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Can Open Government Data Improve City Green Land-Use Efficiency? Evidence from China

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Abstract: This study adopted the double difference method to study the effect of open government data (OGD) on city green land-use efficiency (CGLUE). It was found that opening government data had a significant promotional effect on CGLUE, and a number of robustness tests were the foundation for this finding. A mechanism analysis demonstrated that two key avenues via which government data openness can promote CGLUE are raising public awareness of environmental issues and strengthening urban green innovation potential. A heterogeneity analysis found that the effect of government data openness on CGLUE was more obvious in eastern cities, cities with higher levels of digital finance, and non-resource-based cities. In addition, open government data also reduced urban carbon emissions while improving CGLUE, contributing to China's "double carbon" goal.

Keywords: open government data; city green land-use efficiency; public environmental concerns; urban green innovation; carbon emissions

1. Introduction

Governments worldwide are quite concerned about the distribution and unrestricted flow of data elements as a result of the emergence of the digital era and data-intensive research methodologies [1]. In 2022, China proposed reasonably reducing the barrier for market participants to obtain data and improving their capacity to share data and make them universally accessible. Government data openness, based on land, resources, market supervision, livelihood development, and other administrative subjects, opens data to the community in order to achieve the value of the economic, political, and social three-dimensional expectations of a data set [2]. Not only does it enhance resource efficiency, environmental protection, and sustainable development, but it also provides statistical support for attaining sustainable development goals. The utilization of land resources is crucial for both economic and social progress [3]. As industrialization and urbanization continue to expand, there is a growing need for land, which is limited by both natural conditions and planning regulations [4]. Enhancing the effectiveness of green space utilization in urban areas can address the limitations of land resources and reconcile the imbalance between supply and demand. Additionally, it can facilitate the simultaneous advancement of both high economic productivity and a healthy ecological environment [5,6]. Previous studies have clarified the impact of open public data on urban green innovation. Expanding on this, does open access to public government data have a similar effect on CGLUE? To what extent does it have an impact? Further, what are the key pathways that contribute to improved CGLUE? Are there any heterogeneous effects? These are all questions worthy of in-depth discussion and investigation. Therefore, this study focused on analyzing the correlation between government data openness and CGLUE and exploring the mechanism between these two variables. This work provides valuable theoretical insights and has practical significance for optimizing the allocation of data elements in China and encouraging the high-quality and sustainable development of land resources.

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Previous studies pertaining to the subject of this paper have primarily focused on two areas: open government data and enhancing CGLUE. When studying OGD, scholars have mainly discussed the evaluation of government data openness and its effects [7,8]. First, when evaluating OGD, previous studies have mainly analyzed the security governance of public data openness within the framework of the digital economy and public access to the data factor market model [9]. Secondly, in previous research on the effect of opening government data, scholars have mainly conducted in-depth discussions from macro and micro perspectives. The macro component has focused on the influence of open government data on regional green technology innovation, high-quality economic growth, urban entrepreneurial energy, and optimization of the business environment [10–13]. The effects of open government data on enterprise digital transformation, private enterprise performance, and enterprise innovation have been considered at a small scale [14–16]. Furthermore, this has confirmed the beneficial impacts that the transmission of data in the form of open government data has on China's economic and social progress. Studies in the field of enhancing CGLUE have revealed strong correlations between urban attributes, such as the economic development level, population density, industrial structure, urban scale, spatial structure, and the efficiency of green utilization in urban areas [17–19]; some scholars have studied the effects of economic growth targets, digital infrastructure, energy utilization, environmental protection policies, and other types of socio-economic factors on CGLUE [20–23].

As for research on the relationship between OGD and CGLUE, there are not many direct research results on these two variables in the theoretical field at present. However, with the continuous improvement in the theoretical and empirical system of domestic research on the relationship between government data openness and CGLUE, some scholars have started to pay attention to the green effect of government data openness from an indirect perspective. In previous studies, public data have been widely used in scenarios such as residents' environmental participation, urban traffic management, and green land utilization, generating considerable benefits [24–26]. For example, in the field of resident participation, cities have launched apps based on public environmental data, through which residents can learn about air quality, noise levels, and other information about their environment [27], which motivates them to participate in environmental protection activities. In the area of urban traffic management, cities use public transport data and real-time traffic monitoring to optimize bus routes and schedules and reduce traffic congestion [28], thereby reducing carbon emissions. To improve efficiency and environmental friendliness in the area of land use, governments use GIS and public land data to facilitate scientific land-use planning and improve the green utilization of land [29,30]. They can also use public data to identify damaged ecological areas, formulate ecological restoration plans, monitor changes in forest cover, and promote large-scale afforestation projects. It can be seen that previous studies in China have analyzed the green effect of open government data from an indirect perspective, and there are not many direct studies on the effect of bringing an open government data platform online on the green land-use efficiency of urban land. This provided a new space for exploration when carrying out this study.

Because of this, this study examined the effects of OGD on CGLUE and the mechanism of the role of actual urgency using a quasi-natural experiment based on the government's online data platform. The preservation and wise use of land resources have become crucial concerns for sustainable urban development as a result of the acceleration of urbanization. In order to realize the green and sustainable use of land resources, urban planning and land use can be improved by researching the effects of open public data on land use.

