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The impact of smart city construction on urban energy efficiency: evidence from China

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Abstract

Smart city construction (SCC) has emerged as an innovative approach to address the challenges of urbanization by reconciling economic development and energy utilization. This study employs the difference-in-differences method using data from 284 Chinese cities from 2005 to 2019 to investigate the impact of SCC on energy efficiency and the mediating role of technological innovation. This empirical analysis yields some valuable conclusions. First, the SCC in China has significantly improved urban energy efficiency. Second, the driving effect of SCC on energy efficiency gradually increases over time and produces clustered shaded areas. Third, SCC improves urban energy efficiency through green, configuration, and infrastructure effects derived from technological innovation. Finally, SCC has a positive impact on moderately sized cities enriched with human, material, and financial capital. This study proposes targeted recommendations based on these findings to promote sustainable urban development and technological innovation. These insights could inform policy and decision-making to achieve efficient urban energy systems.

Keywords Smart city · Energy efficiency · Technological innovation · Spatiotemporal heterogeneity

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1 Introduction

Recently, China has undergone rapid urbanization, with an urbanization rate of 64.72% in 2021. This trend has led to a high concentration of population and industry in cities, resulting in increased carbon emissions and energy waste. China's urban CO_2 emissions account for over 64% of the national emissions, whereas the permanent urban population accounts for only 50% of the total population (Wang et al., 2011; Zhou et al., 2022). This case has greatly pressured China to realize energy conservation and emission reduction (ECER). In this context, the green and low-carbon development of Chinese cities should be prioritized, and measures must be implemented to achieve ECER (Khan et al., 2022).

China has implemented a pilot project of smart city construction (SCC) to address the energy and emission issues caused by urbanization. SCC involves the integration of modern digital technologies, such as the Internet of Things and cloud computing, with urban infrastructure to monitor the operation of core urban organizational systems dynamically (Mohamed et al., 2020; Singh et al., 2020). Spatiotemporal information is a fundamental element and premise of SCC, which is crucial for the efficient utilization and allocation of resources (Yang et al., 2017).

SCC is receiving increasing attention from scholars, and its related literature can be divided into two categories. The first category focuses on the impact of SCC on economic development. For example, the results from 309 European metropolitan areas have validated the significant role of SCC in promoting innovation and economic development (Caragliu & Del Bo, 2019). Gao and Yuan (2021) confirmed the promoting effect of SCC in terms of economic development quality based on China's urban data. Song et al. (2022) found that the extent of engagement in SCC could be associated with the speed of local economic development and the local government's performance in China. The authors also concluded that SCC could significantly improve the external efficiency of government investment.

The second category focuses on the impact of SCC on the environment and energy. Regarding environmental pollution, Zawieska and Pieriegud (2018) focused on the transport industry and concluded that SCC could reduce carbon emissions. Su et al. (2021) further documented the evidence of SCC's effect on reducing environmental pollutants. They also found that SCC can significantly improve environmental quality. Concerning ecological efficiency, Yao et al. (2020) concluded that SCC could improve eco-efficiency, which will gradually improve over time. Jiang et al. (2021) verified the key role of SCC in boosting green total factor productivity. In terms of energy consumption, SCC can promote the deep integration of advanced technology and infrastructure, which is conducive to the dynamic monitoring of energy utilization processes (O'Dwyer et al., 2019). In addition, SCC can achieve the efficient operation of five core urban systems in real-time, namely, organization, business, transportation, communication, and energy, through technological innovation (Ismagilova et al., 2019; Hao et al., 2022), thereby strengthening the correlation among various energy utilization links. Therefore, SCC can effectively reduce energy waste and help achieve efficient energy utilization.

Several studies have focused on the role of SCC in economic development, environmental pollution, and energy utilization. However, only a few have integrated these into the framework of sustainable urban development research. Incorporating SCC into sustainable urban development can help optimize energy use, reduce carbon emissions, and enhance the resiliency of urban infrastructure (Young & Lieberknecht, 2019). This result aligns with the overall objectives of SCC, aiming to create sustainable urban environments and enhance the life quality for citizens. Moreover, the COVID-19 pandemic has highlighted the need for intelligent social governance, making SCC an inevitable choice for future urban development.

This study mainly aims to assess the spatiotemporal impact of SCC on urban energy efficiency in China and analyze the mediating effect of technological innovation. China implemented SCC pilots in 2012, integrating ecological and smart concepts into urbanization to achieve ECER and move toward sustainable development. A total of 284 cities in China are chosen based on geographical distribution and data availability, which have different levels of economic development and energy efficiency. This study confirms that SCC plays a crucial role in promoting urban energy efficiency, which has spatiotemporal heterogeneity. Additionally, SCC improves urban energy efficiency through the green, configuration, and infrastructure effects of technological innovation. This study also verifies how urban size and resource endowment moderate the effects of SCC.

This study contributes to sustainable urban development in several ways. First, this study integrates SCC, technological innovation, and energy efficiency into a theoretical framework, providing applicable recommendations for SCC and sustainable urban development. Second, this study analyzes the influence of SCC on energy efficiency and ulteriorly considers the spatiotemporal heterogeneity of the effects. Third, the study investigates the impact mechanism of SCC on urban energy efficiency with multi-level empirical methods and categorizes it into three main effects. Finally, this study provides a theoretical foundation for the rational layout of SCC and expands its research perspective to urban energy management.

The rest of the paper has the following contents. Section 2 summarizes the relevant literature of SCC and proposes the hypotheses of this study. Section 3 provides the modeling process and variable description. Section 4 discusses the results, and Section 5 conducts heterogeneity analysis. Finally, Section 6 proposes policy recommendations for SCC and technological innovation.

2 Literature review and research hypotheses

2.1 SCC and urban energy efficiency

SCC plays a crucial role in improving urban energy efficiency directly. At the level of urban governance, SCC enables intelligent urban governance and improves urban energy efficiency through digital technology that can intelligently and dynamically monitor urban production activities. Specifically, collaborative networks across departments and systems, which are applied by SCC, can collect and integrate production data from multiple industries in real time (O'Dwyer et al., 2019). Then, these data are processed and analyzed by advanced algorithms and machine learning technologies to identify inefficient energy use or energy consumption anomalies in cities (Kannan et al., 2020a). Therefore, SCC can improve the transparency of energy use, achieve efficient resource allocation, and facilitate the government to make targeted management decisions. At the urban industrial structure level, SCC can achieve green transformation of high energy consumption and high emission industries. On the one hand, SCC can effectively promote the development of the clean industry (Hao et al., 2022). SCC requires a large amount of clean energy and advanced energy-saving technology support, which increases the market demand for the clean industry. On the other hand, energy-intensive industries can achieve precise and dynamic management with the help of spatiotemporal information (Hittinger & Jaramillo, 2019). These industries can utilize spatiotemporal information to integrate and utilize multiple energy sources and achieve energy complementarity, thereby improving energy utilization efficiency. In addition, enterprises can use this information to optimize the allocation of multiple energy sources and improve energy utilization efficiency.

