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ARTICLE

# Study on the Spatial Effect of Smart City Construction on Green Total Factor Productivity

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## ABSTRACT

Smart cities, a new kind of urbanization, offer a means of achieving the condition in which environmental conservation and economic growth are mutually beneficial. As a result, it is important to think about whether and how the development of smart cities might support the high-quality growth of urban economies. Based on the panel data of 163 prefecture-level cities in China from 2009–2018, the green total factor productivity (GTFP) of each prefecture-level city is measured using the SBM-GML model, and the appropriate spatial econometric model is screened by various types of tests. The spatial effect of smart city construction on GFTP is studied, and it is concluded that the pilot cities have a significant positive spatial spillover effect. The decomposition econometric model also shows that the pilot cities have a significant positive spatial spillover effect, and it also indicating that the smart city construction can also drive the surrounding cities to jointly improve the quality of economic development. Finally, the robustness of the spatial effect of smart city policy is also verified by changing the spatial measurement model and the type of spatial weight matrix, which also shows that the results of the spatial spillover effect of smart city construction are reliable.

***Keywords:*** Smart Cities; Green Total Factor Productivity; Spatial Durbin Model; High-Quality Development

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# 1. Introduction

Since China's reform and opening, its imprecise economic growth model has created issues with economic growth that will take time to resolve[1]. This approach of sacrificing high input, high consumption, and high pollution for faster and better economic development has long fallen short of contemporary demand. The impact of human activities on the natural environment is a critical concern in today's world.[2–5] findings underscore the importance of considering ecological factors in economic development plans, as changes in land surface temperature can significantly affect the growth and productivity of plants, which in turn influence the food supply and carbon sequestration capabilities of ecosystems. Smart cities utilize data analytics, the Internet of Things, and artificial intelligence to optimize resource use, reduce waste, and improve the quality of life for urban residents. China recognized this issue early and promptly introduced a number of pertinent policies, noting that the 14th Five-Year Plan will continue to follow the path of ecological priority and green development in light of the continual improvement of the ecological environment in the 13th Five-Year Plan. This shows that China will never temporarily sacrifice the environment. This demonstrates China's resolve to never compromise the environment in favour of short-term, high-quality economic development. Construction of smart cities, a crucial component of the development of the digital economy, may not only directly stimulate economic growth in the current environment of China's long-term green development and short-term economic recovery[6–11], but also provide sufficient momentum for high-quality economic development[12–15]. The "establishment of a sound economic system of green, low-carbon, and cyclic development" suggested at the conference has pointed out the clear way for high-quality development, and the 19th National Congress has clearly indicated that China's economy is changing to the stage of high-quality development. The secret to high quality development is strongly tied to green development, which is a significant symbol of China's economic progress towards high quality. It is also closely related to the scale of economic vitality, innovation, and competitiveness. In order to achieve the overarching objectives of continuous technological advancement, rational resource allocation, industrial structure optimization, and pollution emission reduction, cities urgently need better technology levels and management systems. By analyzing and comparing the total cost of ecological selection of vegetation and policy based odd even vehicle allocation selection, it is shown that using vegetation to reduce air pollution is the most cost-effective pollution mitigation method. This indicates that the maximum possible pollution should be eliminated from the source itself, and therefore the transformation through green economic development is of great significance for protecting the ecology. In addition, it is proposed that the primary gross domestic product will be affected by seasonal changes. The increase in high temperature conditions in summer leads to a decrease in gross primary production, while the increase in low temperature in winter promotes the growth of gross primary production. Therefore, ecological changes will also affect the speed of green economic transformation.

GFTP, which is based on TFP and incorporates environment-related variables to produce quantitative statistics that are more commensurate with the quality of modern economic development, was initially proposed by[14–16]. Since then, China has begun to study GTFP rather than high quality economic development. It is crucial to investigate how to increase GTFP in the current context of China's ongoing pursuit of high quality economic development. The spatial spillover impact of smart city development on GTFP was examined in this work using spatial measurement.

