

Original Research Article

The Impact of Digital Service Industry on Urban Energy Consumption in China*Juan Liu**College of Business, Jishou University, Jishou City, Hunan Province, 416000, China*

Abstract: The development of the digital service industry not only fosters new forms of digital industries and creates new drivers for economic growth but also serves as a crucial engine for green and low-carbon urban transformation, offering innovative pathways to improve urban energy efficiency. Using matched data from 280 prefecture-level cities in China, this study empirically examines the relationship between digital service industry agglomeration and urban energy efficiency. The findings reveal that digital service industry agglomeration significantly enhances urban energy efficiency, and this result remains robust even after a series of tests, including the use of instrumental variable methods. Mechanism analysis indicates that both formal and informal environmental regulations play a significant positive moderating role in this process. Furthermore, heterogeneity analysis shows that the impact of digital service industry agglomeration on urban energy efficiency is more pronounced in key cities (provincial capitals and municipalities), non-resource-based cities, and cities located on the southeastern side of the Hu Line. The study concludes that leveraging the energy efficiency gains from digital service industry agglomeration is of great importance for promoting a synergistic transition to digitalization and greening, and for advancing carbon peak and carbon neutrality in a prudent and proactive manner.

Keywords: Digital service industry agglomeration; Energy efficiency; Environmental regulation

1. Introduction

Energy is the fundamental material basis for human survival and development, directly influencing the economic lifeblood and security of nations^[1]. As the largest developing country in the world, China's total energy consumption has been steadily increasing, rising from 571 million tons of standard coal in 1978 to 5.41 billion tons in 2022, surpassing all other countries. Energy has played a crucial role in driving China's economic growth, particularly during the early stages of industrialization^[2]. Given the finite nature of energy supplies and the need to advance carbon neutrality goals, identifying optimal strategies to maximize energy efficiency and mitigate environmental degradation has become paramount.

In recent years, digital technology has been recognized as a key tool for improving energy efficiency by driving the transformation of the energy sector^[3]. As suppliers of digital technologies or products to traditional industries, the digital service industry is typically characterized by low pollution and low energy consumption, thereby significantly enhancing resource utilization efficiency and promoting energy conservation. The development of the digital service industry has shown a clear tendency toward agglomeration^[4], presenting new opportunities for energy conservation and emissions reduction. On the one hand, agglomeration in the digital service industry facilitates knowledge and technology sharing among enterprises^[5], effectively boosting energy efficiency and enabling firms to quickly adapt to green production models. Shared resources and infrastructure within agglomeration zones reduce redundant construction and resource consumption, lower operational costs, and further improve energy efficiency, thus enhancing environmental benefits. On the other hand, digital service industry agglomeration provides a platform for the exchange, openness, and sharing of data elements^[6]. As a key

production factor in the modern economy, data not only drives the development of emerging industries like big data and artificial intelligence, transforming traditional energy usage patterns but also promotes the development of new and clean energy sources, reducing reliance on fossil fuels. Furthermore, data permeates traditional industries, facilitating digital transformation^[7], improving resource utilization efficiency, minimizing energy waste, and accelerating the shift towards a low-carbon, sustainable development model.

This study integrates digital service industry agglomeration and energy efficiency into a unified theoretical framework for empirical analysis, aiming to uncover the mechanisms through which digital service industry agglomeration affects energy efficiency and to provide empirical support for achieving sustainable green development. This study makes the following marginal contributions: First, by focusing on digital service industry agglomeration, we identify the causal relationship between the digital service industry and urban energy efficiency, empirically examining its energy-saving effects. This not only addresses gaps in research on the environmental impacts of the digital service industry but also offers new perspectives for achieving energy-saving and green development goals. Second, from a theoretical standpoint, we incorporate environmental regulation into the analysis as a moderating factor between digital service industry agglomeration and energy efficiency, distinguishing between formal and informal environmental regulations. Third, we find significant heterogeneity in the impact of digital service industry agglomeration on energy efficiency across different city administrative levels, resource types, and geographic locations along the Hu Line. This reveals the contextual factors influencing the effect of digital service industry agglomeration on energy efficiency.