To sum up, SCC can intelligently reduce resource mismatch in urban governance and energy waste in enterprise production, thereby improving urban energy efficiency. The above analysis leads to Hypothesis 1.

Hypothesis 1: SCC can improve urban energy efficiency.

Existing studies have concluded that the connotation of SCC is consistent with the place-based policies widely adopted. The effects of place-based policies are highly heterogeneous. In the time dimension, Cheng et al. (2022) found that the freetrade zone policy initially promoted local employment but only had a positive effect for a short duration. Lu et al. (2019) found that in terms of investment, the positive impact of the policies of China's special economic zone on the firms would decrease over time. Therefore, the effects of SCC will also vary with time. Geographic location could also influence SCC's effects. The theory of spatial economics shows that the central city has siphon effects on the energy of the surrounding cities, leading to a gathering shadow area of the central city (Fujita et al., 2001). If the distance between the surrounding and central areas exceeds a certain value and is outside the gathering shadow area, then the place-based policies can produce a spillover effect to improve the energy efficiency of the surrounding cities. However, the spillover effect disappears when the distance is too far (Kline & Moretti, 2014). This study proposes Hypothesis 2.

Hypothesis 2: Spatiotemporal heterogeneity exists in the impact of SCC on urban energy efficiency.

2.2 SCC and technological innovation

SCC is an innovative mode of urban development based on technological progress and organizational change (Laurini, 2021), including technological innovation, resource allocation innovation, and infrastructure construction innovation (Caragliu & Del Bo, 2019; Deshmukh et al., 2016). This study considers that the technological innovation of SCC can endogenously produce green, configuration, and infrastructure effects, which form an innovation-driven mechanism to improve energy efficiency. Figure 1 shows the influence mechanism.

The green effects refer to improving energy efficiency by applying various green technologies in the urban production activities of SCC. SCC encourages green innovation in various sectors. For instance, SCC can support the consumption of renewable energy sources based on solar panels and wind turbines (Kumar et al., 2020). Additionally, SCC can incen-

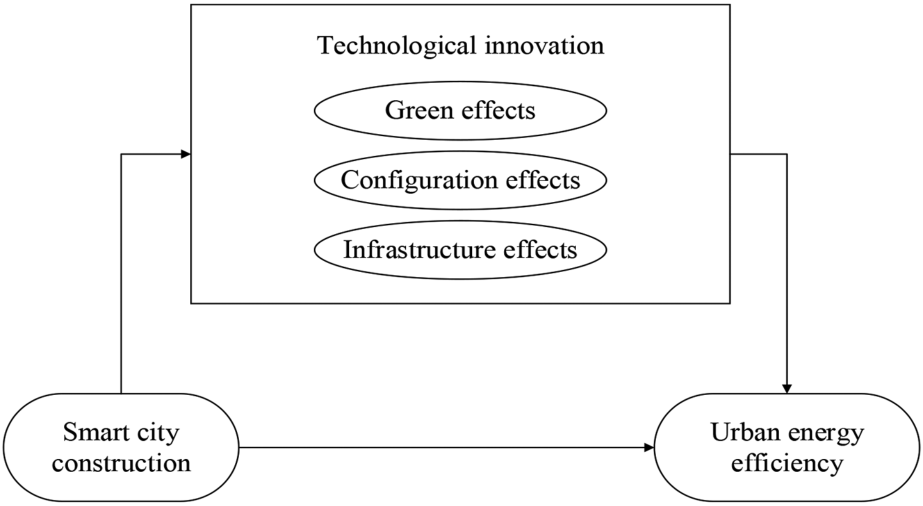

Fig. 1 Influence mechanism

tivize the use of green buildings to improve urban energy efficiency by using eco-friendly building materials (Konstantakopoulos et al., 2019).

The configuration effects mean that SCC can optimize energy allocation mode to balance overall energy demand and supply, thereby improving urban energy efficiency. Regarding energy supply, the smart grid system applied in SCC can accurately schedule energy supply and reduce energy transmission losses (Deshmukh et al., 2016), ultimately improving energy efficiency. Concerning energy demand, SCC encourages enterprises to adopt intelligent demand response strategies. For example, energy-intensive enterprises can adjust energy consumption based on real-time interactive platforms during peak energy demand periods (Antonioli et al., 2018). This case helps energy-intensive companies improve resource allocation efficiency and reduce energy waste.

The infrastructure effects mean that the new infrastructure with wide coverage in SCC can reduce urban carbon emissions and increase energy efficiency. The new generation of information infrastructure in SCC, represented by high-speed intelligent Internet, has formed a highly integrated smart city infrastructure. New infrastructure is conducive to building a stable energy Internet and strengthening the monitoring of environmental emissions (Tang et al., 2021).

This study proposes Hypothesis 3.

Hypothesis 3: Characterized by technological innovation, SCC improves energy efficiency by producing green, configuration, and infrastructure effects.

2.3 SCC and urban characteristics

Large cities can improve their energy efficiency through economic agglomeration effects. The economic agglomeration effect refers to an interactive relationship formed by similar industries based on mutual competition and cooperation, usually forming industrial chains and clusters (Wang et al., 2022). These enterprises in similar industries can collaborate to share resources and reduce production costs, thereby improving energy efficiency (Xu et al., 2022). However, with the increase in population density in large cities, energy waste will be serious, resulting in urban disease (Wang et al., 2014). Therefore, the size of a city will affect the balance between agglomeration effects and city disasters, thereby affecting the effect of SCC on urban energy efficiency (Zawieska & Pieriegud, 2018).

In terms of resource endowment, improving energy efficiency cannot be accomplished by a single system independently but requires the operation of various urban resources (Hittinger & Jaramillo, 2019). SCC needs the support of human, financial, information infrastructure, and other resources. With different resource endowments, the impact of SCC on energy efficiency will be different. This study puts forward Hypothesis 4.

Hypothesis 4: The urban characteristics including the scale and resource endowment can affect the influence of SCC on urban energy efficiency.