# 2. Literature Review and Research Hypothesis

At the current stage, both domestic and foreign scholars have begun to incorporate the green economy into high-quality development, and have also increasingly focused on the study of sustainable development of smart cities. Despite taking into account the operating features of the distribution industry, reference[17] employed the spatial DID model to study the impact of smart city development on the high quality development of the distribution sector. The results were still highly significant. Reference[18] conducted a quantitative study such as spatiality using the positive effect of urbanization on economic growth, and concluded that urbanization can significantly reduce various costs and promote sustainable economic development, which is mainly achieved through the cumulative effects of labor accumulation, technology spillover, demand stimulation and cost reduction. Reference[19] used a multi-period DID approach to confirm that the policy effect of smart city construction on high-quality development was significantly positive, and also found that the effect of pilot policies was more significant in areas with low levels of innovation, low population density, and low administrative hierarchy. Taking green economy transformation as the entry point, reference[20] found that smart city construction can significantly accelerate the transformation of the current economy to a green economy, mainly by promoting urban technological innovation, industrial upgrading, and rational resource allocation. Reference[21] focused on the mechanisms and paths of the impact of smart city construction on the high-quality development of enterprises, and after affirming the positive effects of pilot policies, found through mechanism tests that smart cities promote high-quality development of enterprises from two aspects: alleviating financing constraints and reducing enterprise operating costs.

Smart city construction deepens the social ties between cities and promotes the adequate flow of various factors between cities. Smart cities have achieved intelligent and efficient urban management by introducing advanced technological means such as the Internet of Things, cloud computing, and big data analysis. This not only improves the efficiency of urban management and promotes economic growth, but also promotes resource conservation and environmental protection. At the same time, smart cities have also played an important role in promoting the development of green industries. Through digital technology, smart cities optimize their industrial structure, develop low-carbon, environmentally friendly, and high-tech green industries, and inject new impetus into the economic and social development of cities. Reference[22] found that the economic agglomeration and diffusion effects of smart city construction can accelerate the integration of resource elements and the upgrading of industrial structure in different regions, which will promote local development and also play a role in improving the development quality of surrounding cities. Smart cities can use the Internet of Things to further close the distance between cities and form a network of smart city relationships with a holistic concept. At the same time, the smart city pilot cities will also have agglomeration effect and radiation effect on the surrounding cities, the improvement of technology innovation ability, the optimization of industrial structure and the improvement of environmental quality so that the capital factors gradually flow into the region; and when the economic development of the region to a certain extent, its own economic effect will be radiated to the surrounding cities, and constantly spread outward to improve the GFTP of the surrounding cities, that is It can be assumed that in addition to the impact of smart city construction on the pilot city, it will also have a corresponding impact on the region around the pilot city. To this end, the following hypotheses are proposed based on the above analysis.

Hypotheses: Smart city pilot cities can have spatial spillover effects on the GFTP of surrounding cities.

# 3. Study Design

## 3.1. Selection of Spatial Weight Matrix

It is necessary to generate the spatial distance weight matrix for each city in order to determine the spatial distance between them prior to doing the spatial effect analysis. According to different spatial distance division criteria, different types of spatial weight matrices can be formed, and the current common spatial weight matrices are 0–1 matrix, matrix of inverse of geographic distance, etc.

The geographic distance inverse matrix is the spatial weight matrix commonly used by scholars nowadays. It is a matrix generated as the inverse of the geographical distance between different regions, i.e., the further the distance, the smaller the spatial weight matrix; the closer the distance, the larger the spatial weight matrix. Considering that the purpose of this paper is to investigate the impact of smart city construction on the quality of economic development of prefecture-level cities, the possibility of interaction and association is greater when a city is closer to the policy pilot city. Therefore, this paper selects the geographic distance inverse matrix to participate in the spatial effect analysis, and the specific expression is as follows. Among them , $d_{ij}$ denotes the geographical distance between city i and city j in formula (1)[2]. The geographical distance is calculated by ArcGis software based on city latitude and longitude, i = 1, 2, 3, ..., 163, j = 1, 2, 3, ..., 163.

$$\mathrm{W_{ij}} = \begin{cases} \frac{1}{d_{id}}, i \neq j \\ 0, i = j \end{cases} \tag{1}$$

