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The Impact of Digital Transformation on Electricity Consumption: The Role of Green Technology Innovation and Urbanization

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Abstract

This study examines whether policy-driven digital transformation is associated with changes in urban electricity consumption in China. Exploiting the implementation of the “Broadband China” policy as a quasi-natural experiment, we employ a Difference-in-Differences framework using panel data for 279 prefecture-level cities over the period 2006–2021. The results indicate that cities selected into the policy exhibit lower levels of electricity consumption and electricity consumption intensity following implementation. In the baseline estimates, treated cities experience an average reduction of approximately 7.1% in electricity consumption, while electricity consumption intensity declines by about 10.3%. We further explore heterogeneity and conditional effects across cities. The estimated association between digital transformation and electricity use is systematically stronger in cities with higher levels of green technology innovation and urbanization, suggesting that local innovative capacity and urban development conditions condition the electricity-related implications of digital infrastructure expansion. In addition, heterogeneity analysis shows that the estimated effects are more pronounced in cities with more advanced digital infrastructure, whereas differences in industrial structure do not yield robustly differential responses within the sample period. Overall, the findings indicate that the electricity-related effects of digital transformation are context-dependent and shaped by complementary local conditions. This study contributes to the empirical literature on digitalization and energy use by providing city-level evidence from a large-scale policy intervention and by highlighting the role of digital infrastructure, innovation activity, and urbanization in conditioning the energy implications of digital transformation.

Keywords: digital transformation; electricity consumption; green technology innovation; urbanization



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1. Introduction

Digital transformation is profoundly reshaping the global economic and social structure. According to the International Telecommunication Union (2023), global internet penetration reached 67% in 2022, accelerating structure changes across industries and regions. As one of the fastest-growing digital economies, China has actively promoted digital development through a series of policy initiatives, among which the “Broadband China” policy represents a major expansion of national digital infrastructure and a cornerstone of

China's digitalization strategy [1–3]. Meanwhile, the study of the environmental effects of digital transformation has gradually become a hot topic of widespread concern among scholars [4–10], including the impact of digital transformation on carbon emissions, energy efficiency, sustainable or high-quality development, etc.

Despite the expanding literature, the impact of digital transformation on energy consumption, particularly electricity consumption, remains a controversial issue in the academic community. Some studies find that digital transformation can reduce electricity use by improving energy efficiency and information coordination [11,12], while other studies emphasize that the expansion of digital infrastructure itself may increase electricity consumption demand through rebound effects and rising data-related energy use [13]. These mixed findings suggest that the electricity-related effects of digital transformation are unlikely to be uniform and may depend critically on local economic structures and development conditions.

In this context, green technology innovation and urbanization are frequently highlighted as potential conditioning factors shaping the relationship between digital transformation and energy consumption [14]. Rather than operating as direct causal mechanisms, these factors may moderate how effectively digital infrastructure translates into energy efficiency gains by influencing local absorptive capacity, technological adoption, and scale economies. Drawing on the Technology–Organization–Environment (TOE) framework and agglomeration economy theory as interpretive lenses, this study examines how the electricity-related effects of digital transformation vary systematically with levels of green technology innovation and urbanization. Empirically, we focus on 279 prefecture-level cities in China over the period 2006–2021 and exploit the staggered implementation of the “Broadband China” policy as a quasi-natural experiment. Using a Difference-in-Differences framework with dynamic event-study specifications, we evaluate the association between digital transformation and both electricity consumption and electricity consumption intensity, while exploring conditional and heterogeneous effects across cities.

The findings reveal that digital transformation is associated with lower levels of both electricity consumption and electricity consumption intensity. A series of robustness checks support the stability of these baseline estimates. Further analyses show that the estimated association between digital transformation and electricity use varies systematically with local conditions. In particular, higher levels of green technology innovation and urbanization are associated with stronger electricity-saving effects of digital transformation, consistent with the presence of conditional effects rather than direct causal mechanisms. In addition, heterogeneity analysis based on city characteristics suggests that the estimated reductions in electricity consumption and electricity consumption intensity are more pronounced in cities with more developed digital infrastructure. By contrast, differences in industrial structure do not generate robustly differential responses within the sample period, indicating that industrial composition alone does not systematically condition the electricity-related implications of digital transformation in this context.

Our research contributions can be summarized as follows: first, our study provides city-level causal evidence on how a major digital infrastructure policy affects electricity consumption and electricity intensity, leveraging the staggered rolling out of the “Broadband China” initiative in DID framework with dynamic event-study validation. Second, our study examines moderating effects of green technology innovation and urbanization, highlighting how local absorptive capacity and agglomeration conditions shape the magnitude of policy impacts. Third, our study documents heterogeneous effects across cities with different levels of pre-existing digital infrastructure and discusses why industrial structure differences do not yield robustly differential effects within our sample period, thereby offering more targeted implications for policy design.

2. Literature Reviews

2.1. The Environmental Effects of Digital Transformation

Research on the environmental effects of digital transformation focuses on its impact on energy consumption, particularly electricity consumption, and carbon emissions. Studies often use comprehensive indicators, such as information and communication technology indices, to measure digital transformation, demonstrating its potential to enhance environmental performance at the firm level through reduced energy intensity and improved carbon performance [15,16]. For instance, Gao et al. [17] construct an information and communication technology development index to examine the impact of digital transformation on green total factor energy efficiency in Chinese cities, finding a positive effect moderated by technological innovation and industrial structure.

In contrast, He and Chen [4] exploit the “Broadband China” policy as a quasi-natural experiment to analyze its effect on the carbon performance of listed companies in China, reporting reductions in carbon emissions and intensity. Related studies further explore the Broadband China policy’s impact on electricity consumption, energy savings, and emission reduction, identifying green technology innovation, technological progress, and industrial upgrading as key moderators [11,18]. At the same time, some research emphasizes that digital transformation may increase electricity demand due to the energy requirements associated with the expansion and operation of digital infrastructure, thereby offsetting potential efficiency gains [19].

Furthermore, the “Smart City” construction policy serves as another proxy for digital transformation policies [7]. It has been used to examine the impact of digital transformation on resource sustainability and regional carbon emission levels, with findings indicating that urban digital transformation promotes resource sustainability through technological innovation, structural change, and capital reallocation. Zhao et al. [20] assess the impact of digital transformation on China’s power system, finding improvements in the efficiency of renewable energy utilization. Liu and Wu [21] further show that higher levels of digital transformation contribute to the high-quality development of energy firms. However, evidence from firm-level and sectoral analyses remains mixed, particularly in light of the relatively recent introduction of China’s “dual-carbon” targets [14].

Importantly, international evidence suggests that the environmental effects of digital transformation are highly context-dependent. Huang et al. [5], using data from 43 economies, find that digital transformation reduces carbon intensity only when it is accompanied by sufficient domestic digital resources, technological advancement, favorable industry structure, and improvements in energy consumption patterns. This finding highlights the importance of institutional and structural conditions in shaping the environmental outcomes of digitalization.

Measurement approaches for digital transformation vary widely across studies. Comprehensive indices capture multiple dimensions of digitalization but require extensive data inputs [17], while policy-based proxies offer clearer identification strategies at the cost of finer-grained measurement. Sample selection and time horizons further influence empirical findings, with urban-focused studies often reporting stronger energy-saving effects [5]. From a theoretical perspective, endogenous growth theory posits that digital transformation, as a general-purpose technology, can reduce energy consumption through knowledge spillovers and efficiency gains [22].

