The Impact of Smart City Policies on Urban Technological Innovation Capacity: A Case Study of the Pearl River Delta Region Based on the Double Difference Method

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Abstract: With the acceleration of the global urbanization process, smart city policies are playing an increasingly important role in urban planning and management. The purpose of this paper is to explore the impact of smart city policy on the innovation ability of city science and technology, and to analyze the policy by using the method of difference-difference. First of all, this paper reviews the development of smart city policy and its implementation in different regions of China. Secondly, this paper systematically studies the impact of smart city policies on urban science and technology innovation through the difference-difference method and empirical research. The study found that smart city policies can significantly promote technological innovation activities in cities, improve innovation capacity, and promote economic growth. Finally, the paper explores the potential impact of smart city policies on urban sustainable development, as well as some possible policy recommendations. To sum up, smart city policies play a key role in shaping a city's scientific and technological innovation capacity and are of great significance for future urban development. The findings of this study can help policymakers better understand the impact of smart city policies to develop more targeted and effective policy measures to promote the integration of urban science and technology innovation with sustainable development.

Keywords: smart city, DID policy evaluation, scientific and technological innovation

1. Introduction

1.1 Research Background

With the advancement of technology, the concept of "Smart Cities" was first proposed by IBM in 2010. A "Smart City" refers to the application of intelligent computing technologies such as the Internet of Things, cloud computing, big data, and integrated spatial geographic information in urban planning, design, construction, management, and operation. This integration enables key infrastructure components and services of cities, including urban management, education, healthcare, real estate, transportation, utilities, and public safety, to be more interconnected, efficient, and intelligent. This, in turn, provides citizens with a better quality of life and work, creates a more favorable business environment for enterprises, and empowers the government to operate more efficiently and effectively. The concept of "Smart Cities" has gained widespread attention in China due to its potential to address urban challenges, particularly in densely populated areas, and to promote sustainability. In 2012, the Chinese government established the first batch of pilot "Smart Cities" (with participation from 90 cities across 28 provinces). On August 29, 2014, following the approval of the State Council, eight ministries, including the National Development and Reform Commission, the Ministry of Industry and Information Technology, the Ministry of Science and Technology, the Ministry of Public Security, the Ministry of Finance, the Ministry of Natural Resources, the Ministry of Housing and Urban-Rural Development, and the Ministry of Transport, issued the "Guidance on Promoting the Healthy Development of Smart Cities." This guidance required regions and relevant departments to implement the various tasks outlined in the document to ensure the healthy and orderly development of "Smart City" construction.

During the implementation of "Smart City" policies, many cities have experienced smooth policy execution. As of early April 2020, the Ministry of Housing and Urban-Rural Development had announced 290 pilot "Smart Cities," making China the largest implementing country for "Smart City" construction globally. Technological innovation capacity is a crucial indicator for assessing a city's development level, and "Smart City" policies have a significant impact on the development of a city's technological innovation capacity. Many pilot "Smart

City" cities have introduced new initiatives in technological innovation. For example, Shanghai has established an urban optical network, developed various technologies for wireless broadband, such as 5G and WIFI, and accelerated research and application of new technologies like smart technology, cloud computing, and the Internet of Things, promoting the convergence of the three networks. Guangzhou has built the first official wireless city portal website "led by the government and collaborated with operators" to promote efficient and convenient wireless broadband network services for citizens, businesses, and various sectors of society. In August 2022, China Telecom, in collaboration with Shenzhen Nanshan District, launched the benchmark project of an intelligent city, which leverages 5G to enable the digital transformation of Shenzhen, and it was selected as one of the "Top 10 5G Application Cases in 2022."。