Compared with the existing literature, the marginal contributions of this paper are as follows: First, regarding the subject of this research, this study examined the impact of open public data on CGLUE, which expanded the existing literature on the effect of open public data and addressed gaps in the existing research content. Secondly, it theoretically clarified the effect of OGD on CGLUE, which not only deepened the research on expanding the green environmental benefits of open government data but also identified a new path

for improving CGLUE. Thirdly, it provided policy insights and reference suggestions for the balanced development of the economy and the environment, guided by the national data policy of open government data.

2. Theoretical Analysis and Research Hypothesis

2.1. Impact of Government Data Openness on Urban Green Land-Use Efficiency

Open government data have become an important means of promoting sustainable urban development and green land-use efficiency in today's society. Open government data can provide transparency in urban management, enhance public participation, and promote the efficient allocation of resources, thereby improving green land-use efficiency. First, open government data enhance information transparency [31]. This transparency enables various stakeholders, including government agencies, businesses, NGOs, and the public, to access data on land use, environmental quality, traffic flow, etc. The openness of these data facilitates public participation in the policy-making process [32], allowing the public to monitor and provide feedback on potential environmental impacts, forcing the government to pay more attention to green decision-making, and thus optimizing land use. Second, open public data promote data sharing and cooperation [33]. Data sharing between government departments, as well as between the government and research organizations and enterprises, can form a multi-party collaborative ecosystem that promotes scientific decision-making on land use. This cross-departmental data integration can provide a more comprehensive perspective and help decision-makers balance development and conservation to ensure the green and sustainable use of land resources. Finally, open government data can also incentivize public participation and awareness of social responsibility [34]. By opening environmental and land-use data, the public can better understand their own living environment and thus increase their sense of responsibility and willingness to participate in land resource protection [35]. This stimulates enthusiasm to participate in urban greening and environmental protection activities. The active participation of citizens from the bottom up promotes green land-use efficiency to a certain extent. Based on the above analyses, the following hypothesis was proposed:

H1. *Open government data can promote the efficiency of urban green land use.*

2.2. Mechanisms of Public Environmental Concern and Urban Green Innovation

Opening government data mainly promotes private enterprise performance improvements in two ways.

The first is by enhancing public environmental concerns. Urban green development requires the support of the public, and public environmental concern provides an important foundation for improving CGLUE [36]. Open government data can enhance public environmental concern through information flow, environmental protection supervision, and participation in decision-making. Specifically, it can improve information transparency. On the one hand, through data openness, the government can openly provide information about land use and other fields to society so that the public can more easily understand the urban environmental conditions and problems [37], which enhances the public's level of concern and awareness of environmental issues and thus spontaneously protects natural resources. On the other hand, during the flow of data elements, the government presents complex land-use data in an intuitive form through data visualization, making it easier for the public to understand and pay attention to land use, the green space distribution, ecosystem conditions, etc., thus enhancing their attention to green land use. Second, open government data can increase environmental protection supervision. On the one hand, the public monitors and evaluates the existing environmental conditions using the government's open data, identifies environmental problems [38], puts forward suggestions for improvement, and pushes the government and enterprises to improve environmental management and protection measures [39]. On the other hand, government departments encourage the public to monitor environmental violations by establishing an environmen-

tal reporting platform. Through public exposure to environmental violations and related penalties, public attention to environmental issues is raised, prompting public green land use and low-carbon behaviors [40]. Third, open government data guarantee entitlement to engage in the decision-making process. Through the free flow of data, the government, on the one hand, empowers the public to participate in the discussion and decision-making process of environmental planning and policy-making; on the other hand, in order to respond to the public's needs regarding land use, the government organizes seminars and training activities to interact and communicate with the public, thereby enhancing the public's knowledge and understanding of green land use [36].

Secondly, opening government data enhances a city's green innovation capacity. A city's green innovation capacity is a decisive factor for optimizing CGLUE, which determines the rational allocation efficiency of land by the government and the market [41]. Government data are opened by establishing information platforms, policy incentives, and industrial cooperation to strengthen a city's ability to develop and implement environmentally friendly innovations. Specifically, the government first establishes open data platforms, providing environmental, traffic, and population data. The public and enterprises access these data at the same time to obtain the real-time mastery of the current development and use of land resources and the building and development of land to actively enhance the efficiency of their use in this process [42]. Through real-time mastery of the development and use of land resources, we can better understand their potential and opportunities for green land use so as to proactively embrace environmentally friendly technology and tactics to encourage the sustainable utilization of land resources. Secondly, the government encourages participation in green innovation by formulating environmental protection policies and providing incentives or subsidies to enterprises and organizations that use open government data for green innovation [43]. This behavioral effort contributes favorably to the advancement of green innovation, environmental industry development, urban image enhancement, and sustainable development and promotes the process of moving urban land towards more intensive, low-carbon uses. Thirdly, the government has cooperated with industry to jointly use open government data for green innovation projects, which can facilitate technology transfers and project implementation through the establishment of a public–private partnership mechanism [5]. To a certain extent, this better integrates government and enterprise resources, optimizes land-use planning and development, improves land resource utilization efficiency, reduces resource wastage, and promotes green development.

Drawing on the aforementioned analyses, two possibilities were posited:

H2. *Open government data can enhance public concern for environmental protection, thereby promoting CGLUE.*

H3. *Open government data can strengthen a city's green innovation ability, thereby promoting CGLUE.*

3. Research Design

3.1. Data Source and Description

This study adopted panel data from 267 cities at the prefecture level and above in China from 2011 to 2020. Among them, data related to economic growth targets were extracted from government work reports at all levels, green patent data came from the patent search platform of the State Intellectual Property Office, and the rest of the raw data came from official documents or websites such as *The China Urban Statistical Yearbook*, *The China Urban Construction Statistical Yearbook*, statistical bulletins, the EPS database, etc. Missing values for individual cities were supplemented according to the average growth rate. It should be noted that because some cities in Tibet, Xinjiang, and other provinces had more missing data for key variables and the missing information could not be accurately restored via interpolation, this study excluded these cities to ensure the reliability of the research results.

