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Smart City Pilot Policy and Urban Productivity in China: Based on Difference-in-Differences Model

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Abstract. Urban productivity is a key indicator to measure urban economic performance, which is related to the competitiveness of cities and the economic development of countries and regions. To clarify the mechanism of constructing smart cities and urban productivity, using the panel data of 284 prefecture-level cities from 2011 to 2020, this paper constructs a difference-in-differences model for empirical tests. The study found that the construction of smart cities can promote urban productivity. Meanwhile, the mechanism tests indicate that smart cities mainly improve urban productivity through technological innovation, advanced industrial structure and digital financial empowerment. According to heterogeneity analysis, smart cities in eastern cities and large cities significantly promote urban productivity, while the promotion effect of smart cities in central and western cities and small cities was not significant. This study has vital reference significance for guiding the construction of smart cities and exploring how to improve urban productivity.

Keywords: Smart City Pilot; Urban Productivity; Difference-in-Differences Model; Technological Innovation; Industrial Structure; Digital Finance.

1. Introduction

For the exploration of the wide-ranging impact of the digital economy and cutting-edge trends in urban development, this paper examines the rise of the digital economy as a key field in the modern economic system from a macro perspective. In this context, China has launched a number of policy pilots including smart cities, which aim to explore and verify policy effects through practice, providing experience and models for comprehensive promotion. The implementation of the smart city pilot policy is based on an in-depth understanding of the importance of policy experiments. Policy pilots can not only provide practical support for the modernization of the national governance system and governance capabilities, but promote the local economic characteristics and advantages, and drive the innovative development of regional economies.

The practical and theoretical significance of the smart city pilot policy cannot be ignored. Practically, implementing specific policies and measures has promoted the digital transformation of cities, improved the efficiency of urban management and services, eased employment pressure [1], and enhanced the development of clean energy [2] and digital economy [3], thereby helping to reduce industrial pollution and carbon emissions [4], improving the green and innovative cities. In addition, the smart city pilot policy has promoted the urban digital transformation, thus increasing urban productivity. Through policy pilots, it can provide an experienced model that is promoted nationwide for constructing smart cities. Theoretically, the smart city pilot policy gives new empirical data and case analysis for urban productivity research, which deepens the perception of urban productivity determinants and growth mechanisms, and then enriches urban economic theories.

Although the existing research has in-depth discussions on the development of smart cities and their impact on the quality of urban development and low-carbon environment, there is relatively limited research on urban productivity, especially on the impact of smart city pilot policy on urban productivity. This study aims to fill this gap, explore how smart city pilot policy affects urban productivity, and analyze their impact mechanisms. This paper has the following contributions. Firstly, the smart city pilot policy is a core research object to analyze its impact on urban productivity, which is a gap in previous studies. Secondly, combined with the digital age, a multi-perspective mechanism is built to probe into the impact channels of smart city pilot policy on urban productivity, including technological innovation, industrial structure optimization, and digital financial empowerment. Thirdly, the diversified impact of smart city pilot policy on urban productivity is analyzed from the perspective of regional diversity and urban heterogeneity.

The structure of this paper is as follows. The second chapter is a literature review and research hypotheses. The third chapter is the research design. The fourth chapter reports the empirical test results. The fifth chapter is a further analysis of mechanism and heterogeneity. The sixth chapter is the conclusion and policy suggestions.

2. Research Hypotheses

The smart city pilot policy is an innovative urban management model, which aims to improve the operating efficiency and urban life quality by introducing advanced information technology and management concepts. Implementing this policy provides city managers with new tools and ideas, making them more efficient at planning and implementation. This high efficiency is not only reflected in the convenience and accuracy of urban management, but in the forward-looking and predictive nature of urban development. Therefore, city managers can more actively promote the construction of smart cities, thereby accelerating technological innovation and application, and improving productivity. The deployment of intelligent infrastructure, such as intelligent transportation systems and energy-saving buildings, is the core of constructing smart cities. Through the collection and analysis of real-time data, intelligent transportation systems can effectively reduce traffic congestion and improve the efficiency of road transportation. Energy-saving buildings decrease energy consumption and improve energy utilization efficiency through advanced building technology and design. These improvements enhance the overall urban production efficiency and provide a solid foundation for urban economic development. Based on the above analysis, this paper puts forward the following hypothesis:

H1: Smart city pilot policy helps to improve urban productivity.