3 Method and variables

3.1 Model

SCC is regarded as a quasi-natural experiment that examines spatial temporal heterogeneous influences in terms of urban energy efficiency. Ensuring that the characteristics of SCC pilot cities are similar to non-pilot cities is necessary before applying the difference-in-differences (DID) method (Yu & Zhang, 2021). The propensity score matching (PSM) method is adopted herein. The specific formula for evaluating the impact of SCC on energy efficiency is as follows:

$$\text{Efficiency}_{it} = \alpha_0 + \alpha_1 DID_{it} + \sum_{i=1}^{N} b_j X_{it} + v_i + \mu_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), if city i is engaged in SCC in year t, $DID_{it} = 1$; otherwise, $DID_{it} = 0$; $Efficiency_{it}$ represents the urban energy efficiency after PSM; X_{it} contains other variables that affect $Efficiency_{it}$; v_i and μ_t control the double fixed effects of urban and time; and ϵ_{it} represents the perturbation error.

The following progressive DID model is constructed to test the temporal heterogeneity of SCC effects in Hypothesis 2:

$$\text{Efficiency}_{it} = \beta_0 + \sum_{k=-11,k\neq-1}^{7} \beta_k D_{it}^k + \sum_{i=1}^{N} b_j X_{it} + v_i + \mu_t + \varepsilon_{it} \tag{2}$$

In Eq. (2), D_{it}^k represents the dummy variable. D_{it}^k takes a value of 1 if in year t, SCC has been implemented in city i for k years, and a value of 0 if otherwise. Let $k = t - y_i$, where y_i represents city i established a smart city in year t. For example, when $k = -2$,

$D_{it}^{-2} = 1$; otherwise, $D_{it}^{-2} = 0$. This study takes the year before establishing the smart city pilot, in which the base period corresponds to $k = -1$. The change in the coefficient β_k of D_{it}^{k} reflects the temporal change in the effect of SCC on urban energy efficiency.

This study establishes the following model to examine the spatial heterogeneity of SCC effects:

$$\text{Efficiency }_{it} = \gamma_0 + \gamma_1 DID_{it} + \sum_{s=50}^{500} \delta_s N_{it}^{s} + \sum_{i=1}^{N} b_j X_{it} + v_i + \mu_t + \varepsilon_{it} \tag{3}$$

where s (in kilometers, $s \geq 50$ km) represents the geographic distance measured by the map distance between two cities. N_{it}^{s} takes a value of 1 if there is at least one SCC pilot within the range of $\mathrm{s} - 50$ to s km from the city i in year t and a value of 0 if otherwise. For example, $N_{i2012}^{150} = 1$ means that at least one SCC pilot exists within 100–150 km away from city i in 2012. This study shows the regression results for $s = 50, 100, \ldots, 450, 500$, at an even interval of 50 km. Similarly, the significance of δ_s reflects that the effects of SCC on urban energy efficiency will change significantly in space.

This study applies the following stepwise regression method to verify the intermediary role of technological innovation in Hypothesis 3. In the first stage, this study verifies that SCC drives the above three effects through technical innovation. The following model tests the impact of SCC on comprehensive urban innovation performance:

$$\text{Innovation }_{it} = \alpha_0 + \alpha_1 \text{ DID }_{it} + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{4}$$

In Eq. (4), $Innovation_{it}$ represents the urban technological innovation performance. If the coefficient α_1 is significant, then SCC will promote technological innovation; otherwise, the intermediary effect test will stop. The impact of SCC on the three main effects is verified by the following equation:

$$\text{Green}_{it} (\text{ Confi }_{it}, \text{Infra}_{it}) = \beta_0 + \beta_1 DID_{it} + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{5}$$

In Eq. (5), $Green_{it}$, $Confi_{it}$, and $Infra_{it}$ represent the green, configuration, and infrastructure effects, respectively. In terms of green effects, green innovation is the micro-mechanism that drives sustainable development, and the intensity of patent filings in smart cities has increased significantly (Bibri, 2022). This study uses green technology innovation to represent the green effects. In terms of configuration effects, education plays a fundamental and leading role in the optimization of social resource allocation in SCC (Grimaldi & Fernandez, 2017; Liu et al., 2020). Thus, the configuration of educational resources is used to measure configuration effects (Hsieh & Klenow, 2009). In terms of infrastructure effects, the new infrastructure of SCC promotes energy reform. SCC reduces urban energy consumption by upgrading large-scale energy-consuming infrastructure, such as building roads with virtual models (Kannan et al., 2020b; Konstantakopoulos et al., 2019). Thus, this study uses the actual road area to reflect the infrastructure effects.

If β_1 in Eq. (5) is significant, then SCC has the above three effects. Then, if γ_1 in Eq. (6) is insignificant or decreases, then the technical innovation of SCC will derive the three effects above:

$$\text{Green}_{it}(\text{Confi}_{it}, \text{Infra}_{it}) = \gamma_0 + \gamma_1 \text{DID}_{it} + \gamma_2 \text{Innovation}_{it} + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{6}$$

In the second stage, the impact of the three major effects of SCC on energy efficiency will be verified. First, Eq. (7) is used to verify the impact of SCC on the three effects:

$$\text{Green}_{it}(\text{Confi}_{it}, \text{Infra}_{it}) = \alpha_0 + \alpha_1 \text{DID}_{it} + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{7}$$

If α_1 in Eq. (7) is significant and positive, then SCC can produce the three effects. Second, the following equation is adopted to verify the impact of SCC on energy efficiency:

$$\text{Efficiency}_{it} = \beta_0 + \beta_1 D_{IDit} + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{8}$$

If β_1 in Eq. (8) is significant and positive, then SCC improves energy efficiency. Finally, DID_{it} and the three effects are considered in the regression equation:

$$\text{Efficiency}_{it} = \gamma_0 + \gamma_1 \text{DID}_{it} + \gamma_2 \text{Green}_{it}(\text{Confi}_{it}, \text{Infra}_{it}) + \sum_{i=1}^{N} b_j X_{it} + \varepsilon_{it} \tag{9}$$

If γ_1 in Eq. (9) is insignificant, or the coefficient decreases, then SCC can reduce energy efficiency through the three main effects produced by technological innovation. This result concludes the stepwise regression used to test Hypothesis 3.

3.2 Variables and data

The traditional radial data envelopment analysis (DEA) method is popularly adopted in calculating urban energy efficiency. This method does not consider the slack of inputs or outputs and only increases the undesirable output proportionally. The traditional DEA contradicts the original intention of SCC to reduce carbon emissions while increasing economic output. In addition, the efficiency values of many cities may be equal to 1 when 284 cities are measured by the traditional radial DEA method. Therefore, this study chose the SBM super-efficiency DEA model (Du et al., 2010), considering the undesirable output of CO_2 emissions.

