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RESEARCH ARTICLE

The impact mechanism of smart city construction on digital business environment: A panel data analysis based on 284 Chinese cities from 2009 to 2021

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ABSTRACT

Leveraging the advantages of intelligent planning and management, smart city development can unlock the potential of the digital economy, enhance the efficiency of digital government services, refine data element market rules, and foster a more standardized and orderly digital business environment. Using panel data from 284 Chinese cities (2009–2021), this study employs a multi-time-point difference-in-differences model and a mediation effect model to examine the impact of smart city development on the digital business environment. The findings reveal that smart city development significantly enhances the digital business environment, a conclusion robust to various tests. Moreover, smart city initiatives indirectly improve the digital business environment by optimizing urban resource allocation and fostering talent accumulation. The impact exhibits significant heterogeneity, with city size and administrative level influencing the magnitude of the effects. Based on the empirical analysis, the policy recommendations are offered, such as strengthen digital infrastructure and improve support mechanisms, promote resource allocation optimization and strengthen the interaction between smart cities and the digital business environment, and accelerate talent aggregation and support the digital business environment.

Keywords: digital business environment; smart city; multi-temporal DID; mediating effect

1. Introduction

Digital technology is increasingly integrated into all aspects of human civilization - economic, political, cultural, social, and ecological - introducing new concepts, business forms, and models. It is reshaping industry structures and business environments. The digital economy requires a compatible business environment that fosters technological and business model innovation, guides corporate behavior, and establishes a rational market competition order. The next goal in optimizing the business environment is to build a dual digital ecosystem that integrates both traditional and innovative elements. The digital business environment encompasses new institutional factors and systemic conditions that shape market activities. This environment involves not only the digital transformation of traditional business systems but also the

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conditions necessary for accelerating the development of the digital economy[1]. Burgonov and Kruglov[2] examined entrepreneurship and business model innovation in the digital business environment, noting that while digital technology offers businesses new opportunities, it also introduces challenges such as data security risks, information silos, and regulatory delays . Wielgos and Hombug[3] analyzed cross-country data, finding that the digital business environment enhances business productivity, promotes innovation, boosts competitiveness, improves internal processes, elevates customer satisfaction, increases market share, and ultimately strengthens business performance.

As the global economy enters a new competitive era, China must embrace the digital age by transitioning from optimizing the traditional business environment to enhancing the digital business environment[4]. Further research identifies key elements shaping the digital business environment, including the digital government environment, legal framework, innovation levels, infrastructure, and governance[5,6]. These factors contribute to significant regional disparities in China's digital business environment, with more economically developed regions exhibiting higher levels of digital advancement[7].

Modern cities play a crucial role in the digital business environment. The "smart city" concept, which leverages advanced digital, networked, and intelligent technologies to address urban challenges, serves as a driving force for optimizing the digital business environment in cities. Since IBM introduced the concept in 2008, both academic and business communities have engaged in extensive research and collaboration on it. A "smart city" can be defined as a technology-driven, sustainable approach to urban governance[8]. It emphasizes knowledge spillovers from digitalization and human talent. Its goal is to optimize decision-making, improve implementation, enhance the value of various industries, and maximize socio-economic and ecological outcomes[9]. Caragliu et al.[10] argued that a city can only be considered "smart" by engaging in smart city governance, investing in human and social capital, communication infrastructure, and improving key urban infrastructure and public services. While interpretations may differ, there is a general consensus that the goal of a smart city is to leverage information and digital technology to address urbanization challenges, improve the quality of life for citizens, and achieve sustainable urban development [11]. To further accelerate the optimization of the digital business environment, it is crucial to analyze the impact of smart city construction on the digital business environment, innovate strategies, leverage digital technology, and steadily improve the overall digital business environment[6].

In recent years, China has actively pursued the digital economy strategy, improving digital infrastructure and accelerating the development of new business forms and models. Considerable progress has been made in building the digital business environment. The construction of smart cities has unlocked the potential of digital economic development through intelligent planning and management, enhancing the efficiency of digital government services and fostering a more standardized, orderly digital business environment. China has rolled out a series of policies to promote smart city development and published lists of smart city pilot projects in 2012, 2013, and 2014. Does smart city construction significantly enhance the digital business environment? What other variables impact this process? Is there heterogeneity in this effect, and what are its distribution characteristics? Addressing these questions will help refine smart city pilot policies and is crucial for continuously optimizing China's digital business environment and deeply implementing the digital economy development strategy.