1.2 Significance of the Study

After the emergence of "Smart City" policies, these policies have had a significant impact on various aspects of daily life, such as healthcare, transportation, logistics, finance, communication, education, energy, and environmental protection. However, there is relatively limited research on the specific impacts of "Smart City" policies on various specific aspects. Analyzing the effects brought about by "Smart City" policies in specific areas, as found in relevant literature, can promote China's economic and social development in a well-rounded and expedited manner. Technological innovation, as the primary driving force for industry revitalization and transformation, contributes to the cyclical development of urban industries and injects momentum into economic growth. Technological innovation capacity is an important indicator for assessing a city's level of development, reflecting the integrity and rationality of the city's related industrial structure.。

At present, "Smart Cities" are in the qualitative analysis stage, with limited literature available on the impact of "Smart City" policies on specific regions. There is even less research on the impact of "Smart Cities" on technological innovation capacity. This study focuses on investigating the impact of "Smart City" policies on technological innovation capacity. By combining "Smart City" policies with urban technological innovation capacity, this research enriches the study of factors influencing technological innovation capacity in cities. Additionally, the study employs the Difference in Differences (DID) method, using the Pearl River Delta region as an example, to collect relevant data and assess the impact of "Smart City" development on urban technological innovation capacity. The aim is to provide policy recommendations for the innovative development of "Smart Cities."

1.3 Literature Review

After the concept of "Smart Cities" was introduced, numerous articles from both domestic and international sources have researched and interpreted this concept. IBM, as the originator of the "Smart City" slogan, has established an evaluation system for Smart Cities based on seven aspects, covering communication systems, transportation systems, water supply systems, energy systems, municipal services, business development, and residents' daily lives. Scholars have different perspectives on the constituent elements of "Smart Cities." Nam and Theresa (2011) describe "Smart Cities" as cities formed by the combination of technology, people, and institutions. Giffinger et al. (2015) believe that the assessment of "Smart Cities" should primarily focus on six dimensions: convenient transportation and information flow, residents' quality and talents, residents' quality of life, economic development level, social participation and governance level, and natural resources and environmental protection.

Regarding urban technological innovation capacity, various scholars have approached it from different angles. Regarding urban technological innovation competitiveness, Yang Yunchao and others consider it as the concretization of the concept of urban competitiveness in the field of technological innovation, constituting an essential component of urban competitiveness. Kresl et al. define urban competitiveness as the ability to provide more jobs, higher income, better culture, superior governance, and a more beautiful environment to meet residents' needs. In terms of evaluation indicators for urban technological innovation capacity, Sun Yu and others conduct assessments based on four aspects: economic investment, technological support, infrastructure, and educational reserves. Zhang Zhenshan et al. believe that direct evaluation methods should be used to assess urban technological innovation competitiveness. Gonzalez-Pernia et al. construct a technological innovation indicator system from the perspective of inputs such as R&D personnel and R&D funding. Some scholars directly measure urban technological innovation competitiveness based on technological innovation output.

Regarding the impact of “Smart City” policies on urban innovation, some scholars have researched it from the perspectives of technological innovation and scientific innovation. Liu Qiao et al. (2018) suggest that “Smart City” construction promotes the improvement of the technological innovation level in cities and is of great significance for enhancing urban innovation capacity. Cheng Kaiming’s research demonstrates a strong positive correlation between urbanization and technological innovation, and “Smart City” policies can accelerate the process of urbanization. Wang Xiaoxia (2022) posits that the progress and level of “Smart City” construction significantly affect urban technological innovation, emphasizing the need for cities to effectively balance “Smart City” construction and urban technological innovation during the process of modernization.

2. Research Design

2.1 Model Construction

This study employs the Double Difference method (DID, also known as the “Difference in Differences” method) to assess the technological innovation capacity of pilot cities [2]. The Double Difference method (Difference in Differences) involves calculating the difference between the “experimental group” and the “control group” under the intervention increment using data from observational studies. The Double Difference method can be understood as a simulation of random assignment experiments to verify causality in the absence of randomized trials. This research method is widely used in policy effect evaluation studies to investigate the specific impacts of a given policy. In the model, the “experimental group” refers to the subjects affected by the relevant policies, while the “control group” refers to those not affected by the relevant policies. The first difference involves performing two difference calculations (subtraction) for both the experimental and control groups before and after policy implementation, representing the relative changes in each group before and after the intervention. The second difference involves taking a second difference calculation of the two sets of differences, thereby eliminating the inherent differences between the experimental and control groups, ultimately revealing the static effect brought about by the policy. The basic model of the Double Difference method can generally be represented as:

$$Y_{it}= \alpha_0+\alpha_1 du +\alpha_2 dt +\alpha_3 du*dt +\varepsilon_{it}$$

In this context: The experimental group is assigned a value of 1, while the control group is assigned a value of 0, corresponding to assigning dt in the model as 1 and 0, respectively. Pre-policy implementation is assigned a value of 0, and post-policy implementation is assigned a value of 1, corresponding to assigning du in the model as 1 and 0, respectively. The first difference yields two sets of differences, $\alpha1+\alpha3$ and $\alpha1$. The second difference involves taking another difference of the two sets of differences obtained from the first difference, resulting in the static difference $\alpha3$. The model’s significance is as described in Table 1.

Table 1: Explanation of the DID Model

	Pre-policy implementation（U=0）	post-policy implementation(U=1)	Difference between the two
Experimental group（T=1）	$\alpha_0+\alpha_2$	$\alpha_0+\alpha_1+\alpha_2+\alpha_3$	$\alpha_1+\alpha_3$
control group（T=0）	α_0	$\alpha_0+\alpha_1$	α_1
DID			α_3

In this study, the sample is divided into the “experimental group” and the “control group,” where the former comprises cities that have implemented smart city policies, and the latter includes cities that have not implemented these policies. Since the number of patent applications in a city each year often provides a visual representation of the city’s technological innovation capacity, the number of patent applications in a city is chosen as the variable to measure innovation levels. Virtual variables are introduced in the model, with the experimental group (pilot cities) assigned a value of 1, indicating that the corresponding cities have implemented the policy, and the control group (non-pilot cities) assigned a value of 0, signifying that the corresponding cities have not yet implemented the policy. Time dummy variables are also introduced, with the year of policy implementation set as 1 and the other years set as 0. Based on the fundamental double difference model, the double difference model constructed in this paper is as follows:

$$PT_{it}= \alpha_0+ \alpha_1 T_{i,t}+\alpha_2 U_{i,t} + \alpha_3 DID+\sum\alpha_i X_{i,t} + \lambda_{i,t}$$

$PT_{i.t}$ represents the number of patent applications in a city and serves as the explanatory variable for measuring the city's innovation level. Tit represents the time of smart city policy implementation (in 2012, with a value of 1 for the post-implementation period in the experimental group and 0 for the rest), and its coefficient reflects the implementation effect of smart city policies in the pilot cities. $U_{i.t}$ represents the implementation of smart city policies, assigned a value of 1 for the experimental group and 0 for the control group. $X_{i.t}$ represents the set of control variables. DID represents the policy effect virtual variable, which is the product of T and U. α_0 is a constant, where i denotes one of the sample regions, and t represents a specific year within the sample regions. $\lambda_{i.t}$ represents the random error term.

2.2 Variable Setup and Data Description

This study primarily focuses on nine cities in the Pearl River Delta region, with each city serving as the fundamental unit of analysis. These nine cities are Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Zhongshan, Huizhou, Jiangmen, and Zhaoqing. Additionally, this study collected patent application data for these cities, sourced from the official website of the National Intellectual Property Administration. The data consists of the total number of Chinese patents applied for by each city on an annual basis from 2006 to 2020, including patents in the categories of invention, utility model, and design. These data are used to assess the technological innovation capacity of each city. Furthermore, the list of smart city pilot cities, published in 2012, was obtained through a search on the Baidu search engine.

