land

MDPI

Article

The Heterogeneous Influence of Infrastructure Construction on China's Urban Green and Smart Development—The Threshold Effect of Urban Scale

Lingyan Xu [1,2,*], Dandan Wang [1] and Jianguo Du [1,2]

[1] School of Management, Jiangsu University, 301 Xuefu Road, Zhenjiang 212013, China; 2211910022@stmail.ujs.edu.cn (D.W.); djg@ujs.edu.cn (J.D.)
[2] Research Center for Green Development and Environmental Governance, Jiangsu University, Zhenjiang 212013, China
* Correspondence: xulingyan333@163.com

Abstract: The construction of green and smart cities is an important approach to enhancing the level of high-quality development and modern governance, in which infrastructure construction is the antecedent condition. From the perspective of green total factor productivity (GTFP), this paper adopts the SBM–GML (Slack-Based Model and Global Malmquist–Luenberger) index to measure the urban green and smart development level (GSDL) considering smart input–output factors. Based on the panel data of China's 223 prefecture-level cities from 2005 to 2018, the dynamic impacts, temporal, and spatial differences of energy, transportation, and telecommunication infrastructure construction on the urban GSDL are discussed, and the threshold effects of urban scale are tested. The following conclusions are drawn: (1) On the whole, energy infrastructure inhibits the urban GSDL, while transportation and telecommunication infrastructures significantly promote it. There are distinct spatial and temporal characteristics among the impacts of these three infrastructures on the urban GSDL, in which the facilitating role of transportation and telecommunication infrastructures are further enhanced during the period of 2013–2018. Furthermore, the impacts of these three infrastructures on the urban GSDL all show "U" shape in terms of non-linearity. (2) Economic development level and industrial structure have significant positive effects on the urban GSDL, whereas human capital only has positive effect in the northeast and southwest regions, and government scale shows no positive impact yet. (3) There is a single threshold for the impact of urban scale on these three infrastructures, among which the impacts of energy and transportation infrastructures on the urban GSDL remain consistent before and after the threshold, while the impact of telecommunication infrastructure on the urban GSDL varies from having no significance to being positive when crossing the threshold. Thus, capital investment for infrastructure construction should be further allocated reasonably, the positive potential of human capital should be fully released, and the urban scale should be appropriately controlled in the future.

Keywords: infrastructure construction; urban green and smart development level; urban scale; threshold effect

Citation: Xu, L.; Wang, D.; Du, J. The Heterogeneous Influence of Infrastructure Construction on China's Urban Green and Smart Development—The Threshold Effect of Urban Scale. *Land* **2021**, *10*, 1015. https://doi.org/10.3390/land10101015

Academic Editors: Elizelle Juanee Cilliers and Sarel Cilliers

Received: 30 August 2021
Accepted: 24 September 2021
Published: 27 September 2021

1. Introduction

1.1. Motivation

Urbanization is an important driving force for economic growth [1], which is closely related to capital and also has great impact on the environment [2]. It is shown that the urbanization rate of China has exceeded 60% by the end of 2020 [3]. Although urbanization has promoted industrialization and economic growth remarkably, it has also resulted in serious deterioration of ecology, frequent extreme weather, and other problems, which have been accumulated over the decades [4]. As such, the traditional extensive urban development mode needs to be changed urgently. In this context, the construction of green and smart cities has been successively distributed in various prefecture-level cities with national policies implemented in China [5,6]. The construction of green and smart cities is based on the sustainable and low-carbon development and utilization of the internet, cloud computing, artificial intelligence, and other smart technologies to improve the level of urban production, social management, and public services [7] and eventually optimize the industrial structure, extensively form green production and lifestyles, and promote the urban economic development [8,9]. Faced with the development opportunities of urban green and smart construction, China's cities actively deploy infrastructure construction related to energy, transportation, telecommunication to provide fundamental support in enhancing low-carbon emission reduction, transportation structure, comprehensive transportation network efficiency, and information resource sharing. As such, the urban GSDL would be enhanced [10,11]. However, redundant infrastructure construction is also accompanied by high energy consumption, and the adoption of infrastructures for commodity trade and production will also generate new pollution [12], which will be a bottleneck of the urban GSDL. Therefore, this paper explores the complex relationship between infrastructure construction and the urban GSDL by taking China as an example.

1.2. Literature Review and Contribution

1.2.1. Measurement of the Urban GSDL

Urban development promotes capital accumulation, which in return improves urban development by investing in infrastructure construction [13], such as Barcelona [14]. Furthermore, industrial development and infrastructure construction respond to the needs of capital expansion [14]. In this frame, the urban development modeled by capitalism has brought some distortion development models, which bring about the result that the land price becomes a determinant factor of the economic and political issues [15]. Continuous capitalist pursuit of profit-seeking has led to new speculative real estate booms, such as new office buildings and high-end residential buildings associated with infrastructure and cultural and entertainment spaces [14,16], which are less related to public needs and urban requirements [17]. As Mora and Camerin noted, urban regeneration and reconstruction projects were carried out for rent demand to achieve the goal of capital accumulation [18], which gradually damaged the architectural and urban development framework [3].

On the contrary, the construction of green and smart cities is not only an effective approach to solve urban problems but also an important decision to realize sustainable development [19,20]. Ding and Wang [21] and Du et al. [22] conducted a comprehensive evaluation index from multidimensional perspectives to evaluate the urban GSDL. Others analyzed the urban GSDL by combining PCA–GRA, entropy power, and cloud model [23]. In addition, some literature adopted GTFP (green total factor productivity) from the perspective of input–output efficiency to analyze the green productivity and innovative efficiency of China's provinces and cities [24,25], and the spatial and temporal disparities between regions [26], which provided a new method for estimating the urban GSDL. Existing research also showed that the quality and efficiency of urban development were not only affected by the degree of green development but also related to urban smart elements. Urban smart elements could also promote the efficiency of urban governance and public services through technological innovation and facilitate resource utilization, thus promoting the GTFP and empowering high-quality development [27,28]. Jiang et al. [7] showed that the construction of smart cities provided vital support for urban green development, which promoted the urban GTFP by accelerating technological innovation. Xia and Xu [29] estimated GTFP with non-parametric methods and found that the GDP growth rate was unrelated to the GTFP, while smart city construction could significantly facilitate the green utilization efficiency of urban land [30]. These conclusions suggest that green and smart factors should be considered when we estimate the quality of urban development.

1.2.2. Relationship between Infrastructure Construction and the Urban GSDL

Infrastructure construction is considered as a prerequisite for urban economy, and the development of urban economy also accelerates infrastructure construction. Historically, urban planning and development has been deeply rooted in the process of infrastructure construction, which provides ontological foundations and operation space for cities [31]. However, infrastructure construction, which was the main way of urban regeneration for capitalist cities in the past, often ignored public needs during the process [16,17]. Since the contradiction between environmental and economic development are becoming more and more prominent, a multi-agent participation mode of social capital was adopted in infrastructure construction under the regulation of government; thus, the public welfare and service nature of infrastructure construction was achieved [32].

Literature focuses more on the relationship between infrastructure construction and urban renewal, including the impacts of infrastructure construction on the urban green development or smart development, while green and smart elements are barely taken as a unity to explore their relationship. Scholars mainly expounded the relationship between infrastructure construction and green development or smart development from the following two aspects.