It is complicated for the national smart city pilot policy to improve urban productivity, including many aspects such as policy guidance, technological progress and capital investment [5]. Policy guidance can promote the gathering of production factors such as technology, labor and capital, and form an environment conducive to the development of smart cities. Hence, this paper explores the channels through which smart city policies affect urban productivity from three dimensions including technological innovation, industrial structure, and digital finance.

Smart city pilot policy promotes urban productivity by driving technological innovation. On the one hand, by introducing advanced information technologies such as the Internet of Things (IoT), big data, artificial intelligence (AI), etc., enterprises can manage and operate more effectively, improve the automation and intelligence of production, reduce labor costs and error rate and enhance production efficiency. On the other hand, technological innovation can improve urban services and governance capabilities. The smart city pilot policy can enhance urban public services and management by introducing advanced technologies.

The smart city pilot policy also improves urban productivity by optimizing the industrial structure. Firstly, policies tend to encourage and support the development of high-tech industries with high added value and innovation capabilities that can promote the productivity of the entire city. Secondly, the policy will optimize the industrial structure of the city by guiding the industry to develop in a higher-end and more competitive direction. Such industrial upgrading and structural optimization help to form a more competitive industrial system, thereby improving overall urban productivity.

The smart city pilot policy not only improves urban productivity through digital financial empowerment, but injects new impetus into the development of urban economy. As a new type of financial service, digital finance relies on advanced technologies such as big data, cloud computing, and artificial intelligence to innovate traditional financial services and provide more convenient, efficient, and personalized financial products and services. The development of digital finance can provide urban residents with more employment opportunities and entrepreneurial platforms and attract more outstanding talents for development. At the same time, digital finance can provide enterprises with more convenient financing services, help enterprises solve financing problems, and promote the development and innovation of enterprises. Based on the above analysis, this paper proposes the following hypothesis:

H2: Smart city pilot policy improves urban productivity by promoting technological innovation, optimizing industrial structure, and empowering digital finance.

3. Research Design

3.1. Model Construction

The difference-in-differences model (DID) is a statistical method that uses non-experimental or observational data to analyze the effect of interventions. Its basic idea is to identify the causal effects of policies by controlling for the impact of other synchronous policies, as well as the differences in samples before implementing policies. As for the advantages of the DID model, it can eliminate uncontrollable and unpredictable factors in the time range before and after policy implementation, reducing differences between experimental and control groups after policy implementation [6]. Thus, this paper uses the DID model to test and analyze the impact of the pilot policy on urban productivity, with the following specific model settings:

$$\text{lnpgdp}_{i,t} = \alpha_0 + \alpha_1(\text{treat}_{it} \times \text{year}_j) + \rho X_{i,t} + \delta_i + \theta_t + \mu_{i,t} \tag{1}$$

The explained variable $\text{lnpgdp}_{i,t}$ refers to the urban productivity of city i in year t. The core explanatory variable $(\text{treat}_{it} \times \text{year}_j)$ means the dummy variable of the smart city pilot. $X_{i,t}$ represents a set of control variable vectors that may affect urban productivity. δ_i and θ_t indicate city and year fixed effects respectively. $\mu_{i,t}$ is a random disturbance term.