### 3.2. Variable Description

The quality of economic development is a comprehensive evaluation of the economic development of a country and region, which covers many aspects such as economic, social, and efficiency. Total factor productivity (TFP) is commonly used in academia to replace the quality of economic development, and in recent years, as the country pays more and more attention to environmental and energy issues, more and more scholars have started to introduce environmental factors on the basis of total factor productivity, i.e., GFTP to replace the quality of economic development. In this paper, we refer to [23] and construct the GFTP based on SBM-GML model to replace the quality of economic development with the help of MAXDEA software. Among the inputs, labor input is expressed by using urban year-end employees, and energy input is expressed by all electricity consumption in the year. Capital input is represented by capital stock, which is calculated by Goldsmith's perpetual inventory method with the following formula: $K_{it}$ = (1-d) $K_{i,t-1}$ + $I_{it}$, i and t denote the city and year, respectively, K denotes capital stock, I denotes new fixed asset investment in the city, and d denotes fixed asset depreciation rate, the base period is based on the data of 2000, because the data of this year are more complete. The fixed asset depreciation rate is set to 9.6% by referring to [24], and the capital stock in the base period is derived by referring to the calculation method of[25]. For output, the expected output is expressed as the real urban gross domestic product (GDP) for the whole year, and the base period is chosen as 2003, and the non-expected output is selected from the data of industrial sulfur dioxide emissions (tons), industrial wastewater emissions (tons), and industrial soot emissions (tons) of prefecture-level cities, and the entropy value method is used to construct a comprehensive index of environmental pollution by calculating the weights assigned to each indicator with reference to [26–30] instead of the non- desired output.

This article selected panel data from 285 prefecture level cities for research. However, the establishment of the smart city pilot covers prefecture level and county-level cities. In order to ensure the accuracy of the final results, the following approach was taken based on the practice of Shi Daqian: excluding the prefecture level cities where the county-level cities in the 2012 pilot were located, and adding new pilot prefecture level cities and county-level cities in 2013 and 2014. At the same time, this article will also exclude some cities with severe data missing, and finally use the remaining 163 prefecture level cities as research objects to evaluate the policy effects of smart city construction. Considering the availability and feasibility of data, the pilot cities established in the first batch in 2012 are set up as the experimental group, and a total of 20 pilot cities have been selected as the experimental group sample and the remaining 143 cities as the control group sample in this paper. For the robustness of the empirical results, the new second and third batches of pilot cities have been excluded. $treat_{it}$ represents the dummy variable of the treatment group, when $treat_{it}$ = 1, it means that a city is a pilot city of smart city in 2012, when $treat_{it}$ = 0, it means that a city is not a pilot city of smart city; Periodit represents the dummy variable of the treatment period, when $Period_{it}$ = 1 means that city i is in a period of 2012 and after, and when $Period_{it}$ = 0 means that city i is in a period before 2012. $treat_{it} \times Period_{it}$ is the cross product term of two dummy variables, which means the level of smart city construction.

Based on previous studies, the following seven variables are selected as control variables in this paper: (1) industrial structure change (ind), expressed as the proportion between the total output value of tertiary industry and the total output value of secondary industry; (2) local government budget expenditure (gov), expressed as the proportion of local general budget expenditure (million yuan) to GDP; (3) science and technology and education input (sci), expressed as a proportion of GDP using the sum of local expenditures on science and education (10,000 yuan); (4) foreign investment level (inv), expressed as a proportion of GDP using the actual amount of foreign investment used in the year; (5) financial development level (fin), expressed as a proportion of GDP using the number of deposits and loans of financial institutions at the end of the year; (6) education level (edu), expressed as a proportion of GDP using (6) education level (edu), expressed by the number of local general higher education students as a percentage of all students; (7) infrastructure level (bas), expressed by the sum of total postal services and total telecommunication services as a percentage of GDP.

### 3.3. Data Sources and Descriptive Statistics

The data in this paper are mainly from China Statistical Yearbook, China Environmental Statistical Yearbook, China

Industrial Economic Statistical Yearbook, China Science and Technology Statistical Yearbook, China Energy Yearbook, and China Urban Construction Statistical Yearbook from 2009 to 2019. Among all the data, some cities are missing and omitted, so this paper used the linear interpolation method and the average growth rate to make up for them, and the cities with serious missing data and those that cannot be found were deleted, and finally the 10-year panel data of 163 prefecture-level cities from 2009 to 2019 were obtained. The descriptive statistics of the data are shown in **Table 1**.