3.2. Variable Selection

3.2.1. Explained Variable: Urban Green Land-Use Efficiency (CGLUE)

In this paper, in accordance with Tone [44] and Tan et al. [45], from the perspective of inputs and outputs, we use the SBM model under the assumption of constant returns to scale to measure the CGLUE, which can comprehensively consider the non-expected outputs and correct the slack variables so as to greatly improve the accuracy and practicability; the expression is as follows:

$$\begin{aligned} \rho = min & \frac{1-\frac{1}{N}\times\sum_{n=1}^{N}\frac{S_n^x}{X_{k'n}^{t'}}}{1+\frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{S_m^y}{Y_{k'm}^{t'}}+\sum_{i=1}^{I}\frac{S_i^b}{b_{k'i}^{t'}}\right)} \\ s.t & \sum_{t=1}^{T}\sum_{k=1}^{K} Z_k^t X_{kn}^t + S_n^x = X_{k'n}^{t'}(n=1,2,\cdots N) \\ & \sum_{t=1}^{T}\sum_{k=1}^{K} Z_k^t Y_{km}^t - S_m^y = Y_{k'm}^{t'}(m=1,2,\cdots M) \\ & \sum_{t=1}^{T}\sum_{k=1}^{K} Z_k^t b_{ki}^t + S_i^b = b_{k'i}^{t'}(i=1,2\cdots I) \end{aligned} \quad (1)$$

In Equation (1), ρ is the CGLUE with a value range between (0, 1); N, M, I are the quantities of inputs, desired, and undesired outputs; and their relaxation vectors are characterized by $\left(S_n^x, S_m^y, S_i^b\right)$, respectively. A relaxation vector is a variable used in optimization problems to make the constraints more flexible. It allows the model to have some room for adjustment while satisfying strict constraints, making the solution more realistic and feasible. The relaxation vectors S_n^x, S_m^y and S_i^b are used to adjust the input, desired output and non-desired output constraints so that answers are feasible in the model; $\left(X_{k'n}^{t'}, Y_{k'm}^{t'}, b_{k'i}^{t'}\right)$ are input–output variables; Z_k^t reflects decision unit weights; t indicates a time period or a specific decision-making unit (DMU), showing that the variable changes over time or is associated with different time units; k is used as an index to identify each DMU, while k' typically denotes the set of valid or reference decision units associated with the k'th decision unit.

The input indicators for measuring the CGLUE in this paper are selected from land, capital and labor factors, which are characterized by a built-up area, fixed capital stock, and the number of employees in the secondary and tertiary industries, respectively; the desired outputs take into account the economic, social and environmental benefits at the same time, which are measured by the real added value of the secondary and tertiary industries, the average wage of employees and the greening coverage of the built-up area, respectively. At last, non-desired outputs consider pollution emissions and are characterized by environmental pollution intensity; they are calculated using the entropy method to assign weights to industrial wastewater, soot and sulfur dioxide emissions after taking them into account. The details of each indicator are shown in Table 1.

Table 1. The indicator system of CGLUE.

Variables	Type of Indicator	Classification	Description of Indicators	Unit
CGLUE	Input indicators	Labor	The number of workers in tertiary and secondary industries	Million people
		Capital	City fixed asset investment	CNY 1 billion
		Land	City built-up area	Square kilometers
	Expectation indicators	Economic benefits	Value added by secondary and tertiary industries	CNY 1 billion
		Social benefits	Average employee salary	CNY 1 million
		Ecological benefits	Greening coverage of built-up area	%
	Non-expected indicators	Environmental pollution index	Wastewater treatment plant effluent, sulfur dioxide emissions, and smoke (dust) from industry	%

3.2.2. Explanatory Variable: Open Government Data (DID)

The local government promoted the online data platform of each prefecture-level city, which provided the ideal quasi-natural experimental scenario for the area in this study. This study set the model value logic as follows: if a city successfully went online with a public data platform during the sample period and the observation period included the platform's opening year and after, the city's DID took a value of 1, which indicated that it was affected by the policy; otherwise, the DID took a value of 0, which indicated that it was not affected by the policy. In this paper, the time when each prefecture-level city first went online with a public data platform was set as the time of policy implementation.

3.2.3. Control Variables

To ensure that the degree of urban growth had no bearing on this study's findings, relevant factors were included at the geographical level.

Specifically, the following geographic-level control variables were included:

The level of economic development (GDP, the logarithm of gross domestic product per capita). Cities with higher levels of economic development typically invest more resources in land use, infrastructure development, and public services [45]. This may lead to an increase in land-use efficiency or a shift to green use, so the inclusion of GDP per capita as a control variable helped to exclude its direct effect on CGLUE.

The level of financial development (FIN, selected to reflect the year-end deposit and loan balances of the financial institutions in a city as a share of GDP). The maturity of the financial market affects firms' investment decisions. Cities with high levels of financial development attract more green investments and sustainable projects [46], directly affecting CGLUE. Controlling for this variable helped to determine the impacts of other factors on CGLUE.

