Smart City Construction, Absorptive Capacity, and Open Innovation: Moderating Effects of Property Rights and Factor Marketization

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ABSTRACT

It is widely accepted that the construction of smart cities can improve the overall operational efficiency of cities and stimulate the local economy. At the micro level, there is no doubt that smarter cities can reshape the external environment of firms and change their interactions with the outside world. However, existing research has not yet paid sufficient attention to how firms' activities change in a highly informative smart city environment. Therefore, this paper focuses on the impact of smart city construction on firms' open innovation. In this paper, natural experiments are constructed to test the net effect of smart cities, and a multi-period difference-in-differences model, negative binomial regression model, and panel data fixed effects regression model are used comprehensively. The findings show that smart city construction can significantly increase firms' open innovation and that firms' absorptive capacity mediates this relationship. In addition, firms' open innovation performance in smart cities is higher when the property rights environment is well developed, and the effectiveness of smart city construction is more pronounced in regions with a lower degree of factor marketization.

Keywords: Smart city, Open innovation, Absorptive capacity, Market environment

1. Introduction

Due to technological change, increased competition, and market demand, most organizations strive to be more innovative and competitive [1]. Especially during pandemic periods, organizations worldwide have been forced to make unprecedented responses to mitigate the adverse impact of coronavirus disease 2019 (COVID-19) [2]. The rapid recovery from this crisis has led to an explosion of innovative responses [3], as innovation has long been recognized as one of the key strategies organizations can use to weather economic downturns [4,5]. In a market with insufficient information liquidity, firms tend to follow Schumpeter's closed-end innovation concept; that is, the whole process of innovation is restricted within the enterprise, and they maintain their products' leading competitive position in the market by keeping the development of internal technology strictly confidential [6].This mode, however, is undoubtedly challenging for firms in terms of their internal resources and capacities and imposes enormous pressures concerning research and development (R&D) investment, high management costs, and the risk of failure. The characteristics of closed innovation make it unsuitable for organizations in a recession [1] since firms usually face unprecedented time and resource constraints in times of crisis [7] and have a much lower tolerance for risk and loss.

At the same time, we can observe that the COVID-19 pandemic has accelerated the rapid development of information and communication technology (ICT) and digital platforms. To maintain physical distance, the digital ecosystem may be the only mechanism through which interactions between different entities exist today [8]. Such a rapidly evolving information environment inevitably affects companies' innovation activities. On the one hand, ICT application has led to the construction of a highly transparent social environment, and the channels through which each individual can obtain information have been unprecedentedly widened [9]. In such an environment, information on the company's R&D stage, including R&D direction, R&D process, etc., is inevitably perceived by competitors. Thus, such perceptions encourage competitors to intervene in the follow-up innovation process at an earlier period and launch innovative imitative products within the shortest time after the company's new products are launched to share the excess monopoly profits that can be provided by corporate innovation.

On the other hand, the extensive flow of information also accelerates the mobility of personnel, capital, and technology. Individuals who participate in the internal innovation process of enterprises are equipped with the conditions for independent external entrepreneurship after mastering important technologies to a certain extent. The perfection of the information network further provides efficient financial support for these individuals [10]. In the highly developed informatization environment, firms implementing a closed innovation strategy face a higher order of magnitude of competitors, especially those familiar with their resource endowment conditions and abilities. In addition, the increase in the number of market innovation subjects promotes the improvement of the industry innovation iteration rate, thus putting forward higher requirements for enterprises' innovation ability [11]. Under such circumstances, the pressure of "closed-door" innovation increases daily, and enterprises must consider more carefully how likely their invested innovation resources can achieve an effective output [12].

Considering the above impact of the COVID-19 pandemic and ICT development on corporate innovation behavior, it is not difficult to find that it has been difficult for closed thinking to adapt to the changed innovation environment and that a more realistic choice for enterprises is for them to cooperate with external entities to carry out innovation activities. Many scholars' research results also confirm that enterprises' financial performance and market competitiveness significantly improve after adopting an open innovation strategy [13]. However, the literature has not clarified how the information environment can affect the output of open innovation and the path mechanism through which the information environment acts on open innovation. A smart city constructs a social system with more information and changes the city's original information transmission paradigm and social governance model [14]. Under this system, with the help of extensive connectivity channels, enterprises can obtain external innovation resources more conveniently, and the breadth and depth of their cooperation partners are greatly improved [15]. In addition, the construction of smart cities also provides an excellent technical and policy environment for protecting intellectual property rights and improving the trading market, thus reducing the transaction costs enterprises must pay to participate in open innovation. Smart city construction has potential advantages in improving enterprises' level of open innovation, but the literature has not paid enough attention to this research area [16]. In addition, under the influence of smart city construction, a wide range of network connections are established between companies and external organizations [17], and the level of external information that companies can access significantly increases, increasing the company's absorptive capacity. This increase in absorptive capacity means that the company's R&D capabilities are strengthened, which positively impacts the company's open innovation performance. This transmission path has not yet received full attention from scholars. Based on the gaps in existing studies, this paper intends to explore the influence and mechanism of smart city construction on enterprise open innovation from theoretical and empirical perspectives.

The previous analysis of the relationship between smart city construction and enterprise open innovation performance is based on considering only the basic competition and cooperation relationship between innovation subjects [18]. However, the fact is that no market can achieve an ideal state without any nonmarket resistance. Taking its market environment as an example, China has experienced a period of government-led resource allocation of the factors of production in the process of economic system reform and development, which has objectively caused the deviation in the market price of such factors, imbalance of the supply structure and other problems [19]. Since the reform and opening up, although more marketization conditions have been introduced into factor markets, the uneven development of the degree of marketization among regions has not been completely solved. In an environment with a low level of marketization in certain elements, a firm's innovation process faces more challenges, including increased resource search costs and greater innovation difficulty, thus hindering the development of open innovation potential. The construction of smart cities can precisely provide specific solutions to the innovation problems of enterprises in such regions [18]. Thus, constructing smart cities may have a more significant effect in regions with less developed marketization. In addition, under the shared and interconnected mode of smart city construction, the clear division and differentiated governance of property rights have become prominent problems. Whether the institutional environment related to intellectual property rights is perfect directly impacts the effectiveness of smart city construction. Based on the above analysis, the degree of marketization of the factor market and the legal system environment related to property rights may moderate the relationship between smart city construction and enterprise open innovation. However, the literature does not sufficiently address this issue, which also constitutes the research perspective of this paper.

Our research makes several significant contributions to smart city construction and open innovation. First, from the perspective of the technological and institutional utility of smart cities, this paper verifies the positive impact of smart city construction on corporate open innovation, which enriches the research on the impact of smart city construction on urban micro entities [20]. Second, we investigate the mediating role played by absorptive capacity in the relationship between smart city construction and open innovation. Our study sheds light on the potential mechanisms through which smart city construction links to open innovation, deepening the understanding of the pathways through which smart city construction operates. Third, this paper considers the moderating effect of the market environment on the relationship between smart city construction and enterprise open innovation, providing some important insights for developing smart city policies and implementing innovation strategies.