2. Research Design

2.1. Baseline Model

To verify the relationship between the digital service industry and urban energy efficiency, the following bidirectional fixed-effects model is constructed:

$$EE_{i,t} = \alpha_0 + \alpha_1 ADS_{i,t} + \sum_j \beta_j X_{j,i,t}^c + \eta_i + \pi_t + \varepsilon_{it} \quad (1)$$

In this model, $EE_{i,t}$ represents energy consumption efficiency, $ADS_{i,t}$ denotes the degree of digital service industry agglomeration, and XC stands for control variables. η_i and π_t capture individual-level and time-level fixed effects, respectively. The subscript i denotes the city, t denotes the year, and ε is a random error term. The description of the main variables used in the study and their corresponding symbols are provided in **Table 1**.

2.2. Variables Selection

a) Explained variables: Energy Efficiency (EE)

To measure energy efficiency at the urban level, a super-efficiency DEA-SBM model considering undesirable outputs is employed^[8]. The input variables include urban labor, urban capital stock, and urban energy consumption, while the expected output variable is total urban output, and the undesirable output variable is urban pollutant emissions. Labor is measured by the total number of employed persons at the end of the year in each city, and capital stock is estimated using the perpetual inventory method.

b) Explanatory variable: Digital Service Industry Agglomeration (ADS)

Due to the difficulty in obtaining main revenue data for each industry, this study uses the number of employees in information and communication, software, and information technology industries as a proxy to

measure the agglomeration degree of the digital service industry. A location quotient index is constructed for this purpose, and the calculation formula is as follows:

$$ADS = \frac{x_i / y_i}{\sum x_i / y_i} \tag{2}$$

In this formula, *ADS* represents the location quotient of the digital service industry in city *i*. *x_i* denotes the number of employees in the information transmission, software, and information technology service industries in city *i*, representing the local workforce in the digital service industry. *y_i* represents the total number of employees in city *i*, while $\sum x_i$ and $\sum y_i$ represent the total number of employees in the digital service industry nationwide and the total workforce nationwide, respectively. A larger *ADS* indicates a higher degree of digital service industry agglomeration in the city.

c) Control variables

To minimize measurement errors arising from model specification and drawing on relevant studies, this paper includes several factors that may influence energy consumption as control variables. These factors include the level of economic development (*LnPGDP*), urbanization rate (*Urban*), foreign direct investment (*FDI*), financial development (*FIN*), industrial structure (*INDR*), human capital level (*HR*), and government fiscal expenditure (*GOV*).

Table 1. Description of the main variables

Type	Variable	Measurement method	Symbol
Explained variable	Energy Efficiency	DEA-SBM super-efficiency model	EE
Explanatory variable	Digital Service Industry Agglomeration	The calculation method is shown in Equation (2).	ADS
	Economic development	Natural logarithm of GDP per capita	LnPGDP
	Urbanization	Urban population/total regional population	Urban
Control variables	Foreign investment	Actual amount of foreign capital used/GDP	FDI
	Financial development	Year-end deposit and loan balances of financial institutions/GDP	FIN
	Industrial structure	Value added of the tertiary industry/value added of the secondary industry	INDR
	Human resources level	Average years of schooling in the region	HR
	Government intervention	General budget expenditure/GDP	GOV

Table 1. (Continued).

2.3. Data

Considering data availability and completeness, 280 prefecture-level cities were ultimately selected as the research sample, covering the period from 2006 to 2021. The selected data primarily come from the China Urban Statistical Yearbook and China Regional Economic Statistical Yearbook. For a few missing data points, provincial statistical yearbooks, urban statistical bulletins, interpolation methods, or adjacent year averages were used to fill the gaps.

