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RESEARCH ARTICLE

Do Smart City policies make cities more innovative: evidence from China

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ABSTRACT

The aim of the present study is to reveal the causal effects of Smart City policies on urban innovation. Using the panel data harvested from 103 cities in China, the constructed sample was analysed rigorously based on the combination of the strength of Propensity Score Matching (PSM) and Difference-in-Differences (DID). As suggested by the empirical results, Smart City policies indeed positively and significantly impact urban innovation . Besides, whether policy effects vary with the regional location and city scale is explored; the results reveal that the impact is significantly positive only for the megacities as well as cities in central China.

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1. Introduction

Since the late 1990s, smart city projects have been rolled out globally. According to Deloitte Touche Tohmatsu's report (Deloitte, 2018), the constructions of over 1,000 smart cities have been launched worldwide with 500 policy pilot areas in China, which noticeably outclasses Europe's 90 of the second place. The mentioned projects are capable of not only enhancing the intelligence of specific socio-economic aspects of daily life, but also presenting a considerable number of other benefits, which cover fostering a competitive economy (Giffinger & Haindl, 2010), boosting more feasible governance (Nam & Pardo, 2011), expediting the innovation process (Paskaleva, 2011; Schaffers et al., 2012), advancing social capital (Hodgkinson, 2011), protecting diversity and individuality (Lind, 2012), etc. Nevertheless, some have argued that the potentials or benefits of smart cities have been overestimated; they considered that smart cities may not be as 'smart' as their name suggests (Hollands, 2008). Though considerable capitals have been invested in the advancement of smart cities, smart cities have not achieved their original goals (Yigitcanlar & Lee, 2014). Numerous risks also exist in the application of smart city strategies, e.g., the digital divide resulting from unequal use of ICT (Coe et al., 2001), the replication of technology solutions (Townsend et al., 2010), the overlook of city's requirements and priorities (Caragliu & Del Bo, 2019), the slow progression attributed to budgetary issues and inadequate planning (Shwayri, 2013), etc.

Note that some scholars considered 'smart city is innovation'. Nam and Pardo (2011) highlighted that smart cities manifest city innovation in the aspects of management, policy

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as well as technology. Smart applications, open government data and novel modes of public participation are expediting urban innovation (Veeckman & Graaf, 2014). As knowledge and creativity are extensively introduced in the process of smart city construction, this underpins in-depth knowledge production and innovation of cities (Angelidou, 2015). Nilssen (2019) defined smart city initiatives as urban innovation and elucidated smart urban innovation from four dimensions, namely, technology, organization, cooperation as well as experiment. Caragliu and Del Bo (2019) reported that cities engaging in Smart City policies above the EU average level are inclined to patent more intensively. As a matter of fact, a range of smart cities are labelled to boost their knowledge and innovative economy (e.g., Skolkovo Innovation City in Russia and Sino-Singapore Guangzhou Knowledge City in China). Thus, the question is raised that what is the impact of Smart City policies on urban innovation, and whether Smart City policies make cities more innovative.

In this study, a difference-in-differences propensity score matching (DID-PSM) approach (Heckman et al., 1997) is employed to interpret the mentioned questions by the case study of a country with the maximal urbanization growth rate in China. To tackle down the challenges posed by urbanization, China has substantially invested in the building process of smart cities over the past decade; currently, this country has more smart cities than other countries with 500 policy pilot areas (Deloitte, 2018). For this reason, China is serving as an appropriate case to verify whether Smart City policies affect urban innovation. China has established the first batch of pilot cities for Smart City policies in 2012, covering 90 prefecture-level cities and county-level cities. We generate huge interests in the changes in innovation outputs of the cities after being planned as the pilot areas for Smart City policies; to this end, we take Smart City policies in 2012 as a natural experiment, and apply DID-PSM approach to assess the direct causal effects of Smart City policies on urban innovation.

The rest of this paper is organized below. In Section 2, the literature review is conducted about Smart City policies as well as its effects. In Section 3, the estimating sample, the empirical model as well as the data are illustrated. In Section 4, three subsections are covered. In Section 4.1, the details on Propensity Score Matching are reported, as well as the empirical findings on whether Smart City policies affect urban innovation. In Section 4.2, heterogeneity of the effects is examined. Besides, in Section 4.3, the robustness of the results is tested. In Section 5 of the paper, the conclusions that emerged from the previous text are drawn and some future thoughts are proposed.