The rest of the paper is structured as follows. In Section 2, we develop our hypotheses based on the literature review. Section 3 outlines our research design, including sample and data collection, variables, and Models. Section 4 reports the results of the analysis. Section 5 discusses the findings and theoretical and practical implications and describes the limitations and directions for future research.

2. Theoretical Background and Hypotheses

2.1. The Impact of Smart City Construction on Business

A smart city refers to integrating information and communication technologies, as well as technologies such as the Internet of Things and big data, to intelligently manage and optimize various aspects of a city, aiming to enhance sustainable development [21]. The development of smart cities has brought about extensive and far-reaching effects on enterprises.

Firstly, smart cities provide enterprises with improved infrastructure and services [13], enhancing their operational efficiency and competitiveness. The digital infrastructure and intelligent services of smart cities, such as high-speed internet [22], intelligent transportation systems [23], and smart supply chain management [24], enable enterprises to conduct business operations and management more efficiently. The application of these technologies provides real-time data and analytics, assisting enterprises in better understanding market demands, optimizing production and supply chains, and thus improving production efficiency and resource utilization.

Secondly, smart cities offer enterprises more opportunities and support for innovation [25]. Smart cities' innovation ecosystem and platforms provide enterprises broader collaboration and innovation opportunities. For instance, smart city innovation centers and technology parks offer innovation resources and support, fostering collaboration and knowledge sharing among enterprises [26]. Moreover, smart cities' open data and digital platforms provide enterprises abundant data resources and technological support [5]. Through big data analytics and artificial intelligence, enterprises can identify new business opportunities, optimize products and services, and drive technological and business model innovation.

In conclusion, smart cities influence enterprises, with a particular emphasis on innovation. By providing improved infrastructure and services, innovation opportunities and support, and driving sustainable development and social responsibility, smart cities offer enterprises broader development space and opportunities while presenting higher requirements and challenges. Enterprises should actively adapt to the development trends of smart cities, seize opportunities, and promote innovation and sustainable development to gain a competitive advantage in the smart city environment.

2.2. Smart Cities and Open Innovation

Through the extensive introduction of ICT, including big data, cloud computing, and Internet of Things (IoT) technologies, into the urban governance mode, smart city construction can influence the performance of open enterprise innovation at both the technical and institutional levels.

At the technical level, smart city construction can provide enterprises with a more knowledge-rich external environment, thus expanding the range of options through which enterprises can carry out open innovation activities [27]. With the extensive application of ICT, cities have a higher degree of use of digital resources, and the connections between various city departments become closer [28]. The total and quality of innovation resources available to enterprises are significantly improved. A large amount of data is generated in the daily operation of a city. Under the previous governance mode, much data has not been collected, sorted out, and utilized effectively. The potential for information exchange between different innovation subjects has not been fully released due to problems such as the insufficient carrying capacity of infrastructure and an extensive range of specialties. As a result, more data flows within a department, and it isn't easy to give full play to the utility value of these data. Under the construction mode of smart cities, the extensive application of sensors, radio-frequency identification (RFID), and other IoT technologies in various segments of urban operations enriches the scene and expands the depth of urban data collection [18,29]. More importantly, the data collected are no longer used as a redundant resource to increase the burden on the city but rather as a resource to fully tap the potential economic value hidden behind the numbers with the help of intelligent technologies such as big data and cloud computing. The amount of social knowledge enterprises require to carry out innovative activities increases exponentially [30]. In general, in the environment of smart cities, the external knowledge enterprises can obtain becomes increasingly diversified. According to innovation theory, the starting point of open innovation activities in enterprises comes from excellent creativity [31]. The more diversified external information an enterprise receives, the more divergent its creative process is, and the more abundant creative ideas can effectively improve the scope of its choice in participating in open innovation activities and then promote the improvement of its open innovation performance [32].

At the institutional level, implementing smart cities can enhance the connection between enterprises and other market subjects, thus improving the depth of enterprises' participation in open innovation. Under limited information flow, enterprises and consumers face serious information asymmetry, which means enterprises must pay extra transaction costs to identify partners if they choose to cooperate with external third parties [33]. According to resource dependence theory, the information asymmetry between enterprises and external entities hinders the willingness of both parties to exchange complementary resources, thus inhibiting the improvement of enterprises' open innovation level [19]. In the smart city environment, the efficient flow of information promotes the development of closer relationships between market players, which objectively alleviates the pressure placed on them by information asymmetry [29]. Therefore, enterprises can not only become closer to consumers in the market, obtain timely feedback from the market on their innovation achievements [34], and improve the commercialization efficiency of innovation activities but also efficiently find potential innovation partners in the market that best match their innovation endowments and promote the innovation synergy effect. In addition, the open and shared environment not only introduces complementary technologies and experiences to enterprises but also enables them to be exposed to diversified management concepts and strategic thinking, change the thinking logic of enterprises in a closed environment, and develop organizational structures and cultural characteristics that are more suitable for open innovation. In light of the above aspects, we propose the first hypothesis of this paper:

Hypothesis 1: Smart city construction can have a positive impact on the open innovation of enterprises.

2.3. Mediating Role of Absorptive Capacity

The construction of intelligent cities also improves enterprises' absorption capacity, similar to the scenario described in the smart city construction goal of "making urban subjects smarter" [35]. On the one hand, the construction of smart cities can significantly improve the possession of enterprise data resources and ensure adequate support for R&D activities that are critical to improving the absorptive capacity of enterprises [30,36]. Smart cities allow companies to use extensive data infrastructure at a low cost, meaning enterprises can access higher data resources with limited R&D investment. Against the background of the knowledge economy, data resources have the same weight value in innovation activities as traditional resources such as capital and human resources, and the total increase in innovation input drives the improvement of the absorptive capacity of enterprises [37]. Moreover, smart city construction impacts enterprises' internal communication paradigm, thus allowing them to overcome internal communication friction and promoting enterprises to develop an organizational structure more suitable for improving absorptive capacity. Enterprises in smart cities can effectively alleviate information asymmetry between different innovation departments and improve internal communication efficiency by introducing information-sharing platforms internally. Extant research shows that the smaller the resistance to information transmission within an organization, the better the inner diffusion effect of knowledge absorption by a single organization department, which manifests as an improvement in overall absorption capacity [6].

Previous research conclusions have widely supported the positive impact of absorptive capacity on firm innovation performance [38,39]. In the scenario of open innovation, while enjoying the synergistic advantage brought about by the combination of internal and external innovation resources, enterprises are also faced with the threat of failing to introduce and integrate external innovation resources efficiently, which leads to the adverse situation of innovation input redundancy and the failure of R&D. Absorptive capacity can help enterprises give full play to the advantages of the open innovation mode and avoid the related risks related from two links—knowledge absorption and utilization—and then promote the improvement of the actual output of open innovation. In the process of knowledge absorption, higher absorptive capacity can enable the enterprise to identify the subject with the innovation ability urgently needed by it in the shortest time, and cooperation with the enterprise thus faces a lower difficulty of knowledge integration and gives full play to the knowledge complementary effect in the open innovation mode [40,41]. In knowledge utilization, absorptive capacity is vital in forming open innovation outputs with commercial value [42]. The ultimate purpose of enterprises' open innovation activities is to improve their innovation ability and speed up the iteration of innovative products to help them adapt to the rapid change in market demand. Whether innovation can be commercialized smoothly is an essential factor in judging the success of open innovation. Enterprises with stronger absorptive capacity can internalize and absorb external knowledge more efficiently and give positive feedback to the innovation output process. In conclusion, absorptive capacity significantly contributes to the success of open innovation. Accordingly, the second hypothesis is proposed in this paper:

Hypothesis 2: Absorptive capacity mediates the relationship between smart city construction and enterprise open innovation.