3. Empirical results

3.1. Baseline regression results

Table 2 presents the main empirical regression results based on the bidirectional fixed-effects model. From the results in columns (1) and (2) of Table 2, it can be observed that whether regressing digital service industry agglomeration alone or adding control variables, the regression coefficients are significantly positive at the 1% level. This indicates that urban digital service industry agglomeration can effectively enhance energy efficiency.

Table 2. Baseline regression results

	(1)		(2)	
	<i>EE</i>		<i>EE</i>	
<i>ADS</i>	0.031***	(0.010)	0.029***	(0.009)
LnPGDP			0.011	(0.013)
Urban			-0.041	(0.049)
FDI			-0.196	(0.134)
FIN			0.008*	(0.004)
INDR			-0.069	(0.069)
HR			0.011	(0.024)
GOV			-0.160***	(0.045)
Constant	0.195***	(0.009)	0.094	(0.250)
Year fixed effect	YES		YES	
Individual fixed effect	YES		YES	
Adjustment R^2	0.273		0.282	
F	62.62	[0.0000]	52.32	[0.0000]
N	4480		4480	

Note: The figures enclosed in brackets represent “ Robust standard errors”. The significance level is shown by ***, **, and * at 1%, 5%, and 10%, respectively. The following tables are the same

3.2. Endogeneity analysis

The agglomeration of the digital service industry may influence energy efficiency, but energy supply and consumption patterns could also affect its agglomeration, suggesting the possibility of reverse causality. To ensure the reliability of the empirical results, the average level of digital service industry agglomeration in other cities within the same province is used as an instrumental variable. This variable is related to digital service industry agglomeration but does not directly affect energy consumption, thereby satisfying the relevance and exogeneity conditions of an instrumental variable.

Columns (1) and (2) of Table 3 report the 2SLS regression results for the impact of digital service industry agglomeration on energy efficiency. The first-stage regression shows a significant positive correlation between the instrumental variable and digital service industry agglomeration, with an F-value of 19.92, indicating no weak instrument problem. The results in column (2) of Table 3 demonstrate that digital service industry agglomeration significantly improved energy efficiency, and these findings are consistent with the baseline results, confirming that the baseline results remain robust even when considering endogeneity issues.

3.3. Robustness analysis

To validate the robustness of the impact of digital service industry agglomeration on energy efficiency, this study re-estimates the model by excluding the samples from highly developed municipalities (Beijing, Shanghai, Tianjin, Chongqing) and data from 2019 onward. The results remain consistent with the original findings, confirming the robustness of the outcomes. Additionally, a lagged variable for digital service industry agglomeration (lagged by one period) was introduced for further testing, and the lagged term was significant at the 1% level, with results consistent with the baseline regression. This further reinforces the robustness of the positive effect of digital service industry agglomeration on energy efficiency.

Table 3. Endogeneity analysis and robustness test

	Instrumental Variables Method		Robustness test				
	<i>ADS</i>	<i>EE</i>	<i>EE</i>	<i>EE</i>	<i>EE</i>	<i>EE</i>	
	The first stage	Second stage	Exclude four municipalities	Exclude COVID-19	Lag term test		
	(1)	(2)	(3)	(4)	(5)		
<i>IV</i>	0.488*** (0.101)						
<i>ADS</i>		0.129*** (0.037)	0.028*** (0.009)	0.019*** (0.007)			
<i>L.ADS</i>						0.030*** (0.009)	
Constant	0.496 (0.970)	0.003 (0.970)	0.124 (0.251)	-0.031 (0.396)	0.143 (0.253)		
Control Variables	Yes	Yes	Yes	Yes	Yes		
Year fixed effect	Yes	Yes	Yes	Yes	Yes		
Individual fixed effect	Yes	Yes	Yes	Yes	Yes		
Adjustment R2	0.202	0.281	0.275	0.300	0.223		
F	19.92 [0.000]	51.21 [0.000]	50.42 [0.000]	56.49 [0.000]	45.63 [0.000]		
N	4480	4480	4416	3920	4200		

