China's Smart Cities Policy and Corporate Research and Development Intensity - A Quasi-Natural Experiment

Chunyu Jia(✉)

Wuhan University of Technology, Wuhan, China
309657@whut.edu.cn

Abstract. In this paper, we explore the impact of smart city policies on corporate R&D using a sample of Chinese a-share listed firms from 2008–2018. Our findings show that smart city policies have a catalytic effect on local firms' R&D compared to cities that were not selected as smart cities. In addition, we find that firms with different characteristics exhibit heterogeneity in this process. Specifically, Chinese resource-based cities and southern cities are more influenced by this policy.

Keywords: smart cities · R&D · difference-in-difference · quasi-natural experiment

1 Introduction

Over the past few decades, metropolitan areas around the world have undertaken numerous initiatives aimed at improving urban infrastructure and services with a view to creating better environmental, social and economic conditions and enhancing the attractiveness and competitiveness of cities. The smart city is a growing global phenomenon of the 21st century and has entered the policy debate as a solution to current urbanization challenges [1]. R&D (Research and development) is the most critical determinant of corporate productivity, growth and competitiveness, and has increasingly become an important part of corporate strategy, with strategic importance for innovation and growth in corporate financial performance [2]. Smart city initiatives can be viewed as an arena for multifaceted urban innovation [3]. R&D by local companies is also part of urban innovation. So, can smart city policies improve corporate R&D?

R&D is now not only a goal for companies themselves, but the level of R&D in general is also seen as a decisive factor in the growth of national productivity [4]. To promote R&D development, governments offer incentives such as direct subsidies, tax breaks, and other policies to corporations. Both corporate R&D subsidies and non-R&D subsidies have an incentive effect on corporate R&D investment [5]. By comparing companies that have benefited from the tax break with ordinary companies, the former will have higher R&D expenditures [6].

Most of the literature on the impact of smart cities on innovation has been studied from a macro perspective of overall innovation in cities [7], while few studies have

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been conducted from a micro perspective of firms (I provide empirical evidence on the micro mechanisms of smart city effects on firm innovation by focusing on the innovation performance of firms at the micro level). In addition, most of the existing literature uses a single-point DID approach based on a single point-in-time policy, while as smart cities policy in China currently has three batches of pilot cases, I use a multi-point DID approach to provide evidence from the quasi-natural experiment in China.

2 Policy Background and Theoretical Hypothesis

2.1 Policy Background

Nowadays, the level of urbanization is increasing all over the world. According to data released by the United Nations, the proportion of the world's population living in urban areas is expected to be as high as 68% in 2050[1]. Cities are becoming increasingly central to the global economy and their development is crucial. Smart and sustainable planning is required for rapid urban growth, which includes technological enhancements and interconnections as a key source of knowledge and intelligence. Smart cities are a crucial step in achieving these goals [8].

Smart Cities evolved from the Smart Earth proposed by IBM in 2008. However, the complexity of the smart city concept coupled with the already complex urban issues make it a challenging task. For China, building smart cities is not only a need to achieve information technology development and sustainable urban development, but also a strategic choice to improve comprehensive competitiveness. After a decade of exploration, a growing number of efficient, responsive and sustainable smart cities are growing up in China.

2.2 Theoretical Hypothesis

Smart city policies can promote the innovative development of local enterprises in at least three aspects: education, economy, and openness of the city. Education, as a major contributor to human capital accumulation, facilitates technological innovation through the development of a larger stock of human capital [9]. The implementation of smart cities will further concentrate education and resources in these cities, resulting in increased human capital and innovation levels for cities and enterprises.

In addition to smart city policies that directly promote business innovation with direct government investment and tax breaks, access to finance is considered key to achieving a number of sustainable development goals. Therefore, the financial system of smart cities has to be fully developed, become efficient and inclusive [10]. The establishment of smart cities has led to the emergence of many active "smart" product markets, which creates opportunities for companies in smart cities to access larger markets and promote their level of innovation [11].

Smart city policies can bring open innovation models and a higher degree of urban openness to cities. Open innovation models can enable private sector participation in

[1] Data obtained from https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html.

public collaborations, allowing for the sharing of tangible and intangible assets in a credible and open manner, leading to enriched innovation activities [12].