2.4. Moderating Effect of Property Rights Environment

Smart city construction forms an extensive connectivity within the social environment. In this environment, the information exchange between different subjects in the city, data exchange, and resource exchange reach an unprecedented degree of closeness. Urban innovation forms a stable social network collaboration between departments based on the degree of communication between each party. We maximize the overall efficiency of open innovation in society. However, with the growth of the resource interaction volume and continuous expansion of the interaction scope, the limiting effect of the property rights environment has gradually begun to appear. The adaptability of the existing property rights system and technological development determines the upper limit of the promotion effect of smart city construction on the open innovation of enterprises. According to the theory of property rights, a perfect intellectual property protection system is of great significance for protecting the rights and interests of participants in cooperative innovation and improving the willingness of enterprises to participate in external cooperative innovation [43,44]. Smart city construction provides a widely interconnected social environment in which enterprises are more closely connected with external entities, bringing new challenges to clearly defining property rights. A sound intellectual property environment can reduce enterprises' uncertainty in participating in cooperative innovation and amplify smart city construction's role in driving enterprises' open innovation [45].

A sound property rights system can effectively enhance the open innovation performance of smart city construction, as reflected by these three aspects. First, a sound property rights system can improve the innovation willingness of enterprises by guaranteeing economic interests from such innovation, and the promoting role of smart cities in open innovation can be given full play to the greatest extent [46]. According to the classical incentive theory in the study of intellectual property systems, the legal protection of intellectual property formed by innovation activities is the key factor ensuring that innovation subjects continue participating in innovation activities. In the closed innovation mode, the traditional exclusive intellectual property system can ensure that innovative enterprises monopolize the excess profits brought about by innovation, thus forming positive feedback on the technological innovation of enterprises. However, under the open innovation model, more innovations are chosen to be open to the public in open form. At this time, an overly strict intellectual property system deviates from the goal of knowledge diffusion and hinders the development of open innovation. In contrast, an overly lax intellectual property system infringes on creators' interests and weakens the role of innovation incentives. Therefore, a property right environment matching the technical characteristics of smart city construction is crucial to the effectiveness of smart cities.

Second, a clear definition of ownership division can eliminate uncertain risks and thus improve the breadth and depth of enterprises' participation in open innovation. In this environment, the innovation promotion role of smart city construction is improved [44]. The open innovation model breaks the inherent system of all innovation output property rights privatizations. Suppose the existing intellectual property system cannot divide the boundaries of intellectual property with public attributes. In that case, innovative participants cannot determine whether their open innovation behavior constitutes an infringement of the interests of other parties and need to bear legal responsibility. To avoid such risks, enterprises inevitably limit their overreliance on secondary innovation based on the intellectual property rights of other parties [47]. A sound property rights system can dispel the concerns of enterprises in this respect and improve their information interaction participation in the smart city environment to achieve higher open innovation performance.

Third, a sound property rights system is conducive to reducing moral hazard and influencing enterprises' willingness to participate in open innovation activities, thus improving the influence of smart city construction on enterprises' open innovation. When intellectual property has the characteristic of being a public good, if the corresponding intellectual property system does not balance the rights and obligations of the innovator, then externalities and moral hazards follow. From the overall perspective, when all participants participate in the knowledge-sharing system, each participant can obtain more innovation benefits than in the closed innovation mode [48]. However, for a single innovation subject, when it absorbs more knowledge from the open system at a low cost and announces its R&D results less to competitors, the innovation effect of the subject is greater. Moral hazards can produce an accelerated negative cycle and even lead to the collapse of the innovation-sharing system. Therefore, a complete property rights system constitutes the institutional basis for the effectiveness of smart city construction and determines the upper limit of smart city construction's influence on enterprises' open innovation output.

In summary, although smart city construction has established a foundation for a good external environment for the open innovation of enterprises, its role also depends on whether a perfect intellectual property system matches the external environment. Based on this, the third hypothesis is proposed in this paper:

Hypothesis 3: The property rights environment positively moderates the relationship between smart city construction and enterprise open innovation.

2.5. Moderating Effect of the Development of the Factor Market

In addition to smart cities' technical and institutional attributes, smart city construction also has prominent policy attributes. The existing cases of smart city construction are all carried out under the guidance of government policies, and the construction effect largely depends on the actual situation of the city itself. This paper is expected to explore smart city construction's actual open innovation performance under different factor market endowments [49]. The continuous and high-intensity exchange of innovative elements, such as technology and R&D materials, between enterprises and external entities is the key to ensuring the orderly progress of open innovation. A factor market with a low level of marketization cannot give full play to its functions, such as price discovery and resource allocation optimization, thus leading to a decline in the activity of market participants, shrinking trading volume, and other undesirable situations. In factor markets with a low degree of marketization, on the one hand, it is difficult for enterprises to authorize or transfer redundant innovation resources to other innovation subjects to enhance their innovation resource liquidity and improve the efficiency of innovation resource use [50].

On the other hand, these enterprises also face greater pressure to find innovative partners or innovative resources that can form a complementary relationship with their innovation endowments. From the analysis of the influence mechanism of factor marketization on the open innovation of enterprises, it can be found that the influence of smart cities on open innovation is similar to that of factor marketization, both of which provide a market environment suitable for internal and external exchanges for innovation entities, thereby increasing the willingness of enterprises to participate in open innovation activities and the benefits they can obtain from such activities. That is, all else being equal, if the factor market environment is sufficiently developed and mature, then innovation factors can flow freely and thus optimize resource allocation so that firms are less dependent on smart city construction; conversely, in regions with underdeveloped factor markets, firms need to rely more on the advantages of efficient information and resource flows provided by smart city construction. Following this logic, the relationship between smart city construction and enterprise open innovation will likely become more salient in regions with low factor marketization relative to those with more developed factor markets. Therefore, we propose the following hypothesis:

Hypothesis 4: The positive relationship between smart city construction and corporate open innovation is more salient in regions with low factor marketization than regions with more developed factor markets.

3. Method

3.1. Data and Sample Selection

3.1.1. Dependent variable

In the literature, the measurement of open innovation includes qualitative and quantitative indicators, and the research uses comprehensive data for reflection. The number of patent applications evaluates open innovation performance from two dimensions—innovation output and innovation capability—and this index includes objective data with stronger comparability between different research samples. Based on the above reasons, this study selects the number of applications of patents jointly developed by listed companies and other companies in the last three years (i.e., *T* year, *T*-1 year, and *T* +1 year) as the proxy variable of open innovation performance. To further refine the indicators, invention patents in the past three years have substantially stronger open innovation, and the utility model patents are regarded as catering to stronger open innovation.