On the one hand, from the perspective of the driving force for urban development, infrastructure construction is the hardware foundation to accelerate the marketability of resources and elements, which is of benefit to integrating innovators [6], accelerating economic growth [33], and enhancing the resource allocation efficiency [34]. Wei and Chen [35] noted that the transportation infrastructure played an important role in the construction of energy-saving and low-carbon cities, which was closely related to the construction of green and smart development cities [36]. Other research showed that infrastructure construction made the largest contribution to GTFP when compared with the scheme, technology, and other factors [37,38], which had a more significant effect in relatively backward areas [39]. Furthermore, infrastructure construction could not only directly affect the economy and environment but also indirectly affect the urban smart development, living quality, and low-carbon development through technological innovation [40], international trade [41], industrial, and talents agglomeration [42,43]. For example, transportation infrastructure could reduce trade costs and improve the access to the market, which strengthened the driving force of technological innovation and productivity improvement through resource importation and regional spillover effect [44,45], among which economic agglomeration and market accessibility played a mediating role [46]. Additionally, the telecommunication development was conducive to breaking regional market restrictions and reducing coordination costs of enterprises, which was crucial to regional integrated market construction and beneficial to improving production efficiency through scale and intensive economy [47]. Fully equipped telecommunication infrastructure could accelerate the evolution of production structure through talent gathering and optimization of resources, thus improving the scale and network effect of economic development and urban productivity level [48]. Moreover, due to the marketability of production elements, infrastructure construction may also promote or inhibit the development of adjacent areas [49]. For example, the transportation infrastructure would enhance urban accessibility and promote the agglomeration of innovation elements, strengthen knowledge and technology spillover effect, and, accordingly, the innovation structure among regions could be influenced [50,51]. Meanwhile, developed telecommunication infrastructure would facilitate technological innovation and knowledge-based economy, thus forming spatial preference and agglomeration characteristics by influencing the prospect of adjacent areas through spatial spillover effect [52,53].

On the other hand, infrastructure construction requires a large input of energy and other resources, which will cause consumption and pollution. Moreover, excessive infrastructure construction will also destroy environmental carrying capacity, which is harmful to the sustainable development of the economy and society; therefore, the urban GSDL will be restricted. Wang [54] adopted the GML index and threshold regression model to find that traditional energy consumption would have a negative impact on GTFP with both too much and too low degree, which depended on whether the technology level of energy transformation could meet the production requirements or not [55]. Kong et al. [56] also found that the negative effect of energy infrastructure construction on the environment was more prominent, and the large-scale production caused by the elements aggregation was prone to result in resource monopoly, which resulted in the resource allocation distortion and inefficient utilization, and then vertically deepened the negative externality of energy. Besides, by reducing logistics costs and promoting the marketability of elements, transportation infrastructure also accelerated the flow of resources to big cities, resulting in a "siphon effect" and deepening the degree of regional differentiation [57]. Furthermore, the research even demonstrated such phenomena as "short-term effects" were superior to "long-term effects" [58]. Sun et al. [59] noted that urban and rail transportation showed positive effects on reducing air pollution, while the construction of rail transportation had a negative short-term impact on air quality. In addition, the effect of infrastructure construction on GSDL would also be restricted by other factors, such as economic development level, industrial structure, energy structure, and resource endowment [60]. Particularly, the internal difference such as urban scale could also influence urban construction [61]. Jain and Tiwari [62] showed that improving bus and bicycle infrastructures could minimize equivalent CO_2 emissions, while different strategies should be taken based on the urban scale.

In conclusion, the GTFP is an important criterion to evaluate the quality of economic development. The existing research has provided many important ideas and research methods, while green and smart elements are barely integrated into a unified analytical-framework to measure the urban GSDL from the perspective of total factor productivity (TFP), which could not reflect the two-wheel driving force of green and smart for urban sustainable development. Research has paid more attention to the influence of infrastructure construction on regional innovation, economic development, TFP, and GTFP, while few focused on the heterogeneous effects of infrastructure construction on the urban GSDL from the perspective of their linear and nonlinear relationships. Furthermore, the threshold effect of urban characteristics also needs to be deepened. Therefore, based on the panel data of 223 prefecture-level cities from 2005 to 2018, this paper firstly adopts SBM–GML index to evaluate the urban GSDL by considering the green and smart factors based on the GTFP accounting framework. Secondly, the linear and nonlinear effects of infrastructure construction on the urban GSDL are analyzed. Thirdly, heterogeneous effects of infrastructure construction on urban GSDL are explored from regional and temporal perspectives. Finally, the threshold effects of urban scale are explained.

2. Materials and Methods

2.1. Measure of GSDL

2.1.1. Measure Model Construction

The SBM model is an improved DEA (data envelopment analysis) model, which is developed to evaluate the efficiency of decision units with multiple input and output indicators and eliminate the estimation bias caused by the difference in radial and angle selection. Combined with the GML index, the SBM model could better describe the variation of productivity [63]. The form of non-angular and non-radial SBM model containing the unexpected output is as follows (Formula (1)):

$$\begin{aligned}
&\min\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1+\frac{1}{s_1+s_2}\left(\sum_{i=1}^{s_1} s_r^g / y_{r0}^g + \sum_{i=1}^{s_2} s_r^b / z_{r0}^g\right)} \\
&s.t.\ X\lambda + s_i^- = x_k,\ Y^g\lambda - s_r^g = y_0^g,\ Z^b\lambda + s_r^b = z_0^b \\
&\lambda,\ s_i^-,\ s_r^g,\ s_r^b \geq 0
\end{aligned} \tag{1}$$

In Formula (1), ρ is the ratio of actual input–output relative to the average narrowing and expansion of technological frontier; m, s_1, s_2 denote the quantity of input, expected and unexpected output respectively, and s^-, s^g, s^b are the corresponding relaxation variables.

The GML index from t to t + 1 is defined, and the specific Formula (2) is as follows:

$$\begin{aligned} GML^{\,t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \times \frac{1+D^t(x^t,y^t,b^t)}{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \\ &\times \frac{1+D^G(x^t,y^t,b^t)}{1+D^t(x^t,y^t,b^t)} \times \frac{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \end{aligned} \tag{2}$$

In Formula (2), $GML^{t,t+1}$ represents the GSDL variations of units in period t to t +1. When $GML^{t,t+1} > 1$, it indicates that GSDL has been improved in the current period when compared with that in previous period. The calculation Formula (3) is as follows:

$$GSDL_{2006} = GSDL_{2005} * GML_{2006} \tag{3}$$

2.1.2. Indicators of GSDL Measurement

According to Du et al. [22] and Lu et al. [64], this paper adopts the SBM–GML index to measure the urban GSDL with the following indicators. The input indicators include the fixed capital stock, labor, energy, and the fiscal expenditure of science, technology, and education. The output indicators are comprised of four aspects including economic, green, smart, and undesired environmental elements, among which regional GDP indicates economic output, international internet users and patent application quantity indicate smart output, the harmless disposal rate of domes-tic garbage, sewage treatment rate and greenery coverage of urban area indicate green output, discharge of industrial wastewater, industrial smoke, and dust emissions and SO2 emissions indicate undesired environmental output. The specific indicators are shown in Table 1:

Table 1. Indicators of GSDL.