Table 1 Representation and measurement of variables

Variable classification	Variables	Symbol	Measurement
Independent variable	Smart city construction	*DID*	Binary variable
Dependent variable	Urban energy efficiency	*Efficiency*	-
Input	Energy consumption	-	Industrial electricity consumption
	Capital	-	Fixed capital stock
	Labor	-	Number of employees
Desirable output	GDP	-	-
Undesirable output	CO_2 emissions	-	-
Control variable	Openness	*Open*	Amount of used foreign direct investment
	Economic development	*lnrgdp*	Real GDP per capita
		lnrgdp2	Square of *lnrgdp*
	Industrial structure	*Inds*	Value added of the secondary industry as a share of GDP
Mediator variable	Urban technological innovation performance	*Innovation*	China Innovation and Entrepreneurship Index (Zhang, 2019)
	Green effects	*Green*	Number of green patent authorizations per capita
	Configuration effects	*Confi*	Number of teachers in institutions of higher learning
	Infrastructure effects	*Infra*	Actual road area
Moderator variable	Human capital	*Human*	Average wage level
	Financial support	*Financial*	Proportion of prefecture-level city fiscal expenditure to GDP
	Material resources	*Material*	Number of Internet users

This study also considers other factors that can affect energy efficiency, namely, openness (Hao et al., 2020), industrial structure (Friedl & Getzner, 2003), and economic development (Obiora et al., 2022). Table 1 shows the specific descriptions of the main variables. The

Table 2 Descriptive statistics

VarName	Full sample			Experimental group			Control group		
	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.
lnrgdp	4260	10.710	0.879	810	11.223	0.718	3450	10.590	0.871
lnrgdp2	4260	115.488	20.625	810	126.464	16.067	3450	112.911	20.731
Open	4260	5.532	17.117	810	20.229	34.075	3450	2.081	5.180
Inds	4260	48.504	12.350	810	48.8185	10.974	3450	48.431	12.651

Table 3 Difference test

Variables	Test type	Group	Before policy	After policy	Difference test results
Efficiency	Mean test (T-test)	Non-pilot cities	0.103	0.074	0.028***
		Pilot cities	0.070	0.114	-0.043***
	Median test (χ^2-test)	Non-pilot cities	0.079	0.057	270.564***
		Pilot cities	0.061	0.059	1.984

Note $^{*}p<0.05$
$^{**}p<0.01$
$^{***}p<0.001$

panel dataset of 284 cities in China during 2005–2019 is obtained from the China Urban Statistical Yearbook. Table 2 shows the statistical description for these variables.

The difference test of efficiency results in Table 3 shows that after SCC, the smart city's average energy efficiency has significantly increased. This result preliminarily shows that SCC has improved urban energy efficiency. However, the specific impact of SCC on energy efficiency needs to be further explored.

4 Empirical results

4.1 Premise testing

The premise tests of model assumptions are required before performing DID estimation. The first premise of this study is that the establishment of SCC pilots is not affected by urban energy efficiency, which means that the policy is exogenous. The SCC pilots were first established in large cities and then gradually extended to other cities. Thus, whether local energy efficiency affects the selection of SCC pilots should be examined. The Chinese government defines SCC as an innovative mode of urban planning, construction, and management using smart information technology. Therefore, SCC mainly focused on the informatization and digitization level of the city instead of the local energy performance, and the premise of the applicability of the DID method is preliminarily satisfied.

This study uses the logistic regression model to test whether urban energy efficiency affects the establishment of SCC pilots further, including pilot cities established in 2012, 2013, and 2014. If urban energy efficiency affects the establishment of an SCC pilot, then the regression will face an endogeneity problem. Table 4 shows the regression results of the binary choice model of establishing a smart city, showing that urban energy efficiency

Table 4 Results of the binary choice model

	(1)	(2)	(3)
	T2012	T2013	T2014
L.Efficiency	1.584	1.267	0.399
	(1.04)	(1.18)	(0.58)
L.lnrgdp	12.75**	9.373***	11.03***
	(2.70)	(3.40)	(5.06)
L.lnrgdp2	-0.482*	-0.346**	-0.428***
	(-2.29)	(-2.77)	(-4.34)
L.Open	-0.00797*	-0.0125***	-0.0134***
	(-2.33)	(-4.18)	(-4.79)
L.Inds	-0.0238**	-0.0461***	-0.0543***
	(-2.81)	(-8.17)	(-10.71)
_cons	-80.47**	-58.68***	-66.60***
	(-3.04)	(-3.86)	(-5.55)
N	756	1288	1680

Note t-statistics in parentheses. T2012, T2013, and T2014 respectively represent SCC in 2012, 2013, and 2014

does not affect the establishment of the SCC pilot. On the contrary, this study cannot prove the positive role of SCC in improving urban energy efficiency if urban energy efficiency affects the selection of SCC pilots, that is, cities with high energy efficiency will become SCC pilots. In this case, the high energy efficiency is a characteristic of the city itself, not caused by SCC.

The second premise is that the changing trends of energy efficiency of all cities before SCC remain the same. That is, before SCC, the changing trend of urban energy efficiency in smart cities and other cities should be parallel. The event research method is used to test the parallel trend, which is expressed as follows:

$$\text{Efficiency}_{\ it} = \alpha_0 + \alpha_1 DID_{it} + \sum_{i=1}^{N} b_j X_{it} + v_i + \mu_t + \varepsilon_{it} \tag{10}$$

In Eq. (10), if α_1 is significant, then the trend of energy efficiency between cities is significantly different, and the assumption is not valid. If α_1 is significant, then the difference in energy efficiency between pilot and non-pilot cities may not be caused by SCC. This case leads Eq. (1) to fail to truly reflect the positive effects of SCC. Figure 2 shows that the coefficient for each period before the implementation of SCC is not significant, indicating that the research sample passes the parallel trend test with no significant difference among cities. Thus, after the implementation of SCC, the difference in energy efficiency between pilot and non-pilot cities is caused by SCC.

The third premise is the common supporting assumption. That is, the covariables in the smart cities and other cities should not be significantly different after PSM. Table 5 shows that only urban energy efficiency has significant differences.