Since the concept of smart cities was introduced in 2009, China officially established its first batch of smart city pilot cities in 2012. The initial group of smart city pilot cities included 90 cities at the district and county levels. This study defines the research area as the Pearl River Delta region and designates the five pilot cities in this region that implemented the policy in 2012 as the experimental group (comprising Guangzhou, Shenzhen, Zhuhai, Foshan, and Dongguan). The study also defines the four non-pilot cities in the same region that did not implement the policy as the control group (comprising Zhongshan, Huizhou, Jiangmen, and Zhaoqing).

In this paper, the dependent variable established is the number of patent applications, denoted as PT, which serves as an assessment of a city's technological innovation capacity. The independent variable is DID, representing a policy effect dummy variable, and it can also be expressed as the product of T and U. It is set to 1 for the year of policy implementation and subsequent years, while it is set to 0 for other years. Additionally, to control for other factors that may influence a city's technological innovation level, this paper introduces control variables, denoted as X. These control variables specifically include: (1) the city's economic development level, measured using the city's economic growth rate. A higher growth rate signifies a higher level of economic development. (2) City size, measured by the total population at the end of the year. A larger value indicates a larger city size. (3) Government support, assessed using financial innovation investment in science and technology. A larger value indicates greater government support for research and development. (4) Cultural and educational level, determined by the number of regular higher education institutions in the city. A larger value represents a higher level of cultural and educational development. The names and explanations of each variable are provided in Table 2.

Table 2: Variable Categories Descriptions and Explanations

Variable Category	Variable Name	Variable Description	Data Source
Dependent Variable	Patent Applications（PT）	Assessment of City Technological Innovation Capacity	National Intellectual Property Administration Website
Independent Variable	Policy Effect Dummy（DID）	Set to 1 for post-policy implementation years, 0 for others	Policy implementation year obtained through Baidu search engine
Control Variables	Regional GDP（RGDP）	City's Economic Development Level	Guangdong Provincial Statistical Information Website
	City Size（POPU）	Total Population at Year-End	
	Government Support(RIEF)	Government Investment in City Technological Innovation	
	Cultural and Educational Level(NOC)	Number of Regular Higher Education Institutions in City	

2.3 Descriptive Statistics of Variables

This article includes panel data of 9 prefecture-level cities in the Pearl River Delta region from 2006 to 2020, among which there are 5 pilot cities as the experimental group, and 4 non-pilot cities as the control group. The descriptive statistics of the data are shown in Table 3:

Table 3 Data Statistics Information

	Sample Size	Minimum	Maximum	Mean	Standard Deviation
treated	135	0	1	0.56	0.50
Jsbl (Explanatory Variable)	135	0	1	0.33	0.47
LnPT (Log of Patent Applications)	135	3.74	12.44	8.74	1.74
LnPOPU (Log of Year-end Total Population)	135	4.74	7.47	6.26	0.60
LnGDP (Log of Gross Regional Product)	135	2.50	10.23	7.93	1.55
LnRIEF (Log of Government Support Level)	135	0	7.32	4.04	1.58
LnNC (Log of Cultural and Educational Level)	135	0	4.41	1.95	1.01
Effective N (listwise)	135				

3. Results Analysis

To verify the hypotheses proposed earlier, the results analysis section will conduct a baseline regression analysis and parallel trend test on the collected data. The following text will specifically explain the rationale and operational process of these two methods.

3.1 Baseline Regression

For the errors in the model, this paper mainly considers factors such as time trend effects and selection bias. Time trend effect refers to the phenomenon where the technological innovation capability of both control group and experimental group cities is improving year by year. Selection bias refers to the fact that cities implementing smart city policies inherently possess higher technological innovation capabilities. Subsequently, a baseline regression was conducted on the sample data. This involved analyzing the baseline regression results for four models. Model 1 did not fix time and individual, Model 3 considered the implementation of policy more than Model 1, Model 4 fixed time and individual but did not consider control variables (such as factors of urban economic development), and Model 6, while fixing time and individual, also considered control variables, thereby eliminating the impacts of selection bias and time trend effects. Models 2 and 5 both considered time but not individuals, with Model 5 taking into account more control variable factors compared to Model 2. The results of the baseline regression analysis of the data are shown in Table 4.