The Internet penetration rate (INTEGRATE, the logarithm of the number of people using the Internet). The Internet provides a platform for public participation in policy formulation and monitoring. The greater the number of people using the Internet, the greater the public's interest and participation in government data openness [47], which may lead to more effective government measures of land management and green utilization. Therefore, controlling for this variable facilitated better analysis of the independent impact of open government data on CGLUE.

The urbanization level (URBAN, selected to characterize the urban population as a proportion of the total population). Increasing urbanization levels are usually accompanied by significant changes in land-use patterns. As urbanization progresses, the development and use of land become more intensive and diverse [48], which may affect the efficiency of green land use. Therefore, controlling for the level of urbanization helped us to more accurately assess the independent impact of GOV on land-use efficiency.

Government intervention (GOV, expressed using the share of general government budget expenditure in the GDP). The share of government budget expenditure reflects the government's financial investment in public services, infrastructure development, and environmental protection [49]. A higher proportion of budget expenditure may imply that the government has adequate financial support to promote green land use. Therefore, controlling for this variable helped us to more accurately assess the impact of government data openness on the efficiency of green land use.

The degree of industrialization (IND, the ratio of value added by secondary industry to the GDP of each city) was chosen to portray the level of industrialization development. The degree of industrialization directly affects land use and layout [49]. Highly industrialized cities usually need large amounts of land for industrial facilities, transport infrastructure, etc., which may lead to decreases in land-use efficiency. Controlling for the degree of industrialization helped us to better understand the independent impact of open government data on green land-use efficiency.

Infrastructure (INF, selected to represent the road area per capita in cities). The road area per capita directly reflects the level of infrastructure development in a city. The

construction and layout of roads affect land-use efficiency and functional zoning [50], which in turn affect green use efficiency. Controlling for this variable helped us to better understand the impact of open data on land-use efficiency.

Patents for green inventions in cities (GPI, the logarithm of the number of green inventions patented in a city in a year). An increase in the number of green patents is usually combined with economic growth and can contribute to the formation of a green economy [51]. Therefore, considering the number of green patents when discussing the impact of open government data on land-use efficiency helped us to understand the relationship between economic growth and environmental sustainability.

The strength of environmental regulation (ER, measured using the number of words in sentences containing environmental words for each city as a proportion of the total number of words in entire government work reports). The strength of environmental regulation directly affects decisions made by companies and individuals on land use. Stronger environmental regulation usually drives land use in a more sustainable direction [44], thereby affecting the efficiency of green land use. Therefore, the impact of environmental regulation needed to be controlled when analyzing the impact of open government data on green land-use efficiency.

The energy consumption level (PEGY). (PEGY, with reference to the standard coal conversion coefficients for each energy source in the *China Energy Statistical Yearbook*, the artificial, total natural gas supply, total liquefied petroleum gas supply and total electricity consumption of society as a whole was calculated for each prefecture-level city, converted to 10,000 tons of standard coal and summed up to give the energy consumption, which was measured by taking the logarithm of the number of tons of standard coal). The level of energy consumption directly affects the efficiency and manner of land use. A high energy consumption level may imply high-intensity development and utilization of land resources [52], thereby affecting green land-use efficiency. Therefore, when analyzing the impact of open government data on the efficiency of green land use, controlling for the level of energy consumption helped isolate the impacts of other factors.

Descriptive statistics for the main variables addressed in this article are displayed in Table 2.

Table 2. Descriptive statistical analysis.

	(1)	(2)	(3)	(4)	(5)
Variables	**Count**	**Mean**	**Sd**	**Min**	**Max**
CGLUE	3464	0.2715	0.3314	0.0000	0.9536
DID	3464	0.0479	0.2136	0.0000	1.0000
PGDP	3464	10.6380	0.5602	8.7729	13.0557
FIN	3464	5.5334	0.6435	0.0000	9.0303
INTRATE	3464	2.7350	0.6778	−1.0578	4.9377
URBAN	3464	4.5795	0.0756	3.7887	4.6052
GOV	3464	0.1897	0.0976	0.0439	0.9155
IND	3464	0.4884	0.1017	0.1170	0.8930
GPI	3454	4.0798	1.6135	0.0000	9.2697
ER	3464	0.3993	0.3957	0.0070	5.1003
PEGY	3464	0.0790	0.1479	0.0041	6.2571

3.3. Model Design

To investigate the influence of OGD on CGLUE, we built a benchmark regression model as follows:

$$CGLUE_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 Control_{it} + \mu_j + \theta_t + \varepsilon \quad (2)$$

In Equation (2), the explanatory variable $CLGUE_{it}$ represents the CGLUE of city i in year t. DID_{it} is the implementation of OGD by city i in year t. α_1 captures the impact of open government data on CGLUE. $Control_{it}$ denotes the control variable. ε is the random error term of the model. In addition, the following basic treatments were performed:

Initially, the modified standard errors, grouped at the city level in the regression, were used in all regression models. Second, in order to absorb fixed effects as much as possible, we controlled for both time (θ_t) and city (μ_j) fixed effects.

3.4. Benchmark Regression

The findings estimating the influence of OGD on CGLUE are shown in Table 3. Specifically, column (1) displays the estimation results without fixation or the addition of control variables. The estimation results with the control variables gradually included, accounting for time and individual-level variations, are shown in columns (2) through (11). Column (11) is the basis for the follow-up analyses.