4.2 Effects of SCC on urban energy efficiency

Panel data analysis avoids multicollinearity problems in time series analysis. This study conducts the Hausman test on Eq. (1) to determine the optimal model, in which the obtained

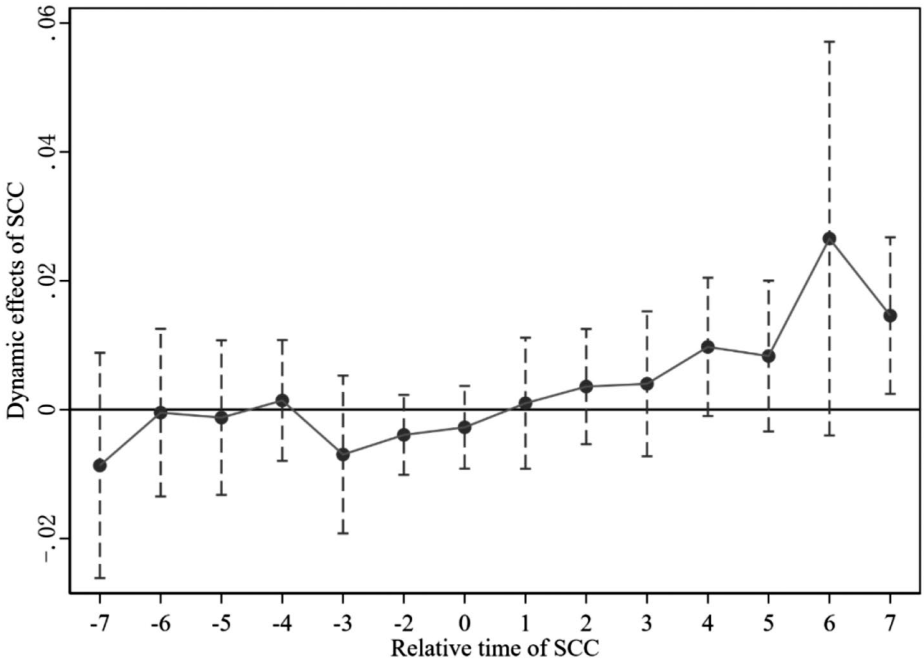

Fig. 2 Parallel trend test results

Table 5 Common supporting assumptions of PSM-DID

Variables	Mean of non-pilot cities	Mean of pilot cities	Difference	T-value	*P*-value
Efficiency	0.080	0.069	-0.011	4.85	0.000***
lnrgdp	10.721	10.708	-0.014	0.46	0.6453
lnrgdp2	115.365	115.037	-0.328	0.51	0.6091
Open	5.505	5.576	0.071	0.21	0.8342
Inds	53.599	53.116	-0.483	0.99	0.3240

concomitant probabilities are all less than 10%. Therefore, the fixed effect model considering the year and urban fixed effects is selected for testing. The regression results in Table 6 confirm that SCC significantly improves urban energy efficiency by approximately 4.04%.

After using the PSM-DID method, SCC could improve the level of urban energy efficiency by approximately 1.89%, which is lower than the results obtained by the DID method. This study uses four matching methods to perform baseline regression to further test whether these results are robust. The obtained estimation results of four matches demonstrated in Table 7 are rather consistent, verifying the robustness of the baseline regression results.

Table 6 Impact of SCC on energy efficiency

	(1)	(2)
Variable	Efficiency	Efficiency
DID	0.0718***	0.0404***
	(4.29)	(3.87)
lnrgdp		-0.121*
		(-2.11)
lnrgdp2		0.00354
		(1.93)
Open		0.00238***
		(3.56)
Inds		-0.0000100
		(-0.02)
_cons	0.144***	0.984**
	(16.30)	(2.62)
Fixed effects	YES	YES
N	4260	4260

Table 7 PSM-DID test

	(1)	(2)	(3)	(4)
	One-to-one neighbor match	One-to-four neighbor match	Radius match	Kernel match
Variable	Efficiency	Efficiency	Efficiency	Efficiency
DID	0.0188*	0.0189*	0.0189*	0.0188*
	(2.38)	(2.38)	(2.38)	(2.38)
lnrgdp	-0.350***	-0.350***	-0.350***	-0.350***
	(-4.39)	(-4.38)	(-4.38)	(-4.39)
lnrgdp2	0.0154***	0.0154***	0.0154***	0.0154***
	(4.12)	(4.12)	(4.12)	(4.12)
Open	0.00200	0.00201	0.00201	0.00200
	(1.96)	(1.96)	(1.96)	(1.96)
Inds	0.000362	0.000361	0.000361	0.000362
	(0.93)	(0.93)	(0.93)	(0.93)
_cons	2.058***	2.057***	2.057***	2.058***
	(4.75)	(4.75)	(4.75)	(4.75)
Fixed effect	YES	YES	YES	YES
N	4078	4075	4075	4078

4.3 Temporal heterogeneity and spatial heterogeneity

Figure 3 shows the variation of the coefficient of the D_{it}^{k} in Eq. (2) over time with a 95% confidence interval. In the initial short term, SCC does not have a significant effect on urban energy efficiency. However, this effect turns negative in the fourth year and then significantly positive after the fifth year. In general, the impact of SCC on energy efficiency first decreases slightly and then increases significantly over time. These results verify that SCC has temporal heterogeneity effects on promoting urban energy efficiency growth and also indicate that SCC is an important strategy that requires long-term implementation.