**Table 1.** Descriptive statistics of variables.

| | Variables (Symbols) | Full Sample | | | Experimental Group | | | Control Group | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Sample size | Average value | Standard deviation | Sample size | Average value | Standard deviation | Sample size | Average value | Standard deviation |
| **Solved Variables** | GFTP | 1630 | 1.027 | 0.172 | 200 | 1.0345 | 0.084 | 1430 | 1.026 | 0.181 |
| **Core Explanatory variables** | treat×period | 1630 | 0.086 | 0.28 | 200 | 0.7 | 0.459 | 1430 | 0 | 0 |
| **Control Variables** | Ind | 1630 | 95.47 | 205.3 | 200 | 76.140 | 32.89 | 1430 | 98.17 | 218.7 |
| | gov | 1630 | 20.65 | 24.23 | 200 | 15.671 | 8.342 | 1430 | 21.37 | 25.6 |
| | Sci | 1630 | 17.76 | 7.709 | 200 | 20.305 | 3.928 | 1430 | 17.4 | 8.035 |
| | Inv | 1630 | 8.527 | 10.28 | 200 | 16.351 | 13.03 | 1430 | 7.433 | 9.325 |
| | Fin | 1630 | 60.94 | 202.5 | 200 | 2.864 | 2.26 | 1430 | 69.07 | 214.9 |
| | edu | 1630 | 197.7 | 163.0877 | 200 | 267 | 198.1 | 1430 | 188.1 | 155.2 |
| | Bas | 1630 | 2.751 | 2.529 | 200 | 2.263 | 1.575 | 1430 | 2.82 | 2.629 |

## 3.4. Spatial Econometric Model Construction

In order to accurately analyze the spatial effect of smart city construction on the high-quality development of urban economy, it is necessary to find out the most suitable spatial econometric model for the study of this paper through a series of relevant tests. In this paper, we propose to screen among three models: panel spatial Durbin model (PSDM), panel spatial error model (PSEM) and panel spatial lag model (PSLM), and the specific selection process is as follows.

First, the paper proposes to determine whether fixed effects or random effects are chosen by Hausman test; second, the LM test is used to determine the applicability of panel space error model (PSEM) and panel space lag model (PSLM); finally, the Wald test is used to analyze whether the panel space Durbin model (PSDM) can be reduced to PSEM or Finally, the Wald test is used to analyze whether the PSDM can be reduced to a PSEM or a PSLM. The results of the tests are shown in **Tables 2** and **3**.

**Table 2.** LM test results of panel space model.

| Panel Effect | Not Standardized | | Standardization | |
|---|---|---|---|---|
| | Statistic | P-Value | Statistic | P-Value |
| LM_lag | 327.649 | 0.000 | 358.904 | 0.000 |
| LM_lag(robust) | 18.356 | 0.000 | 21.011 | 0.000 |
| LM_error | 364.419 | 0.000 | 395.805 | 0.000 |
| LM_error(robust) | 55.126 | 0.000 | 57.913 | 0.000 |

**Table 3.** Results of Wald test and Hausman test for panel space model.

| Inspection Type | Test Statistic | P-Value |
|---|---|---|
| Hausmann Inspection | 106.66 | 0.000 |
| Wald_lag | 16.55 | 0.0206 |
| Wald_error | 16.39 | 0.0218 |

From the results of the above table, the Hausman test statistic is 106.66, which rejects the original hypothesis at 1% significance level and decides to use fixed effects regression. The LM test shows that regardless of whether the spatial weight matrix is standardized or not, and regardless of which spatial econometric model is chosen, the results reject the original hypothesis at 1% significance level, which means that the spatial econometric model can choose both the PSLM and the PSEM, and further comparison reveals that among all effect types of LM tests, the LM test statistics and Robust LM test statistics of the PSEM are significantly larger than those corresponding to the PSLM, so in comparison, the PSEM. The Wald test statistics reject the original hypothesis at the 5% significance level, indicating that the PSDM cannot be reduced to the PSEM or the PSLM. Combining the above analysis, this paper decides to use the PSDM with fixed effects, and the specific mode construction is as follows.

$$\begin{aligned} &\ln GTFP_{\mathrm{it}} = \mu_{\mathrm{i}} + \gamma_{\mathrm{t}} + \alpha_1 \mathrm{treat}_{\mathrm{it}} \times \mathrm{period}_{\mathrm{it}} + \\ &\sum_{\mathrm{i}=2,\mathrm{j}=1}^{\mathrm{n}} \alpha_{\mathrm{i}} \mathrm{x}_{\mathrm{j}} + W\beta_1 \mathrm{treat}_{\mathrm{it}} \times \mathrm{period}_{\mathrm{it}} \\ &+W \sum_{\mathrm{i}=2,\mathrm{j}=1}^{\mathrm{n}} \beta_{\mathrm{i}} \mathrm{x}_{\mathrm{j}} + \varepsilon_{\mathrm{it}} \end{aligned} \tag{2}$$

In Equation (2), W denotes the spatial weight matrix of the inverse of geographic distance, $W \sum_{\mathrm{i}=2,\mathrm{j}=1}^{\mathrm{n}} \beta_{\mathrm{i}} \mathrm{x}_{\mathrm{j}} + \varepsilon_{\mathrm{it}}$ denotes the effect of control variables of other cities on the GFTP of city i, and $W\beta_1 \mathrm{treat}_{\mathrm{it}} \times \mathrm{period}_{\mathrm{it}}$ denotes the effect of core explanatory variables of other cities on the GFTP of city i. Also, in order to eliminate the effect caused by heteroskedasticity, the model takes logarithm to represent both the explained and control variables.