2. Research hypotheses

A smart city is a modern urban development strategy that leverages the integrated and innovative application of digital communication technologies to enable intelligent management and services across all city sectors[12]. By enhancing digital governance, this new model promotes high-quality urban development, helping traditional cities evolve into advanced forms through technological progress and governance reform, thereby contributing to the digital business environment. Information technologies such as big data, cloud computing, and the Internet of Things (IoT) are widely employed, not only enhancing digital infrastructure but also improving government service efficiency and transparency, while reducing time costs and bureaucratic hurdles in enterprise-government interactions. For instance, the development of digital infrastructure like high-speed networks and smart sensors has greatly increased the speed and accuracy of enterprises' access to information in smart cities[13]. In urban transportation governance, smart city development has improved performance and transformed traditional models through widespread information technology use, positively impacting the quality of urban transportation and boosting operational efficiency[14]. Regarding government services, smart cities have digitized and automated business startups, approvals, and oversight by integrating data resources and establishing one-stop service platforms[15].

Smart city construction enhances citizens' digital literacy through education and community activities, stimulates market demand for digital products and services, and fosters greater market diversity. It also strengthens data security and privacy protection, boosting enterprise confidence in data utilization and reducing security risks through a comprehensive protection system. As smart city construction progresses, digital infrastructure will be further developed, and urban governance and government services will be enhanced through stronger technological safeguards. Hence, this paper puts forward the following hypotheses:

Hypothesis 1: Smart city construction can enhance the optimization of the digital business environment.

A primary goal of smart city construction is to enhance resource allocation efficiency, thereby closely linking smart city development with the optimization of the digital business environment. Unlike traditional urban development models, smart city construction is distinguished by their advanced information infrastructure, which leverages Internet of Things (IoT) technology to connect various devices and collect real-time data on transportation, energy, and resource usage. Caragliu et al. [10] noted that the smart energy management system in smart cities ensures energy efficiency by dynamically adjusting energy distribution. Big data technology enables accurate tracking of resource demand and optimization of resource allocation. On one hand, the openness and sharing of data are keys to aligning information production factors across industries. Rational resource allocation requires coordinated efforts from various departments, and data openness can harness high-quality data elements in smart cities, break down information barriers, and promote interdepartmental connectivity. On the other hand, smart city construction focuses on strengthening information infrastructure and building data processing platforms. Integrating offline hardware infrastructure with online big data platforms into an efficient data collection and processing system ensures smooth government, enterprise, and societal operations, laying a strong foundation for improving resource allocation efficiency. Hence, this paper puts forward the following hypotheses:

Hypothesis 2: Smart city construction promotes the optimization of the urban digital business environment by improving resource allocation efficiency.

Talent attraction and aggregation is central to smart city strategies, focusing on attracting and retaining talent by optimizing policies, environment, and services to create a highly concentrated talent pool. Smart city construction significantly improves urban infrastructure and digitalization, thereby creating a superior working, living, and development environment for high-quality talent. Firstly, a favorable working and living environment is essential for attracting and retaining talent. By leveraging digital technology to enhance urban operations, service quality, and residents' quality of life, smart city construction position themselves as key platforms for attracting talent and innovative enterprises[16]. Second, smart city construction not only enhance the external environment but also prioritize creating platforms for talent growth and development. The concentration of universities, research institutions, and innovative enterprises creates numerous research and collaboration opportunities, enriching the innovation ecosystem[17]. Additionally, international projects and exchanges attract global talent, fostering local development and the globalization of urban growth. Finally, the openness and inclusivity of smart cities, with the government service model evolving from offline to a combination of online and offline services, attracts talent from diverse cultural backgrounds. This diversity fosters innovative thinking and creative collaboration, offering a broader perspective for optimizing the digital business environment. Hence, this paper puts forward the following hypotheses:

Hypothesis 3: Smart city construction promotes the optimization of the urban digital business environment by strengthening talent aggregation.

Hypothesis 1 examines the direct impact of smart city construction on the digital business environment, whereas Hypotheses 2 and 3 delve into the potential mediating roles of resource allocation and talent aggregation, respectively.