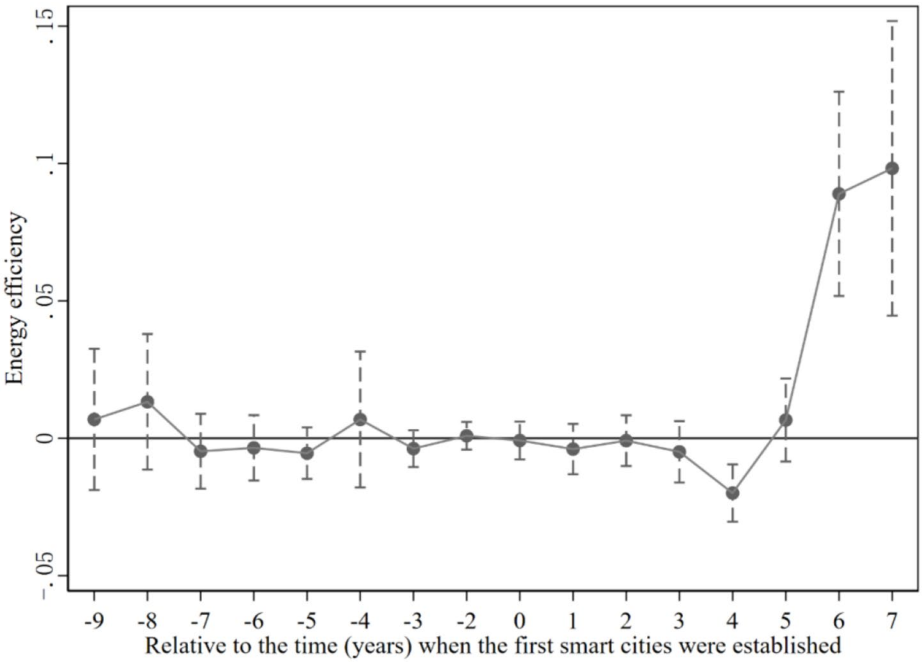

Fig. 3 Temporal heterogeneity of policy effects of SCC

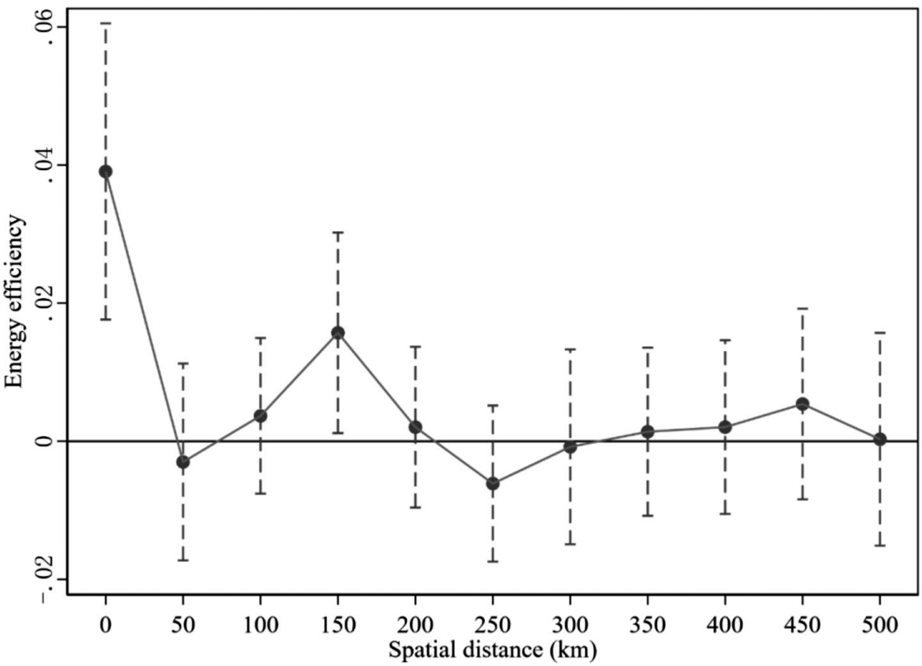

Fig. 4 Spatial heterogeneity of policy effects of SCC

The regression results in Fig. 4 show the varying trend of N_{it}^{s} in Eq. (3) with the distance between cities at a confidence interval of 95%. Specifically, with the increasing distance to the pilots, the overall driving effect of SCC on the energy efficiency of surrounding cities first decreases and then increases. The agglomeration shadow area of SCC is within 100 km of the city where it is located. SCC can positively contribute to improving energy efficiency within the surrounding 100–200 km. The driving effect of SCC is no longer significant when the distance exceeds 200 km. The above results verify the spatial heterogeneity of the driving effect of SCC on urban energy efficiency.

4.4 Robustness test

4.4.1 Placebo test

In the conventional DID model, the policy implementation time of all samples is identical, and the placebo test only requires a fixed number of units randomly selected from all samples as the experimental group (Li et al., 2016). However, the time of SCC in each city is different, and the conventional placebo test is no longer applicable. Thus, this study groups the data by city and randomly selects a year within each group as its SCC time. Finally, this study assigns a new policy dummy variable. Figure 5 shows that the coefficient is normally distributed and insignificant by setting a different pilot time for SCC, which verifies that the improvement of urban energy efficiency results from SCC.

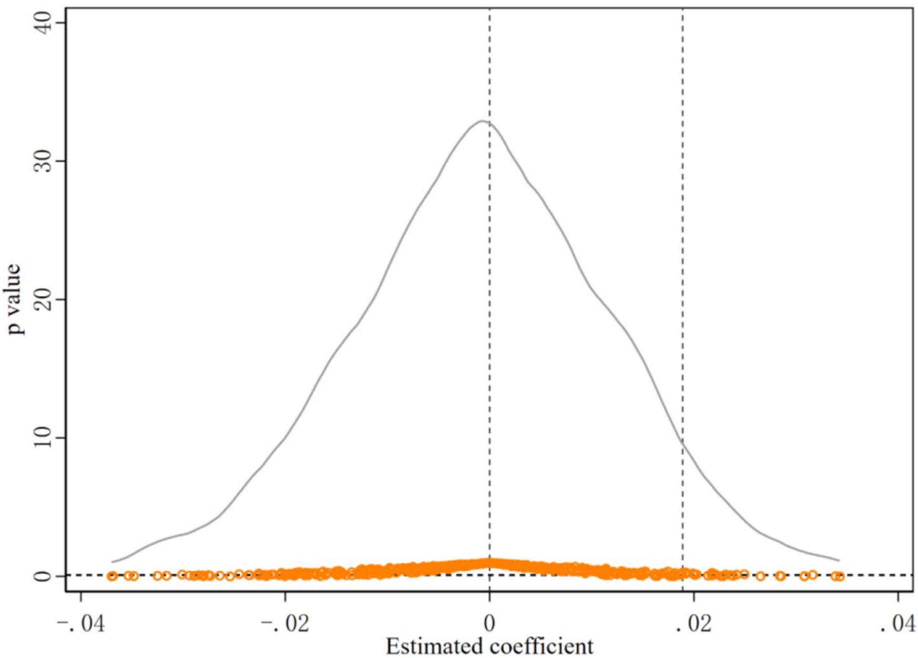

Fig. 5 Placebo test

Table 8 Excluding the impact of other policies

	(1)	(2)
Variable	Efficiency	Efficiency
DID	0.0718***	0.0404***
	(10.62)	(5.87)
d2013	-0.0202**	0.0391**
	(-2.75)	(2.78)
Control	NO	YES
_cons	0.144***	0.984***
	(28.09)	(6.96)
Fixed effects	YES	YES
N	4260	4260

Note "Control" represents all control variables

Table 9 Two batches of smart city policy robustness tests

	(1)	(2)
Variable	Efficiency	Efficiency
T2013	0.0264**	
	(2.60)	
T2014		0.0217*
		(2.37)
Control	YES	YES
_cons	1.031**	1.074**
	(2.61)	(2.74)
Fixed effects	YES	YES
N	4260	4260

4.4.2 Excluding interference from energy policies released in 2013

The effect of SCC on energy efficiency can be overestimated because of the interference of other relevant energy policies. This study searches for other policies that were implemented near the start time of SCC to address this issue. In 2013, the Chinese government attached great importance to energy reform and implemented a series of energy regulations that have produced a synergistic effect. A dummy variable d2013 is added to the benchmark regression to identify the interference of this effect on the results of this study. d2013 = 1, when year = 2013. Table 8 shows that SCC still plays a significant role in improving urban energy efficiency.