At the institutional level, the European Union provides a useful contrast to the Chinese experience. The EU’s “Digital Europe” program (2021–2027) emphasizes the integration of digital technologies with energy efficiency objectives, including smart grids, data governance, and demand-side management, within a mature regulatory and market-based framework [23]. By comparison, China’s digital transformation has largely followed a

policy-driven and infrastructure-first trajectory, exemplified by the “Broadband China” initiative. This distinction implies that the energy implications of digital transformation in China may differ from those observed in the EU, as large-scale infrastructure expansion can simultaneously generate efficiency gains and additional electricity demand. Recognizing these institutional differences is therefore essential for interpreting empirical results and assessing the external validity of findings across regions.

Overall, the mixed findings in the existing literature are closely related to differences in analytical levels, sectoral coverage, outcome variables, and institutional contexts. These differences imply that the environmental and energy implications of digital transformation are inherently context-dependent, which motivates our city-level analysis focusing on electricity consumption and intensity.

2.2. *The Moderating Effect of Green Technology Innovation*

Green technology innovation is frequently highlighted as an important factor shaping the environmental and energy-related implications of digital transformation. Green technology innovation may condition how effectively digital infrastructure and digital technologies translate into improvements in energy efficiency. From this perspective, the Technology–Organization–Environment framework provides a useful interpretive lens, suggesting that local technological capabilities and absorptive capacity influence the outcomes of organizational and infrastructural change [24].

A growing body of empirical research documents a close association between green technology innovation and improved energy or environmental performance. For example, Xu et al. [15] and Gao et al. [17] find that higher levels of green technology innovation—such as the adoption of smart grid technologies—are associated with lower energy intensity through more efficient resource allocation. At the firm level, He et al. [25] demonstrate that digital transformation is positively correlated with the quantity and quality of green technology innovation in manufacturing, suggesting complementarities between digital capabilities and innovative activities.

At the region and city levels, green technology innovation is increasingly recognized as an effective means to balance economic development with environmental governance [26,27]. Xu et al. [26], using prefecture-level city data, find that green technology innovation positively affects carbon emission performance through several channels: energy consumption structure, industrial structure, urbanization, and foreign investment. Meanwhile, Yu et al. [28], using the quasi-natural experiment of the “China’s Innovative Cities” Pilot Program (ICP), show that the program significantly improves local carbon emission performance. International evidence similarly indicates that green technology innovation and renewable energy deployment are associated with lower emissions, although these relationships vary across institutional and economic contexts [29,30].

Importantly, existing studies also emphasize that the environmental benefits of green technology innovation are not uniform. Du et al. [31] examine the impact of green technology innovation on carbon emissions across 71 economies, finding that green technology innovation contributes minimally to carbon emission reductions in economies with income levels below a certain threshold, while its effect is significant in economies with higher income levels. Lin and Ma [27] show that, although green technology innovation contributes to reducing carbon emissions, the difference in impact is significant before and after 2010, with a less pronounced positive relationship before 2010. Zhang et al. [32] quantify the impact of technology progress on carbon intensity in prefecture-level cities, noting that while technology progress is vital in reducing carbon emissions, the rebound effect mitigates these positive impacts.

2.3. The Moderating Effect of Urbanization

Urbanization has long been recognized as an important factor shaping patterns of energy consumption, particularly in rapidly urbanizing countries like China. From a theoretical perspective, agglomeration economy theory suggests that urbanization optimizes energy allocation through scale effects and resource reallocation [33]. At the same time, the environmental Kuznets curve (EKC) hypothesis highlights a non-linear relationship between urbanization and energy use, whereby early stages of urban expansion may increase electricity consumption due to urban sprawl and infrastructure construction, while more advanced stages may reduce energy intensity through efficiency gains and technological upgrading [34].

Consistent with these theoretical perspectives, existing empirical evidence on the relationship between urbanization and energy consumption remains mixed. Several studies find that urbanization is associated with lower energy consumption or improved energy efficiency, often attributed to agglomeration effects, technological progress, and improved infrastructure provision [35–38]. Other studies, however, report positive associations between urbanization and energy consumption or carbon emissions, emphasizing factors such as urban spatial expansion, increased motorization, and the diffusion of energy-intensive lifestyles [39–44].

The divergence in findings suggests that urbanization does not exert a uniform effect on energy use, but instead conditions how other structural changes—such as digital transformation—translate into energy outcomes. In this sense, urbanization may influence the extent to which digital infrastructure can be effectively integrated into urban systems, including energy management, transportation, and public service provision. International experience further supports this view. For example, India’s “Digital India” policy integrates urbanization with digital transformation to enhance energy efficiency in smart cities [45], whereas China’s “Broadband China” program prioritizes large-scale digital infrastructure expansion, reflecting a more infrastructure-led and policy-driven approach.

In summary, the literature indicates that urbanization is best understood as a contextual factor that shapes the electricity-related implications of digital transformation, rather than as a direct causal mechanism. This perspective motivates our empirical focus on the moderating role of urbanization in the relationship between digital transformation and electricity consumption, allowing for heterogeneous effects across cities at different stages of urban development.

3. Model Specification and Data

3.1. Model Specification

To assess the impact of digital transformation on electricity consumption and electricity consumption intensity, we employ the following Difference-in-Differences (DID) regression models:

$$\ln(EC_{it}) = \beta_0 + \beta_1 DT_{it} + X'_{it}\gamma + \mu_i + \varphi_t + \theta_{rt} + \varepsilon_{it} \quad (1)$$

$$\ln(EI_{it}) = \beta_0 + \beta_1 DT_{it} + X'_{it}\gamma + \mu_i + \varphi_t + \theta_{rt} + \varepsilon_{it} \quad (2)$$

where “ $\ln(EC_{it})$ ” represents the logarithm of electricity consumption for city i in year t , the treatment variable “ DT_{it} ” takes the value of one if city i in year t was designated as a “Broadband China” pilot city, and zero otherwise. “ $\ln(EI_{it})$ ” denotes the logarithm of electricity consumption intensity of city i in year t . The vector “ X'_{it} ” includes a series of control variables. The terms μ_i , φ_t , and θ_{rt} account for the fixed effect of city-level, period-level, and region-by-year, respectively. And “ ε_{it} ” is the error term. All regressions include city fixed effects and year fixed effects to control for time-invariant city characteristics and

common shocks. In addition, we include region-by-year fixed effects to absorb time-varying regional shocks, such as region-specific economic cycles, energy policy adjustments, or infrastructure investment trends, which may jointly affect electricity consumption and policy implementation.

In all baseline and extended specifications, standard errors are clustered at the province level. The clustering choice accounts for potential spatial correlation and common shocks shared by cities within the same province, such as regionally coordinated infrastructure investment, energy regulation, and macroeconomic policy adjustments. Importantly, although the regressions include city fixed effects, year fixed effects, and region-by-year fixed effects, residual correlation in the error terms may still persist within provinces over time. Clustering at the province level therefore provides a conservative inference strategy by allowing for arbitrary correlation of shocks across cities within the same province. The sample includes 30 provinces, which satisfies conventional requirements for cluster-robust inference. As such, province-level clustering is appropriate and consistent with standard practice in empirical studies using Chinese city-level panel data.

To examine the dynamic effects of digital transformation on urban electricity consumption and to assess the validity of the parallel-trends assumption, we estimate an event-study specification. Specifically, we interact the treatment indicator with a series of event-time dummies that capture the number of years relative to the first implementation of the “Broadband China” policy in each city.

The event-time indicators include multiple leads and lags relative to the policy implementation year. The year immediately preceding the policy implementation ($t = -1$) is normalized as the omitted baseline period, following standard practice in event-study designs to mitigate concerns about potential anticipatory responses. To preserve sample size, event times beyond the maximum window are grouped into endpoint categories. The estimated coefficients on the lead terms ($t \leq -2$) are small and statistically insignificant, indicating no systematic differences in pre-policy trends in urban electricity consumption between pilot and non-pilot cities. This finding supports the parallel-trends assumption underlying the DID design.