3. Materials and Methods

3.1. Selection of variables

3.1.1. Explained variables

This paper builds a digital business environment evaluation system based on the relevant research by Li et al.[18] and Xu et al.[5], focusing on the availability and feasibility of indicators. The evaluation system comprises five first-level indicators and fourteen second-level indicators: digital infrastructure environment, government service environment, digital human resources environment, market environment, and innovation and digital security environment. (1) Digital Infrastructure Environment: A certain scale and quality of digital infrastructure are required to support data transmission and big data computing activities, such as big data, cloud computing, and blockchain. The second-level indicators are based on the practices of Ma and Chang[19], and include three indicators, such as mobile phone penetration rate, among others. (2) Government Service Environment: Government services are essential for the healthy development of the digital economy. The second-level indicators are based on the research by Zhang et al.[20], including two indicators, such as the number of occurrences of the term "digital economy" in policy documents, among others. (3) Market Environment: A conducive market environment enhances resource allocation efficiency. The second-level indicators are drawn from the research of Ma and Chang[19], and include three indicators, such as the total volume of telecommunications business, among others. (4) Digital Human Resources Environment: Talent is the primary resource for the development of the digital economy. The second-level indicators are based on the research by Li et al.[18], and include three indicators, such as the number of employees in information enterprises, among others. (5) Innovation and Security Environment: Innovation is the primary driver for continuously strengthening, optimizing, and expanding China’s digital economy. The second-level indicators are based on the research by Zhang and Cao [21], Ma and Gao [22], and include three indicators, such as the number of 5G enterprise invention patents authorized, among others.

The detailed content of the evaluation system is presented in **Table 1**.

Table 1. The digital business environment evaluation system.

First-level Indicators	Second-level Indicators	Description of Indicator
Digital Infrastructure Environment	Mobile Phone Penetration	Number of mobile phone users at year-end (ten thousand households)
	Computer Usage	Number of computers used per hundred people (units)

First-level Indicators	Second-level Indicators	Description of Indicator
Government Service Environment	Scale of AI	Number of artificial intelligence companies (units)
	Policy Support	Number of occurrences of the term "digital economy" in policy documents (times)
	Science and Technology Support	Proportion of science and technology expenditure in the general public budget (%)
Market Environment	Economic Development	Per capita GDP (yuan)
	Foreign Capital Utilization	Actual amount of foreign capital used in the year (ten thousand yuan)
	Market Demand	Total volume of telecommunications business (ten thousand yuan)
Digital Human Resources Environment	Human Resource Supply	Number of employees in information transmission, computer services, and software industry (persons)
		Number of employees in scientific research and technical services industry (persons)
	Labor Cost	Average wage of employees in information transmission, computer services, and software industry (yuan)
	Human Resource Reserve	Number of students in ordinary colleges and universities (persons)
Innovation and Security Environment	Innovation Output	Number of 5G enterprise invention patents authorized (units)
	Innovation Scale	Transaction amount of technology market (hundred million yuan)
	Information Security	Information security revenue (ten thousand yuan)

Table 1. *(Continued)*

3.1.2. Core explanatory variables

The core explanatory variable is the difference-in-differences (DID) term, Treat*Post. Specifically, Treat is assigned based on the list of smart cities established in 2012, 2013, and 2014, published by the Ministry of Housing and Urban-Rural Development of the State Council of China. Next, Post is assigned according to the time of establishment of these smart cities. The core explanatory variable, Treat*Post, is derived by multiplying these two variables.

3.1.3. Control variables

Besides the core explanatory variable, several other variables may impact the digital business environment and should be controlled. These include administrative region, population density, urban economic density, financial development level, and international trade scale (see **Table 2**).

Table 2. Control variables.

Indicator Name	Description of Indicator
Administrative Region	Area of the administrative region (square kilometers)
Population Density	Permanent population of the region / urban area (%)
Urban Economic Density	Regional gross domestic product / land area of the administrative region (%)
Financial Development Level	Year-end financial institution deposit and loan balance / regional gross domestic product (%)
International Trade Scale	Total import and export amount (ten thousand yuan)

3.1.4. Mediating variables

The mediating variables in this study are the levels of resource allocation and talent aggregation. The level of resource allocation is measured by the proportion of actual foreign capital used to regional GDP, while the level of talent aggregation is reflected by the ratio of students in ordinary colleges and universities to the total population at year-end.

3.2. Data sources and descriptive statistics

To ensure data comparability and availability, cities with significant data gaps were excluded, resulting in a final sample of 284 prefecture-level and above cities in China (see **Table 3**). The sample encompasses 100 cities in the eastern region, 100 cities in the central region, and 84 cities in the western region, spanning 31 provincial administrative units nationwide. It is representative and reflective of the broader Chinese reality.

Table 3. Regional distribution.