In addition, before using the DID model, we must test the parallel trend of the sample. In other words, before the impact of the smart city pilot policy, there should be no significant difference in urban productivity between the construction of pilot cities and non-pilot cities. This paper specifically uses the event analysis to replace the smart city pilot as dummy variables in the benchmark regression with the pilot dummy variables generated before and after the pilot. The model is set as follows:

$$\text{lnpgdp}_{it} = \alpha_0 + \alpha_j \sum_{j\geq -2}^{7+}(\text{treat}_{it} \times \text{year}_j) + \alpha_2 \sum \text{Controls} + \lambda_i + \eta_t + \varepsilon_{it} \tag{2}$$

year_j is a dummy variable, the value of the current year is 1, the value of other years is 0, and the rest of the variables are set to be consistent with the model (1). In model (2), if $\alpha_j \leq 0$, it is not significant; if $\alpha_j > 0$, it is significant. Thus, model (1) assumes that the smart city pilot policy has an impact on urban productivity through parallel trend hypotheses.

3.2. Measurement and Data of Variables

The digital inclusive finance index originates from the research of the Digital Finance Research Center of Peking University and Ant Financial Services Group [9]. In addition, the innovation index comes from the *China Urban and Industrial Innovation Report in 2017* by the Industrial Development Research Center of Fudan University [8]. The rest of the data are from the *China Urban Statistical Yearbook in 2011-2020* and *China* Regional *Innovation and Entrepreneurship Index*, with Table 2 as the descriptive statistics of each variable.

Table 1. Variable Definitions

Type	Name	Symbol	Definition or Calculation
Explained Variable	Urban Productivity	Inpgdp	Based on the research of Ke Shanzi et al., this paper uses the natural logarithm of per capita GDP in urban districts to measure [7].
Core Explanatory Variable	Smart City Pilot Policy	Smart_policy	The pilot cities announced by the smart city pilot policy and those after 2013 are 1; otherwise, they are 0.
Mechanism Variable	Technological Innovation	Tec	The innovation index of the Industrial Development Research Center of Fudan University is adopted; the innovation index data for 2018-2020 are calculated by the same calculation model [8].
	Industrial Structure	Inst	The ratio of the added value of the tertiary industry output to the added value of the secondary industry output.
	Digital Finance	Dig	Peking University Digital Inclusive Finance Index is used to measure the digital finance in each region [9].
Control Variable	Number of Population	Peo	Regional resident population.
	Urban R&D Expenditure	Urex	The science and technology expenditure of the municipal district is used to calculate.
	Human Capital	Huca	The ratio of the number of students in colleges and universities in the municipal districts to the registered population.
	Fiscal Revenue	Fis	General public budget revenue.
	Urbanization	Urban	The ratio of the urban permanent population in the municipal district to the permanent population, where the permanent population is the sum of the urban permanent population and the rural permanent population.
	Development of Transport Infrastructure	Infra	Road area per capita.
	Informatization	Indu	The ratio of post and telecommunications business revenue to GDP.

Table 2. Descriptive Statistics of the Main Variables

Variable	Sample Size	Mean Value	Standard Deviation	Minimum	Maximum
Indgdp	2 214	6.462	1.162	3.243	10.549
Urex	2 214	77.179	309.581	0.044	4 334.165
Peo	2 214	449.388	351.174	23.320	3 188
Huca	2 214	186.915	244.826	0.592	1 311.241
Fis	2 214	160.010	483.129	1.520	7165.098
Urban	2 214	55.313	14.792	21.400	100
Indu	2 214	12.201	7.815	0.030	49.890
Infra	2 214	17.155	7.190	1.370	60.070

4. Analysis of Empirical Results

4.1. Benchmark Regression Results

To test the effect of smart city pilot policy on urban productivity, the DID model is used for regression. Models (1) and (2) are ordinary panel regression; models (3) and (4) are fixed effects analysis; models (1) and (3) are unadded control variables; models (2) and (4) are added control variables, as listed in Table 3. Based on the analysis of models (1) and (2), the regression coefficients have passed the test at the 1% level, indicating that the smart city pilot policy can promote urban productivity. Through the fixed effects analysis of models (3) and (4), after controlling time, region and adding all control variables, the regression coefficient still passed the test at the 1% level, indicating that implementing the smart city pilot policy can promote the regional urban productivity, thus verifying the rationality of H1.