In contrast, the lag coefficients ($t \geq 0$) capture the dynamic post-treatment effects of digital transformation. The results show that the estimated impact on urban electricity consumption is not immediate but becomes statistically discernible approximately two years after policy implementation and strengthens thereafter. Figure 1 plots the event-study coefficients with 95% confidence intervals, where the vertical line denotes the policy implementation year.

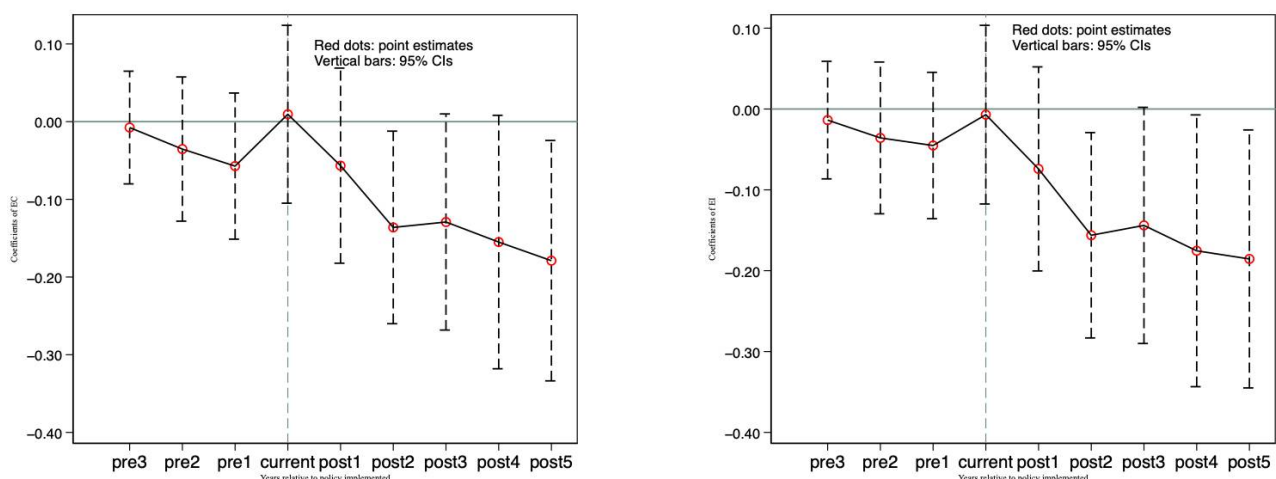


Figure 1. Parallel trend test for the impact of electricity consumption and electricity consumption intensity with their dynamic effects.

3.2. Data

Our study constructs a panel dataset of 279 prefecture-level cities in China from 2006 to 2021 to evaluate the impact of digital transformation on electricity consumption and electricity consumption intensity. The dataset comprises 147 cities designated as “Broadband China” pilot cities, forming the treatment group, and 132 non-pilot cities, constituting the control group. The “Broadband China” policy, officially launched in 2013, was implemented in a staggered manner across three pilot batches, with cities entering the program in 2014, 2015, and 2016, respectively. This staggered rollout provides a quasi-natural experiment for identifying the causal effects of digital transformation [46,47]. The spatial distribution and batch assignment of pilot and non-pilot cities are illustrated in Figure 2. The period begins in 2006 to ensure sufficient pre-policy observations for the parallel trend assumption in the Difference-in-Differences model.

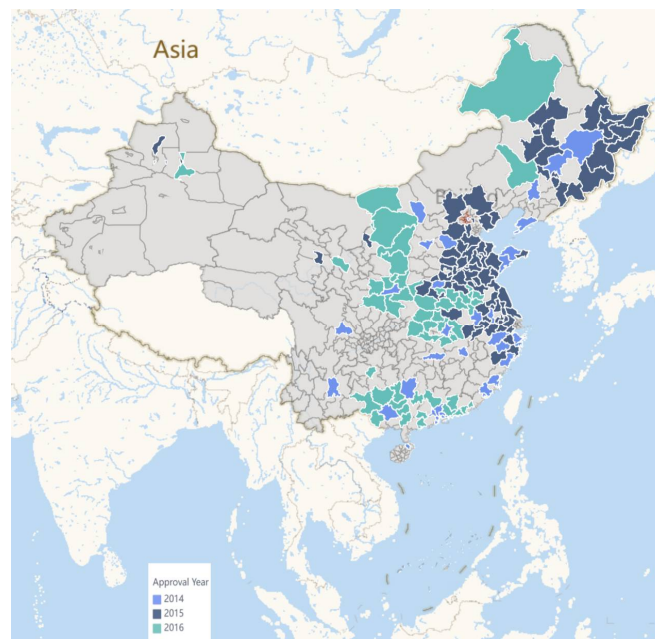


Figure 2. The map of “Broadband China” pilot cities. (Note: The orange five-pointed star marks Beijing, the capital of China.)

As previously mentioned, the proxy variable for electricity consumption is total electricity consumption, and electricity consumption intensity is measured as total electricity consumption divided by the cities’ GDP [11]. Electricity consumption intensity is commonly employed to assess the efficiency of electricity use, with higher values indicating lower efficiency [11,48]. The “ X_{it}^1 ” vector includes various control variables to capture differences in economic characteristics between the treatment and control groups. These variables encompass population size, per capita gross regional product, government spending, industrial structure, retail sales, and population density.

The “Broadband China” pilot city list and designation years were sourced from the Ministry of Industry and Information Technology (<https://wap.miit.gov.cn>) and verified with official policy documents (Ministry of Industry and Information Technology, 2014–2016). Electricity consumption data were obtained from the China Energy Statistical Yearbook and China City Statistical Yearbook. Patent data for green technology innovation were extracted from the National Intellectual Property Administration (<http://www.cnipa.gov.cn>), using green technology patents per the World Intellectual Property Organization’s green inventory. Economic and demographic data (population

size, gross domestic product, industrial structure, population density, retail sales) were compiled from the China Statistical Yearbook and China City Statistical Yearbook.

Thus, data exclusions resulted from missing values, primarily in electricity consumption, electricity consumption intensity, and control variables. The variation in observation counts reflects differences in data availability across sources. Importantly, an examination of the missing patterns about electricity consumption intensity indicates that these missing observations are largely driven by reporting gaps in electricity and GDP statistics rather than being systematically concentrated in specific cities, regions, or policy groups, alleviating concerns about potential sample selection bias. The missing patent data were imputed as zero for cities with no recorded green technology patents, assuming negligible innovation activity. Continuous variables were winsorized at the 1st and 99th percentiles to address outliers, ensuring robust statistical analysis. Monetary variables were adjusted to 2006 constant prices using the consumer price index from the China Statistical Yearbook. The descriptive statistics of the variables are summarized in Table 1.

Table 1. Descriptive statistics.

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
electricity consumption	Log (total electricity consumption (unit: ten thousand kWh))	4158	13.331	1.268	8.994	16.678
electricity consumption intensity	Log (total electricity consumption (unit: ten thousand kWh)/GDP (unit: yuan))	3886	6.122	0.757	3.567	9.571
digital transformation	The city is selected to participate in Broadband China policy would take values 1; Otherwise: 0.	4447	0.230	0.421	0	1
pop	Log (population (unit: ten thousand persons))	4140	5.895	0.681	2.868	8.136
pgdp	Log (GDP per capita (unit: yuan))	4131	10.471	0.717	7.926	13.056
ind	the ratio of secondary industrial output to GDP	4138	0.469	0.111	0.117	0.856
popden	Population (unit: ten thousand persons)/Administrative area (unit: km ²)	4140	0.044	0.038	0	0.862
retail	Total retail sales of consumers goods (unit: ten thousand yuan)/GDP (unit: ten thousand yuan)	4129	0.366	0.104	0	1.013

4. Empirical Results

4.1. Baseline Results

Table 2 reports the baseline Difference-in-Differences estimates of the impact of digital transformation on urban electricity consumption. Columns (1) and (2) indicate that the coefficient on digital transformation is negative and statistically significant at the 10% level, both in specifications without control variables and in those including a full set of covariates. Quantitatively, the estimation results suggest that the implementation of the “Broadband China” policy is associated with an average reduction of approximately 7.1% in total electricity consumption in pilot cities relative to non-pilot cities. The magnitude of the estimated effect remains stable across alternative specifications, suggesting that the result is not driven by the inclusion or exclusion of observable city-level characteristics.