In summary, smart city policies can enhance companies' human capital, financial capital and open capital levels, which in turn can facilitate their R&D intensity. I thus develop the following hypothesis:

H1: Smart city policies will boost the R&D of companies in the city.

3 Models, Variables and Data

3.1 Model Setting

In this study, the pilot smart city is considered as a quasi-natural experiment, and a progressive double difference model is used as the basic regression model to estimate the impact of the pilot smart city on local firms' R&D intensity (R&D). Following existing literature [13, 14], an asymptotic double difference model was set:

$$R\&D = \alpha_1 + \beta_1 * Policy_{it} + \gamma_1 * X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Among them, i and t characterize the industry and year fixed effects respectively. R&D is the dependent variable, representing the R&D intensity of firms; *Policy* is the policy variable for the smart city pilot; X represents a series of control variables; μ_i and λ_t represent industry fixed effects and time fixed effects, respectively; ε_{it} represents the random error term. The policy term in the study is a dummy variable for policy implementation time, which is set to 1 for the year of policy implementation in the pilot city and subsequent years, and 0 for the rest. The policy variables in this study reflect both the experimental group and whether the policy is implemented, and their coefficients can better reflect the policy effect of the smart city pilot.

3.2 Variable Selection

3.2.1 Dependent Variables (*R&D*)

The explanatory variable in this study is R&D. Referring to Wu et al. (2021), firm R&D expense/asset is used as proxy.

3.2.2 Independent Variables (*Policy*)

This study uses dummy variables to characterize the smart city policy variables. If the firm's city becomes a pilot smart city in year t, the *Policy* in year t and subsequent years takes the value of 1; otherwise, it takes the value of 0.

3.2.3 Control Variables

Referring to Wu et al. (2021) and Chen et al., (2020), six control variables are added in this study, which are Age, Size, Leverage, ROA, Dep and Board (Table 1).

Table 1. Definition of variables

Variables	Definitions
Dependent:	
R&D	Ratio of R&D expenditure to total assets of enterprises.
Independent:	
Policy	Dummy variable, which equals 1 if the city where the enterprise is located is a smart city and 0 otherwise.
Control:	
Age	Year of observation – company's year of incorporation
Size	Natural logarithm of total assets
Leverage	Total liabilities/Total assets
ROA	Net income/Average assets
Dep	The number of independent directors as a percentage of the total number of board of directors
Board	The number of shares held by the largest shareholder/Total number of shares

3.3 Variable Descriptive Statistics

The data used in the empirical part of this study are obtained from the China Security Market and Accounting Research (CSMAR) database. The Chinese A-share listed companies from 2008–2018 are selected as the sample for analysis and the following data processing is performed: (1) exclude the samples of financial and insurance listed companies; (2) exclude the samples of listed companies treated as ST, PT, and *ST[2]; (3) exclude the samples with less than 1 year of listing time; and (4) exclude the samples with missing key variables. Finally, 15,819 observations were obtained. I winsorize all continuous variables at top and bottom 1% level to minimize the effect of extreme values and outliers. The results of descriptive statistics are shown in Table 2.

As can be seen from the table, the mean value of R&D is 0.015, the minimum value is 0, and the maximum value is 0.119, which indicates that the R&D varies widely across enterprises. However, the average value of R&D is only 0.015, indicating that the proportion of R&D in the sample companies is very small and there is still much room for improvement. The average value of the policy is 0.755, which indicates that 75.5% of the sample companies are located in smart cities, and is side evidence of the large coverage of China's smart city policy in the country.

[2] ST stocks are the stocks of domestic listed companies that have lost money for two consecutive years and have been given special treatment. PT shares are stocks listed on the stock exchange that have suffered losses for three consecutive years, etc., and are suspended and subject to special transfer services. *ST stocks are stocks listed in the domestic market with losses for three consecutive years.