The East		**The Central**		**The West**	
Province	**Num. of cities**	**Province**	**Num. of cities**	**Province**	**Num. of cities**
Beijing	1	Shanxi	11	Inner Mongolia	9
Tianjin	1	Jilin	8	Guangxi	14
Hebei	11	Heilongjiang	12	Chongqing	1
Liaoning	14	Anhui	16	Sichuan	18
Shanghai	1	Jiangxi	11	Guizhou	4
Jiangsu	13	Henan	17	Yunnan	7
Zhejiang	11	Hubei	12	Tibet	1
Fujian	9	Hunan	13	Shaanxi	10
Shandong	16			Gansu	12
Guangdong	21			Qinghai	1
Hainan	2			Ningxia	5
				Xinjiang	2
Total	100	Total	100	Total	84

The original data for the explained variable, mediating variables, and control variables are sourced from the China Statistical Yearbook, China City Database, EPS Database, provincial and municipal statistical yearbooks, and the National Bureau of Statistics of China website. The digital business environment score is calculated using the entropy weight method. Given that the comprehensive level score represents a relative comparison, the composite score is further processed through a translation procedure to enhance the intuitiveness and analyzability of the results.

During the assessment of the smart city pilot policy, it was observed that in some prefecture-level cities, only specific districts or counties within their jurisdiction engaged in the pilot program. Indiscriminately including these prefecture-level cities in their entirety in the pilot city sample could potentially result in inaccurate estimations. In view of this, this study follows the approach of Shi et al. [23], samples from these prefecture-level cities were excluded. To mitigate dimensionality issues, the entropy weight method was applied to standardize the dependent variable.

Descriptive and econometric data processing was carried out using Stata 17 (64-bit). Two-way fixed-effects regression tests were conducted using the reghdfe command to account for both individual and time effects. Descriptive statistics for the explained variable, digital business environment (DBE), the core explanatory variable, Smart City Pilot Policy (Treat*Post), the mediating variables, resource allocation level (Resource) and talent aggregation level (Talent), and the control variables - administrative region (Reg), population density (Pop), urban economic density (Eco), financial development level (Fin), and international trade scale (Tra) - are presented in **Table 4**.

Table 4. Descriptive statistics.

Variable Name	Abbreviation	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Digital Business Environment	*DBE*	3692	2.414	4.429	0.201	72.49
Smart City Pilot Policy	*Treat*Post*	3692	0.256	0.437	0	1
Resource Allocation Level	*Resource*	3692	1.742	1.855	0	22.87
Talent Aggregation Level	*Talent*	3692	1.995	2.586	0	16.36
Administrative Region	*Reg*	3692	9.353	0.806	7.015	12.47
Population Density	*Pop*	3692	5.723	0.953	0.683	7.882
Urban Economic Density	*Eco*	3692	0.318	0.772	0.002	15.36
Financial Development Level	*Fin*	3692	2.466	1.260	0.588	21.30
International Trade Scale	*Tra*	3692	13.96	2.169	3.526	19.82

3.3. Methods

3.3.1. Benchmark regression model

When public data open is considered a policy experiment, the evaluation of policy effects is generally conducted using the Difference-in-Differences (DID) model. The traditional DID model is limited to assessing the effects of policies implemented at a single point in time[24,25]. In contrast, the multi-temporal DID (time-varying DID) model is better suited for examining the effects of policy implementation at different time points, accounting for the dynamic changes in individuals within the experimental group. Building on the methodologies of Bertrand and Mullainathan[26] and Shi et al.[23], we construct Model (5) as a multi-temporal DID model:

$$DBE_{it} = \mu_i + \lambda_t + \theta Treat_i * Post_{it} + \sum \beta_j x_{it} + \varepsilon_{it} \tag{1}$$

Subscripts *i* and *t* represent city and year respectively, while x_{it} comprises control variables; μ_i signifies individual effects, λ_t signifies time effects, and ε_{it} represents the random error. In this study, *Treat* indicates whether the policy has been implemented. A city is assigned a value of 1 if it appears in the list of smart cities established in 2012, 2013, and 2014, and a value of 0 otherwise. Post represents the time before and after policy implementation, with a value of 0 before the policy is implemented and 1 after.

3.3.2. Mediating effects model

Following the method outlined by Wen and Ye [27], the steps to test the impact mechanism of smart city construction on the digital business environment are as follows: (1) Regress the smart city pilot policy on the digital business environment, using it as the dependent variable. (2) Regress the smart city pilot policy on the two mediating variables - resource allocation level and talent aggregation level - using them as the dependent variables, respectively. (3) Incorporate both the smart city pilot policy and the mediating variables into the model to assess their impacts on the digital business environment. The specific models are as follows:

Step 1, regress the smart city pilot policy on the digital business environment, which is the benchmark regression model (1).