Indicator	Variable	Unit	Computation Method
Input indicators	Fixed capital stock	100 million yuan	Perpetual inventory method
	Labor	10 thousand people	The number of urban employees at the end of year
	Electricity consumption	10 thousand kilowatts	Total electricity consumption
	Education and technology expenditure	10 thousand yuan	Financial expenditure on science, technology, and education
Output indicators	Regional GDP	100 million yuan	Regional GDP of the year
	International internet users	10 thousand people	The number of urban international Internet users
	Patent application quantity	Part	The number of urban patent application
	Harmless disposal rate of domestic garbage	%	Percentage of the disposal of harmless garbage
	Sewage treatment rate	%	Percentage of sewage disposed
	Greenery coverage of urban area	%	Greening coverage rate in built-up areas of the city
	Discharge of industrial wastewater	10 thousand tons	Industrial wastewater discharge volume of the city
	Industrial smoke and dust emissions	Tons	Industrial smoke and dust emissions' volume of the city
	Industrial SO_2 emissions	Tons	Industrial SO_2 emissions' volume of the city

In addition, the capital stock is measured by the perpetual inventory method according to Zhang et al. [65]. Regional GDP is represented by the real GDP, which takes 2003 as the base period. The entropy value method with the time variable is adopted to calculate the expected pro-environmental output and unexpected pollution output.

2.2. Construction of Empirical Model

The construction of energy, transportation, and telecommunication infrastructure has different functions and adoptions, which may result in differentiated impacts on the urban GSDL. Therefore, this paper first tests the linear and nonlinear effects of energy, transportation, and telecommunication infrastructure construction on the urban GSDL. Then, the regional and temporal heterogeneity effects of infrastructures are further analyzed. Finally, the threshold characteristics of urban scale are explored.

2.2.1. Panel Regression Model

According to the research objectives, the static dynamic panel regression model is first constructed as follow (Formula (4)):

$$GSDL_{it} = \beta_0 + \sum_{n=1}^{3} \alpha_n inf_{nt} + \sum_{i=1}^{4} \lambda_i Control_{it} + \varepsilon_{it} \quad (4)$$

In Formula (4), inf_n (n = 1, 2, 3) represents the infrastructure construction of energy, transportation, and telecommunication, respectively. $Control_{it}$ denotes economic development level, industrial structure, human capital level, and government size, respectively. The sum of α_n and β_1 are indicated as the regression coefficient, and ε_{it} is the random error. Based on Formula (4), the first-order lag term of the explained variable is added to explore the long-term influence between the explanatory variable and the explained variable, and the dynamic panel regression model is obtained as follow (Formula (5)):

$$GSDL_{it} = \beta_0 + \beta_1 GSDL_{t-1} + \sum_{n=1}^{3} \alpha_n inf_{nt} + \sum_{i=1}^{4} \lambda_i Control_{it} + \varepsilon_{it} \quad (5)$$

In Formula (5), $GSDL_{t-1}$ is the first-order lag term of the explained variable ($L.GSDL_t$). In order to explore the nonlinear influence relationship between the core explanatory variable and the explained variable, the square term of the explanatory variable is introduced to Formula (5) to construct a nonlinear panel regression model which is as follow (Formula (6)):

$$GSDL_{it} = \beta_0 + \beta_1 GSDL_{t-1} + \sum_{n=1}^{3} \alpha_n inf_{nt} + \sum_{n=1}^{3} \alpha_n inf^2{}_{nt} + \sum_{i=1}^{4} \lambda_i Control_{it} + \varepsilon_{it} \quad (6)$$

In Formula (6), $infn^2$ (n = 1, 2, 3) represents the square term of energy, transportation, and telecommunication infrastructure construction, respectively.

2.2.2. Threshold Regression Model

Previously, the dynamic panel regression model is constructed to test the influence of core explanatory variables and control variables on the urban GSDL. However, it is unable to describe the structural breakpoint of urban scale. Thus, this paper further explores the threshold effect of urban scale by adopting threshold regression model, which is constructed according to Hansen's panel data regression theory as follow (Formula (7)):

$$GSDL_{it} = u_i + \beta_1 X_{it} \cdot 1(q_{it} \le \lambda) + \beta_2 X_{it} \cdot 1(q_{it} > \lambda) + \varepsilon_{it} \quad (7)$$

In Formula (7), GSDL denotes the urban GSDL, X_{it} is the explanatory variable, q_{it} is the threshold variable, γ is the threshold value to be estimated, and ε_{it} is the random disturbance term. On this basis, a double threshold regression model is constructed as follow (Formula (8)):

$$GSDL_{it} = u_i + \beta_1 X_{it} \cdot 1(q_{it} \le \gamma_1) + \beta_2 X_{it} \cdot 1(\gamma_1 < q_{it} \le \gamma_2) + \beta_3 X_{it} \cdot 1(q_{it} > \gamma_2) \quad (8)$$

In Formula (8), the threshold value meets the requirement of $\gamma_1 < \gamma_2$.

2.3. Variable Description

Explained variable: The urban GSDL, which is calculated by SBM–GML.

Explanatory variables: Referring to Yeaple and Golub [66], infrastructures are comprised of energy, transportation, and telecommunication. In this paper, energy infrastructure (lnENER) is measured by the total amount of gas supply, transportation infrastructure (lnTRANS) is expressed by the length of urban highway, and telecommunication infrastructure (lnTELE) is represented by telecommunications revenue.

Threshold variables: Urban scale is the embodiment of regional economic development, which would aggregate resource elements and influence resource utilization efficiency [67]. As such, it is supposed to restrict the impact of infrastructure construction on the urban GSDL. The urban total population at the end of the year is applied to represent the urban scale.

Other control variables: Based on the existing research, this paper adopts economic development level (lnPGDP), industrial structure (STR), human capital level (HC), and government size (GOVER) to control the influence of external factors on the urban GSDL. Specifically, cities with high economic development levels will have greater support for technological innovation and more investment for pro-environmental issues and infrastructure construction. As consequence, the urban GSDL would be enhanced. Furthermore, industrial emissions are the main source of pollution, which directly restrict urban green development; therefore, it is necessary to enhance the urban GSDL by innovation and upgrading the industrial structure [68]. Then, the proportion of the tertiary industry is adopted to evaluate the influence of infrastructure construction on the urban GSDL. Additionally, due to the optimization of human capital elements is conducive to accelerating innovation and technology accumulation [69], this paper adopts the number of college students to represent human capital level. Furthermore, the government scale is measured by the ratio of government fiscal expenditure to GDP.

2.4. Data Source

The data of many urban patent applications before 2005 are missing and their caliber is not consistent; as well, the data in 2019 was incomplete. This paper selected samples from 2005 to 2018 to ensure the credibility of the research. Considering the integrity and continuity of panel data, the samples of cities with more missing data were excluded, and then 223 cities were selected as research samples, among which some missing data were supplemented by the linear interpolation method. As such, the panel data of 223 cities in China from 2005 to 2018 are obtained. The data of variables are mainly from "China Urban Statistics Yearbook", "Statistical Yearbook", and" Science and Technology Yearbooks" from 2006 to 2019 and "Statistical Bulletin" from 2005 to 2018 of provinces and cities.

3. Results

3.1. Linear Regression Analysis

Before the regression analysis, the variance inflation factor test is carried out to avoid estimation bias caused by collinearity. According to the literature, if the VIF of the test is much less than 10, it indicates that there is no colinear problem among variables. In order to overcome the influence of extreme data, all data are truncated by 1% before and after. The regression results are shown in Table 2, where column (1) represents the regression without the control variables, and column (2) to (5) represents the results after the step-by-step addition of control variables, respectively.

According to the results in Table 2, the first-order lag term of the urban GSDL is significantly positive at the 1% level, even adding the control variables, which indicates that the urban GSDL varies dynamically and continuously with self-strengthening and path-dependence effects. While the effect of lnENER on the urban GSDL has fluctuated from positive to negative. The reason is that the traditional energy consumption is still dominant, which would restrict the urban GSDL, even though China's energy consumption structure has been optimized in recent years. The results also show that the positive effect of lnTRANS on the urban GSDL is continuously strengthened and significant at the 1% level, as well as the positive effect of lnTELE is significantly positive at the 5% level. This is mainly due to the role of traffic infrastructure in improving the flow velocity of elements and resources shared among regions. Telecommunication infrastructure can facilitate resource integration and technological innovation, which will inject the power source for urban development.