4.4.3 Regression by changing the batch of SCC pilots

The second and third batches of SCC in 2013 and 2014 are considered in this study to check further the robustness of obtained results. Table 9 shows that SCC still significantly improves urban energy efficiency, further indicating that the estimation results are robust.

4.4.4 Regression by changing the time window width of the sample

This study changes the time window of regression to verify whether the effect of SCC will change with the sample time. The policy occurrence time of 2012 is taken as the mid-

Table 10 Robustness test for changing time window width

	(1)	(2)	(3)	(4)	(5)
	2009–2015	2008–2016	2007–2017	2006–2018	2005–2019
Variable	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency
DID	0.00435	0.0100*	0.0128**	0.0150**	0.0185**
	(1.18)	(2.34)	(2.59)	(2.72)	(2.92)
Control	YES	YES	YES	YES	YES
_cons	3.004*	1.297*	1.046*	1.175**	1.384***
	(2.11)	(2.19)	(2.50)	(3.29)	(4.00)
Fixed effect	YES	YES	YES	YES	YES
N	1386	1939	2486	3028	3562

Table 11 Mechanism test of the impact of SCC on urban energy efficiency (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Innovation	Green effects	Green effects	Configuration effects	Configuration effects	Infrastructure effects	Infrastructure effects
DID	15.19*	2.830***	2.590***	0.191***	0.186***	0.106**	0.0983*
	(2.05)	(4.31)	(4.15)	(3.66)	(3.60)	(2.72)	(2.58)
Innovation			0.0158**		0.000376		0.000509***
			(2.60)		(1.65)		(5.65)
Control	YES	YES	YES	YES	YES	YES	YES
_cons	215.0**	19.15*	15.75*	1.158*	1.077*	2.178***	2.068**
	(2.72)	(2.40)	(2.23)	(2.57)	(2.42)	(3.40)	(3.26)
Fixed effects	YES	YES	YES	YES	YES	YES	YES
N	4260	4260	4260	4260	4260	4260	4260

point, and samples in 2009–2015, 2008–2016, 2007–2017, 2006–2018, and 2005–2019 are selected in the regression. In the sample from 2009 to 2015, the coefficient of DID is positive but not significant, which may be because policy effects take time to appear. Adjusting the time interval for regression reveals that the impact of SCC on energy efficiency with a sample window width of 4–7 years is significantly positive in Table 10, suggesting that the estimated result is relatively robust.

4.5 Intermediary role of technological innovation

This section clarifies the influential mechanism of SCC on energy efficiency. According to Hypothesis 3, SCC has the characteristics of technological innovation, which results in green, configuration, and infrastructure effects to improve energy efficiency.

Table 11 shows that in the first step, SCC significantly improves urban technical innovation performance and achieves innovative development. In the second step, the regression coefficients of DID are significantly positive, indicating that SCC generates these three effects. The results of the third step show that the coefficients of DID are significant but reduced, revealing that the three effects are driven by SCC through technical innovation.

Table 12 Mechanism test of the impact of SCC on urban energy efficiency (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Green effects	Configuration effects	Infrastructure effects	Efficiency	Efficiency	Efficiency	Efficiency
DID	2.830***	0.191***	0.106**	0.0404***	0.0253**	0.0276**	0.0377***
	(4.31)	(3.66)	(2.72)	(3.87)	(2.63)	(3.08)	(3.81)
Green					0.00533*		
					(2.24)		
Configuration effects						0.0667*	
						(2.53)	
Infrastructure effects							0.0254
							(1.06)
Control	YES	YES	YES	YES	YES	YES	YES
_cons	19.15*	1.158*	2.178***	0.984**	0.882*	0.906*	0.928*
	(2.40)	(2.57)	(3.40)	(2.62)	(2.52)	(2.41)	(2.55)
Fixed effects	YES	YES	YES	YES	YES	YES	YES
N	4260	4260	4260	4260	4260	4260	4260

Table 13 Heterogeneity analysis of city size

	(1)	(2)	(3)	(4)	(5)	(6)
	Small cities	Medium-sized cities	Large cities	Large cities of type II	Large cities of type I	Extra-large and above cities
Variable	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency
DID	0.0139	0.00904	0.0473***	0.0129*	0.0144	0.169**
	(0.86)	(1.35)	(3.39)	(2.04)	(0.39)	(3.91)
Control	YES	YES	YES	YES	YES	YES
_cons	0.161	1.712	1.019*	0.738*	12.06*	0.485
	(0.26)	(1.74)	(2.33)	(2.48)	(2.43)	(0.25)
Fixed effects	YES	YES	YES	YES	YES	YES
N	736	1511	2013	1661	166	186

In the second stage, Table 12 shows that SCC can innovatively produce the three effects. The results in Column (4) also reveal that SCC significantly improves energy efficiency. Furthermore, SCC's effects on urban energy efficiency are still significant with decreased coefficients. This result confirms that SCC improves energy efficiency through green, configuration, and infrastructure effects of technological innovation.

4.6 Heterogeneity analysis

4.6.1 City size

This study divides all sample cities into five groups based on the "Notice on Adjusting the Criteria for City Scale Standards" in 2014.

Table 13 shows that SCC improves energy efficiency in cities of all sizes, whereas the coefficients are significant only in large cities, type II large cities, and extra-large cities. The foundations of information and communication technology development in cities of small and medium sizes are insufficient to make the most of the advantages of SCC. For I-type large cities, the insignificant effect of SCC may be caused by the urban disease arising from development (Wang et al., 2014).

4.6.2 City resource endowment

SCC is a complex project constrained by urban resource endowments. The impacts of SCC on urban energy efficiency will show dependence on different resource endowments. According to the previous analysis, the investment level of human, financial, and material resources is crucial to SCC. Thus, analyzing the city resource endowment can provide insightful guidance for the policy design of intelligent construction. This study analyses the heterogeneity of the role of SCC in improving energy efficiency from the aspects of human, financial, and material resources. Specifically, cities are divided into three groups according to their human capital level, namely, low, medium, and high human capital groups. The grouping method of financial support and material resources is the same as above.