Step 2, regress the smart city pilot policy on the mediating variables, respectively.

$$M_{it} = \mu_i + \lambda_t + \gamma Treat_i * Post_{it} + \sum \phi_j x_{it} + \varepsilon_{it} \tag{2}$$

Step 3, regress the smart city pilot policy and the mediating variables on the digital business environment.

$$DBE_{it} = \mu_i + \lambda_t + \eta_1 Treat_i * Post_{it} + \eta_2 M_{it} + \sum \tau_j x_{it} + \varepsilon_{it} \quad (3)$$

Where M_{it} represents the mediating variables, and the other variables are consistent with the benchmark regression model (1).

4.Results

4.1. Benchmark regression results

Table 5 presents the benchmark regression results, examining the impact of the smart city pilot policy on the digital business environment. Column (1) uses Treat*Post as the core explanatory variable. The multi-temporal DID model results reveal that the p-value of the Treat*Post coefficient is well below the significance level, suggesting that the smart city pilot policy significantly promotes the improvement of the digital business environment. Columns (2) incorporate control variables, including administrative region (Reg), population density (Pop), urban economic density (Eco), financial development level (Fin), and international trade scale (Tra). The regression results indicate that the p-values of the smart city pilot policy coefficients on the digital business environment are consistently below the significance threshold. In summary, Hypothesis 1 is supported. Moreover, the coefficient of Treat*Post and the value of adjusted R^2 remains stable even after including the control variables, indicating that the chosen control variables adequately capture other potential influences.

Table 5. Benchmark regression results.

	(1) ***DBE***	**(2)** ***DBE***
*Treat*Post*	0.198**	0.213**
	(1.979)	(2.538)
Reg		6.149***
		(19.831)
Pop		0.078
		(0.602)
Eco		2.586***
		(37.274)
Fin		-0.033
		(-0.962)
Tra		-0.011
		(-0.216)
N	3,692	3,692
adj.R2	0.902	0.932
Individual Effects	Yes	Yes
Time Effects	Yes	Yes

The standard errors are noted in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

4.2. Parallel trends test

A key assumption for the accuracy of DID in estimating policy effects is that the changes in outcome variables for both the treatment and control groups, before and after policy implementation, follow a parallel trend[28]. Given that the smart city pilot policy is implemented in phases, with different cities affected at various times, this study employs a multi-temporal DID model. The implementation timeline of the pilot policy is represented by a dummy variable: -1 for the year before the pilot, -2 for two years prior, and 1, 2, ... for subsequent years following the pilot.

The results are presented in **Figure 1**. The coefficients for the relative time dummy variables prior to the implementation of the smart city pilot policy are all insignificant and small, suggesting no significant difference in the digital business environment between the treatment and control groups before the policy implementation. Following the policy implementation, a significant difference in the digital business environment between the treatment and control groups emerges, showing a time-lag effect. Specifically, the policy's effect on optimizing the digital business environment becomes significantly noticeable starting from the third year after implementation.

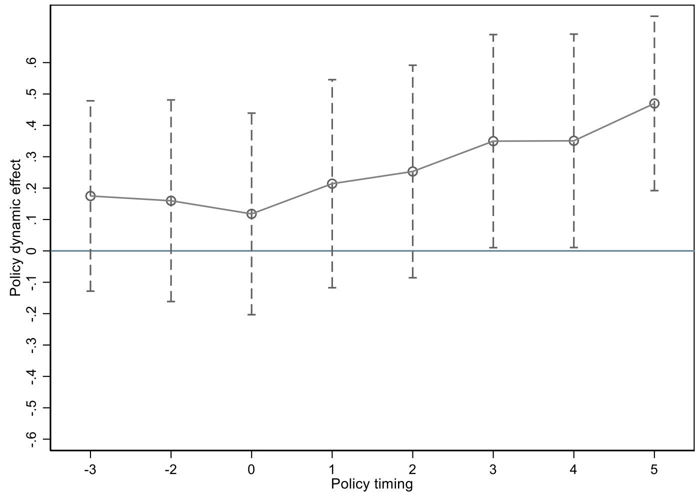

Figure 1. Parallel trends test.

4.3. Robustness

4.3.1. Propensity score matching test

To verify the robustness of the benchmark regression results, this study uses a Propensity Score Matching - Difference-in-Differences (PSM-DID) model to address sample selection bias, placebo tests to reduce random variability, and instrumental variable tests to account for reverse causality and omitted variable bias.