Table 2. Dynamic linear regression.

	(1)	(2)	(3)	(4)	(5)
	Urban GSDL	**Urban GSDL**	**Urban GSDL**	**Urban GSDL**	**Urban GSDL**
L.GSDL	0.6251 *** (0.0149)	0.5861 *** (0.0149)	0.5571 *** (0.0155)	0.5561 *** (0.0155)	0.5557 *** (0.0155)
lnENER	0.0533 *** (0.0178)	−0.0693 *** (0.0201)	−0.0830 *** (0.0201)	−0.0832 *** (0.0201)	−0.0838 *** (0.0201)
lnTRANS	0.1088 *** (0.0466)	0.1604 *** (0.0199)	0.1604 *** (0.0495)	0.1663 *** (0.0496)	0.1655 *** (0.0496)
lnTELE	0.0783 *** (0.0145)	0.0232 ** (0.0148)	0.0233 ** (0.0147)	0.0229 *** (0.0147)	0.0219 ** (0.0147)
lnPGDP		0.2409 *** (0.0200)	0.2331 *** (0.0199)	0.2233 *** (0.0206)	0.2191 *** (0.0211)
STR			0.1397 *** (0.0227)	0.1350 *** (0.0228)	0.1345 *** (0.0228)
HC				0.0021 * (0.0012)	0.0022 * (0.0012)
GOVER					0. 0719 (0.0738)
CONS	−5.0399 *** (0.3568)	−2.9332 *** (0.3892)	−2.7627 *** (0.3875)	−2.7434 *** (0.3875)	−2.6855 *** (0.3920)

Note: The values in parentheses are standard deviations. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

From the view of control variables, the lnPGDP and STR can strongly promote the urban GSDL at the level of 1%. This indicates that China's policy of developing economy and adjusting the urban industrial structure is valid, which has effectively ensured the growth of urban GSDL. However, the effect of HC on the urban GSDL is only significant at the level of 10%, which shows limited influence and is not consistent with the expectation. This may be because the human capital level may be inconsistent with the urban GSDL, such as the contradiction between the structure and low equilibrium of talents possibly leading to the dilemma of "excessive competition" or "curse of talents" [70]. Moreover, the impact of GOVER on the urban GSDL is insignificant, indicating that the urban GSDL would be increased by optimizing the structure and utilization efficiency of fiscal expenditure rather than by simply expanding fiscal expenditure.

3.2. Nonlinear Regression Analysis

Based on the linear regression tested above, the explanatory variables of energy, transportation, and telecommunication infrastructures' square term are further adopted into the dynamic regression equation to test the nonlinear impact of infrastructures on the urban GSDL. The results are shown in Table 3.

Columns (1) to (3) represent the nonlinear relationship of energy, transportation, and telecommunication infrastructure construction with urban GSDL, respectively. Table 3 shows that the coefficients of $\ln ENER^2$, $\ln TRANS^2$, and $\ln TELE^2$ are all positive significantly at the 1% level, which indicates that the long-term impact of infrastructure construction on the urban GSDL has a U-shaped nonlinear effect with the trend of first inhibiting and then promoting. The reason for this is that infrastructure construction requires long-term, large invest and resource consumption, which is usually at a low level in the early stage and then reaches the inflection point after a large amount of resource input to achieve scale effect and agglomeration effect. With the improvement of infrastructure construction, network connection among regions, energy utilization, and transport efficiency, communication sharing would be enhanced, and the cost of industrial structure transformation and economic model transformation would be reduced. Eventually, innovation and productivity will be increased, and the urban GSDL will be promoted accordingly.

Table 3. Nonlinear regression.

	(1)	(2)	(3)
	Urban GSDL	**Urban GSDL**	**Urban GSDL**
L.GSDL	0.5709 *** (0.0150)	0.5540 *** (0.0163)	0.5553 *** (0.0155)
lnENER	−1.6591 *** (0.1882)		
$lnENER^2$	0.0589 *** (0.0072)		
lnTRANS		−1.3411 *** (0.3899)	
$lnTRANS^2$		0.0649 *** (0.0220)	
lnTELE			−0.4372 ** (0.1893)
$lnTELE^2$			0.0184 ** (0.0076)
lnPGDP	0.3601 *** (0.0207)	0.3147 *** (0.0203)	0.2556 *** (0.0181)
STR	0.3722 *** (0.0259)	0.3789 *** (0.0257)	0.3849 *** (0.0261)
HC	0.0003 (0.0013)	0.0029 ** (0.0013)	0.0020 (0.0013)
GOVER	0.1335 (0.0873)	0.1007 (0.0881)	0.0875 (0.0889)
CONS	8.4869 *** (1.1943)	4.1780 ** (1.7588)	0.5696 (1.1481)

Note: The values in parentheses are standard deviations. **, *** indicate significance at 5% and 1% levels, respectively.

3.3. Heterogeneity Regression Analysis

3.3.1. Regional Heterogeneity Analysis

Due to the differences in developing speed and quality, the impacts of infrastructure construction on different regions of urban GSDL are heterogeneous. Therefore, this paper refers to the existing classification criteria and divides research samples into six regions to explore the regional differences. The specific results are shown in Table 4.

As shown in Table 4, the relationship between the first-order lag GDSL and the urban GSDL is significantly positive at the 1% level in all regions, which indicates that the urban GSDL variations are consistent in time and path-dependent among regions. The lnENER has no significant effect on the urban GSDL in central, southern, and southwest China while showing obvious inhibitory effects in other regions. The possible reason is that the resource curse phenomenon brought by the resource-based cities are mostly in north China, the large proportion of manufacturing industry in the northeast of China, and the imbalance of energy supply and demand caused by “light abandonment” and “wind abandonment” are mainly in the western region. All these problems exert a negative impact on the improvement of urban GSDL. The lnTRANS significantly improves urban GSDL in east, southwest, and northwest China at the 1% level. By contrast, the lnTELE only promotes urban GSDL in east, central, and southern China at the 5% level. This is mainly because the east and center of China are highly developed regions in China, such as Shanghai, Hangzhou, and Shenzhen, which have comparatively advanced technologies, a high level of innovation, and the strong radiation capacity to form strong motivation for the development of urban GSDL.

Table 4. Regional heterogeneity regression.

	North China	Northeast China	East China	Central South	Southwest China	Northwest China
	Urban GSDL	Urban GSDL	Urban GSDL	Urban GSDL	Urban GSDL	Urban GSDL
L.GSDL	0.5385 *** (0.0485)	0.5081 *** (0.0536)	0.5255 *** (0.0288)	0.5628 *** (0.0296)	0.5153 *** (0.0511)	0.5952 *** (0.0553)
lnENER	−0.1223 * (0.0656)	−0.3265 *** (0.0814)	−0.0877 ** (0.0431)	0.0119 (0.0370)	−0.1007 (0.0634)	−0.1085 ** (0.0468)
lnTRANS	0.1929 (0.2006)	0.1247 (0.2193)	0.2212 *** (0.0768)	0.0878 (0.1026)	0.3315 *** (0.1265)	0.3249 *** (0.1552)
lnTELE	−0.0018 (0.0623)	0.0487 (0.0589)	0.0331 ** (0.0278)	0.0192 ** (0.0221)	0.0604 (0.0447)	0.0605 (0.0481)
lnPGDP	0.2679 *** (0.0900)	0.2350 *** (0.0797)	0.1883 ** (0.0404)	0.1893 *** (0.0370)	0.1090 *** (0.0353)	0.1100 * (0.0654)
STR	−0.0003 (0.0023)	0.2590 *** (0.0773)	0.2475 *** (0.0588)	0.0598 (0.0451)	0.2112 *** (0.1063)	0.1721 ** (0.0767)
HC	−0.0009 (0.0036)	0.0180 ** (0.0070)	0.0022 (0.0025)	0.0038 (0.0021)	0.0119 *** (0.0046)	−0.0004 (0.0024)
GOVER	0.2828 (0.8695)	0.3113 (0.6601)	0.1394 (0.0610)	0.1046 (0.2405)	−0.2219 (0.1697)	0.2303 (0.4910)