Although the statistical significance of the coefficient is at the 10% level, the estimated effect is economically meaningful in size and comparable to magnitudes reported in related studies examining the energy implications of digital technologies [49,50]. In line with recent empirical evidence, this pattern is consistent with the notion that improvements in

digital infrastructure may be associated with reductions in aggregate electricity demand, potentially through efficiency-enhancing adjustments in production processes, information flows, and energy management. At the same time, given the relatively modest level of statistical significance, the estimated effect is interpreted as suggestive rather than definitive evidence, and its broader implications are discussed with appropriate caution in the Discussion section.

Columns (3) and (4) present the corresponding estimates using electricity consumption intensity as the dependent variable. Consistent with the results for aggregate electricity consumption, the coefficient on digital transformation remains negative and statistically significant, indicating a decline in electricity consumption per unit of GDP following policy implementation. Compared with the consumption regressions, the intensity-based estimates suggest that the association between digital transformation and electricity use is more pronounced when electricity demand is evaluated relative to economic output, rather than in absolute terms. This finding implies that digital transformation is more closely related to improvements in electricity-use efficiency than to proportional reductions in total electricity consumption alone.

Notably, several control variables—including population size and per capita GDP—exhibit different coefficient patterns across the consumption and intensity specifications. This reflects the fact that these variables capture distinct economic margins depending on the dependent variable. When total electricity consumption is considered, population and income primarily proxy for scale effects in electricity demand. In contrast, when electricity consumption intensity is used, these variables capture differences in electricity use per unit of economic output, thereby reflecting efficiency, density, and agglomeration-related effects. Accordingly, changes in the magnitude or significance of these coefficients across specifications are expected and do not indicate instability in the estimated policy effect.

Table 2. Baseline results: Digital transformation and urban electricity use.

	(1) Electricity Consumption	(2)	(3) Electricity Consumption Intensity	(4)
digital transformation	−0.112 ** (0.046)	−0.071 * (0.040)	−0.110 * (0.059)	−0.103 ** (0.044)
pop		−0.070 (0.300)		−0.758 *** (0.255)
pgdp		0.390 ** (0.151)		−0.230 (0.174)
ind		0.599 (0.399)		0.170 (0.441)
popden		−1.049 * (0.574)		−1.060 ** (0.502)
retail		0.166 (0.220)		0.425 * (0.237)
cons	12.489 *** (0.039)	8.796 *** (2.512)	6.232 *** (0.085)	12.679 *** (2.236)
Year Fixed	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
Region * Year Fixed	Yes	Yes	Yes	Yes
N	4158	3654	3886	3654
R-sq	0.765	0.763	0.451	0.460

Notes: Robust standard error is reported, and clustered at the province level. *, **, *** represent that the significant level below 10%, 5%, 1%, respectively.

In conclusion, the baseline results provide coherent evidence that digital transformation, as proxied by the “Broadband China” policy, is associated with lower levels of both aggregate electricity consumption and electricity consumption intensity in pilot cities. While these associations are broadly consistent with existing empirical findings on the energy-related effects of digital technologies [5,11], we refrain from drawing strong causal or mechanistic conclusions at this stage. Instead, these baseline estimates serve as a foundation for the subsequent analysis, in which we further explore dynamic patterns, robustness, heterogeneity, and potential channels through which digital transformation may be linked to urban electricity use.

4.2. Robustness Test

(1) Parallel Trend Test

To ensure the robustness of our baseline estimation results, it is crucial to verify that the Difference-in-Differences specification satisfies the parallel trend assumption [51,52]. The assumption is fundamental to validating causal inferences, as it ensures that any observed changes in urban electricity consumption are attributable to the “Broadband Chin” policy rather than pre-existing differences in trends between the treatment and control groups.

While the baseline estimates provide valuable insights into the average effect of the “Broadband Chin” policy on urban electricity consumption, they do not capture the policy’s dynamic impact over time. To address this limitation, we employed an event study approach [53,54]. The method allows us not only to test the parallel trend assumption but also to examine the dynamic effects of the policy on urban electricity consumption.

Figure 2 reports the event-study estimates results. The year immediately preceding policy implementation ($t = -1$) is normalized as the omitted baseline period, following standard practice to mitigate concerns about potential anticipatory responses. The estimated coefficients on the lead terms ($t \leq 2$) are small in magnitude and statistically insignificant, and their 95% confidence intervals, depicted by vertical bars, all include zero. This indicates no systematic differences in pre-policy trends between pilot and non-pilot cities and supports the parallel-trends assumption underlying the DID framework. In contrast, the post-treatment coefficients suggest that the policy effect is not immediate. The impact of the “Broadband China” policy on electricity consumption becomes statistically discernible approximately two years after implementation and continues to strengthen thereafter, consistent with a gradual adjustment process associated with infrastructure deployment and technology adoption. For clarity, Table 3 summarizes the definition and windowing of the event-time dummy variables used in the event-study specification.

Table 3. Definition of event-time indicators in the event-study specification.

Event-Time Indicator	Definition
pre_3 and earlier	Years ≤ 3 before policy implementation (binned)
pre_2	Two years before implementation ($t = -2$)
pre_1	One year before implementation ($t = -1$, omitted baseline)
current	Year of policy implementation ($t = 0$)
post_1	One year after implementation ($t = +1$)
post_2	Two years after implementation ($t = +2$)
post_3 and later	Years ≥ 3 after implementation (binned)

(2) PSM-DID Method

To further strengthen our findings’ reliability and mitigate potential biases resulted from sample selection [55], we applied the Propensity Score Matching (PSM) method to re-estimate the baseline DID model. This approach involved calculating propensity scores

for each city using a set of covariates and then matching pilot cities with control cities that exhibited similar characteristics. The matched sample was subsequently used for the benchmark regression analysis [56]. The PSM-DID estimation results, as reported in Table 4, are consistent with the baseline findings, though the estimated policy effect is slightly smaller. This slight reduction suggests that any potential overestimation due to selection bias is minimal. Overall, our analysis robustly supports the conclusion that the “Broadband Chin” policy could significantly reduce electricity consumption and improves electricity consumption intensity in pilot cities, reinforcing the broader narrative of digital transformation contributing to energy efficiency and sustainability.

Table 4. PSM-DID estimation results.

	(1) Electricity Consumption	(2) Electricity Consumption	(3) Electricity Consumption Intensity	(4) Electricity Consumption Intensity
digital transformation	−0.097 ** (0.039)	−0.066 * (0.038)	−0.098 * (0.053)	−0.096 ** (0.043)
pop		−0.151 (0.297)		−0.838 *** (0.253)
pgdp		0.285 * (0.147)		−0.330 * (0.181)
ind		0.857 * (0.439)		0.427 (0.488)
popden		−1.145 * (0.560)		−1.169 ** (0.491)
retail		0.129 (0.215)		0.379 (0.233)
cons	12.409 *** (0.030)	10.176 *** (2.393)	6.188 *** (0.035)	13.987 *** (2.204)
Year Fixed	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
Region * Year Fixed	Yes	Yes	Yes	Yes
N	3559	3559	3559	3559
R-sq	0.756	0.764	0.462	0.479

Notes: This table reports PSM-DID estimation results. Robust standard errors are clustered at the province level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Although the PSM-DID approach helps mitigate sample selection bias by improving the comparability between treated and control cities, it cannot fully eliminate potential estimation bias arising from unobserved time-varying confounders [57,58]. To further assess whether such unobserved factors may drive our baseline results, we conduct a placebo test based on the non-parametric permutation procedure proposed by La Ferrara et al. [59].

