reform in China. *J. Environ. Manag.* **2025**, *373*, 123572. [[CrossRef](#)]
32. Zhou, Y.; Lin, B. Exploring the fiscal context of electricity consumption in China: Does the Chinese-style fiscal decentralization matter? *J. Environ. Manag.* **2024**, *371*, 123116. [[CrossRef](#)]
33. Yin, S.; Bai, C.; Xiao, W. Spatial-temporal evolution of the allometric growth between economic scale and carbon emissions in China's cities and its driving mechanism. *Environ. Dev. Sustain.* **2024**, *26*, 269–302. [[CrossRef](#)]
34. Bai, T.; Qi, Y.; Li, Z.; Xu, D. Digital economy, industrial transformation and upgrading, and spatial transfer of carbon emissions: The paths for low-carbon transformation of Chinese cities. *J. Environ. Manag.* **2023**, *344*, 118528. [[CrossRef](#)]
35. Niu, X.; Ma, Z.; Ma, W.; Yang, J.; Mao, T. The spatial spillover effects and equity of carbon emissions of digital economy in China. *J. Clean. Prod.* **2024**, *434*, 139885. [[CrossRef](#)]

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