## 3.5. Empirical Analysis

### 3.5.1. Spatial Correlation Analysis

In this paper, we propose to use the most common Moran I index and Geary C index to test global spatial autocorrelation. Moran I index is suitable for measuring global spatial autocorrelation and can provide an overall evaluation of the degree of spatial clustering or dispersion in the entire study area; The Geary C index is better at capturing local variations and non-uniformity in spatial data. Other metrics such as Getis Ord-Gi* index focus on analyzing local spatial autocorrelation. Therefore, when selecting an index, research needs and data characteristics should be fully considered to ensure the accuracy and reliability of the analysis results. Both indices focus on the classification of aggregations with different values in adjacent regions and in the same aggregation. Since this paper focuses on the improvement of GFTP after the policy period, the global spatial autocorrelation test is conducted by intercepting some years after 2012, and the specific test results are shown in **Table 4**.

**Table 4.** Global spatial autocorrelation test results.

| Year | Moran I | Moran I Index Z-Statistic | P-Value | Geary C | Gilley C Index Z-Statistic | P-Value |
|---|---|---|---|---|---|---|
| 2013 | 0.018** | 2.253 | 0.024 | 0.959 | −1.405 | 0.16 |
| 2014 | 0.001 | 0.65 | 0.516 | 0.956* | −1.706 | 0.088 |
| 2017 | 0.038*** | 3.906 | 0.000 | 0.911*** | −4.383 | 0.000 |
| 2018 | 0.023** | 2.521 | 0.012 | 0.957** | −2.396 | 0.017 |

Note: *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively.

As can be seen from **Table 4**, both the Moran I index and the Geary C index are greater than 0. In the four years selected for testing, the Moran I index of GFTP in Chinese prefecture-level cities in 2013, 2017 and 2018 all reject the original hypothesis at least at the 5% significance level, and the Geary C index of GFTP in Chinese prefecture-level cities in 2014, 2017 and 2018 all reject the original hypothesis at least at the by observing the trends of the two indices in these four years, we can learn that the changes of the two indices show a fluctuating upward trend, and this trend is especially obvious in the Moran I index, which indicates that in the years after the implementation of the smart city pilot policy, there is a significant spatial positive correlation in the index of GFTP, which represents high-quality development. This indicates that there is a significant spatial correlation, i.e., a strong spatial correlation, in the years after the implementation of the smart city pilot policy.

This paper further performs spatial autocorrelation tests on local regions as a complement to the global spatial autocorrelation tests. In this paper, we will continue to use the most commonly used Moran index I to test local spatial autocorrelation, and select the indicators of 2017 and 2018, which passed the significance test in the previous section, for the study, and construct Moran scatter plots. The specific test results are as follows.

**Figure 1** and **Figure 2** show the Moran scatter plots of local autocorrelation in 2017 and 2018, respectively. Each number in the scatter plot refers to a different prefecture-level city, and the distribution of each number is a reflection of the local spatial autocorrelation. From the figure, it can be seen that the GFTP of each city is mostly concentrated in quadrants one and three and most of them pass the significance test of 10%. This indicates that Chinese prefecture-level cities have obvious spatial aggregation characteristics and convergence in the pursuit of high-quality development. It also indicates that the choice of spatial regression model is appropriate.