Specifically, we randomly draw 147 prefecture-level cities from the full sample—matching the actual number of “Broadband China” pilot cities—to construct a placebo treatment group, while the remaining cities form a placebo control group. For each placebo-treated city, a pseudo-policy implementation year is randomly assigned from the period 2006–2021. We then re-estimate the baseline DID specification using this artificially re-assigned treatment status and timing. This randomization-and-estimation procedure is repeated 1000 times, generating an empirical null distribution of placebo estimates for both electricity consumption and electricity consumption intensity.

Figure 3 presents the kernel density distributions of the 1000 placebo coefficients for each outcome, with the standard normal density overlaid for reference. In both cases, the placebo estimates are symmetrically distributed around zero, with sample means close to zero and no evidence of systematic skewness or location shifts. This pattern

indicates that, under random assignment of treatment status and timing, the estimator does not mechanically generate spurious negative effects. Importantly, the baseline DID estimates (-0.071 for electricity consumption and -0.103 for electricity consumption intensity) lie in the extreme left tails of their respective placebo distributions. Virtually none of the 1000 placebo estimates attain magnitudes as large as the baseline coefficients in the negative direction, implying that the corresponding two-sided placebo p -values are close to zero. The result suggests that the observed baseline estimates are highly unlikely to arise purely from random assignment or unobserved confounders that are orthogonal to the policy intervention.

The placebo test provides supportive evidence that the negative association between the “Broadband China” policy and urban electricity use is not driven by spurious correlations or estimation artifacts. While the test cannot rule out all forms of endogeneity, it strengthens confidence in the internal validity of the DID estimates and supports the interpretation that the observed effects reflect systematic policy-related differences rather than random variation.

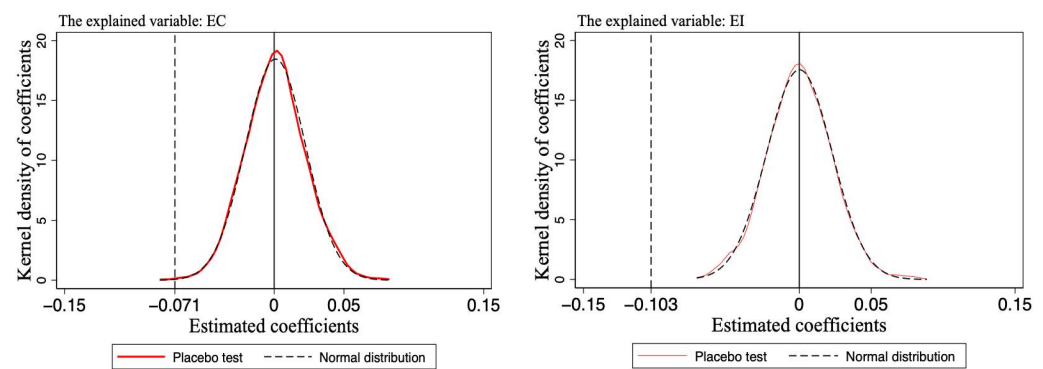


Figure 3. Distribution of estimates in placebo test.

4.3. The Moderating Effects of Green Technology Innovation and Urbanization

The extensive literature review highlights the critical roles that green technology innovation and urbanization play as moderating variables in assessing the environmental impact of digital transformation. In our study, green technology innovation is proxied by the logarithm of per capita green patent applications, capturing cross-city differences in the intensity of environmentally oriented innovative activity, while urbanization is measured by the city-level urbanization rate, reflecting the degree of population concentration and urban development. These moderators are therefore interpreted as indicators of local absorptive capacity and urban context rather than direct policy instruments.

To examine whether the association between digital transformation and electricity use varies systematically with these local characteristics, we incorporate interaction terms between the “Broadband China” policy dummy and each moderator into the baseline model. The results are presented in Table 5. Columns (1) and (3) illustrate that the interaction terms between digital transformation and green technology innovation are negative and statistically significant at the 1% level for both electricity consumption and electricity consumption intensity. These results indicate that the association between digital transformation and electricity use becomes increasingly negative as the level of green technology innovation rises. In other words, while the estimated main effect of digital transformation reflects the conditional effect evaluated at low levels of green innovation, higher green innovation activity systematically strengthens the electricity-saving association of digital transformation. The finding is consistent with previous research from Wang et al. [60]; Ren and Li [61].

A similar but quantitatively stronger pattern is observed for urbanization. Columns (2) and (4) in Table 5 focus on the interaction between urbanization and digital transformation. The results indicate that the interaction terms between digital transformation and urbanization are negative and highly significant across both outcome variables. These estimates suggest that the electricity-related effects of digital transformation are substantially more pronounced in more urbanized cities. Importantly, the positive coefficients on the digital transformation main effect in these specifications should be interpreted in conjunction with the interaction terms, as they represent the conditional effect evaluated at low levels of urbanization rather than the average policy effect.

Although the interaction coefficients—particularly those involving urbanization—appear large in magnitude, their interpretation should be considered in light of variable scaling. Urbanization is measured as a proportion, such that the reported coefficients correspond to changes over the full [0, 1] range. When evaluated at economically plausible changes, such as a one-standard-deviation increase in urbanization or green technology innovation, the implied marginal effects on electricity consumption are moderate and consistent with observed cross-city variation.

Table 5. The estimation results of moderating effects.

	(1) Electricity Consumption	(2) Electricity Consumption	(3) Electricity Consumption Intensity	(4) Electricity Consumption Intensity
digital transformation	−0.078 * (0.043)	0.803 *** (0.160)	−0.113 ** (0.048)	0.927 *** (0.16836)
Green Technology Innovation	0.085 *** (0.027)		0.086 *** (0.028)	
digital transformation * Green Technology Innovation	−0.113 *** (0.023)		−0.141 *** (0.023)	
Urbanization		0.392 ** (0.148)		0.375 ** (0.157)
digital transformation * Urbanization		−1.421 *** (0.246)		−1.675 *** (0.255)
pop	0.091 (0.259)	0.126 (0.254)	0.116 (0.398)	−0.535 ** (0.223)
pgdp	0.323 ** (0.147)	0.262 (0.163)	−0.892 ** (0.344)	−0.377 * (0.187)
ind	0.547 (0.364)	0.630 (0.380)	0.265 (0.222)	0.206 (0.415)
popden	−0.905 ** (0.439)	−0.817 ** (0.363)	−0.561 ** (0.209)	−0.795 *** (0.262)
retail	0.042 (0.210)	−0.019 (0.212)	−0.310 * (0.173)	0.209 (0.221)
cons	8.751 *** (2.189)	8.721 *** (2.395)	12.542 *** (1.957)	12.636 *** (2.318)
Year Fixed	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
Region * Year Fixed	Yes	Yes	Yes	Yes
N	3631	3654	3631	3654
R-sq	0.769	0.771	0.482	0.485

Notes: This table presents the regression results of moderating effects. Robust standard errors are clustered at the province level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Overall, these findings highlight that the relationship between digital transformation and electricity consumption is highly heterogeneous across local contexts. Cities with higher levels of green technology innovation and urbanization tend to exhibit stronger electricity-

saving associations following digital infrastructure expansion. These interaction effects capture systematic moderation rather than direct causal mechanisms and highlight the importance of local conditions in shaping the energy implications of digital transformation.