Table 3. Benchmark regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**
DID	0.1365 **	0.1365 **	0.1362 **	0.1354 **	0.1348 **	0.1354 **	0.1304 **	0.1300 **	0.1290 **	0.1309 **	0.1308 **
	(0.0646)	(0.0646)	(0.0648)	(0.0648)	(0.0650)	(0.0652)	(0.0644)	(0.0631)	(0.0632)	(0.0626)	(0.0627)
PGDP		−0.0004	0.0050	0.0079	0.0062	0.0383	−0.0036	0.0013	0.0050	0.0126	0.0111
		(0.0576)	(0.0584)	(0.0588)	(0.0588)	(0.0709)	(0.0827)	(0.0832)	(0.0834)	(0.0819)	(0.0822)
FIN			−0.0199	−0.0199	−0.0210	−0.0431	−0.0500	−0.0524	−0.0520	−0.0533	−0.0535
			(0.0396)	(0.0394)	(0.0395)	(0.0565)	(0.0633)	(0.0631)	(0.0622)	(0.0629)	(0.0628)
INTRATE				−0.0101	−0.0107	−0.0112	−0.0108	−0.0105	−0.0159	−0.0143	−0.0145
				(0.0210)	(0.0210)	(0.0212)	(0.0207)	(0.0206)	(0.0206)	(0.0204)	(0.0204)
URBAN					0.1995	0.1855	0.1243	0.1200	0.1209	0.1068	0.1026
					(0.2641)	(0.2605)	(0.2559)	(0.2518)	(0.2500)	(0.2523)	(0.2521)
GOV						0.3345	0.4303	0.4163	0.3855	0.4042	0.4030
						(0.2971)	(0.3017)	(0.2974)	(0.2937)	(0.2915)	(0.2916)
IND							0.4837 **	0.4931 **	0.5097 **	0.5055 **	0.4987 **
							(0.2168)	(0.2184)	(0.2180)	(0.2141)	(0.2135)
INF								−0.0052	−0.0053	−0.0053	−0.0053
								(0.0037)	(0.0037)	(0.0038)	(0.0038)
GPI									−0.0209	−0.0205	−0.0204
									(0.0129)	(0.0128)	(0.0128)
ER										−0.0654 *	−0.0650 *
										(0.0357)	(0.0356)
PEGY											−0.0245
											(0.0278)
City Fe		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fe		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cons	0.4019 ***	0.4066	0.4591	0.4561	−0.4317	−0.6492	−0.1406	−0.0748	−0.0211	−0.0108	0.0310
	(0.0031)	(0.6125)	(0.6142)	(0.6141)	(1.3473)	(1.3557)	(1.3850)	(1.3650)	(1.3581)	(1.3562)	(1.3552)
N	3454	3454	3454	3454	3454	3454	3454	3454	3454	3454	3454
R^2	0.7286	0.7286	0.7287	0.7288	0.7289	0.7293	0.7312	0.7326	0.7339	0.7354	0.7354

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The accuracy of Hypothesis 1 is confirmed by the regression results in columns (1)–(11) in Table 3, which show that all estimated DID coefficients passed the significance test at the 5% level. This suggests that the level of CGLUE is greatly increased by using OGD. Open government data can provide more information and references for urban planners and decision-makers, helping them to formulate land-use policies more scientifically. This fosters a certain degree of equilibrium between urban expansion and the preservation of natural resources, thereby encouraging the establishment of environmentally friendly policies [53]. Simultaneously, the transparency of government data aids in comprehending the present state and requirements of land utilization, facilitating the efficient planning and allocation of land resources to attain the most advantageous distribution and utilization of land [54].

3.5. Robustness Tests

3.5.1. Parallel Trend Test

Prior to using the DID model to ascertain the correlation between government data transparency and the efficiency of urban green land use, it was necessary to ensure that the experimental and control groups adhered to the premise of parallel trends. Thus, this research utilized the event study method to perform a parallel trend test. The *y*-axis represents the impact of opening government data on CGLUE, while the *x*-axis represents

the year of policy implementation. Figure 1 illustrates that the influence on CGLUE was negligible prior to the policy's implementation but became a significant factor afterwards.

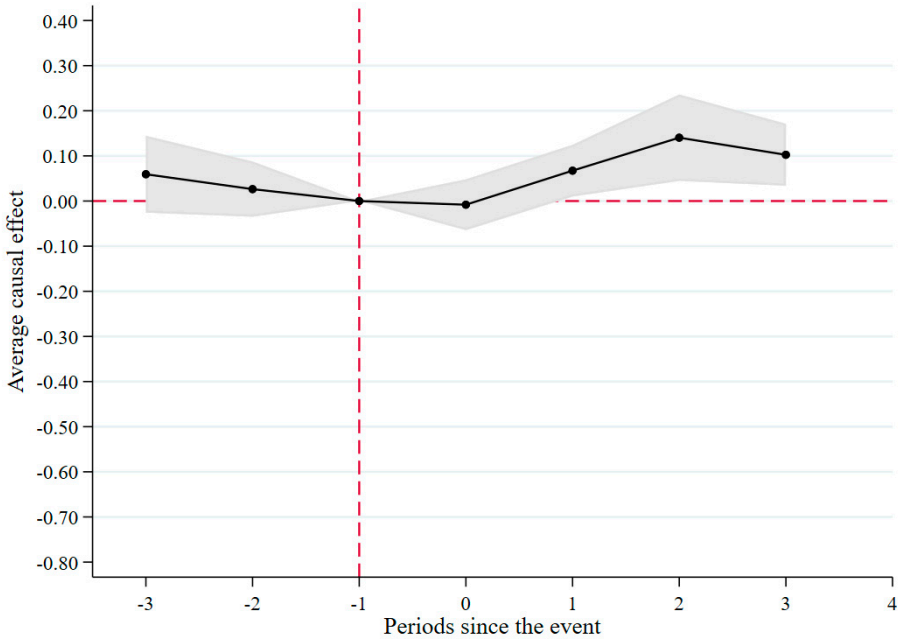

Figure 1. Parallel trend test.