4. Mechanisms and heterogeneity

4.1. Mechanism analysis

Since energy consumption has externalities, new structural economics advocates achieving low-carbon goals through the combined efforts of a proactive government and an effective market. Environmental regulation, aimed at controlling pollution and protecting the environment, can be divided into formal and informal regulation. Formal regulations, such as environmental policies, influence corporate behavior, thereby impacting the role of the digital service industry in improving energy efficiency. Informal regulations, driven by public environmental awareness, increase pressure on companies to reduce energy consumption, potentially enhancing the digital service industry’s contribution to energy efficiency.

This study follows Chen et al.^[9] to measure formal environmental regulation intensity by counting the frequency of environmental keywords such as “green” and “energy-saving” in government reports at the prefecture level. For informal regulation, we adopt the approach of Wu et al.^[10], using the Baidu Haze Index to reflect public environmental concern as a proxy for informal regulatory strength. Columns (1) and (2) of Table 4 test whether formal and informal environmental regulations moderate the relationship between digital service

industry agglomeration and energy efficiency. The results show that both formal and informal environmental regulations positively moderate this relationship. Specifically, formal regulations, through policy and legal constraints, encourage companies to adopt more efficient energy use technologies and management practices, while informal regulations, via social norms and public oversight, drive companies to voluntarily improve their energy efficiency.

Table 4. Mechanism test

	<i>EE</i>		<i>EE</i>	
	(1)		(2)	
ADS	0.029***	(0.004)	0.018***	(0.007)
ER1	-1.845**	(0.719)		
ADS*ER1	2.357*	(1.346)		
ER2			-0.004	(0.006)
ADS*ER2			0.016**	(0.007)
Constant	0.087	(0.125)	-0.002	(0.125)
Control Variables	YES		YES	
Year fixed effect	YES		YES	
Individual fixed effect	YES		YES	
Adjustment R2	0.284		0.110	
F	66.19	[0.0000]	16.97	[0.0000]
N	4480		3036	

4.2. Heterogeneity Analysis

a) City administrative level heterogeneity

Unlike the flatter administrative systems in Western cities, Chinese cities have distinct administrative hierarchies. Higher-level cities typically have greater tax revenues, better infrastructure, and more authority over resource allocation. This leads to differences in the impact of digital service industry agglomeration on energy efficiency based on city management levels. To explore this, the sample was divided into key cities (provincial capitals, sub-provincial cities, and municipalities) and general cities. **Table 5** shows that digital service industry agglomeration significantly improves energy efficiency in key cities but has no significant effect in general cities. Key cities benefit from their higher administrative status, resource advantages, and policy support, while general cities face challenges due to limited resources and policies.

b) City resource type heterogeneity

Differences in industrial structure, development strategies, and green development goals between resource-based and non-resource-based cities also affect the impact of digital service industry agglomeration on energy efficiency. **Table 5** shows that digital service industry agglomeration significantly improves energy efficiency in non-resource-based cities but not in resource-based cities. Non-resource-based cities leverage diverse industries, innovation, and green development, while resource-based cities, dominated by traditional energy-intensive industries, face difficulties achieving similar improvements.

c) Hu Line heterogeneity

The Hu Line, a key geographic divide in China, highlights differences in population density and

environmental conditions between the eastern and western regions. Heterogeneity analysis shows that digital service industry agglomeration significantly improves energy efficiency in cities southeast of the Hu Line but has no significant effect northwest of the line. Southeastern cities benefit from high population density, better infrastructure, and favorable policies, while northwestern cities struggle due to slower economic development, inadequate infrastructure, and limited market demand.