Note: The values in parentheses are standard deviations. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

The influence of control variables demonstrates regional differences, as well. The lnPGDP always plays a significant role in promoting the urban GSDL, indicating that the current green economic development mode and smart city construction could promote the improvement of the ecological environment and urban operation efficiency in China. Overall, the coefficients and significance of STR are in line with expectations, which dramatically promote the urban GSDL, indicating that the function of industrial structure adjustment in China is confirmed. The impact of HC on the urban GSDL only passes the test at the 5% significance level in the northeast and southwest China. According to the estimated coefficients, the urban GSDL will increase by 1.8% and 1.2% when HC increases by 1% in northeast and southwest China, respectively. It could be attributed that adjacent regions' human capital encourages technological innovation, which requires more energy input, resulting in more pollution emissions. The "rebound effect" induced by technology offsets the improvement effect of human capital on the urban GSDL [71]. Additionally, the role of GOVER is not significant, which may be related to the structure of fiscal expenditure. The excessive government intervention is not conducive to guiding market elements flow to the productive departments, consequently hindering the innovation of urban green production technology and the construction of smart infrastructure.

3.3.2. Period Heterogeneity Analysis

The construction of low-carbon cities and smart cities launched in 2010 and 2012, respectively, which intensified infrastructure construction consisting of energy, transportation, and telecommunication. Therefore, this paper takes 2012 as the time demarcation point to study the different impacts of infrastructure construction during 2005–2012 and 2013–2018. Specific results are shown in Table 5.

According to the regression results in Table 5, the lnENER significantly inhibits urban GSDL at the level of 1%, while the impact of lnTRANS and lnTELE on the urban GSDL is not significant from 2005 to 2012. In contrast, the negative impact of lnENER on urban GSDL is greatly reduced, while the positive impacts of lnTRANS and lnTELE are dramatically enhanced from 2013 to 2018. Furthermore, the lnTRANS and lnTELE increase by 1%, and the urban GSDL would be enhanced by 26.19% and 6.02%, respectively. The possible reason for this is that the economic crisis in 2008 brought a series of sequelae to China. In order to stimulate economic vitality, the 4 trillion Yuan expansion plan "Ten Major Industrial Revitalization Plan" was launched, which might result in the imbalance of China's economic structure [72]. Therefore, the effective role of infrastructure in promoting capital, trade, and marginal productivity in this period was limited, and the efficiency of the scale economy was low. Afterward, the low carbon cities and smart cities construction policies were launched successively in 2010 and 2012, which further strengthened the construction of green development and enhanced the technical level and investment efficiency. As such, the innovation compensation and scale economy effect of infrastructure construction on urban development were well enhanced, and the allocation efficiency of resource elements was effectively consolidated, which all promoted the development of urban GSDL.

Table 5. Time heterogeneity regression results.

Time	2005–2012 Urban GSDL	2013–2018 Urban GSDL
L.GSDL	0.3281 *** (0.0242)	0.3845 *** (0.0276)
lnENER	−0.1152 *** (0.0340)	−0.0590 (0.0375)
lnTRANS	0.0935 (0.0681)	0.2619 ** (0.1104)
lnTELE	0.0011 (0.0188)	0.0602 ** (0.0275)
lnPGDP	0.0946 ** (0.0371)	0.1867 *** (0.0392)
STR	0.1080 (0.0728)	0.1485 *** (0.0313)
HC	0.0066 *** (0.0021)	0.0042 * (0.0026)
GOVER	0.1776 (0.1453)	−0.0811 (0.1190)
CONS	−0.0023 (0.5975)	−3.8485 *** (1.1300)

Note: The values in parentheses are standard deviations. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

3.4. Threshold Regression Analysis

The threshold test can not only explore the relationship among variables but also depict breakpoint of the relationship. China has huge developing differences among regions, and this urban scale is adopted for further analysis of threshold effect on the urban GSDL, which can reflect urban characteristics to some extent. The threshold regression results are shown in Table 6.

According to the results in Table 6, the p values of the single threshold are all less than 0.1, while the p values of the double threshold are all more than 0.1, indicating that only the single threshold effect is significant. Furthermore, the lnENER and lnTRANS show a significantly negative impact on the urban GSDL both before and after crossing the threshold, while their inhibitory effect weakens after crossing the threshold. This may be due to the expansion of the urban scale, which is usually accompanied by the increase in energy consumption and waste discharge. When the urban scale is smaller than 588, the urban GSDL will decrease by 19.40% if the lnTRANS increases by 1%. While the urban scale is beyond 588, the inhibitory effect of lnTRANS on the urban GSDL would be weakened even still significant. When the urban scale is smaller than 588, the impact of lnTELE on the urban GSDL is not significant; however, the urban GSDL will increase by 5.04% for every 1% increase of lnTELE when the urban scale is greater than 588. This is because large cities are more likely to form low-lying areas where resource elements are prone to be gathered; thus, more employment opportunities would be generated, the matching efficiency of information resources under the digital economy would be improved, and, finally, the urban GSDL would be promoted.

Table 6. Threshold effect test.

	Single Threshold			**Double Threshold**		
	Urban GSDL	**Urban GSDL**	**Urban GSDL**	**Urban GSDL**	**Urban GSDL**	**Urban GSDL**
H_0 H_1		No threshold Has single threshold			Has single threshold Has double threshold	
Threshold value	588	588	588	198.43 588	198.43 588	198.43 588
F statistics	137.21 ***	136.84 ***	136.69 ***	125.44 ***	125.17 ***	124.01 ***
p value	0.023	0.026	0.036	0.2740	0.2870	0.3800
Th−0	−1.1414 *** (0.0235)	−0.1940 *** (0.0343)	0.0238 (0.0176)	−0.1697 *** (0.0242)	−0.2584 *** (0.0367)	−0.0143 (0.0120)
Th−1	−0.1162 *** (0.0235)	−0.1194 *** (0.0232)	0.049 *** (0.0178)	−0.1375 *** (0.0234)	−0.2018 *** (0.0342)	0.0249 (0.0176)
Th−2				−0.1131 *** (0.0234)	−0.1678 *** (0.0343)	0.0504 *** (0.0178)
Conclusion	reject	reject	reject	accept	accept	accept
lnENER		−0.1361 *** (0.0235)	−0.1360 *** (0.0235)		−0.1378 *** (0.0234)	−0.1364 *** (0.0234)
lnTRANS	−0.1852 *** (0.0342)		−0.1851 *** (0.0342)	−0.2015 *** (0.0343)		−0.2113 *** (0.0347)
lnTELE	0.0299 * (0.0176)	0.0296 * (0.0176)		0.0250 (0.0175)	0.0249 (0.0175)	
lnPGDP	0.3783 *** (0.0241)	0.3800 *** (0.0241)	0.3794 *** (0.0241)	0.3858 *** (0.0241)	0.3873 *** (0.0241)	0.3857 *** (0.0241)
STR	0.3927 *** (0.0257)	0.3929 *** (0.0257)	0.3928 *** (0.0257)	0.3880 *** (0.0256)	0.3886 *** (0.0256)	0.3877 *** (0.0256)
HC	0.0026 ** (0.0013)	0.0026 ** (0.0013)	0.0026 ** (0.0013)	0.0026 ** (0.0013)	0.0025 * (0.0013)	0.0030 ** (0.0013)
GOVER	0.1120 (0.0875)	0.1107 (0.0875)	0.1125 (0.0875)	0.1116 (0.0871)	0.1102 (0.0872)	0.1168 (0.0873)