2. Literature review

2.1 What is Smart City policy

Though smart cities are being actively constructed globally, people may misunderstand the meanings of smart city and Smart City policy for the complexity of the smart city content and the diversifications among cities. Accordingly, these two concepts should be clarified.

A wide range of definitions of smart city have been discussed. According to Caragliu et al. (2011), a city is considered being smart 'when sustainable economic growth and a high quality of life are fuelled by the investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure, with a wise management of natural resources, through participatory governance'. Besides, it is associated with the concept of 'sustainable cities' (Ahvenniemi et al., 2017), with specific attention to environmental issues and ICT (Caragliu & Del Bo, 2019). Researchers have recently noticed the emergence of the so-called 'smart city 2.0'. Trencher (2019) compared the critical attributes of the first- and second-generation smart city paradigms. As he proposed, 'smart city 1.0' stresses the diffusion of smart technologies for economic benefits, while the latter highlights the application of smart technologies to cope with social challenges and satisfy the requirements of citizens, as an attempt to strengthen policies and governance and motivate citizen's participation.

Smart city policy refers to a vital means formulated by the government to guide the construction of smart city, directly determining the success of smart city construction projects. At the strategic level, Smart City policies refer to a type of strategy employed to reorganize governance and processes to cope with the 'urban disease' attributed to urban population growth and rapid urbanization. To be specific, the policies consist of the use of smart computing technologies to fabricate the critical infrastructure components and services of a city, covering city administration, education, healthcare, public safety, real estate, transportation, and utilities, which aims to be more intelligent, interconnected, and efficient (Washburn et al., 2010). Smart City policies may stress a country or a nation, or concern a more local level (e.g., a province, city, counties or even a district). Irrespective of what the scale is, the critical issue is to figure out what the problems are and how they can be solved using targeted policies of the policy makers.

Smart cities are expanding globally, exhibiting similar characteristics (e.g., the use of innovative technologies and environmental protection globally) (Dameri et al., 2019). Governments in various countries had introduced numerous policies to promote smart cities. For instance, the U.S. government has set numerous policy documents (e.g., *White House Smart Cities Initiative, A Strategy for American Innovation, and Smart and Connected Communities Framework*) to cope with 'urban disease', which cover traffic jams, crime, environmental pollution and resource shortage, etc. To achieve sustainable development, the European commission introduced *Europe 2020 Strategy, EU's new Smart Cities and Communities Initiative, Smart Cities and Communities European Innovation Partnership*. Chinese central government has formulated *national new urbanization plan (2014–2020)* to introduce the construction of smart cities into national strategic planning. Australian government released *Investment to Create Smart Agriculture* as an attempt to boost agricultural productivity. Singapore government declared *Intelligence Nation 2025*, with the focus on issues (e.g., personnel training, technological innovation, smart business and smart communities).

In the meantime, smart cities are also a local phenomenon since each city exhibits its own specificity and faces distinct problems (Dameri et al., 2019). When formulating Smart City policies, local governments stress the development of local characteristics and the adaption to local needs, thereby making the implementation of each smart city a unique reality. For instance, New York chose equity and security; London focused on open data and transport; Paris attached high importance to artificial intelligence and tourism; Amsterdam stressed open data and energy; Rio de Janeiro was prone to transport and security. The research object of this study – China has a vast geographical space, and the development diversifications between regions exist objectively, thereby forming the different construction focuses of smart cities, for instance, Shenzhen in Smart service, Shanghai in Smart economy, Guangzhou in Smart transportation, Shenyang in Smart industry, etc.

Some scholars have noticed the mentioned types of smart city projects and attempted to interpret the differences. Angelidou (2014) reviewed that the factors including existing resources, critical areas, political cooperation, moral & ethical issues, stakeholder engagement, physical & institutional changes, and pilot projects can interpret the differentiated policies for the development of smart cities. Angelidou (2017) also studied the Smart City plans of 15 world-wide major cities in 2017; he reported that ICT is a major factor capable of improving urban systems and ultimately fostering urban innovation. As reported by Zhongqingyang et al. (2017), the implementation effect of Smart City policies in China was uneven, with a significant gap in the construction capacity of each city; they proposed four influential factors that resulted in the significant gap, namely, information resources, network security, innovative technology and development mechanism.

2.2 The effects of Smart City policies

The construction of smart cities has been carried out for 20 years. Given this, what type of effect does it produce, has its grandiose visions come true, and how do things really go?