Table 4 Baseline Regression Results

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
did	2.422*** (0.239)	1.837*** (0.253)	1.944*** (0.303)	-0.116 (0.089)	0.133 (0.176)	0.158** (0.792)
treated			0.716** (0.287)		0.682*** (0.166)	
Level of Economic Development					0.322*** (0.068)	0.738*** (0.136)
Government Support					0.610*** (0.109)	0.003* (0.077)

City Size					-0.654*** (0.156)	-0.987*** (0.284)
Cultural and Educational Level					-0.093* (0.056)	0.206*** (0.073)
Time Fixed	Not Controlled	Controlled	Not Controlled	Controlled	Controlled	Controlled
Individual Fixed	Not Controlled	Not Controlled	Not Controlled	Controlled	Not Controlled	Controlled
Constant	7.929*** (0.138)	8.123*** (0.129)	7.689*** (0.166)	8.775*** (0.036)	7.569*** (0.946)	8.594*** (2.241)
Observations	135	135	135	135	135	135

Note: *, **, *** respectively indicate that the regression coefficients are significant at the 10%, 5%, 1% confidence levels.

3.2 Analysis of Baseline Regression Results

The regression results show that smart city policies can enhance a city's technological innovation capabilities. The sixth column of Table 4 shows that the key variable of smart city policy, did, is significant at the 5% level. Among the control variables, the level of economic development is significant at the 1% level, and government support is significant at the 10% level, while city size and cultural and educational level are significant at the 1% level. The implementation of smart city policies allows the government to invest more in urban construction and gather talent, thereby enhancing the city's overall innovation capability, and naturally, its technological innovation capability will also correspondingly improve. The significant impact of economic development level on a city's technological innovation capability is mainly because a higher GDP indicates that the government can invest more funds in the field of technology, attract numerous scientific researchers, and thus advance the city's scientific research drive, ultimately leading to an improvement in the city's technological innovation capability. Government investment in science and technology indicates direct support from the government for the city's technological sector, which can greatly increase the city's technological innovation and research and development, thereby promoting the city's technological innovation capability. A higher number of higher education institutions in a city suggests that the city can cultivate more scientific researchers, who will later also contribute to enhancing the city's technological innovation capability.

3.3 Parallel Trend Test

The primary purpose of the parallel trend test is to verify whether the implementation of the policy has a significant impact on the innovation capability index of the cities in the experimental group. As the economy grows rapidly, the innovation capability index of the control group cities will also increase. The parallel trend test can show whether the innovation capability index of the experimental group grows faster relative to the control group. This reflects the additional role of the policy in enhancing the city's technological innovation capability.

For the parallel trend test, this paper also used Stata software to process the data. Subsequently, a graph of the innovation capability index against the corresponding years was plotted to more intuitively demonstrate the impact of policy implementation. The graph, combined with the data, shows that the results conform to the parallel trend test. The graph is shown in Figure 1 below.

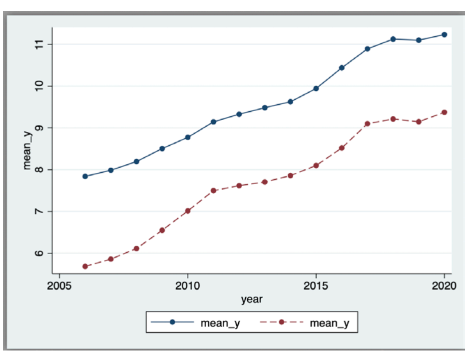

Figure 1 Parallel Trend Test Graph

3.4 Robustness Check

There are two commonly used methods for robustness checks. The first method involves using a lag effect test, and the second method involves changing the dependent and independent variables from the variable's perspective. This paper chooses to replace the dependent variable with the number of patent grants and conducts a robustness check. The specific results are as shown in Table 5:

Table 5 Robustness Check

	Model 1	Model 2
did	0.250* (0.155)	0.559*** (0.156)
Control Variables	Not Controlled	Controlled
Time Fixed	Controlled	Controlled
Individual Fixed	Controlled	Controlled
Constant	0.649 (4.424)	6.617*** (0.064)
Sample Size	135	135

Through the robustness check, it can be concluded that whether control variables are included or not, the impact of the smart city policy pilot cities on the city's technological innovation capability is significant, being significant at the 10% level and 1% level, respectively. This further verifies the robustness of the data.