Table 3. Benchmark Regression Results

	(1)	(2)	(3)	(4)
VARIABLES	lndgdp	lndgdp	lndgdp	lndgdp
did	0.605***	0.279***	0.065***	0.053***
	(9.018)	(18.850)	(2.789)	(3.206)
Constant	6.345***	-3.732***	6.459***	-2.262***
	(215.700)	(-16.150)	(987.000)	(-2.691)
Observations	1,894	1,870	1,892	1,869
Control Variables	NO	YES	NO	YES
ID FE	NO	NO	YES	YES
year FE	NO	NO	YES	YES
adjusted R^2	0.0433	0.931	0.974	0.985

Robust t-statistics in parentheses

* * * p<0.01, * * p<0.05, * p<0.1

4.2. Parallel Trend Test

According to the parallel trend test and dynamic effect analysis in Figure 1, the impact of the smart city pilot policy on the productivity of the pilot cities is not significant before the implementation, which proves that there is no significant difference in the urban productivity before the pilot, meeting the parallel trend hypothesis. One year after implementing the smart city policy, the urban productivity of the pilot cities has increased significantly, which shows that with the deepening implementation of the policy, its positive impact on urban productivity has increased. It is consistent with the benchmark regression results in this paper.

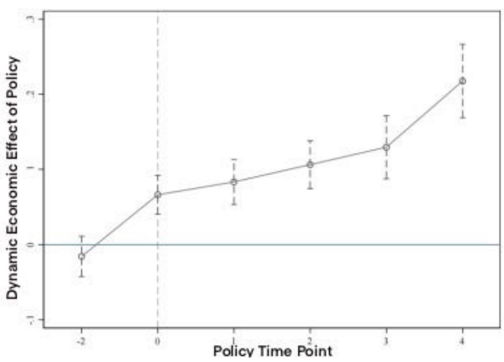

Figure 1. Parallel Trend Test

4.3. Heterogeneity Analysis

(1) Regional Heterogeneity

Considering the differences in economic growth, population size, infrastructure and other aspects of cities in different regions, this paper divides the research sample into three groups according to geographical location. The construction of smart cities has significantly promoted urban productivity in all regions with the best policy effect in the eastern cities, followed by the western cities and the central cities.

(2) Urban Heterogeneity

Generally, a larger city tends to have more opportunities and development potential, which can improve the efficiency of local resource allocation and use by exerting economic agglomeration. On this basis, this paper uses the urban permanent population with a population of 3 million as the boundary, divides the whole sample into large and small cities, and conducts regression tests again. According to the estimation results, the estimation coefficients of the smart city pilot policy for the urban productivity of large cities are significantly positive, but not for small cities, indicating that the effect of the smart city pilot policy on improving urban productivity in large cities is more apparent.

Table 4. Heterogeneity Analysis

	Regional Heterogeneity			Urban Heterogeneity	
	Eastern Cities	Central Cities	Western Cities	Small Cities	Large Cities
VARIABLES	lndgdp	lndgdp	lndgdp	lndgdp	lndgdp
did	0.080***	0.028	0.041	0.031	0.084***
	(2.845)	(1.159)	(1.339)	(1.579)	(2.646)
Constant	3.989***	-3.936***	-5.712***	0.694	-4.468***
	(2.593)	(-3.304)	(-3.458)	(0.607)	(-3.188)
Observations	723	617	529	1,154	712
Control Variables	YES	YES	YES	YES	YES
ID FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES
adjusted R^2	0.985	0.986	0.978	0.985	0.970