Table 5. Heterogeneity analysis

	Urban administrative level		Urban resource type		Hu Line	
	Key cities	General cities	Resource-based	Non-resource-based	Southeast of the Hu Line	Northwest of the Hu Line
	(1)	(2)	(3)	(4)	(5)	(6)
ADS	0.024*	0.008	-0.002	0.043***	0.036***	-0.004
	(0.012)	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)
Constant	0.154	0.127	0.606***	-0.244	-0.094	0.457
	(0.397)	(0.234)	(0.190)	(0.419)	(0.135)	(0.499)
Control Variables	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES
Individual fixed effect	YES	YES	YES	YES	YES	YES
Adjustment R2	0.748	0.428	0.436	0.765	0.445	0.264
F	1966.94	95.25	8.38	85.34	44.96	25.83
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
N	560	3920	1808	2672	3536	944
Chow Test	0.044		0.000		0.008	

5. Conclusions

Based on panel data from 280 prefecture-level cities in China from 2006 to 2021, the study reveals: (1) digital service industry agglomeration significantly enhances energy efficiency; (2) both formal and informal environmental regulations positively moderate the impact of digital service industry agglomeration on energy efficiency; and (3) the influence of digital service industry agglomeration on energy efficiency exhibits heterogeneity across different city administrative levels, resource types, and geographic locations, with the effect being particularly pronounced in key cities, non-resource-based cities, and cities southeast of the Hu Line.

In light of these findings, policymakers should consider the following recommendations to optimize the contribution of the digital service industry to energy efficiency: First, governments should recognize the role of the digital service industry in improving energy efficiency, especially in key cities and non-resource-based cities, by formulating supportive policies such as tax incentives and increasing investment in information and communication technology (ICT) infrastructure to drive digital economic development. Second, both formal and informal environmental regulations play a crucial role in enhancing energy efficiency. Governments should strengthen environmental laws and regulations, set strict energy standards, and encourage public participation and social oversight. Incentives such as environmental awards or certifications could motivate businesses to fulfill their environmental responsibilities and promote sustainable development.

References

- [1] Sharma, V., Greig, C., & Lant, P. (2021). What is stopping India's rapid decarbonisation? Examining social factors, speed, and institutions in Odisha. *Energy Research & Social Science*, 78, 102117.
- [2] Csereklyei, Z., Rubio-Varas, M. D. M., & Stern, D. I. (2016). Energy and economic growth: the stylized facts. *The Energy Journal*, 37(2), 223-256.
- [3] Song, M., Peng, L., Shang, Y., & Zhao, X. (2022). Green technology progress and total factor productivity of resource-based enterprises: A perspective of technical compensation of environmental regulation. *Technological Forecasting and Social Change*, 174, 121276.
- [4] Liu, H., Shi, Y., Sun, B., & Yang, X. (2024). Agglomeration of the Digital Services Industry and Digital Transformation: Evidence from China. *Emerging Markets Finance and Trade*, 60(5), 855-869.
- [5] Yang, H., Lu, F., & Zhang, F. (2020). Exploring the effect of producer services agglomeration on China's energy efficiency under environmental constraints. *Journal of Cleaner Production*, 263, 121320.
- [6] Norton, R. D., & Rees, J. (2007). The product cycle and the spatial decentralization of American manufacturing. *Regional Studies*, 41(S1), S61-S71.
- [7] Criado, J. I., & Gil-Garcia, J. R. (2019). Creating public value through smart technologies and strategies: From digital services to artificial intelligence and beyond. *International Journal of Public Sector Management*, 32(5), 438-450.
- [8] Lv, Y., Chen, W., & Cheng, J. (2020). Effects of urbanization on energy efficiency in China: New evidence from short run and long run efficiency models. *Energy Policy*, 147, 111858.
- [9] Chen, Z., Kahn, M. E., Liu, Y., & Wang, Z. (2018). The consequences of spatially differentiated water pollution regulation in China. *Journal of Environmental Economics and Management*, 88, 468-485.
- [10] Wu, L. B., Yang, M. M., & Sun, K. G. (2022). Impact of public environmental attention on environmental governance of enterprises and local governments. *China Popul. Resour. Environ*, 32(2), 1-14.