The key aspect of matching is identifying a control group with similar observable characteristics to the treatment group, allowing the policy impact to be measured by comparing the differences between the two groups after the policy implementation. The matching method relies on two key assumptions: the Conditional Independence Assumption (CIA) and the Common Support Condition (CSC). The CIA assumes that the selection of pilot cities is random and not influenced by potential outcomes, meaning cities are not selected for policy implementation based on their expected performance. The CSC ensures that there is overlap in the propensity scores between the treatment and control groups, allowing for meaningful comparison. The PSM method suggests that when samples have multiple observable characteristics, these multi-dimensional variables are converted into a one-dimensional propensity score through a functional relationship, and matching is performed based on these scores.

The PSM-DID model in this study is structured as follows: First, model selection is carried out. Since the core explanatory variable, Treat*Post, is binary, and a Probit model is used. The second step involves selecting control variables, such as administrative region (Reg), population density (Pop), urban economic density (Eco), financial development (Fin), and international trade scale (Tra), for use in the matching process. The results of the matching process are presented in **Table 6.**

Table 6. The results of the sample matching experiment.

Variable Name	Matching	Mean		Standard Deviation	t	p-value
		treatment group	control group			
Reg	U	9.334	9.3722	-4.8	-0.39	0.698
	M	9.3247	9.3373	-1.6	-0.12	0.907
Pop	U	5.7321	5.7358	-0.4	-0.03	0.975
	M	5.7597	5.7302	3.1	0.23	0.815
Eco	U	0.3348	0.329	0.8	0.06	0.949
	M	0.3379	0.2979	5.7	0.48	0.631
Fin	U	2.7557	2.5485	15.8	1.33	0.183
	M	2.6778	2.6605	1.3	0.10	0.919
Tra	U	13.968	13.909	2.7	0.22	0.826
	M	13.979	13.882	4.5	0.32	0.749

The third step is to re-estimate the policy impact using a multi-temporal DID model with the updated dataset. As shown in **Table 7**, the core explanatory variable (Treat*Post) significantly improves the digital business environment at the 5% level. Compared to the benchmark regression model, the smart city pilot policy also has a substantial effect on the digital business environment, reinforcing the robustness of the benchmark regression results.

Table 7. The results of PSM-DID.

	(1)	(2)
	DBE	***DBE***
*Treat*Post*	0.213**	0.175**
	(2.538)	(2.343)
Reg	6.149***	1.394***
	(19.831)	(4.332)
Pop	0.078	0.149
	(0.602)	(0.817)
Eco	2.586***	3.857***
	(37.274)	(44.904)
Fin	-0.033	-0.016
	(-0.962)	(-0.382)
Tra	-0.011	0.054
	(-0.216)	(1.121)
N	3,692	3,633
adj.R2	0.932	0.944
Individual Effects	Yes	Yes
Time Effects	Yes	Yes

The standard errors are noted in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

4.3.2. Placebo tests

To further verify the robustness of the smart city pilot policy's impact on the digital business environment, a placebo test is conducted. The test aims to determine whether the model can distinguish the real policy effect from random noise by creating a fictitious treatment group. A randomly selected subset of cities from the sample is designated as the “fictitious treatment group”, with the remaining cities serving as the control group. The model is re-estimated using this fictitious treatment group, and the coefficients of the double-difference term (Treat*Post) are tested for significance. This procedure is repeated 500 times to generate the coefficient distribution for the fictitious treatment group. If the dummy coefficients deviate significantly from the original regression coefficients, it would confirm the robustness of the original double-difference regression. The results indicate that the coefficient distribution for the dummy treatment group is concentrated around 0 (see **Figure 2**), with most coefficients having a p-value greater than 0.1. This suggests that the coefficients for the dummy treatment group are not significant, further supporting the reliability of the benchmark regression results.