Robust t-statistics in parentheses

* * * p<0.01, * * p<0.05, * p<0.1

4.4. Robustness Test

(1) Placebo Test

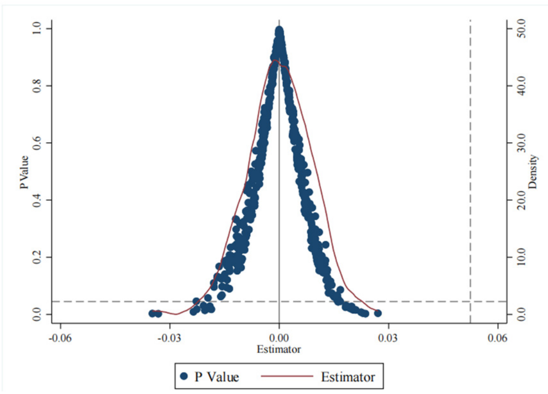

Figure 2. Placebo Test

To improve the robustness of empirical research and eliminate the interference of non-observational factors, the samples are selected as the experimental group by computer random simulation in this paper, with the placebo test carried out. The specific method is to use stochastic simulation to create multiple batches of pilot smart cities, and construct corresponding virtual policy variables to replace treat*time for regression analysis.

(2) PSM-DID

To avoid the impact of sample selection bias on model estimation, fully considering the gap of population (Peo), Urban R&D expenditure (Urex), human capital (Huca), fiscal revenue (Fis), urbanization (Urban), transportation infrastructure (Infra) and informatization (Indu), the differentiation characteristics between the above cities are used as matching variables. Meanwhile, the control group samples are matched and the matching score is calculated through the logit model, so as to select the control group relatively similar to the experimental group, with the sample re-analyzed by DID. If the normalization deviation of all variables is significantly smaller after matching, there is no significant difference between the two groups of samples after matching. In other words, there is no significant difference between the two groups after matching and DID analysis can be conducted. As shown in Figure 3, the above variables are matched by the kernel density matching and the matching scores are calculated, with a total of 1324 research samples obtained. After the two sets of data are matched, the samples show a high consistency and the normalization deviation is significantly reduced, in line with the common trend assumption. Hence, DID analysis can be carried out on this basis.

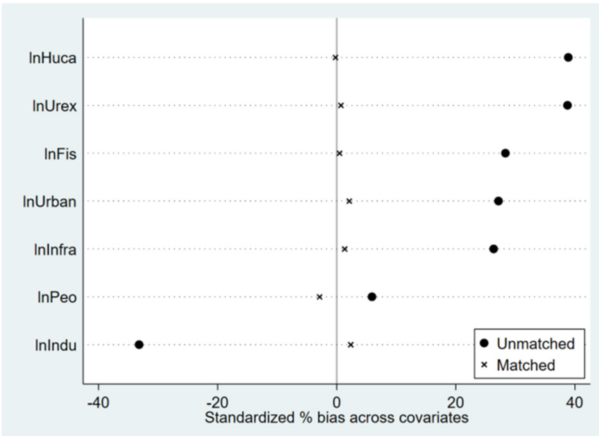

Figure 3. Matching Variables

(3) Exclude the Year When the Policy is Introduced

Considering that the data of the year when the policy is introduced may interfere with the net effect of the smart city pilot policy on urban productivity, this paper conducts regression analysis again after excluding the data in 2013.

5. Mechanism Analysis

To profoundly explore the mechanism of the impact of smart city construction on urban productivity, this paper needs to test H2, that is, whether smart city construction will improve urban productivity by promoting technological innovation, optimizing industrial structure, and empowering digital finance. To avoid the introduction of new endogenous problems, this paper draws on the method of Dell (2010) and Dinkelman (2011) to conduct mechanism analysis. For this reason, the regression analysis of the role channel of smart city construction on urban productivity [10] [11] is carried out with the model constructed as follows:

$$lnpgdp_{i,t} = \alpha_0 + \alpha_1(\,treat_{it} \times year_j\,) + \rho X_{i,t} + \delta_i + \theta_t + \mu_{i,t} \tag{3}$$

$$Median_{i,t} = \vartheta_0 + \vartheta_1(\,treat_{it} \times year_j\,) + \rho X_{i,t} + \delta_i + \theta_t + \mu_{i,t} \tag{4}$$