Table 2. Variable descriptive statistics

Variables	Mean	Sd	Min	Max	N
R&D	0.015	0.023	0.000	0.119	12,894
Age	2.866	0.303	2.080	3.584	12,808
Size	22.208	1.352	18.950	26.074	12,810
Leverage	0.513	0.211	0.073	1.211	12,810
ROA	0.036	0.067	−0.235	0.251	12,812
Dep	0.366	0.050	0.300	0.571	12,812
Board	0.352	0.150	0.087	0.735	12,812
Policy	0.755	0.430	0.000	1.000	12,894

4 Empirical Results

4.1 Basic Regression

In this study, the basic regression model is estimated by regression through stepwise regression. Controlling for time fixed effects and industry fixed effects the detailed results are presented in Table 3. Column (1) shows the estimation results without adding control variables. The regression coefficient of the core explanatory variable *Policy* is 0.017, which is statistically significant at the 10% level, indicating that the smart city pilot policy can significantly contribute to the increase in R&D intensity of enterprises. After gradually adding the six control variables, the magnitudes of the regression coefficients of the core explanatory variables remain almost the same. But almost all of them become significant at the 5% level, which further verifies that the smart city pilot policy can significantly promote the improvement of R&D intensity of local enterprises.

The regression results of the control variables show that the estimated results of all four variables, Size, Leverage, ROA, and Board, show significant results, except for Age, Dep, which are not significant. This indicates that a firm's R&D investment is closely related to the firm's own financial status. The regression results of Size are significantly positive, while the regression results of Leverage and ROA are significantly negative.

The regression results for Board are also significantly positive. This may be due to the fact that the more powerful the largest shareholder of a firm is, the more likely it is to invest in R&D activities. However, when firms have greater leverage, they are less likely to risk investing in R&D activities. The results show that firms' ROA and R&D are negatively correlated, which may be explained by the fact that firms with high R&D investment ratios are generally in the start-up phase, when they are relatively unprofitable. In contrast, profitable firms in the mature stage invest relatively less in R&D.

4.2 Heterogeneity Analysis of Urban Interaction Terms

The above progressive DID model can assess the overall effect of the smart city selection policy, but because the development-driving effect of the smart city selection potentially

Table 3. Basic regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R&D	R&D	R&D	R&D	R&D	R&D	R&D
Policy	0.017^{*}	0.018^{**}	0.017^{*}	0.018^{**}	0.018^{**}	0.018^{**}	0.018^{**}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age		0.055	0.045	0.051	0.050	0.051	0.040
		(0.072)	(0.072)	(0.072)	(0.071)	(0.072)	(0.072)
Size			0.014^{**}	0.015^{***}	0.016^{***}	0.015^{***}	0.017^{***}
			(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Leverage				-0.043^{**}	-0.054^{***}	-0.054^{***}	-0.055^{***}
				(0.018)	(0.020)	(0.020)	(0.020)
ROA					-0.071^{**}	-0.071^{**}	-0.065^{*}
					(0.035)	(0.035)	(0.035)
Dep						−0.073	−0.074
						(0.050)	(0.050)
Board							-0.092^{**}
							(0.036)
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Constant	0.058	−0.082	−0.350	-0.366^{*}	-0.373^{*}	−0.347	−0.325
	(0.041)	(0.182)	(0.216)	(0.216)	(0.215)	(0.214)	(0.214)
N	12,809	12,805	12,803	12,803	12,803	12,803	12,803
r2_a	0.292	0.292	0.294	0.295	0.295	0.295	0.297

Note: ***, **, * denote regression results significant at the 1%, 5%, and 10% levels, respectively. Coefficients in parentheses are standard errors of clustering at the city level.

varies across cities, the analysis based on the overall observation sample may ignore the impact of the differences between cities. In order to avoid this problem, this study constructs interaction terms $Citytype * Policy$, $Citylocation * Policy$ under the conditions of city orientation and north-south location of the city, respectively, and analyzes their heterogeneous effects on the R&D intensity of enterprises in turn.

4.2.1 Heterogeneity Analysis of City Types

The industrial structure of most resource-based cities mainly relies on local resources and has a single industrial structure. How to adopt policies for their transformation and revitalization has been the focus of local governments [15]. Smart city construction can stimulate green innovation, enhance industrial structure and promote its transformation and revitalization. Therefore, resource-based cities can enjoy more marginal benefits from the construction of smart cities [16], generating stronger incentives for innovation and R&D.