Table 14 shows that SCC plays a significant role in improving urban energy efficiency only in urban with high human capital, indicating that human capital is conducive to enhancing the benefits of SCC. The foundation of SCC is based on modern information technology, which puts forward high requirements for employees. A city with high-level human capital can cope well with this challenge and is conducive to the high-quality development of SCC (Moretti, 2004), which further improves urban energy efficiency. In terms of financial support, the impact of SCC on energy efficiency in cities with high financial support is higher than that in other cities. Financial support reflects the government's administrative intervention in SCC. When local governments make reasonable interventions to promote SCC, they overcome the shortcomings of pursuing short-term economic benefits by pursuing sustainable development goals. If government intervention is increased, then the effect of SCC in improving energy efficiency will also be improved (Li et al., 2016). In addition,

Table 14 Heterogeneity analysis of urban resource endowment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low-human	Medium-human	High-human	Low-financial	Medium-financial	High-financial	Low-material	Medium-material	High-material
Variable	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency
DID	0.000102	0.00217	0.0591***	0.0377***	0.0138	0.0646**	0.0206	0.0289	0.0484**
	(0.01)	(0.18)	(3.98)	(3.35)	(1.14)	(2.96)	(1.70)	(1.93)	(3.29)
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
_cons	0.802	2.694*	0.806	-0.0354	1.380	1.609*	1.595	0.416	1.100
	(1.08)	(2.49)	(1.17)	(-0.08)	(1.91)	(2.19)	(1.93)	(1.46)	(1.54)
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1410	1425	1425	1410	1425	1425	1410	1425	1425

the fiscal expenditure can provide sufficient financial input for SCC. Thus, the effects of improving energy efficiency are great in SCC with a high level of fiscal expenditure. The effects of SCC with different levels of material support are all positive but significant only in cities with high material support, which shows that the advanced construction of information infrastructure can provide material guarantee for SCC. Therefore, improving the city's human capital, financial, and material support level is an important task of SCC.

5 Discussion

Figure 3 shows that the impact of SCC on urban energy efficiency first decreases and then increases, which can be explained by the learning curve effect (Ferioli et al., 2009). At the beginning of SCC, cities did not have sufficient knowledge and experience. However, over time, cities learn from experience and gradually become proficient in utilizing SCC to achieve better urban energy efficiency. Therefore, the driving effect of SCC on urban energy efficiency increases over time.

In terms of spatial heterogeneity, SCC creates clustered shadow areas, as show in Fig. 4. On the one hand, pilot cities absorb the element resources from surrounding cities, which have a negative agglomeration shadow effect on the surrounding cities. On the other hand, the pilot cities spill over knowledge and technology to the surrounding cities, which play a driving role in improving the energy efficiency of nearby cities. Overall, within 100–200 km of the smart cities, SCC has more prominent spillover effects on the energy efficiency of surrounding cities than gathering shadow effects. However, in other regions, the holistic effect of SCC is not significant.

The results in Tables 11 and 12 confirm that SCC improves energy efficiency by innovatively producing green, configuration, and infrastructure effects. The main reasons are as follows. First, green technologies in SCC, such as energy-saving buildings, can help reduce energy consumption to improve energy efficiency (Yan et al., 2023). Second, SCC also generates infrastructure effects, such as smart public transportation systems, based on innovative operation and maintenance of urban infrastructure (Serrano, 2018). Finally, SCC innovatively optimizes the design and allocation of urban resources through information platforms, minimizing energy use to the greatest extent possible, resulting in a configuration effect (Pierce et al., 2017).

In heterogeneity analysis, this study finds that the impact of SCC on energy efficiency in type I large cities is not significant (Table 13). This conclusion contrasts sharply with the traditional point that the larger the urban scale, the more favorable the SCC. The key to solving the energy problem is not to expand the size of the city, but to innovate the urban governance mode and energy policy.

6 Conclusion

6.1 Research conclusion

This study utilizes panel data from 284 cities in China from 2005 to 2019 to investigate the effects of SCC on urban energy efficiency. This study derives several valuable research conclusions. First, smart cities have higher average energy efficiency than other non-pilot cities, implying that China has considerable ECER potential. Second, the results from the PSM-DID method show that SCC significantly improves urban energy efficiency by approximately 1.89% and verify the effectiveness of SCC. Third, with the increase in pilot establishment time, the impact of SCC on urban energy efficiency first decreases and then increases. Fourth, when the surrounding city is too close to an SCC pilot, the effect on energy efficiency is not significant. SCC will have significant influences to promote the increase of surrounding urban's energy efficiency only outside the shadow area of agglomeration. However, the driving effects of SCC become insignificant when the distance from the smart city is too far. Fifth, SCC improves urban energy efficiency through green, configuration, and infrastructure effects generated by technological innovation. Finally, this study finds that SCC only plays a significantly positive role in improving the urban energy efficiency of large cities, large cities of type II cities, and megacities and above. A high level of human and financial and material resources can significantly promote the effects of SCC.

6.2 Policy recommendations

Considering the aforementioned conclusions, this study proposes the following suggestions. First, this study suggests expediting SCC in a green way from the perspectives of the government and the market. For the local government, relevant departments should allocate appropriate subsidies to highly technical and difficult green innovation projects to stimulate the technological innovation of SCC in a greener way. Furthermore, the marketization process should be sped up, and the feedback mechanism of green consumption in the process of SCC must be strengthened.

Second, the positive role of SCC in promoting energy efficiency in surrounding cities implies that promoting ECER of China by SCC is a feasible solution. However, the spatial distribution of existing SCC in China is still uneven, particularly in densely populated important urban agglomerations, where the construction of smart projects still needs to be deepened. In the next stage, the Chinese government should prioritize supporting SCC in core cities of the Hubei metropolitan area, the Central Plains Economic Belt, and the Hefei metropolitan area. The government should also accelerate SCC in these areas to establish a radiation effect and give play to external effects.

Third, the intermediary mechanism tests verify that SCC improves urban energy efficiency through technological innovation. Therefore, supporting the development of green industries and new infrastructure construction characterized by innovation is beneficial for policymakers, creating a new impetus to promote the sustainable development of SCC. The new infrastructure construction in SCC will also help improve the emergency management capacity of the urban energy systems in the age of intelligence and stimulate the SCC's potential for technical innovation in improving energy efficiency.

Fourth, heterogeneity analysis results indicate that SCC should categorize cities based on their specific characteristics, including economic development and resource endowment. The cities with weak financial development could pay more attention to accelerating the process of industrial upgrading, which will expand the ECER effect of SCC.

Overall, this study analyzes the spatiotemporal effects of SCC on urban energy efficiency. Smart projects mainly contain multiple dimensions, of which smart environment, smart transportation, and smart governance may also contribute to energy efficiency. Further investigations are needed in the future.

Data availability Data will be made available on reasonable request.

Declarations

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