As mentioned above, Smart City policies are conducive to improving infrastructure, developing economy, protecting environment, solving 'urban disease', elevating quality of life, and making cities more liveable, flexible and smart. Numerous studies and reports have proven that some progresses have indeed been made. The following evidences were presented by McKinsey Report (Mckinsey, 2018): urban casualties reduced by 8–10%, commuting time cut by 15–20%, medical burden reduced by 8–15%, as well as air pollution down-regulated by 8–15%. Moreover, it is estimated that the global market for smart urban systems for transport, energy, healthcare, water and waste will reach nearly 400 billion USD per annum by 2020 (Yigitcanlar, 2016).

Nevertheless, the implementation of the Smart City policies has not been as smooth as expected by its grandiose visions. First, smart city characterized as innovation acts as a living laboratory (Cairney & Speak, 2000), faced with unavoidable risks. For this reason, Smart City policies are an innovation driver as well as an effort to manage risks of innovation. As reported by Whittaker (1999), three commonest reasons for the failure are: poor project planning, a weak business case, as well as the lack of top management support. Similar to that of any other policy, the goal of Smart City policies may not be achieved rapidly. Yigitcanlar and Kamruzzaman (2018) suggested that city smartness and carbon dioxide emissions are not linearly linked, and the impact of city smartness on carbon dioxide emissions does not vary over time. Si-chen and Yi-kun (2017) highlighted a certain degree of time lag effect, i.e., these policies may not positively impact city smartness in the short term, whereas they will be feasible in the long term. Besides, the digital divide cannot be overlooked. Glasmeier and Christopherson (2015) stated that 'over 26 global cities are expected to be smart cities in 2025, 50% of which will come from Europe and North America'. In other words, smart cities in Asia, Africa and Latin America display relatively low development level. On the whole, it is worth expecting that the potential of smart city construction still requires further exploration, since even the world's leading smart cities (e.g., New York, Seoul, Stockholm) have only achieved two-thirds of their potential (Mckinsey, 2018).

3. Empirical framework

3.1 Estimating sample

When the first batch of pilot cities for Smart City policies was organized in 2012, some counties or districts at the prefecture level were arranged as pilots (e.g., Pudong New Area in Shanghai and Zhaoyuan county in Daqing). If these prefecture-level cities are taken as samples, the impact exerted by Smart City policies on urban innovation will be under-estimated. Thus, these cities are eliminated from the sample. To expand the time range of the policy estimates as far as possible, the city set as the pilot for Smart City policies in 2012 is taken as the treatment group, and the newly emerging pilot smart cities in 2013 and 2014 are excluded.

A difference-in-differences propensity score matching (DID-PSM) approach is applied (Heckman et al., 1997). The key to the application of difference-in-differences (DID) method is the selection of control group. The levels of innovation in the treatment and control groups should be ensured to be similar prior to the Smart City policies. For instance, some cities can become the pilot for Smart City policies because of favourable conditions, e.g., higher economic development level and higher financial development level, suggesting that these cities may have higher innovation level than non-pilot cities even without policy intervention. If non-treated cities act as the control group directly, sample selection bias will be caused, and then the effects of the implementation of Smart City policies on urban innovation will be overestimated.

Accordingly, Propensity Score Matching (PSM) was applied in this study to construct a matched control group. We first estimated the Logit model to derive the propensity score for both treated and non-treated cities. The propensity score assesses the probability of receiving treatment, i.e., being set as a pilot for Smart City policies based on observable characteristics. Subsequently, the predicted propensity scores should be adopted to match treated cities with non-treated cities that possess similar observable city characteristics and use successfully matched non-treated cities as control group rather than all non-treated cities. In such a way, the observable heterogeneity between treated and control groups is controlled.

3.2 Model specification

The PSM technique is employed in conjunction with the DID approach to address the selection bias and endogenous problem. The DID empirical model is expressed as:

$$PATENT_{it}=\beta_0+\beta_1\mathrm{SMART\_CITY}+\beta_2\mathrm{TIME}+\beta_3(\mathrm{SMART\_CITY} * \mathrm{TIME}) + \sum_{j=1}^{n}\lambda_j X_{jit}+\varepsilon_{it}$$

where ($\mathrm{PATENT}_{\mathrm{it}}$) denotes the innovation level of No. i city at time t; SMART_CITY is a dummy variable taking the value of 1 if city i belongs to the treatment group; TIME is a dummy variable of the time before or after the implementation of Smart City policies; (SMART_CITY*TIME) refers to the interactive variable of the multiplication of the SMART_CITY and the TIME; $\mathrm{X}_{\mathrm{jit}}$ denotes other variables that may affect urban innovation; $\varepsilon_{\mathrm{it}}$ is the error term.