Note: The values in parentheses are standard deviations. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

4. Discussion

Against the background of green and smart city construction in China, it is urgent for cities to seize the opportunity and break through the shackles of the black economic development model to enhance their urban GSDL and social governance quality. Therefore, cities actively deploy energy, transportation, telecommunication, and other infrastructure construction to provide circulation conditions and sharing platforms for the urban GSDL. Based on this background, this paper develops the GTFP by adopting smart input–output factors to evaluate the urban GSDL of 223 samples in China from 2005 to 2018 and explores the linear and nonlinear effects of energy, transportation, and telecommunication infrastructure construction on the urban GSDL. The heterogeneous effects of spatial and temporal are also analyzed, and the threshold characteristics are identified from the perspective of urban scale.

Firstly, in the part of empirical analysis, this paper considers the linear and nonlinear relationships of infrastructures and adds the first-order lag term of explained variable and the square term of explanatory variables to make the research results more consistent with reality. The results show that the lnENER inhibits the urban GSDL in general, due to the incomplete transformation of energy consumption structure and the insufficient ability of energy industry technology [59]. The lnTRANS and lnTELE have significantly positive effect on the urban GSDL, which is attributed to the improvement of elements circulation and expansion of resource sharing brought by transportation infrastructure construction, as well as the technical innovation and information sharing promoted by telecommunication [73]. Secondly, this paper verifies the heterogeneous effects of infrastructure construction on the urban GSDL from spatial and temporal characteristics, which could further the existing research and provide policy reference for the urban government. Additionally, as the outbreak of COVID−19 becomes the biggest challenge of this century by far, a safer and disaster-resilient public transport is required, which can also meet the needs of private vehicle-owning individuals after the unprecedented disease [74]. In light of the background and these requirements, infrastructures are supposed to be constructed appropriately advanced. Thirdly, the threshold regression effect provides a new perspective for the government to take urban scale and other urban characteristics into consideration during the construction of green and smart cities. Urbanization has accelerated the movement of people to cities, with nearly half the world's population now living in urban settlements. However, rapid urban growth is mostly accompanied by environmental degradation and traffic congestion, which outstrip urban service capacity [75]. Thus, the urban scale should be reasonably controlled to maximize the positive effect of infrastructure construction.

In the future, how to effectively solve the endogenous problem of the empirical model and the appropriate instrumental variables need to be further deepened. Additionally, the influence mechanism of the spatial spillover effect is also conducive to further expanding the depth of research. Finally, it is also meaningful to consider the long-term impact of civilian infrastructure on urban development, such as medical care, culture, and education.

5. Conclusions

Based on the above elaboration, this paper evaluated the urban GSDL of 223 cities in China from 2005 to 2018. Then, the dynamic impacts and temporal and spatial differences of energy, transportation, and telecommunication infrastructure construction on the urban GSDL were discussed, and the threshold effects of urban scale were tested. The main research conclusions are as follows:

(1) Transportation and telecommunication infrastructures play significant roles in promoting the urban GSDL, and the effects are further strengthened during 2013–2018, while energy infrastructure shows an insignificant effect on the urban GSDL. From the perspective of nonlinear relationships, the impact of infrastructures on the urban GSDL shows a U shape.

(2) There are regional differences in the influence of the control variables on the urban GSDL. Among them, the economic development level and industrial structure promote the urban GSDL in general, while the positive relationship between the human capital level and the urban GSDL is only significant in the northeast and southwest regions. Additionally, the government scale shows an insignificant positive impact on the urban GSDL.

(3) From the perspective of the threshold effect, there is only a single threshold effect of urban scale on the infrastructures. The impacts of energy and transportation infrastructures on the urban GSDL remain consistent before and after the threshold, while the impact of telecommunication infrastructure on the urban GSDL varies from having no significance to being positive when crossing the threshold.

In view of the conclusions, this paper puts forward the following policy recommendations. First, reasonable allocation of capital investment in infrastructure construction is crucial to achieving the dislocation of regional development. Different measures should be taken according to urban conditions to promote the ordered and high-quality quantification of infrastructure construction and form the integrated development power through the construction of energy, transportation, and telecommunication infrastructure. Second, it is obligatory to fully unleash the positive potential of elements and strengthen coordination among regions. On the one hand, industrial structure adjustment, human capital level, and urban scale should be integrated for the urban GDSL. On the other hand, the administrative barriers among regions should be broken, and those backward regions such as the central and western regions and northeast China should be encouraged to cooperate with the eastern regions through entrusted management and investment cooperation to realize complementary advantages and mutual benefits. Finally, the urban scale should be reasonably controlled, and cities can learn from the superblock model of Barcelona, which reclaims public space for people, reduces motorized transport, and promotes sustainable mobility and active lifestyles, and consequently achieve green development and mitigate the effects of climate change [76]. Governments, enterprises, and scientists should make more efforts to break through the technical difficulties of adopting renewable energy and releasing the side-effects of energy demand caused by urban population and spatial expansion. Moderate investment is also required to ensure the sustainability of new infrastructure investment and thus to avoid the low efficiency of financial investment caused by large-scale government investment.

Author Contributions: Conceptualization, L.X. and J.D.; methodology, L.X. and D.W.; software, D.W.; validation, L.X. and J.D.; formal analysis, L.X. and D.W.; data checking, D.W.; writing—original draft preparation, D.W.; writing—review and editing, L.X. and D.W.; visualization, D.W.; supervision, L.X. and J.D.; funding acquisition, L.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the National Nature Science Foundation of China (72174076, 71704066, 72174054, 71704068, and 91846203), National Social Science Foundation of China (20BGL191),Special research project of think-tanks in Grand Canal Cultural Belt Construction Research Institute (DYH21YB08), Youth Talents Cultivation Program of Jiangsu University (411160001), 2021 Jiangsu Graduate Scientific Research Innovation Plan project (KYCX21_3316). The APC was funded by the National Nature Science Foundation of China (72174076).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgments: The authors would like to thank the anonymous reviewers for their valuable comments.