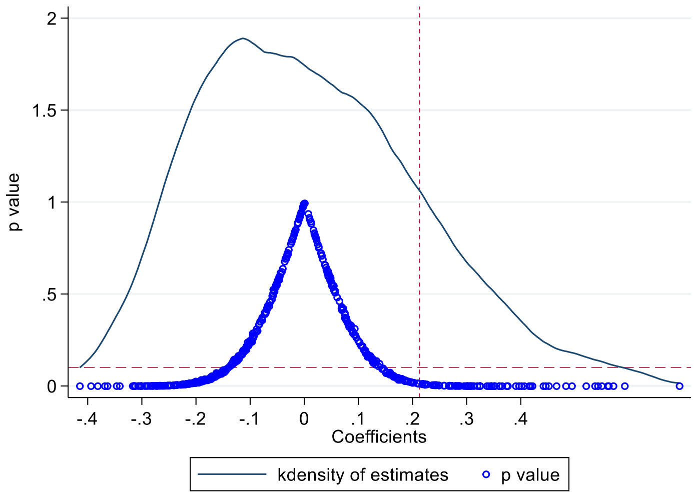

Figure 2. Placebo tests.

4.3.3. Endogeneity

The relationship between the smart city pilot policy and the digital business environment is strong. The former can enhance the latter, and the latter can provide better development conditions for the former in return. To address potential endogeneity caused by bidirectional causality, this study adopts the approach of Liu and Ma[29] and Liu et al.[30], selecting the topographical relief of a city as the first instrumental variable. As an objectively existing geographical factor, topographical relief meets the exogeneity requirement of an instrumental variable. Cities with lower topographical relief tend to have better infrastructure, social governance efficiency, and economic development, and since smart city applications are highly correlated with these factors, the relevance condition is satisfied.

It is important to note that in the benchmark regression model, the endogenous variable Treat is expressed as an interaction term Treat*Post. Therefore, the endogenous variable in this study is the interaction term Treat*Post. When using instrumental variables, the corresponding instrumental variable for the interaction term Treat*Post is Iv*Post. In the first stage, the interaction term is formed by multiplying Iv and Post, which is then included in the regression model to test the relevance of the instrumental variable.

The regression results are presented in **Table 8**. Column (1) shows that the coefficient of the first-stage instrumental variable interaction term is significant. Column (2) reveals that the coefficient of the core explanatory variable Treat*Post remains significantly positive in the second-stage regression. This indicates that, after addressing endogeneity, smart city construction still significantly promotes the optimization of the regional digital business environment. The results also suggest that the regression findings of the multi-temporal DID model in the benchmark regression are not due to sample selection bias, indicating that the instrumental variable is not weak. In conclusion, the estimation results remain robust after accounting for endogeneity concerns.

Table 8. Test of the instrumental variable.

	(1) **first stage** ***Treat*Post***	**(2)** **second stage** ***DBE***
*Iv*Post*	0.003***	
	(37.031)	
*Treat*Post*		4.322***
		(17.691)
Constant	1.592***	-31.297***
	(11.906)	(-26.495)
Reg	-0.095***	1.837***
	(-9.273)	(19.964)
Pop	-0.066***	1.153***
	(-6.834)	(13.330)
Eco	-0.030***	2.577***
	(-3.203)	(30.134)
Fin	0.026***	0.762***
	(5.116)	(16.039)
Tra	-0.014***	0.439***
	(-3.797)	(13.506)
N	3,692	3,692
adj.R2	0.291	0.435
Individual Effects	Yes	Yes
Time Effects	Yes	Yes

The standard errors are noted in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

4.4. Moderating effects

To further investigate the mechanisms at play, the resource allocation level and talent aggregation level are set as mediating variables. Mediating effect models are employed, with two-way fixed effects for both individuals and time included to ensure robustness.

Table 8 presents the results of the mediating effects. Column (2) shows that the regression coefficient for smart city construction on resource allocation is positive and significant at the 5% level, suggesting that smart city construction boosts the resource allocation level. Column (3) indicates that both the regression coefficients of the core explanatory variable Treat*Post and the mediating variable Resource are positive and significant at the 5% and 1% level. This implies that smart city construction can enhance the digital business environment by promoting resource allocation, thus confirming Hypothesis 2. The results in Column (4) reveal that the regression coefficient for smart city construction on talent aggregation is positive and significant at the 1% level. Column (5) shows that the regression coefficient for the core explanatory variable Treat*Post is positive and significant at the 5% level, and the coefficient for the mediating variable Talent is positive and significant at the 5% level. This suggests that smart city construction optimizes the digital business environment by improving talent aggregation, confirming Hypothesis 3.

Table 9. Moderating effects.