Though there are some shortcomings of using patents to measure innovation, for instance, many innovation activities were not patented, and the economic value brought by patents was quite different (Klette & Griliches, 1996), patent data is an appropriate and credible way to measure the innovation output across cities. Accordingly, following the literature (Griffith et al., 2006; Hsu et al., 2014; Pradhan et al., 2018; Tang & Tan, 2013), we employ the number of newly granted patents ($PATENT_{it}$) as a proxy for urban innovation.

The coefficient of SMART_CITY (β_1) indicates the invariable diversification of the innovation level of cities in the treatment group against that of cities in the control group. The coefficient of TIME (β_2) denotes the impact of other invariable factors other than Smart City policies on the urban innovation in the control group before and after 2012. The coefficient of (SMART_CITY*TIME) is considered our main interest, capturing the causal effect of 2012 Smart City policies on urban innovation. A positive β_3 reveals that Smart City policies are conducive to urban innovation, while a negative β_3 suggests an opposite impact. λ_j is the impact coefficient of control variables.

To ensure the effectiveness of the DID results, we control several factors that are likely to affect urban innovation, as represented by the X_{jit} (detailed definitions of the variables can be found in Table 1). The control variables first cover the gross regional product per capita (PGRP), indicating the economic growth. Though innovation Granger causes economic growth (Agénor & Neanidis, 2015; Guloglu & Tekin, 2012), a range of empirical studies reported that economic growth noticeably impacts innovation (Furman et al., 2002; Pradhan et al., 2016, 2018). To avoid omitting variable bias in the estimation of the impact of Smart City policies on innovation, the variable of economic growth should be controlled.

Subsequently, economic openness is controlled, covering foreign direct investment (FDI) and trade openness (TRADE). The FDI is ascertained by the proportion of actual foreign direct investment in gross regional product. According to Phuc Canh et al. (2018), FDI inflow and innovation were demonstrated to be positively related, while Romer (1990) and Young (1998) argued that the influx of foreign capital may shift the urban workforce from R&D to the final product sector, thereby adversely affecting urban innovation. TRADE is measured by total import and export that take up the proportion of gross regional product. With the use of directed acyclic graphs technique, Pan et al. (2019) found that trade openness exert direct effects on technological innovation.

The third control variable is financial development (FIN), as ascertained by the ratio of loan balance to deposit balance of financial institutions. The development of financial markets critically impacts a nation's innovation (Schumpeter, 1911). It was reported that technological innovation is impacted by financial development (Pan et al., 2019; Rajan & Zingales, 1998), and an advanced financial market contributes to the up-regulation of innovation efficiency (Li et al., 2017).

The National Innovation System theory (Nelson, 1993) says that government acts as a critical factor affecting innovation ability. Several scholars revealed that government intervention is indeed critical to affect the innovation performance by offering financial assistance (Wang, 2018), procuring products (Georghiou et al., 2014), publishing technology specifications, arranging IPR transfer, organizing training (Gao, 2015), convening diverse interests and facilitating cooperation (Wang & Kim, 2007), etc. Given this, government intervention (GOV) measured by the proportion of government expenditure on science and technology (S&T) in gross regional product is controlled.

Table 1. Variables list.

Variable name	Variable symbol	Unit	Variable description
Dependent variables			
Urban innovation	PATENT	10,000piece	The number of newly granted patents in a given year of the city
DID method variables			
Whether set as pilot smart city in 2012 or not	SMART_CITY	/	A dummy variable that is equal to one if a city is approved by the state as a Smart City policies pilot city in 2012, and zero if otherwise
The year before or after 2012	TIME	/	A dummy variable that is equal to zero if the year is before 2012, and one if otherwise
The interactive variable of SMART_CITY and TIME	SMART_CITY * TIME	/	Interactive variable of the multiplication of the SMART_CITY and the TIME
Control variables			
Economic growth	PGRP	10,000yuan	Gross regional product per capita
Economic openness	FDI	%	The proportion of actual foreign direct investment in gross regional product.
	TRADE	%	Total import and export accounts for the proportion of gross regional product.
Financial development	FIN	%	the ratio of loan balance to deposit balance of financial institutions
Government intervention	GOV	%	The proportion of government expenditure on science and technology in gross regional product.
Industrial structure	TS	%	The ratio of output value of the third industry to that of the secondary industry.
Science and technology human capital	HC	%	The ratio of the number of personnel engaged in S&T activities to working population

Industrial structure (TS) is also controlled. A diversified industrial structure in an urban region is capable of facilitating innovation; by enriching local knowledge resources (Jacobs, 1969), this structure can provide a dynamic urban environment for inter-industry interactions and generate positive externalities (Ning et al., 2016). In this study, we employ the ratio of output value of the third industry to that of the secondary industry to proxy the degree of industrial structure optimization.