3.5.2. Placebo Test

This work employed an indirect placebo test, based on research conducted by other researchers, to mitigate the impact of unobservable variables on the research findings. This test was repeated 500 times for greater accuracy. Specifically, a pseudo-variable False_DID was constructed for each randomly assigned city. It was then used to replace the true DID and re-estimate the baseline model, and this step was iterated 500 times. Figure 2 shows the distribution of T-values for the estimation based on the False_DID. In Figure 2, it can be seen that the T-values of the 500 placebo tests were normally distributed and centered on 0. Only a few results were close to the true T-value (the red dashed line), which suggests that some unobserved macroscopic or time-varying factors did not affect the main results of this study.

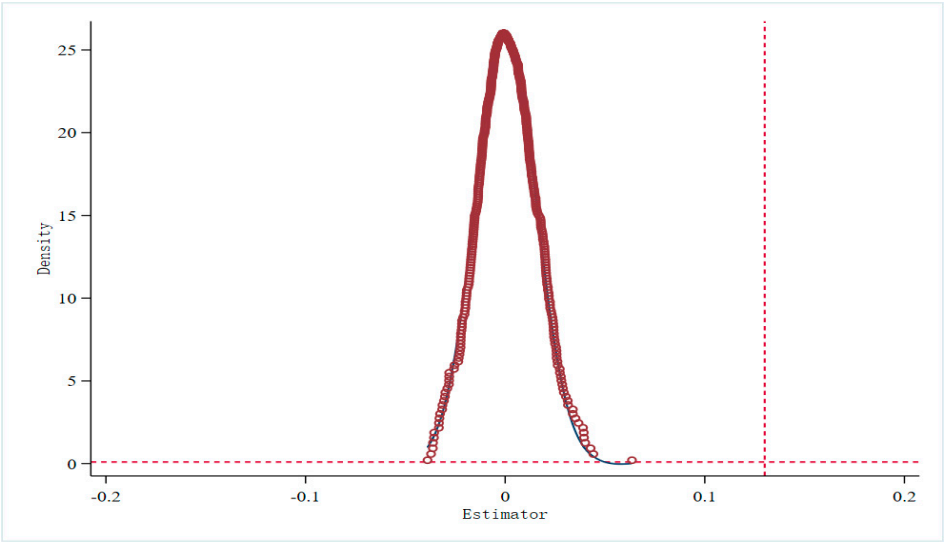

Figure 2. Placebo test.

3.5.3. Propensity Score Matching

Through the random selection of treatment and control groups, propensity score matching successfully mitigates the endogeneity problem resulting from selectivity bias. Additionally, propensity score matching can lessen the heterogeneity bias in treatment and control groups caused by other unobservable characteristics. Thus, propensity score matching was used in this study for robustness testing, and the particular model was built as follows:

$$P(treat = 1) = f(PGDP, FIN, INTRATE, URBAN, GOV, IND, INF, GPI, ER, PEGY) \quad (3)$$

We utilized k nearest zero matching with k = 4 to determine the propensity score, denoted as P. Based on the regression results presented in Table 4, it is evident that the variable DID continued to have a significant impact on the variable CGLUE. In addition, we employed caliper and kernel matching to conduct additional robustness checks. Based on the regression results, our benchmark regression was still confirmed.

Table 4. Propensity score matching test.

	(1)	(2)	(3)
Variables	**CGLUE**	**CGLUE**	**CGLUE**
DID	0.147 **	0.147 **	0.140 **
	(0.0616)	(0.0617)	(0.0623)
Constant	−0.894	−0.934	−0.307
	(1.086)	(1.082)	(1.267)
Control Variables	YES	YES	YES
City Fe	YES	YES	YES
Year Fe	YES	YES	YES
Observations	3389	3397	3453
R-squared	0.547	0.547	0.537

Standard errors in parentheses. ** $p < 0.05$.

3.5.4. Excluding Interference from Other Policies

To eliminate the influence of other policies on the efficiency of green land use in urban areas, we gathered and organized relevant policies, such as Big Data Pilot Cities (DID1) and Smart Cities (DID2), that coincided with the time frame of our study. We then incorporated dummy variables for these policies into the basic regression analysis. The estimated coefficients of the Difference-in-Differences (DIDs) method in columns (1)–(3) of Table 5 passed the significance test at the five percent level. These coefficients remained positive even after accounting for the effects of these policies, both individually and together. This indicates the strength and reliability of the findings.

Table 5. Exclusion of interference from other policies.