3.1.2. Independent variable

In the multistage difference-in-differences (DID) model, we take the variable DID as the indicator reflecting the net effect of smart city construction, the assignment idea of which is as follows: the value of DID is 0 in the year before the effect of external events and 1 in the year after the effect of external events. The value of the control group is 0 in the years before and after the external events [51].

3.1.3. Mediating variable

As an important part of absorptive capacity, internal R&D investment can effectively reflect the ability of enterprises to absorb, understand, and apply external knowledge. In the empirical literature, R&D investment intensity is widely adopted as a proxy variable of absorptive capacity. This paper refers to Wu et al.'s index construction idea. and selects the proportion of enterprise R&D expenditure (including expensed and capitalized expenditure) in current operating income as a proxy variable of absorptive capacity.

3.1.4. Moderating variables

The moderating variables in this study are property rights environment and factor marketization level. Regarding these two variables, we obtain relevant information from the "China Market Index Database," which was established and published by scholars Fan Gang, Wang Xiaolu et al. for the years 2008-2018. This database evaluates the marketization level of China's 31 provinces (municipalities) from five dimensions: the completeness of factor markets, the development of market intermediary organizations and the legal environment, the development of product markets, the relationship between government and the market, and the development of the non-state economy. It also gives the marketization scores of each district by item. In the subsequent empirical research, the effectiveness of the marketization index is fully verified. In this study, we divided the sample into a low-marketization group and a high-marketization group based on the marketization scores of the corresponding segments at the company's main office location. If the marketization score of a company's location exceeds the national average, the company is classified in the high group, and the corresponding variable is assigned a value of 1; otherwise, it is 0.

3.1.5. Control variables

Based on the previous research results on the influencing factors of enterprise innovation characteristics, enterprise size, duration of existence, capital structure, profitability, and other factors, enterprise innovation performance is affected to varying degrees. Therefore, this paper selects 7 variables as the control variables of the model to eliminate their influence, as they may interfere with the experimental results. The description and measurement methods of each variable are as follows: enterprise age, which is the natural logarithm of the company's years of establishment; company size, which is the natural logarithm of the number of employees; company assets, which is the natural logarithm of the company's total assets at the end of the period; cash flow position, which is net cash flow from operating activities; profitability, which is the weighted average return on total assets; ownership structure, which is the shareholding ratio of institutional investors; and control status, which is the voting rights held by the controlling shareholders of the company.

3.2. Models

This paper intends to test the impact of independent external events on smart city construction. A practical approach is constructing a control experiment, which divides the whole sample into a treatment group affected by external circumstances and a control group unaffected by external events. The problems of endogeneity and omitted variables can be solved to a large extent by adopting the DID method to estimate the net effect of external events accurately. The DID model has been widely used in econometric scenarios to estimate processing effects, and many studies have verified its validity. Since the pilot construction of smart cities nationwide is carried out in three batches (that is, the samples of different treatment groups are affected by external events at different time points), this paper adopts the processing method of multistage DID for model construction. The basic form of the multistage DID model is as follows:

$$y_{it} = \alpha_0 + \alpha_1 x_{it} + \alpha_2\, Treat_{it} * Year_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where

i represents the sample individual;

t represents for time;

y_{it} represents explained variable;

x_{it} represents control variable;

$Treat_{it}$ is a dummy variable reflecting whether the sample individual is included in the treatment group. If the sample individual is affected by external events, the value is 1; otherwise, it is 0;

Year is a dummy variable used to measure whether the sample individual is in the state after the impact of external events. When individual i has been affected by external events at point T, the value is 1; when individual i has not, the value is 0;

μ_i represents individual fixed effects;

λ_t represents time fixed effects;

ε_{it} represents the residual term.

The proxy index of the open innovation of the explained variable is a nonnegative discrete counting variable, which does not conform to the assumptions of normal distribution and homoscedasticity. The ordinary least squares (OLS) regression method produces biased coefficient estimation results. For counting models, Poisson and negative binomial regressions are usually adopted. Poisson regression assumes that the distribution of explained variable y_i conforms to the Poisson distribution with λ_i as a parameter, the function expression of the basic model of which is as follows:

$$P(Y_i = y_i) = \frac{e^{-\lambda_i}{\lambda_i}^{y_i}}{y_i!} \quad (2)$$

This paper intends to adopt the model processing idea of negative binomial regression, take the three batches of smart city pilot projects in 2012, 2013, and 2015 as external events to construct quasi-natural experiments, and use the multistage DID method to construct models to test the net effect of smart city construction. Specifically, the main effect regression model in this chapter is set as follows:

$$E(OI_{it}) = exp\ exp\ (\alpha_0 + \alpha_1 Treat_{it} * Year_{it} + \alpha_2 Control\ Variables + \mu_i + \ \lambda_t + \varepsilon_{it}) \quad (3)$$

This study intends to test the causal stepwise regression method by constructing the following model:

$$Absorb_{it} = \alpha_0 + \alpha_1 Treat_{it} * Year_{it} + \alpha_2 Control\ Variables + \mu_i + \lambda_t + \ \varepsilon_{it}) \quad (4)$$

$$E(OI_{it}) = \alpha_0 + \alpha_1 Treat_{it} * Year_{it} + \alpha_2 Absorb_{it} + \alpha_3 Control\ Variables + \mu_i + \lambda_t + \varepsilon_{it}) \quad (5)$$

In Model 4, the panel data fixed effects regression method is adopted to test the influence of smart city construction on enterprises' absorptive capacity. Based on Model 3, mediating variables are introduced in Model 5 to test the net effect of absorptive capacity on open innovation under the influence of controlling for explanatory variables. Comprehensive regression analysis of Models 3, 4, and 5 can provide a basis for the mediating effect of absorptive capacity.

Since the degree of marketization of the moderating variables and the completeness index of the legal system are all 0-1 dummy variables, this study intends to test the moderating effect by grouping regression and judge the results by comparing the significance of the regression coefficients of each group.

4. Results

4.1. Descriptive Statistics

Table 1 shows the descriptive statistics of the variables involved in the empirical study in this chapter. It can be seen from the table that the standard deviation of variable OI is much higher than the mean, indicating that the gap in the level of open innovation between sample companies is obvious. This data feature is also applicable to variables OI_invent and OI_app. The average value of Absorb is 3.4%, which reflects the low level of R&D investment of listed companies in China. The mean values of variable Factor and Legal are both near 0.5; that is, the number of samples included in low Factor market perfection/Legal system perfection is equal to the number of samples included in high Factor market perfection/Legal system perfection, and the sample division of grouped regression is reasonable. From the perspective of the data distribution of control variables, with the variables related to the company's operating results, such as cash flow generated through business activities

(Cash) and total return on assets (ROA) of the more obvious difference between individuals, and other characteristics of indicators such as the length of time in which the company has operated (Age), ownership structure, Instit (Right) significantly better than the average standard deviation, there is little variation between individuals.

Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std.Dev	Min	Max
OI	11347	7.104	73.611	0.000	4689
OI_invent	11347	3.526	38.786	0.000	2650
OI_app	11347	3.085	35.707	0.000	2122
DID	11347	0.310	0.463	0.000	1.000
Absorb	8526	0.034	0.044	0.000	1.694
Factor	8663	0.613	0.487	0.000	1.000
Legal	8663	0.504	0.500	0.000	1.000
Age	11347	2.747	0.371	1.386	3.401
Pop	11347	7.590	1.204	3.912	10.689
Size	11347	21.866	1.216	19.027	25.281
Cash	11347	10.434	15.665	-21.231	22.690
ROA	11347	0.034	0.067	-0.289	0.217
Right	11347	34.834	17.603	0.000	75.780
Instit	11347	28.170	23.619	0.053	82.180

Source: By authors.

4.2. Correlation Analysis

Table 2 shows the correlations between variables. A significant positive correlation can be observed between DID and variables OI, OI_invent, and OI_app, which measure enterprise open innovation, thus providing preliminary evidence for the hypothesis that smart city construction promotes enterprise open innovation. Among the control variables, enterprise age, enterprise size, number of employees, profitability, and other variables are significantly and positively correlated with the explained variables to varying degrees, indicating that the control variables selected in this paper are reasonable. There is no significant correlation between the correlation coefficient between the absorbing variable and the explained variable OI, mainly because this relationship is not linear. In contrast, the correlation coefficient between the explained variable and the explained variable with a linear relationship shows a significant positive relationship. Whether absorptive capacity can mediate the relationship between smart city construction and enterprise open innovation still needs further model regression testing to determine.

Table 2. Correlation coefficient matrix

Variables	OI_all	OI_invent	OI_app	DID	Absorb	Legal	Factor	Age	Pop	Size	Cash	ROA	Right	Instit
OI_all	1.000													
OI_invent	0.963*	1.000												
OI_app	0.964*	0.870*	1.000											
DID	0.038*	0.038*	0.033*	1.000										
Absorb	0.013	0.016	0.008	0.098*	1.000									
Legal	0.028*	0.022	0.032*	-0.092*	0.064*	1.000								
Factor	0.021	0.012	0.025	-0.070*	0.096*	0.478*	1.000							
Age	0.051*	0.051*	0.046*	0.187*	-0.009	-0.104*	-0.060*	1.000						
Pop	0.127*	0.109*	0.125*	0.033*	-0.170*	-0.072*	-0.071*	0.095*	1.000					
Size	0.131*	0.118*	0.128*	0.134*	-0.157*	-0.086*	-0.065*	0.192*	0.730*	1.000				
Cash	0.032*	0.030*	0.032*	0.019	-0.040*	0.034*	0.013	0.046*	0.194*	0.125*	1.000			
ROA	0.032*	0.033*	0.024	-0.028*	-0.027	0.093*	0.067*	-0.082*	0.039*	0.033*	0.221*	1.000		
Right	0.000	-0.002	-0.001	0.026*	-0.056*	-0.019	0.010	-0.112*	0.141*	0.141*	0.044*	0.133*	1.000	
Instit	0.021	0.020	0.018	0.156*	-0.073*	-0.047*	-0.067*	0.198*	0.193*	0.247*	0.068*	0.011	0.249*	1.000

Note: *** p<0.01, ** p<0.05, * p<0.1

Source: By authors

4.3. Regression Analysis Results

The test results for the main effects in this chapter are shown in Table 3. Models 1-3 use OI, OI_app, and OI_invent as the explained variables to perform regression. As Model 1 shows, the coefficient on the DID term is significantly positive (0.101, p<0.1), which indicates that enterprises' degree of open innovation has been significantly improved under the influence of smart city construction and that Hypothesis 1 is supported. Models 2-3 further examine how smart city construction impacts the two dimensions of open innovation; the results show that the DID coefficient in Model 2 is 0.123, which is significantly positive, while that in Model 3 is not significant. This result shows that in terms of the current construction effects in China, the promotion of open innovation of enterprises through the construction of smart cities is more embodied in catering rather than substantive levels.

Regarding the impact of the control variables, the coefficient of Pop is significantly negative, indicating that redundancy in human resources can harm corporate cooperative innovation. The coefficients of the variables Size and ROA, which reflect the amount of redundant innovation resources available to the enterprise, are estimated to be significantly positive. From the perspective of organizational theory, the redundancy of resources can effectively create a buffer environment for enterprise innovation failure, including managers and participants in innovation activities, such as employees who can immerse themselves in projects in the future that may form innovative output [52].

Table 3. Model regression results (1)

VARIABLES	Model_1 OI	Model_2 OI_app	Model_3 OI_invent
DID	0.101*	0.123*	0.041
	(1.85)	(1.68)	(0.68)
Age	-0.045	-0.176	-0.091
	(-0.45)	(-1.28)	(-0.79)
Pop	-0.086**	-0.100*	-0.071
	(-2.15)	(-1.72)	(-1.53)
Size	0.152***	0.128**	0.165***
	(4.01)	(2.37)	(3.71)
Cash	0.001	0.001	0.001
	(0.66)	(0.58)	(1.09)
ROA	0.832**	1.004**	0.795**
	(2.54)	(2.22)	(2.33)
Right	0.002	0.005***	0.001
	(1.22)	(2.89)	(0.51)
Instit	-0.001	-0.001	-0.001
	(-0.79)	(-0.78)	(-0.52)
Year	Control	Control	Control
FE	Control	Control	Control
Constant	-3.741***	-3.257***	-3.687***
	(-5.91)	(-3.72)	(-5.09)
Observations	5,694	3,750	5,227
Wald chi2	560.73***	299.76***	632.57***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors

Table 4 uses a causal stepwise regression method to test the mediating effect of absorptive capacity. Model 4 is the basic regression model, Model 5 examines the impact of smart city construction on the absorptive capacity of enterprises, and Model 6 introduces the intermediary variable Absorb based on Model 4 as an independent variable for regression, thus examining the elimination of the explanatory variable DID in determining the impact of absorptive capacity on the company's open innovation. From the results of the stepwise regression in Model 5, the effect of the DID term on absorptive capacity is significant and positive (0.003, p<0.1), which suggests that the construction of smart cities can effectively enhance enterprise absorptive capacity. After introducing the mediating variable in Model 6, the coefficient on the explanatory variable DID is no longer significant. In contrast, that of the mediating variable Absorb positively correlates with OI at the 1% level. This result indicates that smart city construction can improve the absorptive capacity of enterprises, which in turn improves their level of open innovation, and that absorptive capacity plays a completely mediating role in this process.