Lastly, S&T human capital (HC) is controlled. Dakhli and De Clercq (2004) supported the view that the human capital has a positive impact on innovation. Furthermore, Lu et al. (2014) considered that intellectual capital is critical to induce innovation. To measure the intensity of S&T human capital, the ratio of the number of personnel engaged in S&T activities to working population is taken.

3.3 Data

In the present study, our data are harvested primarily from two sources. Basic information on city characteristics is acquired from the China National Statistical Bureau's '*China Statistical Yearbook for City*', providing gross regional product per capita of the cities, deposit and loan balance of financial institutions, actual foreign direct investment, total import and export, government expenditure on S&T, number of personnel undertaking S&T activities, output value of the secondary industry and third industry, etc. The patent data are harvested from the State Intellectual Property Office (SIPO) patent database, offering application and publication numbers of the patent, application and grant year and other pieces of information all patents granted in China. The sample is restricted to exclude cities with missing values for any of the variables covered in the model; thus, one city is excluded. The final estimating sample consists of 1030 observations from 103 cities in China from 2008 to 2017.

The summary statistics are listed in Table 2, covering the number of observations, mean and standard deviations across the entire examination period. Table 2 also lists the means of the variables divided between pilot cities for Smart City policies and non-pilot cities, and all the variables are reported to be significantly different across the two groups. On average, pilot cities have a higher number of newly granted patents, whereas it cannot be concluded from this simple analysis that the pilot cities are more innovative than the non-pilot cities for the potential impact of our control variables. We find that on average pilot cities reveal to possess higher financial development level, more foreign direct investment and import and export trade, more adequate government support, and more intensive S&T human capital than the non-pilot cities, and the industrial structure

Table 2. Summary statistics.

	Total			Non-pilot cities			Pilot cities			
Variables	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	MeanDiff
PATENT	1030	0.210	0.373	780	0.160	0.270	250	0.364	0.563	−0.203***
PGRP	1030	4.607	20.05	780	4.309	22.96	250	5.536	3.365	−1.227
FIN	1030	59.63	24.15	780	57.44	25.62	250	66.49	17.16	−9.049***
TRADE	1030	20.77	39.59	780	17.70	31.43	250	30.34	57.15	−12.644***
FDI	1030	2.054	2.306	780	1.821	2.234	250	2.781	2.379	−0.959***
GOV	1030	0.285	0.390	780	0.258	0.387	250	0.368	0.391	−0.110***
TS	1030	78.37	37.31	780	80.18	38.67	250	72.72	32.12	7.457***
HC	1030	1.207	0.635	780	1.114	0.466	250	1.497	0.935	−0.383***

Notes: *, **, *** denote significance levels of 10%, 5% and 1%.

is significantly different. Accordingly, we will apply the Propensity Score Matching (PSM) method next, and test whether Smart City policies will make cities more innovative based on matching treated cities with non-treated cities that possess similar city characteristics.

4. Empirical findings

4.1 Main results

Given the discussion in Section 3.1, the aim of using the PSM approach is to organize the matched control group. First, stepwise regression analysis was used to select suitable matching variables. Covariates for matching are calculated by two logit regression, covering financial development (FIN), trade openness (TRADE), foreign direct investment (FDI), industrial structure (TS) and S&T human capital (HC). Second, with the propensity score calculated from logit regression, pilot cities (treatment group) are matched with non-pilot cities (control group) based on 1-nearest neighbour matching. We choose the year before the implementation of the smart city policy as the matching time point, namely 2011. Thirdly, the matching results should be verified. As Table 3 shows, our matching is well balanced. No covariate was significantly different after the match completed, indicating that the treated and the matched control groups on average exhibit similar city characteristics. The 53 cities not paired successfully are removed, and lastly, 25 cities are acquired in the treatment group corresponding to 25 cities in the control group.

After the successful PSM, we now aim to verify whether Smart City policies affect urban innovation. The estimation of the ordinary least square (OLS) method is first reported. As column (1) of Table 4 shows, when there are no control variables, the level of urban innovation is positively associated with Smart City policies and statistically significant at the 1% level. When control variables are covered in the regression equation, the regression coefficient value of (SMART_CITY * TIME) will be down-regulated from 0.1549 to 0.1359, which remained statistically significant at the 1% level (column (2)).