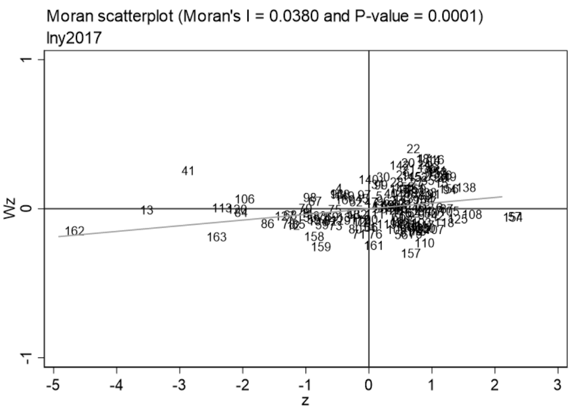


**Figure 1.** Local autocorrelation Moran scatter plot in 2017.

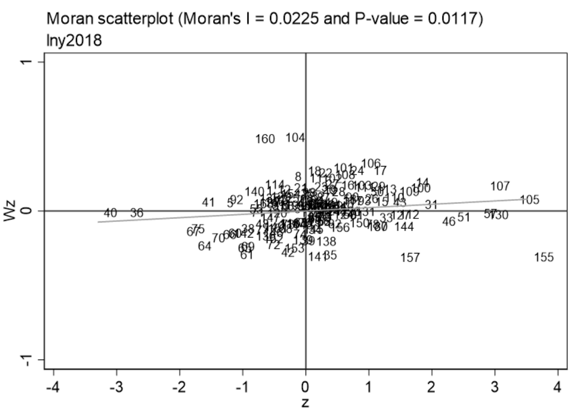


**Figure 2.** Local autocorrelation Moran scatter plot in 2018.

### 3.5.2. Spatial Regression Analysis

Based on the above analysis, this paper uses the generalized panel space Durbin model (PSDM) for regression, and the regression results are shown in **Table 5**.

As shown in **Table 5**, the spatial auto regressive coefficient of the double fixed model of PSDM is 0.18 and passes the 5% significance level test, which indicates that there is a spatial effect on the level of high quality development of Chinese cities. For example, advanced cities in the eastern region have had a positive driving effect on the central and western regions through technology diffusion, industrial transfer, and other means. At the same time, some cities in the central and western regions have continuously improved their development level by learning and imitating the successful experiences of the eastern region. The regression coefficient of the core explanatory variable did is positive and passes the 1% significance test, which indicates that the existence of smart cities will significantly drive the high quality development of the economy and enhance GFTP. From the spatial lag term, the regression coefficient of the core explanatory variable did was also significantly positive and passed the 5% significance level test, which indicates that the smart city policy improves the GFTP of the pilot city and also improves the GFTP of other cities in the vicinity of the pilot city, which fully demonstrates that the construction of smart cities has a significant positive spatial correlation to the high quality development of cities effect and spatial spillover effect. Therefore, it can be proved that hypothesis H holds. This discovery enriches the theoretical research on the relationship between smart cities, high-quality economic development, and GFTP, providing new perspectives and evidence support for research in related fields. It may prompt scholars to further explore the intrinsic mechanisms, influencing factors, and comprehensive impact of smart city development on the economy and society.

### 3.5.3. Decomposition of Spatial Effects

Based on the proof that the spatial spillover effect exists and is positive, the spatial effect is further decomposed to understand the degree of influence of different effects in detail. The spatial effect can be decomposed into three effects, namely, direct effect, indirect effect and total effect, by means of partial differentiation. Among them, the direct effect is the effect of the pilot city on the local GFTP; the indirect effect is the effect of the pilot city on the GFTP of the neighboring cities; the total effect is the sum of the direct effect and the indirect effect. The specific test results are shown in **Table 6.**

**Table 5.** Spatial Durbin model regression results.

| Variables | Main | Wx |
|---|---|---|
| Did | 0.0326*** (0.0133) | 0.3934** (0.1836) |
| Lnx1 | −0.011 (0.0269) | −0.166 (0.147) |
| Lnx2 | −0.042 (0.0395) | 0.3958** (0.178) |
| Lnx3 | −0.07 (0.0435) | 0.3536 (0.218) |
| Lnx4 | 0.0019 (0.0111) | −0.0611 (0.048) |
| Lnx5 | −0.006 (0.0058) | 0.027 (0.066) |
| Lnx6 | −0.023 (0.03) | −0.184 (0.169) |
| Lnx7 | −0.023 (0.0143) | −0.121 (0.143) |
| Spatial_rho | 0.18** (0.088) | |
| sigma2_e | 0.0218*** (0.004) | |
| R-side | 0.142 | |
| Individual effects | YES | |
| Point-in-time effect | YES | |
| Number of samples | 1630 | |

Note: Standard errors are in parentheses, *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