Considering the regional differences in resource endowments, this study refers to the National Sustainable Development Plan for Resource-based Cities (2013–2020) published by the State Council of China to set up groupings[3], and then constructs city location dummy variables and cross-multiplies them with double difference terms to test the validity of the research findings. Column (1) in Table 4 reports the heterogeneous impact of the smart city selection policy on the innovation intensity of firms in resource-based and non-resource-based cities. The regression coefficient of the city types interaction term ($Citytypes * Policy$) is significant at the 5% level, indicating the effect of policy influence is more pronounced in resource-based cities in driving firms' innovative R&D.

4.2.2 Analysis of the Heterogeneity of the North-South Location of the City

There are differences of regional innovation resources and the degree of innovation activity in different regions in China. For example, capital investment and R&D manpower investment in southern cities have long been stronger than those in northern cities [17]. Since southern cities themselves have certain advantages in innovation capital, after becoming "smart cities", southern companies will also have a more significant development in innovation intensity compared to northern companies.

Considering that the disparity between the north and south regions of China is a prominent issue affecting the sustainable development of China's regions [18]. In this study, I construct city location dummy variables based on whether the city is south or north and interact with the double difference term. Column (2) of Table 4 reports the heterogeneous impact of the smart city selection policy on the innovation R&D intensity of firms in southern and northern cities in China. The regression coefficient of the city location interaction term ($Citylocation * Policy$) is significant at the 5% level, indicating that the effect of policy influence is more pronounced in southern Chinese cities in driving firms' innovative R&D.

The above discussion shows that, compared with non-resource-based cities and cities in the north, resource-based cities and cities in the south have more significant R&D growth in local enterprises with the support of smart city policies.

4.3 Robustness Tests

4.3.1 Parallel Trend Test

Satisfying the parallel trend assumption is a necessary prerequisite for asymptotic double difference estimation, and in this study, referring to Beck et al. (2010), I test whether the observed sample has a parallel trend through event study analysis, and the detailed model is set as follows:

$$R\&D_{it} = \theta_0 + \theta_1 * Policy_{it}^{-4} + \cdots + \theta_{10} * Policy_{it}^{6} + \theta_{11} * X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

[3] Data obtained from http://www.gov.cn/zwgk/2013-12/03/content_2540070.htm.

Table 4. Heterogeneity analysis: interaction term regression results

	(1)	(2)
	City types	City location
Policy	0.001** (0.001)	0.002*** (0.001)
Age	−0.007*** (0.001)	−0.007*** (0.001)
Size	0.062*** (0.015)	0.064*** (0.015)
Leverage	−0.014*** (0.001)	−0.014*** (0.001)
ROA	0.090*** (0.033)	0.085*** (0.033)
Dep	−0.013 (0.036)	−0.011 (0.036)
Board	−0.062*** (0.012)	−0.061*** (0.012)
*City type*Policy*	0.003** (0.001)	
*City location*Policy*		−0.001** (0.001)
N	11,430.000	11,430.000
R^2	0.425	0.425

Note: ***, **, * denote regression results significant at the 1%, 5%, and 10% levels, respectively, and the coefficients in parentheses are the standard errors of clustering at the city level.

Among them, $Policy_{it}^{\pm j}$ is a series of dummy variable and $Policy_{it}^{-j}$ ($Policy_{it}^{j}$) takes the value of 1 when the treatment group is in year j before and after becoming the smart city.

Figure 1 shows the regression coefficients and their corresponding 95% confidence intervals for $Policy_{it}^{\pm j}$. The regression results of *Policy* are not significant when $j = -4, -3, -2, -1$, which indicates that there is no significant change in the innovation R&D intensity of enterprises in the treatment and control groups before the implementation of the "smart city" selection policy, i.e., the hypothesis of parallel trend is satisfied. When $j = 0, 1, 2, 3, 4, 5$, the estimation result of *Policy* is basically significant, and when $j = 6$, the regression coefficient of *Policy* is significantly positive, which can be considered to satisfy the parallel trend hypothesis.