Based on constructing the matched control group, the differences of urban innovation before and after Smart City policies are compared between pilot cities and non-pilot cities by using DID method. The estimated results are reported in column (3) and column (4) of Table 4. The urban innovation is again reported to be positively and significantly associated with policy intervene, respective of whether other variables are regulated. As shown in column (4), the regression model F statistics value was 28.08, having reached

Table 3. Balance tests before and after PSM.

	Unmatched	Mean		%reduct	t-test	
Variable	Matched	Treated	Control	%bias	t	p>|t|
FIN	U	47.44	57.44	−44.6	−1.94	0.053
	M	47.44	41.12	34.4	1.22	0.229
TRADE	U	26.70	17.70	21.4	1.38	0.169
	M	26.70	20.58	13.1	0.46	0.646
FDI	U	2.317	1.821	24.4	1.10	0.273
	M	2.317	1.684	36.8	1.30	0.200
TS	U	62.29	80.18	−53.6	−2.29	0.022
	M	62.29	60.42	7.6	0.27	0.790
HC	U	1.420	1.114	40.6	3.09	0.002
	M	1.420	1.198	30.4	1.08	0.287

Table 4. Smart city policies with urban innovation.

	(1)	(2)	(3)	(4)
	OLS	OLS	DID-PSM	DID-PSM
SMART_CITY * TIME	0.1549***	0.1359***	0.1705**	0.1236*
	(0.052)	(0.048)	(0.074)	(0.064)
TIME	0.1344	0.0755***	0.1188**	−0.0368
	(0.256)	(0.025)	(0.052)	(0.049)
SMART_CITY	0.1104***	0.0515	0.1401**	0.0970*
	(0.040)	(0.038)	(0.057)	(0.050)
PGRP		0.0002		0.0196***
		(0.001)		(0.007)
FIN		0.0015***		0.0035***
		(0.000)		(0.001)
TRADE		0.0027***		0.0005
		(0.000)		(0.000)
FDI		−0.0002		−0.0114
		(0.005)		(0.007)
GOV		0.0926***		0.1930***
		(0.032)		(0.059)
TS		0.0009***		0.0045***
		(0.000)		(0.001)
HC		0.0486***		0.0273
		(0.017)		(0.024)
cons	0.0798***	−0.1719***	0.0500	−0.5483***
	(0.020)	(0.037)	(0.041)	(0.073)
Observations	1030	1030	500	500
F statistics	43.66	36.66	26.74	28.08
R-squared	0.1132	0.2573	0.1392	0.3648
Adj R-squared	0.1106	0.2646	0.1340	0.3518

Notes: Robust standard errors are reported in parentheses; *, **, *** denote significance levels of 10%, 5% and 1%.

the 1% significance level. The adjusted R2 value was 0.3518, implying that the model had about 35% explanatory power. The coefficient value of SMART_CITY is 0.097, with statistical significance, denoting the innovation level between pilot cities and non-pilot cities before the release of Smart City policies is different. The coefficient of TIME becomes insignificant with the addition of control variables, revealing that the innovation level of non-pilot cities has not varied significantly before and after the implementation of smart city policy. A statistically significant and positive estimate for the interaction term (SMART_CITY * TIME) is identified, proving a positive effect of Smart City policies on urban innovation. Moreover, the estimated coefficient value of interaction term is 0.1236, suggesting that the number of newly granted patents increased by 12.36% on average if the city was set as a pilot for Smart City policies. Nevertheless, the estimation coefficient is much smaller than the estimated result using OLS. This is primarily because of the use of PSM in advance, which can effectively correct for selection bias when evaluating the innovation-driven effects of Smart City policies.

Besides FDI, all the control variables positively impact urban innovation. The empirical results suggest that the higher the economic development level of a city, the higher the level of innovation will be. Besides, the results reach the 1% level of significance, confirming the research findings of Pradhan et al. (2016) and Pradhan et al. (2018). The degree of financial development (FIN) has been found to significantly and positively impact urban innovation, which is in line with the theoretical expectations and the research results of Li et al. (2017). As for the two variables that reflect the economic openness – – TRADE and FDI – – they have different influences.