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

References

1. Dong, L.-Y.; Shang, J.; Ali, R.; Rehman, R.-U. The coupling coordinated relationship between new-type urbanization, eco-environment and its driving mechanism: A case of Guanzhong, China. *Front. Environ. Sci.* **2021**, *9*, 128. [CrossRef]
2. McNeill, D. Mapping the European urban left: The Barcelona experience. *Antipode* **2003**, *35*, 74–94. [CrossRef]
3. He, Y. Remodeling and regeneration: Evolution logic, dynamic mechanism and action framework of urban renewal. *Mod. Econ. Discuss.* **2021**, *6*, 94–100.
4. Han, J. Can urban sprawl be the cause of environmental deterioration? Based on the provincial panel data in China. *Environ. Res.* **2020**, *189*, 109954. [CrossRef] [PubMed]
5. Xin, B.; Qu, Y. Effects of smart city policies on green total factor productivity: Evidence from a quasi-natural experiment in China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 2396. [CrossRef] [PubMed]
6. Qian, Y.; Liu, J.; Cheng, Z.; Forrest, J.-Y.-L. Does the smart city policy promote the green growth of the urban economy? Evidence from China. *Environ. Sci. Pollut. Res.* **2021**, *163*, 1–15.
7. Jiang, H.; Jiang, P.; Wang, D.; Wu, J. Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. *Sustain. Cities Soc.* **2021**, *69*, 102809. [CrossRef]
8. Li, X.; Fong, P.; Dai, S. Towards sustainable smart cities: An empirical comparative assessment and development pattern optimization in China. *J. Clean. Prod.* **2019**, *215*, 730–743. [CrossRef]

9. Shamsuzzoha, A.; Niemi, J.; Piya, S.; Rutledge, K. Smart city for sustainable environment: A comparison of participatory strategies from Helsinki, Singapore and London. *Cities* **2021**, *114*, 103194. [CrossRef]
10. Nondo, C. Is there a relationship between information and communication technologies infrastructure, electricity consumption and total factor productivity? *Int. J. Energy Econ. Policy* **2018**, *8*, 207–218.
11. Zhang, S.-D.; Yan, Y.; Li, B. Urban infrastructure, talent gathering and innovation. *Soft Sci.* **2020**, *12*, 1–12.
12. Wu, Z.-D.; Ye, Q.-L. Water pollution loads and shifting within China's inter-province trade. *J. Clean. Prod.* **2020**, *259*, 120879. [CrossRef]
13. Pacione, M. Development pressure and the production of the built environment in the urban fringe. *Scott. Geogr. Mag.* **2008**, *107*, 162–169. [CrossRef]
14. Camerin, F. From "Ribera Plan" to "Diagonal Mar", passing through 1992 "Vila Olímpica". How urban renewal took place as urban regeneration in Poblenou district (Barcelona). *Land Use Policy* **2019**, *89*, 104226. [CrossRef]
15. Savini, F.; Aalbers, M.-B. The de-contextualisation of land use planning through financialisation: Urban redevelopment in Milan. *Eur. Urban Reg. Stud.* **2016**, *23*, 878–894. [CrossRef]
16. Katz, C. Vagabond capitalism and the necessity of social reproduction. *Antipode* **2001**, *33*, 709–728. [CrossRef]
17. Sklair, L. *The Icon Project: Architecture, Cities, and Capitalist Globalization*; Oxford University Press: New York, NY, USA, 2017; pp. 26–49.
18. Mora, A.-Á.; Camerin, F. La herencia del "urban renewal" en los procesos actuales de regeneración urbana: El recorrido renovación-regeneración a debate. *Ciudad Y Territ. Estud. Territ.* **2019**, *51*, 5–26.
19. Chen, J. Innovation ecosystem for green smart city building in China. *Front. Eng. Manag.* **2015**, *2*, 325–330. [CrossRef]
20. Albino, V.; Berardi, U.; Dangelico, R.-M. Smart cities: Definitions, dimensions, performance, and initiatives. *J. Urban Technol.* **2015**, *22*, 3–21. [CrossRef]
21. Ding, H.-F.; Wang, Y.-H. The evaluation and analysis of the Chinese urban economic intelligence index. *Stat. Decis. Mak.* **2016**, *13*, 16–20.
22. Du, J.-G.; Wang, Y.; Zhao, A.-W. Study on the effect of smart city construction on urban development and green development. *Soft Sci.* **2020**, *34*, 59–64.
23. Chen, L.; Zhang, H.-X. Evaluation of green smart city in China based on enropy weight-cloud model. *J. Syst. Simul.* **2019**, *31*, 136–144.
24. Zhang, J.-S.; Tan, W. Study on the green total factor productivity in main cities of China. *Zb. Rad. Ekon. Fak. Rijeci Cas. Za Ekon. Teor. Praksu* **2016**, *34*, 215–234.
25. Liu, G.; Wang, B.; Zhang, N. A coin has two sides: Which one is driving China's green TFP growth? *Econ. Syst.* **2016**, *40*, 481–498. [CrossRef]
26. Huang, X.-L.; Han, X.-F.; Ge, P.-F. Spatial temporal evolution and influence mechanism of green total factor productivity in "Belt and Road" countries. *Econ. Manag.* **2017**, *39*, 6–19.
27. Mitra, A.; Sharma, C. Infrastructure, information & communication technology and firms' productive performance of the Indian manufacturing. *J. Policy Modeling* **2016**, *38*, 353–371.
28. Ji, X.; Yao, Y.-X.; Long, X.-L. What causes pm2.5 pollution? Cross-economy empirical analysis from socioeconomic perspective. *Energy Policy* **2018**, *119*, 458–472. [CrossRef]
29. Xia, F.; Xu, J.-T. Green total factor productivity: A re-examination of quality of growth for provinces in China. *China Econ. Rev.* **2020**, *62*, 101454. [CrossRef]
30. Wang, A.; Lin, W.; Liu, B.; Wang, H.; Xu, H. Does smart city construction improve the green utilization efficiency of urban land? *Land* **2021**, *10*, 657. [CrossRef]
31. Neuman, M.; Smith, S. City planning and infrastructure: Once and future partners. *J. Plan. Hist.* **2010**, *9*, 21–42. [CrossRef]
32. Schomaker, R.-M. Public-private governance regimes in the global sphere. *Public Organ. Rev.* **2017**, *17*, 121–138. [CrossRef]
33. Xu, Z.; Das, D.-K.; Guo, W.; Wei, W.-D. Does power grid infrastructure stimulate regional economic growth? *Energy Policy* **2021**, *155*, 112296. [CrossRef]
34. Yang, K.-Z. New logic of the coordinated development of Beijing, Tianjin and Hebei: Local quality-driven development. *Econ. Manag.* **2019**, *33*, 1–3.
35. Wei, T.; Chen, S.-Q. Dynamic energy and carbon footprints of urban transportation infrastructures: Differentiating between existing and newly-built assets. *Appl. Energy* **2020**, *277*, 115554. [CrossRef]
36. Zhang, M.; Liu, X.-X.; Ding, Y.-T. Assessing the influence of urban transportation infrastructure construction on haze pollution in China: A case study of Beijing-Tianjin-Hebei region. *Environ. Impact Assess. Rev.* **2021**, *87*, 106547. [CrossRef]
37. Bresson, G.; Etienne, J.-M.; Mohnen, P. How important is innovation? A Bayesian factor-augmented productivity model based on panel data. *Macroecon. Dyn.* **2016**, *20*, 1987–2009. [CrossRef]
38. Piselli, P.; Bronzini, R. Determinants of long-run regional prouctivity: The role of R&D, human capital and public infrastructure. *Reg. Sci. Urban Econ.* **2009**, *39*, 187–199.
39. Kodongo, O.; Ojah, K. Does infrastructure really explain economic growth in Sub-Saharan Africa? *Rev. Dev. Financ.* **2016**, *6*, 105–125. [CrossRef]
40. Agenor, P.-R.; Alpaslan, B. Infrastructure and industrial development with endogenous skill acquisition. *Bull. Econ. Res.* **2014**, *70*, 313–334. [CrossRef]
41. Wang, R.-Z.; Ou, G.-L.; Wang, Q.-P. Can trade liberalization increase total-factor productivity? Based on regulatory effects of traffic infrastructure. *J. Beijing Jiao Tong Univ. (Soc. Sci. Ed.)* **2019**, *18*, 38–47.