	(1)	(2)	(3)
Variables	**CGLUE**	**CGLUE**	**CGLUE**
DID	0.1307 **	0.1314 **	0.1315 **
	(0.0627)	(0.0627)	(0.0627)
DID1	−0.0025		0.0020
	(0.0217)		(0.0207)
DID2		−0.0401 *	−0.0403 *
		(0.0221)	(0.0213)
Control Variables	YES	YES	YES
City Fe	YES	YES	YES
Year Fe	YES	YES	YES
Cons	0.0324	0.1336	0.1329
	(1.3545)	(1.3356)	(1.3362)

Table 5. *Cont.*

	(1)	(2)	(3)
Variables	**CGLUE**	**CGLUE**	**CGLUE**
N	3454	3454	3454
R^2	0.7354	0.7362	0.7362

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$.

3.6. Mechanism Analysis

The above empirical analyses verified the positive effect of OGD on CGLUE. In a theoretical analysis, this paper argues that government data openness promotes CGLUE by increasing urban green innovation capacity and public environmental concern. Urban green innovation capacity (INNOVATION) was measured using urban green patent applications, while public environmental concern (PEC) was measured using the public haze search index.

We confirmed the validity of this statement, and Table 6 presents the outcomes of an examination of how OGD impacts CGLUE.

Table 6. Mechanism tests.

	(1)	(2)	(3)	(4)
Variables	**INNOVATION**	**INNOVATION**	**PEC**	**PEC**
DID	0.5169 **	0.4734 *	0.1019 *	0.0880 *
	(0.2564)	(0.2404)	(0.0564)	(0.0500)
Control Variables	NO	YES	NO	YES
City Fe	YES	YES	YES	YES
Year Fe	YES	YES	YES	YES
Cons	0.6925 ***	12.3092 ***	4.3950 ***	2.8531
	(0.0123)	(4.4299)	(0.0027)	(2.2613)
N	3464	3454	3447	3438
R^2	0.7959	0.8129	0.9422	0.9480

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 displays the effect of OGD on green innovation capability. Column (1) represents the impact without the control variables, whereas column (2) represents the impact with the control variables. The analysis revealed that the estimated coefficient of the DID was statistically significant and positive, with a significance level of at least 10%. This suggests that the openness of government data has a positive impact on a city's green innovation potential, supporting Hypothesis 2. According to Guo et al. [55], the unrestricted movement of data components facilitates the swift implementation of scientific and technical advancements. With the support of data, new technologies and concepts can be verified faster in urban practice, thereby improving CGLUE. Meanwhile, the openness of data elements provides a common information platform for all parties in society. Experts from different fields can cooperate based on shared data resources and can jointly explore innovative paths for green urban land use [56].

Columns (3) and (4) in Table 6, respectively, indicate how public environmental concerns were affected by OGD with and without the control factors. It can be seen that the estimated coefficients passed at the 10% significance level, suggesting that open government data increase public environmental concern by promoting CGLUE. Therefore, Hypothesis 3 was verified. Public concern for the environment can stimulate demand for green technologies and innovations [57]. OGD makes it easier for the public to understand urban environmental problems and resource utilization, triggering public demand for innovative technologies and methods to solve these issues [58]. Due to this need, businesses and academic institutions have increased their funding for studying and developing green technologies, encouraging the growth of green innovation and enhancing CGLUE. At

the same time, the public's increased concern for the environment has prompted the government to develop environmental policies and plans that are more in line with the public's needs [23]. When formulating urban land-use policies, the government will give more consideration to the public's demands and expectations and will listen to the public's opinions and suggestions so as to formulate more scientific policies that are more in line with the concept of green development and improve CGLUE.

3.7. Heterogeneity Analysis

The preceding section primarily confirmed, from the standpoint of the entire sample, the promotional effect of government data availability on CGLUE. In order to explore potential areas for policy focus to further enhance CGLUE through data openness, this study delved deeply into the heterogeneity of government data openness affecting CGLUE based on the geographical characteristics of location, digital financial characteristics, and resource-based city characteristics.

3.7.1. Location Heterogeneity

The location characteristics (EAST) dummy variable created in this study had values of 1 for cities in the eastern area and 0 for cities in the central and western regions. The results are displayed in columns (1) and (2) of Table 7, respectively. The coefficient of the DID had a more pronounced impact on the CGLUE in the eastern cities. This was because the eastern cities typically exhibit greater levels of economic growth and population density, with greater pressure on land resources [59]. Open government data can help these cities to more effectively address the challenges of limited land resources and high environmental pressure and can guide these cities towards green and sustainable development. Meanwhile, in the eastern region of China, the national policy orientation towards green development and sustainable city building is clear [60]. Government data openness is more likely to be supported by the government and society in such a policy context and is more likely to be incorporated into urban development planning and practice, thereby more significantly influencing improvements in CGLUE.

Table 7. Heterogeneity results.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**	**CGLUE**
DID	0.2734 ***	0.0109	0.1897 **	0.0939	0.0092	0.1752 **
	(0.0925)	(0.0361)	(0.0754)	(0.1041)	(0.0390)	(0.0755)
Control Variables	YES	YES	YES	YES	YES	YES
City Fe	YES	YES	YES	YES	YES	YES
Year Fe	YES	YES	YES	YES	YES	YES
Cons	−1.9810	0.2881	−1.8936	0.1160	−0.2207	−0.1651
	(3.3388)	(1.3931)	(1.9683)	(1.5285)	(2.2888)	(1.4816)
N	1036	2418	1883	1621	1381	2073
R^2	0.6814	0.7778	0.7903	0.6948	0.7363	0.7487

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

3.7.2. Heterogeneity of Digital Financial Characteristics

This study measured the level of digital financial development (DF) in cities using their digital financial inclusion knowledge. A value of 1 was assigned to scores above the median DF, and a value of 0 was assigned to those below it. The outcomes are displayed in columns (3) and (4) of Table 7, respectively, and the DID coefficients were proven to be more significant for CGLUE with larger amounts of digital finance. This was because cities with higher levels of digital finance tend to prioritize the use and utilization of data and are more likely to embrace data-driven decision-making models in land planning, resource management, and environmental protection. Open government data provide these cities with more accurate data support, which can help decision-makers better analyze and assess land use and formulate more scientific and effective green development strategies [61]. At

the same time, cities with higher levels of digital finance tend to have more developed financial systems and capital markets and can more easily obtain financial support and investment. Government data openness can increase the transparency of the urban environment and land-use situation, enhance investor confidence in green projects [62], and promote improvements in CGLUE.