To be specific, trade openness (TRADE) has been found to be positive correlated with urban innovation, while the regression coefficient value of foreign direct investment (FDI) is insignificantly negative. The influx of foreign capital may be the cause that shifted the urban workforce from R&D to the final product sector (Romer, 1990; Young, 1998), adversely affecting urban innovation. Furthermore, cities acquiring more government support (GOV), having a more advanced industrial structure (TS), or owning more S&T human capital (HC) have been found to be more innovative. It is probably because they have greater resources and better environment to innovate. Besides, the estimation coefficient of GOV is the highest among all the variables, suggesting that the government intervention plays an important role in stimulating urban innovation. With the increase of the government's financial investment in science and technology work, the innovation capacity of the city has been continuously improved, which is reflected in the rapid growth of patent authorization.

4.2 Heterogeneous effects

We further examine the heterogeneity effects of the 2012 Smart City policies on urban innovation. We particularly concern about whether policy effects vary with the regional location and city scale.

Regional differences

There are gaps in regional innovation capacity in China (Li et al., 2017; Xia et al., 2019). China's mainland region can be generally split into three economic regions (the east, the central and the west). To verify whether urban innovation's responses to the Smart City policies are heterogeneous across regional location, our samples are split into three sub-groups. Estimates for different regions are listed in the first three columns of Table 5. The coefficients of the interaction terms (SMART_CITY * TIME) hold positive in all regions. Nevertheless, the Smart City policies only significantly increased the number of patents granted to cities in central China. According to the mentioned results, the effects of the Smart City policies on urban innovation varied across regions.

Table 5. Estimates for different regional location and city scale.

	City location			City scale		
	(1) East	(2) Middle	(3) West	(4) Medium-sized cities	(5) Large cities	(6) Megacities
SMART_CITY * TIME	0.2141	0.1211*	0.0230	0.0170	0.0124	0.4443**
	(0.134)	(0.073)	(0.016)	(0.031)	(0.041)	(0.220)
TIME	−0.0603	−0.0365	0.0223**	0.0028	0.0168	0.0073
	(0.106)	(0.059)	(0.010)	(0.026)	(0.031)	(0.148)
SMART_CITY	0.2938***	−0.0029	0.0128	−0.0834***	0.0289	0.3066*
	(0.106)	(0.058)	(0.012)	(0.028)	(0.032)	(0.156)
Control variables	YES	YES	YES	YES	YES	YES
Observations	160	250	90	28	371	85
F statistics	14.478	25.416	9.711	8.456	38.444	15.154
R-squared	0.4927	0.5154	0.5514	0.8326	0.5164	0.6719
Adj R-squared	0.4588	0.4951	0.4946	0.7341	0.5030	0.6276

Notes: Robust standard errors are reported in parentheses; *, **, *** denote significance levels of 10%, 5% and 1%.

City scale differences

The city scale is classified into five types (small cities, medium-sized cities, large cities, megacities and super megacities) according to the '*Notice on the adjustment of standards for the division of city scale*' issued by the State Council of the People's Republic of China in 2014, with the city resident population as the statistical calibre. Due to the limited sample size, the number of small cities and super megacities are small, which makes the regression results are not credible. Accordingly, we only report the results of medium-sized cities, large cities and megacities. Column (6) of Table 5 indicates that the estimated impacts of Smart City policies for megacities with a population range from 5 million to 10 million remain almost the same with results of cities in central China, i.e., positive and significant on urban innovation. It is noteworthy that the coefficient value of (SMART_CITY * TIME) reaches 0.4443 with the 5% significance level. Given such statistically significant result, we believe that the construction of smart city can strengthen the effects of innovation factor agglomeration in the expansion of urban scale, to improve the innovation level of the cities. Nevertheless, for the sample of medium-sized cities with a population range from 0.5 million to 1 million and large cities with a population range from 1 million to 5 million, smart city construction does not play a significant role in promoting urban innovation.

4.3 Robustness check

Lastly, we provide additional robustness checks regarding the significant positive relationship between Smart City policies and urban innovation by performing a test of counter-factual method, using an alternative proxy for urban innovation and regulating the control variables.

The objective of the counter-factual method is to verify the innovation effect of the Smart City policies by resetting a pilot time point. If the regression result exhibits insignificance, the improvement of urban innovation level is attributed to the implementation of Smart City policies rather than other factors. The pilot time of Smart City policies is assumed as 2011, and the propensity score matching (PSM) and difference in difference (DID) of the previous text are re-performed. The estimation results (see Table 6, **Panel A**) show that the regression coefficient of (SMART_CITY * TIME) is no longer significant. It is therefore suggested that Smart City policies released in 2012 indeed facilitated urban innovation.