Table 5. Estimation and Elimination of the Year When the Policy is Introduced After Matching

	Post-Match Estimation		Exclude the Year When the Policy is Introduced	
VARIABLES	lndgdp	lndgdp	lndgdp	lndgdp
did	0.270***	0.049***	0.279***	0.056***
	(17.420)	(2.601)	(17.370)	(3.204)
Constant	-4.229***	-1.786*	-3.733***	-2.111**
	(-16.070)	(-1.906)	(-15.200)	(-2.289)
Observations	1,340	1,324	1,644	1,642
Control Variables	YES	YES	YES	YES
ID FE	NO	YES	NO	YES
year FE	NO	YES	NO	YES
adjusted R^2	0.943	0.990	0.930	0.984

Robust t-statistics in parentheses

* * * p < 0.01, * * p < 0.05, * p < 0.1

Where Median represents mechanism variables, including technological innovation (Tec), industrial structure (Inst), and digital finance (Dig).

With mechanism analysis results shown in Table 7, the estimation coefficients of columns (1) (2) (3) are all significantly positive, which shows that the construction of smart cities will significantly promote technological innovation, optimize industrial structure, and promote digital financial empowerment. As mentioned in the previous theoretical analysis, the improvement of technological innovation, the upgrading of the industrial structure, and the empowerment of digital finance are all conducive to improving urban productivity, which is in line with theoretical logic. The results of the mechanism analysis validate H2.

Table 6. Mechanism Test

	(1)	(2)	(3)
VARIABLES	Tec	Inst	Dig
did	24.690**	0.116**	2.693**
	(2.169)	(2.511)	(2.321)
Constant	778.200*	4.500***	117.900***
	(1.917)	(3.442)	(3.383)
Observations	1,469	1,472	1,472
Control Variables	YES	YES	YES
ID FE	YES	YES	YES
year FE	YES	YES	YES
adjusted R^2	0.823	0.877	0.994

Robust t-statistics in parentheses

* * * p<0.01, * * p<0.05, * p<0.1

6. Conclusion

This paper focuses on the impact of smart city pilots on urban productivity, and uses the DID model to conduct empirical research to study the mechanism and heterogeneity of smart city construction on urban productivity. The research finds that: Firstly, the construction of smart cities can promote urban productivity. Secondly, the mechanism test indicates that the construction of smart cities mainly promotes urban productivity through technological innovation, advanced industrial structure and digital financial empowerment. Thirdly, heterogeneity research proves that the construction of smart cities in eastern and large cities can significantly promote urban productivity. However, in central and western cities and small cities, the construction of smart cities cannot significantly promote urban productivity.

Based on the above conclusions, this paper proposes corresponding policy suggestions as follows:

Firstly, the industrial structure should be optimized to promote industrial upgrading. The smart city pilot policy should focus on the development of high-tech industries and guide the industry to develop in a high-end and competitive direction. Policy support and intelligent transformation will help enhance the competitiveness of the industrial chain. Enterprises should be encouraged to develop and innovate, improve product quality and added value, strengthen industrial chain cooperation, and realize the optimization and upgrading of the industrial chain. Attention should be paid to emerging industries such as artificial intelligence, big data, and the IoT, so as to promote the optimization and upgrading of industrial structure, thereby improving urban productivity.

Secondly, we should develop digital finance and improve financial services. The smart city pilot policy should promote digital finance and provide convenient, efficient and personalized financial services. Financial institutions can use big data and artificial intelligence to conduct customer analysis and provide customized services. At the same time, we should strengthen financial supervision, prevent systemic risks, and ensure market stability. Public financial literacy can be improved to popularize financial knowledge and enhance risk identification capabilities. For example, financial institutions can use big data to provide personalized services and improve customer experience. The strengthening of financial supervision will help prevent systemic risks, ensure a healthy and stable market, and improve urban productivity.

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