3.7.3. Resource Endowment Heterogeneity

This work aimed to create dummy variables, referred to as RBCs, to represent urban resource endowment. These variables were constructed using a list of cities that are known for their resource-based economies. More precisely, RBCs were represented as 1 to indicate resource-based cities or 0 to indicate non-resource-based cities. The coefficients of the DID analysis had a greater impact in non-resource-based cities, as shown in columns (5) and (6) of Table 7. This was because non-resource-based cities lack the advantages of natural resources and therefore rely more on innovation and development to drive economic growth and ensure sustainability. Open government data help these cities achieve sustainable development [63]. This assistance helps guide cities in adopting environmentally friendly and sustainable approaches to land use. Additionally, the utilization of OGD has the potential to improve the reputation and level of transparency in cities that do not rely on natural resources [64,65]. This, in turn, can help attract skilled individuals and investments. Urban innovation and development, as well as green land use and sustainable development, can be stimulated by influxes of talent and cash.

4. Further Analyses: The Carbon-Reducing Effects of Open Government Data

We conducted a comprehensive evaluation of the influence of open government data on carbon emissions ($LNCO_2$) in order to examine the effects of the policy on carbon levels. The results of this estimation are displayed in Table 8. The impact of open government data on CO_2 is demonstrated in columns (1) and (2) of Table 8. Column (1) represents the effect when the green land-use efficiency of urban land was above the median, while column (2) represents the effect when it was below the median. The analysis revealed that the estimated coefficient of DID was significantly negative, with a minimum significance level of 5%, when the level of CGLUE was higher. This suggests that as CGLUE increases, the carbon emission reduction effect of open government data becomes more pronounced. This demonstrates that the utilization of open government data leads to decreases in carbon emissions in urban areas while simultaneously enhancing CGLUE. This will also help China achieve its "dual-carbon" objective.

Table 8. Further analysis.

	(1)	(2)
Variables	**$LNCO_2$**	**$LNCO_2$**
DID	−0.1790 **	−0.0117
	(0.0726)	(0.0749)
Control Variables	YES	YES
City Fe	YES	YES
Year Fe	YES	YES
Cons	5.9374 ***	3.1804
	(2.1540)	(4.5218)
N	1637	1810
R^2	0.9538	0.9609

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions

This study empirically examined the impact of government data openness on CGLUE. It was found that government data openness significantly improved CGLUE. Further mechanism analyses showed that government data openness improved CGLUE by in-

creasing public environmental concern and enhancing the urban green innovation capacity. Heterogeneity analyses showed that the effect of open government data on CGLUE was more obvious in eastern cities, cities with higher levels of digital finance development, and non-resource-based cities.

Based on the aforementioned findings, this report presents the following specific policy recommendations:

First, government departments should establish a unified open government data platform to ensure data standardization, easy access, and open sharing and to promote data interconnectivity among city departments. In addition, government departments at all levels should take the initiative to disclose relevant environmental and land-use data and encourage private institutions and individuals to use these data for green project development and innovation. On the other hand, a system for evaluating CGLUE should be established, and urban green projects should be evaluated and monitored on a regular basis so that policies and measures can be adjusted in a timely manner.

Secondly, education and publicity campaigns targeting environmental protection and green utilization should be carried out to raise public awareness and bring attention to environmental issues. In addition, a green innovation fund can be established to encourage enterprises, scientific research institutions, and others to develop green technological innovations and carry out projects. Collaboration among governmental departments, corporations, research institutes, and social organizations should be facilitated to collectively enhance CGLUE.

Finally, for eastern cities, the construction of open government data platforms should be strengthened to improve the comprehensiveness of the data and ensure they are updated in real time to facilitate urban management and meet citizens' needs. For cities with high levels of digital finance, financial institutions should be pushed to increase their investments in and support for green projects, to establish green financial products and service systems, and to direct capital flows to environmental protection and sustainable areas. For non-resource-based cities, special green innovation funds should be set up to support green technology enterprises and projects, the application and dissemination of green technology should be promoted in urban land use, and green enterprises should be attracted by establishing green industrial parks and demonstration zones to generate a green industrial agglomeration effect and promote CGLUE.

6. Research Limitations

This study tried to open the black box of opening public government data from the perspective of their relationship with urban green land-use efficiency. However, the impact of government data openness on urban green land-utilization efficiency may also be closely related to the effects of data openness, public participation, and trust, as well as the differences in the policy environments and development stages of different cities; the variations in these social factors may not have been adequately taken into account in this study. Therefore, it will be of great practical significance to clarify the heterogeneous effects of public data elements on urban green land-utilization efficiency in different contexts in future studies to increase CGLUE effectively.

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