To ensure that our main results are not entirely driven by our proxy selection for a city's innovation level, the number of newly applied patents per year further acts as an alternative measure for urban innovation based on research by Ning et al. (2016), Gao et al. (2017), Phuc Canh et al. (2018), and Pan et al. (2019); the results are listed in **Panel B of** Table 6. Consistently, we find positive and significant coefficient estimate of the interaction terms (SMART_CITY * TIME), though the regression coefficient value is slightly higher compared with the main results in Table 3.

Moreover, given that urban innovation is a source of income growth, the gross regional product per capita (PGRP), representing economic growth, may not be suitable as a control variable. For this reason, PGRP is removed from the model. Smart City policies are reported again to have a positive and statistically remarkable effect on urban innovation, and the symbols and significance of most variables do not noticeably differ from the previous text, which still supports the previous conclusion (see Table 6, **Panel C**). Thus far, we have proved the robustness of our results.

Table 6. Robustness checks.

	(1)	(2)	(3)
Panel A: test of counter-factual method			
SMART_CITY * TIME_2011	0.0694		
	(0.073)		
F statistics	21.45		
R-squared	0.3049		
Adj R-squared	0.2907		
Observations	500		
Control variables	YES		
Panel B: use an alternative proxy for urban innovation			
SMART_CITY * TIME		0.2086*	
		(0.109)	
F statistics		31.92	
R-squared		0.3949	
Adj R-squared		0.3826	
Observations		500	
Control variables		YES	
Panel C: remove GRP per capita			
SMART_CITY * TIME			0.1311**
			(0.065)
F statistics			29.96
R-squared			0.3549
Adj R-squared			0.3431
Observations			500
Control variables			YES

Notes: Robust standard errors are reported in parentheses; *, **, *** denote significance levels of 10%, 5% and 1%.

5. Conclusion and discussion

The present paper aims to evidence whether Smart City policies make cities more innovative – in the case of Chinese cities. To accurately estimate the policy effect, Propensity Score Matching (PSM) and Difference-in-Differences (DID) are integrated to eliminate some biases that might affect the effectiveness of this study. To be specific, PSM technique is adopted to construct the matched control group that possesses similar observable city characteristics with treatment group. Subsequently, DID approach is employed to estimate the differences of those groups' treatment effects before and after the policy implementation. Besides, our results comply with several existing studies (Caragliu & Del Bo, 2019; Veeckman & Graaf, 2014), revealing that Smart City policies indeed stimulate urban innovation. Though innovative is not a major objective of implementation of Smart City policies, our findings have demonstrated a positive spill-over effect of the policies on urban innovation. Compared with similar non-pilot cities, pilot cities of smart city policy are granted more patents.

We also addressed the question of whether the city scale and regional location have altered the effects of Smart City policies by conducting separate analyses for different regional locations and city scales. In terms of regional location, the results imply that Smart City policies positively and significantly impact urban innovation for cities in central China. However, for the sample of eastern and western cities in China, urban innovation is not significantly affected by policy. For city scale, the impact has been found to be noticeably positive only for China's megacities. In other words, Smart City policies' innovative effects seem to be only realized in part of cities. This may be related to the different priorities and developmental paths of smart city construction in each city. For instance, Hangzhou focuses on the use of artificial intelligence technology to innovate urban management, and Shenzhen attaches great importance to the application of IOT technology, while Ningbo is more prone to the development of urban big data. The mentioned findings require subsequent in-depth research and more effective optimization of Smart City policies to fully exploit the innovation-driven effect. Furthermore, the robustness test is performed by a test of counter-factual method, using an alternative proxy for urban innovation and regulating the control variables. And the results reveal that the conclusion of this study is robust.

However, some caveats should be clarified. First, we used the number of newly granted patents to measure urban innovation due to the limitations in data availability, which could only reflect innovation in the fields of industry and technology but ignore innovation at the organizational and policy levels.

Second, the empirical results suggest that Smart City policies' innovation-driven effects vary with the city scale and regional location. If so, what are the explanations or mechanisms for the observed differences? Further empirical research of the impacting mechanism of Smart City policies on urban innovation is thus needed.

Lastly, though no direct positive correlation is found between Smart City policies and urban innovation for cities in eastern China and western China, our aim is originally not to question the inherent value of Smart City policies, e.g., its significance for the sustainable development of cities. Besides, the indirect effects of Smart City policies on urban innovation may require further study.

Disclosure statement

No potential conflict of interest was reported by the authors.

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