4.4. Heterogeneity Analysis

Table 6 presents the heterogeneity analysis examining whether the effects of digital transformation vary across cities with different levels of digital infrastructure and industrial structure. The sample is divided into subgroups based on above- and below-median values of these city-level characteristics. Digital infrastructure is measured by the number of Internet broadband access users per 10,000 registered residents, capturing differences in population-adjusted broadband penetration and basic digital connectivity across cities. Industrial structure is proxied by the ratio of secondary to tertiary industry value added, reflecting the relative dominance of industrial versus service-oriented economic activities.

The results, which are shown in columns (1) to (4) of Table 6, indicate that the negative association between digital transformation and both electricity consumption and electricity consumption intensity is larger in magnitude and statistically stronger in cities with more developed digital infrastructure. In contrast, the corresponding coefficients for cities with relatively lower broadband penetration are smaller and, in some specifications, statistically insignificant. These patterns suggest that the electricity-related effects of the “Broadband China” policy are more pronounced in urban environments where basic digital connectivity is already relatively well established. It is in line with the study from Sun [62]. The finding suggests that advanced digital infrastructure plays a critical role in amplifying the energy-saving effects of digital transformation initiatives [63,64].

Table 6. Heterogeneity analysis results.

	(1) Electricity Consumption	(2) Electricity Consumption	(3) Electricity Consumption Intensity	(4) Electricity Consumption Intensity	(5) Electricity Consumption	(6) Electricity Consumption	(7) Electricity Consumption Intensity	(8) Electricity Consumption Intensity
digital transformation	−0.165 *** (0.044)	0.030 (0.056)	−0.188 *** (0.050)	0.012 (0.057)	−0.100 (0.070)	−0.043 (0.051)	−0.140 * (0.071)	−0.068 (0.056)
pop	−0.273 (0.400)	0.657 (0.441)	−0.750 ** (0.351)	−0.164 (0.461)	−0.362 (0.339)	0.284 (0.405)	−1.031 *** (0.292)	−0.417 (0.375)
pgdp	0.376 *** (0.120)	0.209 (0.274)	−0.125 (0.181)	−0.580 ** (0.272)	0.539 *** (0.161)	0.298 (0.189)	−0.043 (0.179)	−0.338 (0.219)
ind	−0.038 (0.897)	1.117 ** (0.478)	−0.502 (0.982)	0.851 * (0.479)	0.213 (0.660)	0.668 (0.451)	−0.100 (0.666)	0.187 (0.508)
popden	−0.688 ** (0.313)	0.268 (2.059)	−0.685 ** (0.283)	0.973 (2.390)	−0.586 *** (0.213)	−6.183 (5.239)	−0.602 *** (0.166)	−5.361 (5.103)
retail	0.604 ** (0.291)	−0.304 (0.335)	0.985 *** (0.320)	−0.197 (0.338)	0.851 *** (0.295)	−0.365 (0.259)	1.139 *** (0.317)	−0.135 (0.279)
cons	11.032 *** (2.618)	5.634 (3.993)	12.125 *** (1.970)	11.955 *** (4.072)	9.250 *** (2.828)	7.813 ** (3.011)	12.485 *** (2.707)	11.979 *** (2.861)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1062	2592	1062	2592	1278	2376	1278	2376
R-sq	0.766	0.788	0.414	0.535	0.755	0.777	0.473	0.481

Notes: This table displays the results of heterogeneity analysis. Robust standard errors are clustered at the province level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

On the other hand, the analysis results, which are shown in columns (5) to (8) of Table 6, report the corresponding results for cities grouped by industrial structure. Unlike digital infrastructure, the estimated effects of digital transformation do not display a clear or consistent pattern across cities with different industrial compositions. While some coefficients remain negative, they are generally weaker and statistically less robust. This indicates that, within the sample period considered, differences in industrial structure do not systematically condition the association between digital transformation and urban electricity use.

The heterogeneity analysis highlights the context-dependent nature of digital transformation policies. While digital infrastructure appears to play a salient role in shaping the observed electricity-related effects, industrial structure exhibits a more limited and heterogeneous influence. These results should be interpreted as evidence of differential associations across city types rather than as confirmation of specific causal mechanisms.

5. Discussion, Policy Implications, and Limitations

5.1. Discussion

Our study examines the relationship between policy-driven digital transformation and urban electricity use in China by exploiting the “Broadband China” policy as a quasi-natural experiment. The empirical results indicate that digital transformation is associated with reductions in both aggregate electricity consumption and electricity consumption intensity. Importantly, the dynamic event-study evidence suggests that these effects do not materialize immediately after policy implementation but emerge gradually over time, becoming statistically detectable several years after implementation. As such, the estimated effects primarily reflect medium-term adjustments associated with the diffusion and effective utilization of digital infrastructure rather than short-run shocks or long-run equilibrium outcomes. Moreover, the estimated effects are generally statistically significant at the 10% level and therefore warrant cautious interpretation. This section situates the findings within the existing literature, interprets the observed heterogeneity across cities, and clarifies the implications of statistically modest but economically meaningful estimates.

Overall, the results are broadly consistent with a strand of the literature documenting energy-saving or efficiency-enhancing effects of digital technologies and digital infrastructure [6,11,49]. These studies emphasize that digital transformation can improve information flows, reduce coordination costs, and facilitate more efficient energy management. At the same time, our findings also resonate with studies reporting weak, neutral, or even positive effects of digitalization on energy consumption, often attributed to rebound effects or the electricity demand associated with the expansion of digital infrastructure itself [13,19]. The relatively modest statistical significance observed in our estimates suggests that these opposing forces may coexist, with the net effect depending on local structural and infrastructural conditions.

Both the moderating effect analysis and the heterogeneity analysis point to substantial cross-city variation in the electricity-related implications of digital transformation. In particular, the heterogeneity results indicate that the electricity-saving associations of digital transformation are more pronounced in cities with higher levels of digital infrastructure, while being weaker or statistically insignificant in cities with less developed digital foundations. This pattern is consistent with the notion of complementarity between digital infrastructure and local absorptive capacity. Cities with more advanced digital infrastructure are better positioned to integrate digital technologies into production processes, public governance, and energy management systems, thereby translating digital transformation into observable efficiency gains. In contrast, in cities where basic digital

connectivity remains underdeveloped, potential benefits may be constrained by adjustment costs, institutional frictions, or limited capacity to effectively utilize digital technologies.

By contrast, we find limited and unstable heterogeneity with respect to industrial structure. The absence of a clear pattern suggests that differences in industrial composition do not systematically condition the relationship between digital transformation and electricity use within the sample period. One possible interpretation is that the presence of energy-intensive industries dampens the observable electricity-saving associations of digital transformation. While digital technologies may improve efficiency at the margin, these gains can be offset by the scale and rigidity of electricity demand in manufacturing-dominated cities. This interpretation is in line with prior studies indicating that the environmental benefits of digitalization often depend on deeper structural transformation and sustained industrial upgrading.

Several key coefficients in the baseline, moderating, and heterogeneity analyses are statistically significant at the 10% level. Following recent methodological guidance, we interpret these estimates as suggestive rather than definitive evidence. While the estimated magnitudes are economically meaningful and robust across alternative specifications, they should not be interpreted as conclusive proof of strong causal effects. Instead, the results point to systematic and theoretically consistent associations that merit further investigation using alternative identification strategies or longer time horizons.

5.2. Policy Implications

Despite the above caveats, the findings offer several policy-relevant insights for the design and implementation of digital transformation strategies in the context of energy conservation and sustainable development.