4.3.2 PSM-DID Method Test

In this study, propensity score matching (PSM) was performed on the samples by taking kernel matching. Immediately after the matching, the regression was re-run on the

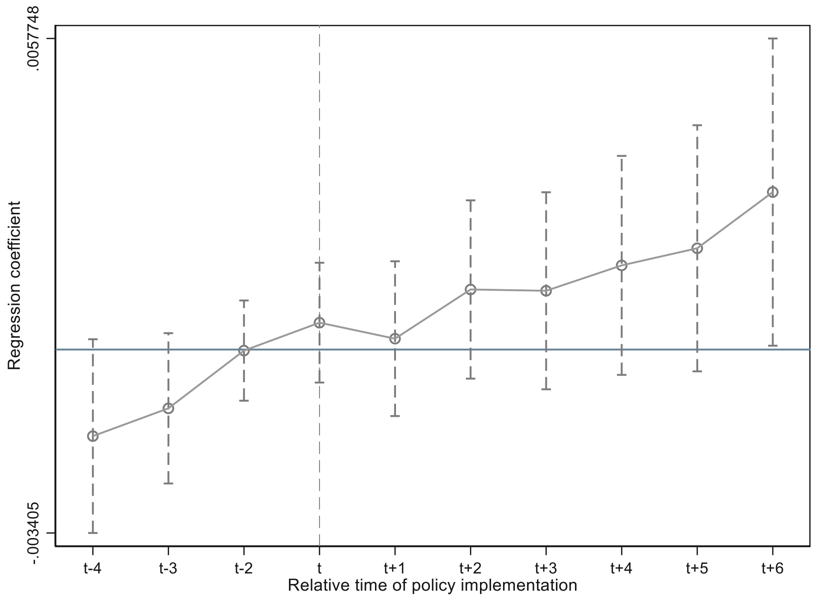

Fig. 1. Parallel trend test

matched samples. The regression results are reported in Table 5. The results are consistent with the results of the main regression as seen from the data in Table 5.

4.3.3 Counterfactual Test

Assuming that the cities before the implementation of smart city policy remain unchanged, if city i is rated as a smart city in year t in reality, any one year from the time range $[2012, t-1]$ is randomly chosen as the time when city i is classified as a smart city, and the Kernel density estimate is constructed to re-estimate the basic regression model to obtain the regression coefficients of the core explanatory variables. The above process was repeated 1000 times to obtain the results in Fig. 2. The results show that the mean value of *Policy* regression coefficient is 0.0438, which is much smaller than the basic regression result of 0.0018, indicating that the effect of smart city selection on economic quality development is relatively robust, i.e., it promotes the increase of enterprise innovation intensity.

4.4 Discussion on the Issue of Endogeneity

The main causes of endogeneity issues include measurement errors, omission of variables and reverse causality. Since smart city policy is a macro policy at the national level, it is difficult for individual firms' innovation behavior to influence the policy, so there is almost no reverse causality between firms' innovation activities and smart city policy. Meanwhile, the control variables were chosen rationally with reference to Wu et al. (2021) and Chen et al., (2020). The year and industry fixed effects are also strictly

Table 5. The results of PSM matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R&D	R&D	R&D	R&D	R&D	R&D	R&D
Policy	0.018**	0.018**	0.017*	0.018**	0.018**	0.018**	0.018**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age		0.056	0.045	0.051	0.050	0.051	0.040
		(0.072)	(0.072)	(0.072)	(0.071)	(0.072)	(0.072)
Size			0.014**	0.015***	0.016***	0.015***	0.017***
			(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Leverage				−0.043**	−0,054***	−0.054***	−0.055***
				(0.018)	(0.020)	(0.020)	(0.020)
ROA					−0.071**	−0.071***	−0.065***
					(0.040)	(0.035)	(0.035)
Dep						−0.073	−0.074
						(0.050)	(0.050)
Board							−0.092**
							(0.036)
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Constant	0.054	−0.084	−0.350	−0.366*	−0.373*	−0.347	−0.325
	(0.041)	(0.182)	(0.216)	(0.216)	(0.215)	(0.214)	(0.214)
N	12,803	12,803	12,803	12,803	12,803	12,803	12,803
r2_a	0.292	0.292	0.294	0.295	0.295	0.295	0.297

Note: ***, **, * denote regression results significant at the 1%, 5%, and 10% levels, respectively. Coefficients in parentheses are standard errors of clustering at the city level.

controlled in the empirical study to avoid the endogeneity problem caused by omitted variables and measurement errors.