Table 4. Model regression results (2)

VARIABLES	Model_4 OI	Model_5 Absorb	Model_6 OI
DID	0.101*	0.003*	0.0844
	(1.85)	(1.69)	(1.48)
Absorb			2.516***
			(3.56)
Age	-0.045	-0.024***	-0.002
	(-0.45)	(-3.39)	(-0.02)
Pop	-0.086**	0.001	-0.139***
	(-2.15)	(0.28)	(-3.21)
Size	0.152***	-0.005*	0.240***
	(4.01)	(-1.67)	(5.79)
Cash	0.001	0.001	0.001
	(0.66)	(-1.61)	(1.13)
ROA	0.832**	-0.051***	0.635*
	(2.54)	(-4.01)	(1.83)
Right	0.002	-0.001	0.001
	(1.22)	(-0.02)	(0.04)
Instit	-0.001	-0.001	-0.001
	(-0.79)	(-0.60)	(-0.93)
Year	Control	Control	Control
FE	Control	Control	Control
Constant	-3.741***	0.179***	-5.180***
	(-5.91)	(3.14)	(-7.36)
Observations	5,694	8,526	4,877
Wald chi2/F	560.73***	11.88***	422.15***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Models 7-10 in Table 5 further examine the regulatory role of the legal property rights environment. Since the regulatory variable Legal is a 0-1 dummy variable, this hypothesis still uses group regression to verify this assumption. The coefficient of the DID term in Model 7 is 0.249, which is significantly positive at the 1% level, while the regression result of Model 8 shows that the coefficient of the DID term is not significant. This regression result is consistent with the assumptions proposed in Hypothesis 3; that is, the legal system of property rights is an important infrastructure that determines the effectiveness of smart city construction, and its completeness directly regulates the relationship between smart city construction and open innovation. Models 9 and 10 further test the differences in the impact of smart city construction on strategic open innovation under different legal property rights, the results of which show that the DID coefficient in Model 9 is positive and significant (0.353, p<0.01), while that in Model 10 is not significant, indicating that the moderating role of the legal property rights environment affects the strategic innovation level of enterprises to a greater extent and that its impact on substantive innovation is more limited.

Table 5. Model regression results (3)

VARIABLES	Model_7 OI Legal=1	Model_8 OI Legal=0	Model_9 OI_app Legal=1	Model_10 OI_app Legal=0
DID	0.249***	0.118	0.353***	0.137
	(2.73)	(1.24)	(2.74)	(1.07)
Age	0.279*	-0.565***	0.191	-0.815***
	(1.72)	(-3.08)	(0.82)	(-3.33)
Pop	-0.163**	-0.317***	-0.150	-0.372***
	(-2.54)	(-3.93)	(-1.58)	(-3.21)
Size	0.191***	0.362***	0.168*	0.412***
	(3.13)	(4.67)	(1.90)	(3.80)
Cash	0.002	0.001	0.003	-0.003
	(1.10)	(0.04)	(1.09)	(-0.91)
ROA	1.428**	0.941	1.183	2.636***
	(2.38)	(1.47)	(1.44)	(2.69)
Right	0.002	0.001	0.006**	0.003
	(1.09)	(0.32)	(2.10)	(0.83)
Instit	-0.003*	0.001	-0.003	-0.001
	(-1.74)	(0.27)	(-1.54)	(-0.09)
Year	Control	Control	Control	Control
FE	Control	Control	Control	Control
Constant	-4.595***	-4.809***	-4.641***	-5.087***
	(-4.44)	(-3.80)	(-3.18)	(-2.95)
Observations	2,161	1,665	1,449	1,108
Wald chi2	246.73***	125.44***	189.57***	72.44***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Models 10-13 in Table 6 use the processing ideas of group regression to test the difference in the impact of the implementation of smart city construction on enterprises' open innovation in regions with different levels of factor marketization. Models 10-11 and 12-13 use OI and OI_invent as the explanatory variables to compare and examine the regression of the high- and the low-factor-marketization groups. The results show that in the regression of the latter (Models 11 and 13), the DID coefficients are all significantly positive at the 1% level. In contrast, in that of the former (Models 10 and 12), the coefficient of the DID term is not significant. The results show that the construction of smart cities has more positive significance for regions with relatively backward factor marketization, which can significantly stimulate enterprises in this region to carry out more substantial open innovation activities and is more important for factor marketization. For high-factor-marketization areas, smart cities have limited influence on the degree of open innovation of local enterprises. Thus, the argument in Hypothesis 4 is empirically supported.

Table 6. Model regression results (4)

VARIABLES	Model_10 OI Factor=1	Model_11 OI Factor=0	Model_12 OI_app Factor=1	Model_13 OI_app Factor=0
DID	0.127	0.356***	0.353***	0.137
	(1.57)	(3.07)	(2.74)	(1.07)
Age	0.194	-1.023***	0.186	-1.025***
	(1.37)	(-3.46)	(1.09)	(-2.87)
Pop	-0.178**	-0.156***	-0.208***	-0.071
	(-2.96)	(-1.57)	(-2.88)	(-0.63)
Size	0.202***	0.226***	0.213***	0.183*
	(3.43)	(2.52)	(3.00)	(1.80)
Cash	0.002	0.001	0.003	0.001
	(0.92)	(0.20)	(1.36)	(0.10)
ROA	1.700***	1.683**	1.664***	1.557**
	(3.02)	(2.30)	(2.83)	(2.00)
Right	0.003	-0.003	0.004*	-0.001
	(1.62)	(-1.06)	(1.88)	(-0.24)
Instit	-0.000	-0.004**	0.001	-0.005**
	(0.00)	(-1.96)	(0.78)	(-2.38)
Year	Control	Control	Control	Control
FE	Control	Control	Control	Control
Constant	-4.370***	-2.070	-4.039***	-1.535
	(-4.40)	(-1.46)	(-3.46)	(-0.91)
Observations	2,527	1,185	2,283	1,095
Wald chi2	196.69***	189.88***	217.72***	155.79***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

4.4. Robustness Checks

The important assumption based on the DID model processing idea is that the control and treatment group samples should have the same time trend when they are not affected by external events; that is, the common trend assumption. However, this hypothesis is too harsh. In real experiments, finding a control sample that fully meets the counterfactual standards is often difficult. Therefore, in empirical testing, scholars have widely adopted the propensity score matching (PSM) approach developed by Heckman et al. in 1997 [53] to process samples, that is, matching one or more control group individuals who are highly similar to their characteristics for each treatment group individual. Using the processed sample population for DID testing supports the common trend hypothesis well, thereby obtaining robust and stronger conclusions. This chapter uses the PSM method of 1:4 nearest-neighbor matching, radius matching, and kernel matching to process samples. It puts the matched samples back into the abovementioned empirical model for testing. For example, let us consider the 1:4 nearest-neighbor matching test. Table 7 describes the sample matching situation. It can be seen that the t-values of the matched treatment and control group samples are not significant in the difference test of each variable, indicating that after matching, the two groups of individuals no longer have significant differences and that the matching effect is good. Tables 8 to 10 present the results of regression tests on the samples after screening, which show that the hypothesis can still be supported, thus proving that the regression conclusions in this chapter are robust. The inspection results of radius and kernel matching are the same as those of neighbor matching. Due to space limitations, the inspection results of the two above matching types are not repeated.