First, the results suggest that investments in digital infrastructure are more likely to generate electricity-saving benefits in cities that already possess relatively strong digital foundations. Policymakers may therefore consider a differentiated approach to digital infrastructure investment. In digitally advanced cities, further upgrading of broadband networks and digital platforms may enhance efficiency gains in energy use. In less developed cities, complementary investments in digital readiness—such as human capital development, institutional capacity building, and basic digital services—may be necessary before substantial energy-related benefits can be realized.

Second, the stronger associations observed in more urbanized cities indicate that digital transformation policies may be more effective when aligned with broader urbanization and smart city strategies. Integrating digital infrastructure development with urban planning, intelligent energy management systems, and public service digitization could help amplify potential efficiency gains associated with digitalization.

Third, the limited role of industrial structure heterogeneity highlights the importance of coordinating digital transformation policies with industrial and energy policies. In cities with a high concentration of energy-intensive industries, digital technologies alone may be insufficient to generate large reductions in electricity consumption. In such contexts, digital transformation should be complemented by policies promoting industrial upgrading, stricter energy efficiency standards, and the adoption of cleaner production technologies.

Finally, policymakers should remain attentive to potential rebound effects and distributional consequences associated with digital infrastructure expansion. While digital transformation may improve efficiency, it can also stimulate new forms of electricity demand. Balancing efficiency improvements with demand-side management will be critical to ensuring that digitalization contributes to long-term energy sustainability.

5.3. Limitations and Future Research

Our study has several limitations that should be acknowledged. First, the “Broadband China” policy indicator captures a specific, policy-driven dimension of digital transformation and may not fully reflect its multidimensional nature, such as differences in usage intensity, quality of digital services, or the diffusion of complementary digital applications.

Second, although the quasi-natural experiment design and a series of robustness checks mitigate concerns about endogeneity, unobserved factors correlated with pilot city selection cannot be entirely ruled out. Future research could employ alternative identification strategies, such as instrumental variable approaches or natural experiments in other institutional settings, to further strengthen causal inference.

Third, the analysis is confined to the period up to 2021. As digital technologies continue to evolve rapidly, the longer-term energy implications of more recent developments—such as advanced artificial intelligence applications or next-generation communication technologies—remain uncertain. Extending the time horizon and incorporating richer measures of digital transformation would be a valuable direction for future research.

Finally, the focus on Chinese prefecture-level cities may limit the generalizability of the findings to countries with different institutional environments or digitalization pathways. Comparative studies across countries or regions could provide additional insights into how institutional context shapes the energy impacts of digital transformation.

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References

1. Liu, Y.; Fan, Y.; Wang, Y.; Huang, J.; Xun, H. City innovation ability and internet infrastructure development: Evidence from the “Broadband China” policy. *Bull. Econ. Res.* **2024**, *76*, 121–146. [\[CrossRef\]](#)
2. Jiao, S.; Sun, Q. Digital economic development and its impact on economic growth in China: Research based on the perspective of sustainability. *Sustainability* **2021**, *13*, 10245. [\[CrossRef\]](#)
3. Xie, H.; Yang, S.; Liu, Y.; Li, M. Can Internet construction promote enterprise upgrading? *Econ. Res. Ekon. Istraž.* **2023**, *36*, 1933–1959. [\[CrossRef\]](#)
4. He, L.-Y.; Chen, K.-X. Digital transformation and carbon performance: Evidence from firm-level data. *Environ. Dev. Sustain.* **2023**, *27*, 23639–23664. [\[CrossRef\]](#)
5. Huang, C.; Lin, B. Promoting decarbonization in the power sector: How important is digital transformation? *Energy Policy* **2023**, *182*, 113735. [\[CrossRef\]](#)

6. Huang, Y.; Hu, M.; Xu, J.; Jin, Z. Digital transformation and carbon intensity reduction in transportation industry: Empirical evidence from a global perspective. *J. Environ. Manag.* **2023**, *344*, 118541. [CrossRef] [PubMed]
7. Jiang, Z.; Zhang, X.; Zhao, Y.; Li, C.; Wang, Z. The impact of urban digital transformation on resource sustainability: Evidence from a quasi-natural experiment in China. *Resour. Policy* **2023**, *85*, 103784. [CrossRef]
8. Kunkel, S.; Matthess, M. Digital transformation and environmental sustainability in industry: Putting expectations in Asian and African policies into perspective. *Environ. Sci. Policy* **2020**, *112*, 318–329. [CrossRef]
9. 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]
10. Feroz, A.K.; Zo, H.; Chiravuri, A. Digital transformation and environmental sustainability: A review and research agenda. *Sustainability* **2021**, *13*, 1530. [CrossRef]
11. Wang, Q.; Hu, A.; Tian, Z. Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. *Energy Econ.* **2022**, *115*, 106346. [CrossRef]
12. Wu, H.; Hao, Y.; Ren, S.; Yang, X.; Xie, G. Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* **2021**, *153*, 112247. [CrossRef]
13. Lin, B.; Huang, C. How will promoting the digital economy affect electricity intensity? *Energy Policy* **2023**, *173*, 113341. [CrossRef]
14. Li, Z.; Shi, Y.; Wojewodzki, M.; Wei, Y.; Guo, M. The impact of new-type urbanization policy on urban green total factor productivity: New evidence from China. *Sustainability* **2024**, *16*, 5220. [CrossRef]
15. Xu, Q.; Zhong, M.; Cao, M. Does digital investment affect carbon efficiency? Spatial effect and mechanism discussion. *Sci. Total Environ.* **2022**, *827*, 154321. [CrossRef]
16. Sheng, H.; Feng, T.; Liu, L. The influence of digital transformation on low-carbon operations management practices and performance: Does CEO ambivalence matter? *Int. J. Prod. Res.* **2023**, *61*, 6215–6229. [CrossRef]
17. Gao, D.; Li, G.; Yu, J. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* **2022**, *247*, 123395. [CrossRef]
18. Wu, H.; Xue, Y.; Hao, Y.; Ren, S. How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ.* **2021**, *103*, 105577. [CrossRef]
19. 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]
20. Zhao, Y.; Xia, S.; Zhang, J.; Hu, Y.; Wu, M. Effect of the digital transformation of power system on renewable energy utilization in China. *IEEE Access* **2021**, *9*, 96201–96209. [CrossRef]
21. Liu, P.; Wu, J. Can digital transformation enable the energy enterprises to achieve high-quality development? An empirical analysis from China. *Energy Rep.* **2023**, *10*, 1182–1197. [CrossRef]
22. Romer, P.M. Endogenous technological change. *J. Political Econ.* **1990**, *98*, S71–S102. [CrossRef]
23. European Commission. Digital Europe Programme 2021–2027. 2023. Available online: <https://digital-strategy.ec.europa.eu> (accessed on 26 September 2025).
24. Tornatzky, L.G.; Fleischer, M. *The Processes of Technological Innovation*; Lexington Books: Lanham, MD, USA, 1990.
25. He, Q.; Ribeiro-Navarrete, S.; Botella-Carrubi, D. A matter of motivation: The impact of enterprise digital transformation on green innovation. *Rev. Manag. Sci.* **2023**, *18*, 1489–1518. [CrossRef]
26. Xu, L.; Fan, M.; Yang, L.; Shao, S. Heterogeneous green innovations and carbon emission performance: Evidence at China's city level. *Energy Econ.* **2021**, *99*, 105269. [CrossRef]
27. Lin, B.; Ma, R. Green technology innovations, urban innovation environment and CO₂ emission reduction in China: Fresh evidence from a partially linear functional-coefficient panel model. *Technol. Forecast. Soc. Change* **2022**, *176*, 121434. [CrossRef]
28. Yu, C.; Long, H.; Tu, C.; Tan, Y.; Zang, C.; Zhou, Y. Assessing the effectiveness of innovative city pilots in improving urban carbon emission performance: A spatial difference-in-difference approach. *Front. Environ. Sci.* **2022**, *10*, 983711. [CrossRef]
29. Rehman, S.U.; Kraus, S.; Shah, S.A.; Khanin, D.; Mahto, R.V. Analyzing the relationship between green innovation and environmental performance in large manufacturing firms. *Technol. Forecast. Soc. Change* **2021**, *163*, 120481. [CrossRef]
30. Meirun, T.; Mihardjo, L.W.W.; Haseeb, M.; Khan, S.A.R.; Jermisittiparsert, K. The dynamic effect of green technology innovation on economic growth and CO₂ emission in Singapore: New evidence from bootstrap ARDL approach. *Environ. Sci. Pollut. Res.* **2021**, *28*, 4184–4194. [CrossRef]
31. Du, K.; Li, P.; Yan, Z. Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. *Technol. Forecast. Soc. Change* **2019**, *146*, 297–303. [CrossRef]
32. Zhang, F.; Deng, X.; Phillips, F.; Fang, C.; Wang, C. Impacts of industrial structure and technical progress on carbon emission intensity: Evidence from 281 cities in China. *Technol. Forecast. Soc. Change* **2020**, *154*, 119949. [CrossRef]
33. Glaeser, E.L. *Triumph of the City*; Penguin Press: New York, NY, USA, 2011.
34. Grossman, G.M.; Krueger, A.B. Economic growth and the environment. *Q. J. Econ.* **1995**, *110*, 353–377. [CrossRef]