5 Conclusions and Policy Recommendations

Based on the data of Chinese A-share listed companies from 2008–2018, this study investigates the impact of smart city policies on corporate innovation R&D intensity using double difference method, and finds that smart city policies have a significant positive impact on corporate R&D. The specific empirical process is as follows: first and foremost, by conducting a basic regression on the sample. Its results prove that smart city policies significantly help to promote enterprise R&D compared with cities that are not selected as smart cities. Then, by conducting heterogeneity analysis on the type and location of cities, it is found that the impact of smart city policy is more

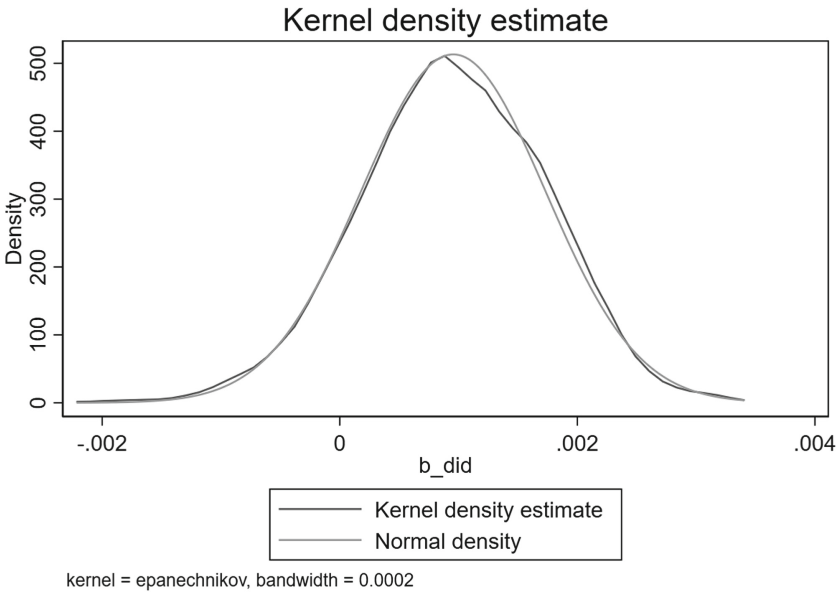

Fig. 2. Kernel density estimate

obvious in resource-based cities and southern cities. Finally, three robustness tests were conducted: first, the significance of the DID model was demonstrated by conducting a parallel trend test, and the following conclusion was found: the R&D intensity of firm innovation was basically improved after about two periods of smart city policy implementation. However, there is a lag effect on the driving effect of smart city policy on the innovation intensity of enterprises. Second, this study conducted Propensity Score Matching (PSM) on the sample by kernel matching and re-run the regression on the matched sample, which proved to be consistent with the results of the main regression. Third, by conducting Counterfactual test on the sample, it proves that the effect of smart city policy on the enhancement of corporate R&D is robust. After the empirical analysis of the data is completed, the endogeneity issue is discussed.

This study provides empirical evidence on the positive externalities of the smart city selection on the R&D intensity of firms. Combining the findings of the study, I propose the following policy recommendations:

Firstly, the smart city policy has sufficiently promoted the improvement of enterprise innovation and R&D intensity. Chinese government should promote the implementation of smart city policy, insist on empowering traditional industries with high technology and continue to empower enterprises' innovation level and competitiveness. However, there are still many problems in the concrete implementation of the smart city policy, and more reasonable development methods need to be explored.

Secondly, local governments should adhere to the basic principle of city-specific policies. In the process of continuing to carry out smart city policy, local governments should pay attention to summarizing, sharing and promoting the lessons learned from pilot cities. The country should focus on introducing the successful experience of southern cities and resource-based cities into cities where the policy dividend has not yet been fully released, and play a leading role in the smart city policy.

Finally, increase government support for high-tech industries in pilot cities. At this stage, the policy dividend of high-tech industry development has not yet been fully released. Local governments should accelerate the flow of key factors such as human capital and financial capital, release the capital pressure of enterprises, reduce operating costs and improve the business environment in order to promote innovation of enterprises.

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