**Table 6.** Decomposition results of spatial effects.

| | Direct Effect | Indirect Effects | Total Effect |
|---|---|---|---|
| Did | 0.0346** (0.014) | 0.5134** (0.238) | 0.548** (0.243) |
| lnx1 | −0.0125 (0.026) | −0.198 (0.185) | −0.211 (0.177) |
| lnx2 | −0.0363 (0.038) | 0.472** (0.22) | 0.436** (0.218) |
| lnx3 | −0.0683 (0.0432) | 0.451 (0.293) | 0.383 (0.283) |
| lnx4 | 0.0015 (0.011) | −0.073 (0.058) | −0.072 (0.0505) |
| lnx5 | −0.00554 (0.0057) | 0.0252 (0.084) | 0.0197 (0.082) |
| lnx6 | −0.0248 (0.03) | −0.219 (0.202) | −0.244 (0.2) |
| lnx7 | −0.0239* (0.0134) | −0.16 (0.172) | −0.184 (0.1712) |
| Individual effects | YES | YES | YES |
| Point-in-time effect | YES | YES | YES |
| Number of samples | 1630 | 1630 | 1630 |

Note: Standard errors are in parentheses, *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

From **Table 6,** the direct effect of smart city construction on GFTP is 0.0346, and it passes the 5% significance test, which is consistent with the results obtained in the spatial Durbin model, and once again proves that smart city construction will significantly improve GFTP and promote the high-quality development of urban economy. From the indirect effect, the indirect effect of smart city construction on GFTP is 0.5134, and it passes the significance test of 5%, which indicates that the smart city construction can significantly improve the GFTP of the neighboring cities, and fully drive the high quality development level of the neighboring cities, and the spillover effect is greater than the direct effect, because the pilot cities themselves have better economic level or infrastructure construction or other aspects than the pilot cities. This is because the pilot cities are relatively better than other nearby cities in terms of economic level or infrastructure construction or other aspects, so when the pilot cities produce economic spatial spillover effects on the nearby cities, they will also have a greater demonstration and diffusion effect on the pilot cities, and the cities around the pilot cities that are relatively backward will usher in better and faster economic development, i.e., the indirect effect is greater than the direct effect.

### 3.5.4. Robustness Test

Considering the need of robustness testing, this paper will also use PSEM and PSLM for regression. In addition, the spatial weight matrix will be changed to a 0-1 adjacency matrix based on the PSDM to re-run the regression, so as to verify the robustness of the empirical results. The specific results are shown in **Table 7**.

**Table 7.** Spatial measurement robustness tests.

| | **Return (1)** | **Return (2)** | **Return (3)** | |
|---|---|---|---|---|
| Models | SEM | SLM | SDM | |
| Matrix | Geographical distance countdown | Geographical distance countdown | 0–1 adjacency matrix | |
| | | | Main | Wx |
| Did | 0.0226* | 0.0232* | 0.0239* | 0.0067 |
| | −0.0123 | −0.012 | −0.012 | −0.0334 |
| Lnx1 | −0.014 | −0.0146 | −0.00336 | −0.054 |
| | −0.0272 | −0.0266 | −0.0293 | −0.053 |
| Lnx2 | −0.0335 | −0.03 | −0.0467 | 0.0869 |
| | −0.0415 | −0.041 | −0.0432 | −0.066 |
| Lnx3 | −0.0553 | −0.05 | −0.0537 | 0.0321 |
| | −0.0448 | −0.043 | −0.042 | −0.051 |
| Lnx4 | −0.0034 | −0.0049 | −0.004 | −0.0065 |
| | −0.0093 | −0.008 | −0.0098 | −0.0133 |
| Lnx5 | −0.0055 | −0.005 | −0.0015 | −0.0007 |
| | −0.0054 | −0.005 | −0.0055 | −0.0122 |
| Lnx6 | −0.0344 | −0.038 | −0.029 | −0.031 |
| | −0.032 | −0.031 | −0.033 | −0.0368 |
| Lnx7 | −0.0217 | −0.022 | −0.018 | −0.035 |
| | −0.014 | −0.014 | −0.014 | −0.0313 |
| Spatial_lambda | 0.378*** | 0.344*** | 0.108*** | |
| | −0.099 | −0.0895 | −0.0234 | |
| sigma2_e | 0.022*** | 0.0222*** | 0.022*** | |
| | −0.004 | −0.004 | −0.0041 | |
| Individual effects | YES | YES | YES | |
| Point-in-time effect | YES | YES | YES | |
| Number of samples | 1630 | 1630 | 1630 | |

Note: Standard errors are in parentheses, *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

As can be seen from **Table 7**, whether the model is changed to a panel spatial error model (PSEM) or a panel spatial lag model (PSLM), or the spatial weight matrix is changed to a 0-1 adjacency matrix based on the original model, the core explanatory variables pass the test at the 10% significance level, and the regression coefficients are all positive. This further verifies the robustness of the experimental results and confirms the spatial effect of the impact of smart city construction on the high-quality development of urban economy.