35. Lin, B.; Zhu, J. Impact of China's new-type urbanization on energy intensity: A city-level analysis. *Energy Econ.* **2021**, *99*, 105292. [CrossRef]
36. Lin, B.; Zhu, J. Energy and carbon intensity in China during the urbanization and industrialization process: A panel VAR approach. *J. Clean. Prod.* **2017**, *168*, 780–790. [CrossRef]
37. Bilgili, F.; Koçak, E.; Bulut, Ü.; Kuloğlu, A. The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. *Energy* **2017**, *133*, 242–256. [CrossRef]
38. Lv, Y.; Chen, W.; Cheng, J. Direct and indirect effects of urbanization on energy intensity in Chinese cities: A regional heterogeneity analysis. *Sustainability* **2019**, *11*, 3167. [CrossRef]
39. Zhao, P.; Zhang, M. The impact of urbanisation on energy consumption: A 30-year review in China. *Urban Clim.* **2017**, *24*, 940–953. [CrossRef]
40. Sheng, P.; Guo, X. Energy consumption associated with urbanization in China: Efficient-and inefficient-use. *Energy* **2018**, *165*, 118–125. [CrossRef]
41. Elheddad, M.; Djellouli, N.; Tiwari, A.K.; Hammoudeh, S. The relationship between energy consumption and fiscal decentralization and the importance of urbanization: Evidence from Chinese provinces. *J. Environ. Manag.* **2020**, *264*, 110474. [CrossRef]
42. Yu, Y.; Zhang, N. Low-carbon city pilot and carbon emission efficiency: Quasi-experimental evidence from China. *Energy Econ.* **2021**, *96*, 105125. [CrossRef]
43. Sufyanullah, K.; Ahmad, K.A.; Sufyan Ali, M.A. Does emission of carbon dioxide is impacted by urbanization? An empirical study of urbanization, energy consumption, economic growth and carbon emissions—Using ARDL bound testing approach. *Energy Policy* **2022**, *164*, 112908. [CrossRef]
44. Yan, X.; Xin, B.; Cheng, C.; Han, Z. Unpacking energy consumption in China's urbanization: Industry development, population growth, and spatial expansion. *Res. Int. Bus. Financ.* **2024**, *70*, 102342. [CrossRef]
45. Ministry of Electronics and IT. Digital India Programme. 2023. Available online: <https://digitalindia.gov.in> (accessed on 30 April 2025).
46. Ma, L.; Li, X.; Pan, Y. Employee allocation efficiency in the context of the digital economy: Evidence from “Broadband China” demonstration cities. *Econ. Anal. Policy* **2024**, *82*, 735–752. [CrossRef]
47. Meng, X.; Wang, X.; Nisar, U.; Sun, S.; Ding, X. Mechanisms and heterogeneity in the construction of network infrastructure to help rural households bridge the “digital divide”. *Sci. Rep.* **2023**, *13*, 19283. [CrossRef] [PubMed]
48. Mendiluce, M.; Pérez-Arriaga, I.; Ocaña, C. Comparison of the evolution of energy intensity in Spain and in the EU15. Why is Spain different? *Energy Policy* **2010**, *38*, 639–645. [CrossRef]
49. Lange, S.; Pohl, J.; Santarius, T. Digitalization and energy consumption: Does ICT reduce energy demand? *Ecol. Econ.* **2020**, *176*, 106760. [CrossRef]
50. 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]
51. Dette, H.; Schumann, M. Testing for equivalence of pre-trends in difference-in-differences estimation. *J. Bus. Econ. Stat.* **2024**, *42*, 1289–1301. [CrossRef]
52. Marx, P.; Tamer, E.; Tang, X. Parallel trends and dynamic choices. *J. Political Econ. Microecon.* **2024**, *2*, 129–171. [CrossRef]
53. Roth, J. Pretest with caution: Event-study estimates after testing for parallel trends. *Am. Econ. Rev. Insights* **2022**, *4*, 305–322. [CrossRef]
54. Roth, J.; Sant'Anna, P.H.C.; Bilinski, A.; Poe, J. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *J. Econom.* **2023**, *235*, 2218–2244. [CrossRef]
55. Heinrich, C.; Maffioli, A.; Vazquez, G. *A Primer for Applying Propensity-Score Matching*; SPD Working Papers 1005; I of Strategic Planning and Development Effectiveness (SPD): Washington, DC, USA, 2010.
56. Austin, P.C. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivar. Behav. Res.* **2011**, *46*, 399–424. [CrossRef] [PubMed]
57. Baek, S.; Park, S.H.; Won, E.; Park, Y.R.; Kim, H.J. Propensity score matching: A conceptual review for radiology researchers. *Korean J. Radiol.* **2015**, *16*, 286–296. [CrossRef] [PubMed]
58. Becker, S.O.; Ichino, A. Estimation of average treatment effects based on propensity scores. *Stata J.* **2002**, *2*, 358–377. [CrossRef]
59. La Ferrara, E.; Chong, A.; Duryea, S. Soap operas and fertility: Evidence from Brazil. *Am. Econ. J. Appl. Econ.* **2012**, *4*, 1–31. [CrossRef]
60. Wang, H.; Li, Y.; Lin, W.; Wei, W. How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China. *J. Environ. Manag.* **2023**, *325*, 116524. [CrossRef]
61. Ren, Y.; Li, B. Digital transformation, green technology innovation and enterprise financial performance: Empirical evidence from the textual analysis of the annual reports of listed renewable energy enterprises in China. *Sustainability* **2023**, *15*, 712. [CrossRef]
62. Sun, X. The impact of digital infrastructure on energy-environmental efficiency: Empirical evidence from China [Original research]. *Front. Energy Res.* **2023**, *11*, 1277333. [CrossRef]

63. Zhang, W.; Fan, H.; Zhao, Q. Seeing green: How does digital infrastructure affect carbon emission intensity? *Energy Econ.* **2023**, *127*, 107085. [[CrossRef](#)]
64. Shabalov, M.Y.; Zhukovskiy, Y.L.; Buldysko, A.D.; Gil, B.; Starshaia, V.V. The influence of technological changes in energy efficiency on the infrastructure deterioration in the energy sector. *Energy Rep.* **2021**, *7*, 2664–2680. [[CrossRef](#)]

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