Table 7. Sample balance test

Variable	Unmatched Matched	Mean Treated	Control	%bias	t-test t	p> | t |
Age	U	2.7559	2.7398	4.3	2.30	0.021
	M	2.7559	2.7526	0.9	0.46	0.648
Pop	U	7.6329	7.5505	6.8	3.64	0.000
	M	7.6329	7.6486	-1.3	-0.66	0.507
Size	U	21.953	21.788	13.5	7.23	0.000
	M	21.953	21.959	-0.5	-0.24	0.809
Cash	U	10.391	10.474	-0.5	-0.28	0.778
	M	10.391	10.352	0.2	0.13	0.898
ROA	U	0.0331	0.0343	-1.8	-0.94	0.346
	M	0.0331	0.0343	-1.8	-0.94	0.347
Right	U	35.08	34.613	2.7	1.41	0.159
	M	35.08	35.326	-1.4	-0.72	0.470
Instit	U	29.036	27.391	7.0	3.71	0.000
	M	29.036	29.182	-0.6	-0.32	0.751

Source: By authors.

Table 8. Robustness test (1)

VARIABLES	Model_1 OI	Model_2 Absorb	Model_3 OI
DID	0.108**	0.004*	0.091
	(1.96)	(1.82)	(1.58)
Absorb			2.588***
			(3.65)
Age	-0.048	-0.023***	-0.013
	(-0.48)	(-3.37)	(-0.12)
Pop	-0.089**	0.001	-0.140***
	(-2.20)	(0.24)	(-3.17)
Size	0.153***	-0.005*	0.240***
	(3.98)	(-1.72)	(5.69)
Cash	0.001	-0.001*	0.001
	(0.50)	(-1.68)	(0.98)
ROA	0.879***	-0.051***	0.679*
	(2.63)	(-3.85)	(1.91)
Right	0.002	0.001	-0.001
	(1.13)	(0.10)	(-0.00)
Instit	-0.001	-0.001	-0.001
	(-0.67)	(-0.48)	(-0.76)
Year	Control	Control	Control
FE	Control	Control	Control
Constant	-3.726***	0.179***	-5.146***
	(-5.80)	(3.22)	(-7.20)
Observations	5,521	8,271	4,722
Wald chi2/F	531.17***	11.06***	392.88***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Table 9. Robustness test (2)

VARIABLES	Model_4 OI Factor=1	Model_5 OI Factor=0	Model_6 OI_invent Factor=1	Model_7 OI_invent Factor=0
DID	0.136*	0.358***	-0.005	0.353***
	(1.68)	(3.05)	(-0.06)	(2.87)
Age	0.201	-1.072***	0.198	-1.099***
	(1.41)	(-3.52)	(1.15)	(-2.99)
Pop	-0.172***	-0.178*	-0.209***	-0.082
	(-2.83)	(-1.78)	(-2.84)	(-0.72)
Size	0.204***	0.243***	0.221***	0.191*
	(3.41)	(2.68)	(3.06)	(1.87)
Cash	0.002	0.001	0.003	0.001
	(0.83)	(0.09)	(1.34)	(0.02)
ROA	1.751***	1.891**	1.740***	1.824**
	(3.05)	(2.54)	(2.90)	(2.31)
Right	0.003	-0.003	0.004*	-0.001
	(1.55)	(-0.93)	(1.84)	(-0.18)
Instit	0.001	-0.004**	0.001	-0.005**
	(0.10)	(-1.96)	(0.81)	(-2.43)
Year	Control	Control	Control	Control
FE	Control	Control	Control	Control
Constant	-4.487***	-2.137	-4.256***	-1.432
	(-4.46)	(-1.49)	(-3.59)	(-0.84)
Observations	2,452	1,159	2,215	1,072
Wald chi2	185.69***	190.94***	207.71***	158.67***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Table 10. Robustness test (3)

VARIABLES	Mode1_8 OI Legal=1	Model_ 9 OI Legal=0	Model_10 OI_app Legal=1	Model_11 OI_app Legal=0
DID	0.257***	0.133	0.367***	0.136
	(2.80)	(1.38)	(2.83)	(1.05)
Age	0.290*	-0.582***	0.174	-0.814***
	(1.78)	(-3.14)	(0.74)	(-3.30)
Pop	-0.150**	-0.333***	-0.152	-0.380***
	(-2.30)	(-4.10)	(-1.57)	(-3.27)
Size	0.189***	0.378***	0.182**	0.425***
	(3.05)	(4.83)	(2.04)	(3.90)
Cash	0.002	0.001	0.003	-0.003
	(0.88)	(0.06)	(0.92)	(-1.04)
ROA	1.524**	1.020	1.156	2.484**
	(2.49)	(1.56)	(1.38)	(2.52)
Right	0.002	0.001	0.006**	0.003
	(1.06)	(0.27)	(2.10)	(0.79)

Instit	-0.002	0.001	-0.003	0.001
	(-1.56)	(0.27)	(-1.36)	(0.08)
Year	Control	Control	Control	Control
FE	Control	Control	Control	Control
Constant	-4.676***	-5.002***	-4.965***	-5.295***
	(-4.47)	(-3.91)	(-3.36)	(-3.04)
Observations	2,093	1,629	1,403	1,087
Wald chi2	234.30***	125.96***	180.75***	72.49***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Another concern brought about by using the DID method to test the effects of external events is that it is not the external events that we anchor that affect the observations but rather other events that happen to change in the year in which the event is implemented or external factors. To eliminate this concern, this work adopts a more mature placebo test method to verify the robustness of the conclusions. The treatment aim of the placebo test is to artificially construct an implementation year of an external event to test the significance of the policy treatment effect in this situation. If the policy treatment effect is still significant in the fictitious year of implementation, then it indicates that external events do not affect the change in the explained variable. This chapter assumes that the implementation years of smart city construction are 2010, 2014, and 2016. The regression results of the model show that the coefficients are no longer significant; that is, if the impact of the smart city construction event is not considered, then the open innovation performance of the treatment and control sample groups shows a consistent changing trend. Therefore, this result shows that the empirical conclusions obtained in this chapter are robust.

Table 11. Robustness test (4)

	Mode1_12	Model_ 13	Mode1_14
VARIABLES	OI	OI	OI
DID_2010	0.077		
	(1.32)		
DID_2014		0.080	
		(1.39)	
DID_2016			0.035
			(0.56)
Age	-0.044	-0.046	-0.047
	(-0.44)	(-0.46)	(-0.47)
Pop	-0.083**	-0.085**	-0.084**
	(-2.07)	(-2.13)	(-2.11)
Size	0.148***	0.150***	0.148***
	(3.91)	(3.96)	(3.92)
Cash	0.001	0.001	0.001
	(0.69)	(0.67)	(0.67)
ROA	0.815**	0.823**	0.806**
	(2.50)	(2.52)	(2.51)
Right	0.002	0.002	0.002
	(1.24)	(1.23)	(2.48)
Instit	-0.001	-0.001	-0.001
	(-0.74)	(-0.74)	(1.27)
Year	Control	Control	Control

FE	Control	Control	Control
Constant	-3.675***	-3.690***	-3.664***
	(-5.82)	(-5.84)	(-0.76)
Observations	5,694	5,694	5,694
Wald chi2	558.40***	558.99***	556.94***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

Table 12. Robustness test (5)