# 4. Conclusions

This paper focuses on the effect of smart city construction on GFTP from 2009 to 2019 using a spatial panel model, ultimately leading to the following conclusions.

The results of the spatial effects of smart city policies obtained by using the spatial analysis method show that, in the global spatial autocorrelation test, whether using the Moran I index or the Geary C index, the results confirm the positive spatial correlation of GFTP, which has a strong spatial correlation, and in the local spatial autocorrelation test, it is found that the cities roughly present the phenomenon of the eastern cities In the local spatial autocorrelation test, it is found that there is a “high-high” concentration in the eastern cities and a “low-low” concentration in the western cities. And after a series of model screening tests, it is found that the panel spatial Durbin model is a suitable spatial econometric model for this study. The final results of the panel spatial Durbin model regression show that there is indeed a positive spatial spillover effect of smart city construction on the green all-factor of surrounding cities, and the further decomposition of the effect once again verifies the spatial spillover effect of smart city construction, and the effect is significantly larger than the direct effect on the pilot cities, indicating that the smart city construction can also drive the surrounding cities to jointly improve the quality of economic development. Finally, the robustness of the spatial effect of smart city policy is also verified by changing the spatial measurement model and the type of spatial weight matrix, which shows that the results of the spatial spillover effect of smart city construction are reliable.

Based on the findings reached in the previous section, the following recommendations are made.

(1) Continue to implement the pilot construction work of smart cities and strive to achieve nationwide coverage of the policy. Smart city construction has an extremely important role in economic growth, especially the quality of economic growth, which can make the level of social management, people's quality of life, environmental protection capabilities, effective allocation of resources and other aspects to achieve a comprehensive and effective improvement. Therefore, it is necessary to continue to increase the implementation of the smart city pilot policy, to continuously enrich and improve the system construction in the process of policy implementation, to determine the implementation measures of each key area by the coordination and cooperation of various departments, to promote the sharing of information resources and business synergy between horizontal and vertical, and to construct a set of interconnected smart city planning system.

(2) Further implement the innovation-driven development strategy. It is important to grasp the key nodes of information technology and urban green transformation, bearing in mind that the inexhaustible power of smart cities originates from innovation-driven. Rely on the Internet to create a high-quality big data platform, increase investment in scientific and technological research and development, and provide a set of incentive mechanisms that can meet the differentiated needs of the masses so that the general public can actively participate. It is necessary to strengthen the exchange and collaboration between cities, with the spillover effect of smart city construction, strengthen the integrated planning and collaborative layout of smart cities and neighboring cities, and make full use of the technological innovation brought about by information technology to better play its radiating role to improve the development capacity of cities.

(3) From the perspective of top-level design, it is necessary to adhere to the local conditions and promote the overall high-quality development of the region. Because different cities geographic location, resource endowment and unbalanced development and other characteristics, coupled with the spatial agglomeration effect between cities, making the construction process of smart cities is very complex and different, so a uniform policy is no way to meet the needs of urban development, so it is necessary for governments at all levels to combine the city's own development characteristics, play the city's comparative advantage, do a good job of the overall construction of smart cities Layout, to maximize the construction effect. For example, cities like the eastern cities with generally more developed economies and a higher degree of information technology need to steadily implement technological innovation and maintain the good momentum of collaboration between smart city construction and high-quality development; while cities like the central and western cities need some special support and theoretical guidance, and strive to cultivate a number of model cities with developed information technology, which can drive high-quality development in the surrounding areas and produce a diffusion effect, and Promote the synergistic development of regional economy.

(4) Promoting data resource sharing and openness: Data is the core resource for smart city construction. To break down data barriers between departments, establish a unified data platform, and achieve data sharing and exchange. The government should strengthen the integration and management of data resources, establish data standards and specifications, and ensure the accuracy, completeness, and security of data. At the same time, we should promote the openness of data resources, encourage enterprises and the public to develop and utilize data resources, and stimulate innovation vitality. For example, opening up urban public transportation, meteorological, environmental and other data to provide support for enterprises to develop intelligent travel, intelligent environmental protection and other applications.

# Authors contributions

Y.S.R. (Conceptualization, Methodology, Investigation, Validation, Data Curation, Visualization, Writing—Original Draft, Supervision); F.Y. (Methodology, Writing—Review & Editing; M.I. (Writing—Review & Editing; Visualization).

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## Conflict of Interest

No potential conflict of interest was reported by the authors.

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