4. Conclusions and Policy Recommendations

4.1 Research Conclusions

Enhancing technological innovation capabilities is a key factor in promoting high-quality development of a city, and this point has also been mentioned in many policies and related documents by the Chinese government. Based on theoretical analysis and taking the Pearl River Delta region as an example, this paper collects panel data of the corresponding cities from 2006 to 2020 and uses methods such as DID (difference in differences) to empirically test the hypotheses initially proposed in this paper. The conclusions of this paper are as follows:

（1）Smart city policies have a positive effect on the technological innovation capabilities of cities. By analyzing and assessing the commonly used policy evaluation method of the difference-in-differences approach, this study examined 15 years of panel data of cities in the Pearl River Delta region and conducted tests such as baseline regression. The results show that smart city policies can significantly enhance the technological innovation capabilities of cities, specifically reflected in the number of patent applications of cities (one way used in this paper to demonstrate the technological innovation capabilities of cities).

（2）Smart city policies have a significant effect on the technological innovation capabilities of cities with both higher and lower levels of development. For cities with higher levels of development, the government has already invested a significant amount of funding in scientific research, and there are many higher education institutions. With this good foundation, the introduction of smart city policies has an additional promotional effect on the technological innovation capabilities of cities. For cities with lower levels of development, where technological development is still in its early stages, smart city policies provide new innovative resources, allowing the city to develop rapidly in the middle stage and enhance the speed of technological innovation development in these cities.

（3）Strengthening investment in scientific research can also improve the level of technological innovation in cities. The analysis of control variables in the third part of the article shows that this aspect has a close relationship with the technological innovation capabilities of cities, which can be specifically reflected in the regression coefficients.

4.2 Policy Recommendations

Firstly, the Chinese government should continue to promote the construction of smart cities and implement smart city policies. The implementation should focus on three main areas. The first point is to strengthen the connection between the central and local governments to accelerate the implementation of smart city policies, ensuring that these policies are implemented even in remote areas. The second point is to enhance the city's infrastructure, such as transportation, environment, and resource utilization. By continuously optimizing the city's infrastructure, a solid platform can be provided for the implementation of smart city policies. Moreover, improved infrastructure can also play an additional role in the technological innovation development of the city, attracting more scientific researchers. The third point is to extend smart city policies to more cities, not just limited to the Pearl River Delta and the Beijing-Tianjin-Hebei region, and to continue to analyze and assess the effects of these policies.

Secondly, the government's implementation of smart city policies should adopt different strategies for different cities. For cities with higher levels of technology, it is necessary to continuously optimize their technological innovation capabilities and cultivate scientific talent, injecting continuous momentum into the city's technological innovation development and achieving sustainable development goals in technological innovation. For cities with lower levels of technology, it is necessary to focus on two aspects simultaneously: raising the city's economic development and uncovering the potential for technological innovation, accumulating a "latecomer advantage" for the city's development.

Finally, there is the control of potential risks. Smart city policies may not be successfully implemented in every city or region. For cities where the implementation is poor or has failed, subsequent strategies and contingency plans need to be developed. There are two main approaches to consider. The first is to no longer include cities with poor implementation outcomes in the pilot smart city policy. The second is to adjust the policy to make it more suitable for the actual situation of the city. This includes strengthening cooperation with local governments and businesses in that city to create a better market and technological innovation environment. Different methods entail different costs, so it is necessary to consider the current state of available resources and take a comprehensive approach to different situations.

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