	Mode1_15	Model_ 16	Mode1_17
VARIABLES	Absorb	Absorb	Absorb
DID_2010	0.004		
	(1.51)		
DID_2014		0.004	
		(1.60)	
DID_2016			0.001
			(0.43)
Age	-0.023***	-0.023***	-0.023***
	(-3.30)	(-3.30)	(-3.31)
Pop	0.001	0.001	0.001
	(0.26)	(0.24)	(0.24)
Size	-0.004	-0.004	-0.004
	(-1.38)	(-1.36)	(-1.35)
Cash	-8.46e-05*	-8.65e-05*	-8.43e-05*
	(-1.66)	(-1.67)	(-1.66)
ROA	-0.055***	-0.055***	-0.055***
	(-4.38)	(-4.38)	(-4.39)
Right	2.87e-06	1.55e-06	2.18e-06
	(0.11)	(0.06)	(0.08)
Instit	-2.45e-05	-2.50e-05	-2.46e-05
	(-1.26)	(-1.29)	(-1.27)
Year	Control	Control	Control
FE	Control	Control	Control
Constant	0.159***	0.158***	0.158***
	(2.79)	(2.78)	(2.77)
Observations	8,639	8,639	8,639
R-squared	0.039	0.039	0.039
F	13.38***	13.41***	13.29***

Note: *** p<0.01, ** p<0.05, * p<0.1. Z values are shown in parentheses.
Source: By authors.

5. Discussions and Conclusions

Research on the utility of smart city construction has gradually aroused the interest of scholars in recent years. However, the literature pays little attention to the possible impact of smart city construction on urban micro entities—enterprises. This article uses this topic as an entry point to discuss the impact of smart city construction on enterprises' open innovation. In terms of empirical testing, this article builds a natural experimental model based on China's nationally implemented smart city pilot policies in 2012, 2013, and 2015 to test the effects. Specifically, this study uses all A-share listed companies as the research sample, divides the sample into control and treatment groups according to whether the company's main office is located within the scope of the impact of smart city construction, and then adopts a multiperiod DID processing approach to test whether the level of open innovation of enterprises is significantly improved after being affected by this pilot policy. The empirical results of this paper show that the construction of smart cities can significantly improve the open innovation level of enterprises and that absorptive capacity plays an intermediary role in this process. In addition, our research also finds that implementing smart city construction in areas with a lower degree of factor marketization achieves better results and that the completeness of the property rights environment further affects the extent to which smart cities' open innovation promotion effect can be exerted.

5.1. Theoretical Contributions

This research has made certain theoretical contributions to exploring the impact mechanism of smart city construction on corporate open innovation and, to a certain extent, fills the gaps in the current literature on corporate innovation from the perspective of smart cities. In addition, this article comprehensively uses resource dependence theory and agency theory to explain the relationship between smart cities and enterprise innovation output, enriches the applicable connotation of related theories, and provides ideas for subsequent research. Specifically, the theoretical contributions of this article are reflected in the following aspects.

First, this article discusses the impact mechanism of smart city construction on enterprise open innovation, thereby supplementing the existing research on the factors that influence open innovation [54]. At present, little research exists on the pre-influencing factors of enterprises' open innovation performance, especially on how the willingness and ability of enterprises to carry out open innovation activities in the open and shared smart city environment are affected [55]. In addition, the research in this direction is based mainly on case analysis and lacks direct empirical evidence. Therefore, this article explores the positive impact of smart city construction on the open innovation output of enterprises from the perspectives of the technical and institutional utility of smart cities and empirically verifies the conclusions, filling the literature gaps.

Second, this article explores the impact of smart city construction on enterprises' open innovation and innovation quality by improving their absorptive capacity, thus enriching the research on absorptive capacity [56] . The impact of absorptive capacity on corporate innovation activities has always been an issue of widespread concern for scholars at home and abroad. However, no research has focused on the mediating role of absorptive capacity in the relationship between smart city construction and open innovation [57]. This article takes this topic as an entry point. It proposes that smart city construction can significantly promote enterprises' absorptive capacity by improving their internal and external informatization levels. At the same time, absorptive capacity positively impacts open innovation from two dimensions—knowledge absorption and knowledge application. Therefore, this article expands the research related to corporate absorptive capacity.

Third, this research considers the moderating role of the market environment in the relationship between smart city construction and enterprise open innovation and expands the research on smart cities and the market environment [58]. The existing research on the utility of smart cities considers the actual implementation effects of smart cities more from the perspective of policy formulation, and less research focuses on the possible moderating effects of the property rights and factor environments [59]. This research focuses on whether the level of marketization in various dimensions can adapt to the impact of ICT development on the utility of smart cities. The research results show that first, the property rights environment can produce complementary effects; that is, under the premise of a perfect property rights system, the impact mechanism of smart city construction, which promotes open innovation and the improvement of enterprises through interconnection and intercommunication, is given full play. Second, in areas with lower factor marketization, implementing smart city construction can help these areas play a more important role in promoting open innovation.

5.2. Managerial Implications

The conclusions obtained in this study have positive significance in guiding policymakers, enterprises, and other subjects to take innovation-related actions. The specific practical enlightenment includes the below aspects.

First, for policymakers, smart city construction is a policy tool that can be considered and selected. Especially in the post-epidemic period, through the construction of smart cities, developing countries can stimulate the open innovation vitality of small and medium-sized enterprises and enhance their overall innovation strength to meet the challenges of such a crisis. Against the social background emphasizing innovation and development, how to effectively improve the innovation willingness and ability of social innovation subjects is a key concern of policymakers. The research in this article provides evidence that smart city construction can increase enterprises' innovation output. In addition, in areas where the degree of marketization of China's factors is low, the exchange of innovative resources between enterprises is restricted, which hinders the development of open innovation. The results of this study show that smart cities can propose targeted solutions, which are of great significance for reducing regional development imbalances.

Second, in implementing smart city construction, the government should focus on strengthening the integrity of the property rights system to ensure its full use of its innovation promotion role. The research results of this article show that the completeness of the property rights system has both negative and positive effects on the implementation of smart city construction.

Third, for business operators, the extensive application of ICT within the enterprise can significantly reduce the information asymmetry between governance and management, thereby restricting management from occupying innovative resources and applying innovative resources to uneconomic areas while waiting for various opportunities. Therefore, business operators can consider the information transformation and upgrading of the enterprise's organizational structure to improve the efficiency of using innovative resources.

5.3. Limitations And Directions For Future Research

There are still limitations in the design and implementation of this research, and thus, future studies can expand on and perfect this research. First, limited by the beginning of the practice of smart city construction, the cases of smart city construction in the market are relatively limited, and the conclusions obtained in this article need more empirical support from subsequent samples. Second, the research object of this paper is the construction of smart cities in China. As smart city construction plans show strong regional differences, the applicability of the conclusions obtained in this paper is limited to a certain extent. Finally, this article focuses on the impact of smart city construction on corporate open innovation by affecting the absorptive capacity of companies. There is still a lack of attention paid to other impact paths. Future research should focus more on the impact paths of smart cities on corporate innovation through in-depth exploration.

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