42. Huang, Q.-H.; Shi, P.-H.; Hu, J.-F. Industrial agglomeration and high-quality economic development: Examples of 107 prefecture-level cities along the Yangtze River Economic Belt. *Reform* **2020**, *1*, 87–99.
43. Hulten, C.-R.; Bennathan, E.; Srinivasan, S. Infrastructure, externalities, and economic development: A study of the Indian manufacturing industry. *World Bank Econ. Rev.* **2006**, *20*, 291–308. [CrossRef]
44. Sun, X.-H.; Liu, X.-L.; Xu, S. The agglomeration effect of transportation infrastructure and service industry—Comes from the multi-layer linear analysis at the provincial and municipal levels. *Adm. Rev.* **2017**, *29*, 214–224.
45. Abe, K.; Wilson, J.-S. Investing in port infrastructure to lower trade costs in East Asia. *East Asian Econ. Rev.* **2011**, *15*, 3–32.
46. Cao, Y.-Q.; Yang, Y.-L.; Xiang, H. Study on the impact of transportation infrastructure on total factor productivity in the service industry—Based on productive capital stock data. *Explor. Econ. Probl.* **2021**, *4*, 37–50.
47. Zhao, W.; Deng, F.-H.; Huo, W.-D. Trade effect of internet infrastructure in countries along the "Belt and Road"—Mediation effect analysis based on trade cost and total factor productivity. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2020**, *26*, 19–33.
48. Pradhan, R.-P.; Bagchi, T.-P. Effect of transportation infrastructure on economic growth in India: The VECM approach. *Res. Transp. Econ.* **2013**, *38*, 139–148. [CrossRef]
49. Wang, C.; Lim, M.-K.; Zhang, X.-Y.; Zhao, L.-F.; Lee, P.-T.-W. Railway and road infrastructure in the belt and road initiative countries: Estimating the impact of transport infrastructure on economic growth. *Transp. Res. Part A Policy Pract.* **2020**, *134*, 288–307. [CrossRef]
50. Salas-Olmedo, M.-H.; García, P.; Gutiérrez, J. Accessibility and transport infrastructure improvement assessment: The role of borders and multilateral resistance. *Transp. Res. Part A* **2015**, *82*, 110–129. [CrossRef]
51. Yang, S.-Y.; Li, Z. Influence of the opening of high-speed railway on the regional innovation pattern and its mechanism of action. *South. Econ.* **2020**, *5*, 49–64.
52. Liu, J.-G.; Zhang, W.-Z. Spatial spillover association effect of regional total factor productivity in China. *Geogr. Sci.* **2014**, *34*, 522–530.
53. Keller, W. Geographic localization of international technology diffusion. *Am. Econ. Rev.* **2002**, *92*, 120–142. [CrossRef]
54. Wang, Y.-L. Research on the relationship between green energy use, carbon emissions and economic growth in Henan province. *Front. Energy Res.* **2021**, *9*, 701551. [CrossRef]
55. Wang, M.; Feng, C. Decoupling economic growth from carbon dioxide emissions in China's metal industrial sectors: A technological and efficiency perspective. *Sci. Total Environ.* **2019**, *691*, 1173–1181. [CrossRef] [PubMed]
56. Kong, J.-J.; Zhang, C.; Han, C.-F. Research on the interactive growth strategies of infrastructure systems and natural ecology. *China's Popul. Resour. Environ.* **2018**, *28*, 44–53.
57. Puga, D. European regional policies in light of recent location theories. *J. Econ. Geogr.* **2002**, *2*, 113–150. [CrossRef]
58. Xie, J. Infrastructure construction and China regional total factor productivity—Is based on the spatial measurement analysis of 285 prefecture-level cities. *Sci. Decis.-Mak.* **2018**, *4*, 71–94.
59. Sun, C.-W.; Zhang, W.-Y.; Luo, Y.; Xu, Y.-H. The improvement and substitution effect of transportation infrastructure on air quality: An empirical evidence from China's rail transit construction. *Energy Policy* **2019**, *129*, 949–957. [CrossRef]
60. Liu, H.-J.; Yang, Q. Spatial difference and impact factors of TFP growth in China under resource environment constraints. *Manag. Sci.* **2014**, *27*, 133–144.
61. Kumo, W.-L. Infrastructure investment and economic growth in South Africa: A granger causality analysis. *Afr. Dev. Bank Group Work. Pap. Ser.* **2012**, *160*, 505–532.
62. Jain, D.; Tiwari, G. How the present would have looked like? Impact of non-motorized transport and public transport infrastructure on travel behavior, energy consumption and CO_2 emissions—Delhi, Pune and Patna. *Sustain. Cities Soc.* **2016**, *22*, 1–10. [CrossRef]
63. Yang, X.; Li, X.-P.; Zhong, C.-P. Study on the evolution trend and influencing factors of industrial biased technology progress in China. *Quant. Econ. Tech. Econ. Res.* **2019**, *36*, 101–119.
64. Lu, P.; Liu, J.-H.; Wang, Y.-X.; Ruan, L. Can industrial agglomeration improve regional green total factor productivity in China? An empirical analysis based on spatial econometric. *Growth Chang.* **2021**, *52*, 1011–1039. [CrossRef]
65. Zhang, J.; Wu, G.-Y.; Zhang, J.-P. Estimation of Chinese inter-provincial material capital stock: 1952–2000. *Econ. Res.* **2004**, *10*, 35–44.
66. Yeaple, S.-R.; Golub, S.-S. International productivity differences, infrastructure, and comparative advantage. *Rev. Int. Econ.* **2007**, *15*, 223–242. [CrossRef]
67. Teng, Z.-W. Spatial separation and drivers of green total factor productivity in China's service industry. *Quant. Res.* **2020**, *37*, 23–41.
68. Zhang, W.-D.; Ding, H.; Shi, D.-Q. Influence of smart city construction on total factor productivity—Based on quasi-natural experiments. *Tech. Econ.* **2018**, *37*, 107–114.
69. Florida, R. The rise of the creative class. *Wash. Mon.* **2002**, *35*, 593–596.
70. Yin, Q.; Li, Z.-W. How innovation overflow affects inter-provincial environmental total factor productivity—Based on DEA-ESDA method. *Sci. Technol. Prog. Countermeas.* **2019**, *36*, 45–54.
71. Zhang, W.; Hu, Y. Effect of innovative human capital on green total factor productivity in Yangtze River Delta—Empirical analysis of space Dubin model. *China Popul. Resour. Environ.* **2020**, *30*, 106–120.
72. Fang, F.-Q.; Tian, G.; Xiao, H. Influence of infrastructure on China economic growth and mechanism research on expansion–Based on barro growth model. *Econ. Theory Econ. Manag.* **2020**, *12*, 13–27.

73. Zhou, W.-W.; Li, X.-P.; Li, J. Space overflow effect of infrastructure construction on whole factor productivity—Based on 271 prefecture-level panels under the background of "One Belt and One Road". *Econ. Probl. Explor.* **2020**, *6*, 64–76.
74. Thombre, A.; Agarwal, A. A paradigm shift in urban mobility: Policy insights from travel before and after COVID-19 to seize the opportunity. *Transp. Policy* **2021**, *110*, 335–353. [CrossRef]
75. Moore, M.; Gould, P.; Keary, B.-S. Global urbanization and impact on health. *Int. J. Hyg. Environ. Health* **2003**, *206*, 269–278. [CrossRef] [PubMed]
76. Mueller, N.; Rojas-Rueda, D.; Khreis, H.; Cirach, M.; Andrés, D.; Ballester, J.; Bartoll, X.; Daher, C.; Deluca, A.; Echave, C.; et al. Changing the urban design of cities for health: The superblock model. *Environ. Int.* **2019**, *134*, 105132. [CrossRef] [PubMed]