	Benchmark Regression	Resource Allocation Level		Talent Aggregation Level	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	DBE	***Resource***	***DBE***	***Talent***	***DBE***
*Treat*Post*	0.213**	0.195**	0.198**	0.138***	0.204**
	(2.538)	(2.322)	(2.365)	(2.980)	(2.433)
Resource			0.076***		
			(4.453)		
Talent					0.062**
					(1.998)
Reg	6.149***	-0.465	6.184***	6.149***	-1.711***
	(19.831)	(-1.499)	(19.994)	(19.831)	(-9.945)
Pop	0.078	-0.111	0.086	0.078	-0.323***
	(0.602)	(-0.860)	(0.669)	(0.602)	(-4.518)
Eco	2.586***	-0.330***	2.611***	2.586***	-0.166***
	(37.274)	(-4.750)	(37.615)	(37.274)	(-4.313)
Fin	-0.033	-0.073**	-0.028	-0.033	-0.135***
	(-0.962)	(-2.101)	(-0.804)	(-0.962)	(-6.982)
Tra	-0.011	0.160***	-0.023	-0.011	-0.034
	(-0.216)	(3.162)	(-0.458)	(-0.216)	(-1.224)
N	3,692	3,692	3,692	3,692	3,692
adj.R2	0.932	0.611	0.932	0.932	0.939
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes

The standard errors are noted in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

4.5. Heterogeneity

The previous studies demonstrate that smart city construction has a significant positive effect on the digital business environment. However, does this impact vary across cities with different characteristics? To explore this, heterogeneity tests are conducted from two perspectives: city size and administrative level.

City size is defined by the number of permanent residents. Cities with 1 million or fewer residents are classified as small cities (Mid), those with more than 1 million but fewer than or equal to 5 million as large cities (Big), and those with more than 5 million as megacities (Sup). Columns (1), (2), and (3) in **Table 9** reveal that the policy effects are significant across cities of varying sizes. The coefficients for small and megacities are higher than those for large cities. This may be due to small cities experiencing a notable improvement in resource allocation and utilization efficiency under the smart city policies, which leads to a more substantial impact on the digital business environment. In contrast, megacities, through the implementation of smart city pilot policies, enhance their economic agglomeration effects.

Regarding administrative levels, all sample cities are categorized into high-level cities (including sub-provincial cities and provincial capitals) and general-level cities (ordinary prefecture-level cities) for separate regressions. Columns (4) and (5) in **Table 9** show that the policy effects of smart city pilot policies differ across cities of varying administrative levels. The policy effects in high-level cities, such as provincial capitals and sub-provincial cities, are significant at the 1% level, while those in ordinary cities are significant at the 10% level.

Table 10. Heterogeneity.

	City Size			City Administrative Level	
	small cities	**large cities**	**megacities**	**high-level**	**general-level**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Mid	0.141***				
	(2.757)				
Big		0.109***			
		(4.633)			
Sup			0.553**		
			(2.353)		
High				1.481***	
				(2.823)	
Ord					0.043*
					(1.856)
Reg	1.002**	0.495***	13.590***	12.940***	0.604***
	(2.160)	(5.567)	(17.105)	(10.601)	(6.153)
Pop	0.080***	-0.573***	-0.224	0.316	0.158***
	(3.146)	(-10.339)	(-0.467)	(0.649)	(3.851)
Eco	3.016***	2.637***	2.762***	2.511***	2.652***
	(4.960)	(31.928)	(22.488)	(12.955)	(51.036)
Fin	0.050***	-0.054***	0.222	-0.486**	-0.042***
	(2.968)	(-6.192)	(1.310)	(-2.475)	(-4.248)
Tra	-0.061	0.055***	-0.332*	-0.703	0.060***
	(-1.565)	(4.232)	(-1.950)	(-1.475)	(4.530)
N	169	2,353	1,170	468	3,224
adj.R2	0.841	0.894	0.936	0.927	0.934
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes

The standard errors are noted in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

5. Discussion

As a key aspect of modern urban development, smart city construction significantly enhances the digital business environment. First, it improves market transparency and decision-making efficiency. A core feature of smart cities is the collection, integration, and sharing of data. By establishing a unified data platform, both the government and market participants can access real-time city operation data, improving information disclosure and resource utilization efficiency. This enables better understanding of market demand, industry trends, and policy changes, benefiting business strategies and fostering fair competition. Secondly, smart city construction has accelerated the digital transformation of government services. As internet applications expand, the variety of government services continues to grow. Through e-government systems, administrative tasks such as registration, approvals, and tax declarations can now be processed online, significantly reducing processing times and administrative costs. Additionally, smart city initiatives promote the intelligentization of infrastructure. The widespread use of intelligent infrastructure provides market players with a more stable and efficient operating environment, reducing operational costs and encouraging innovation. Finally, smart city construction focuses on fostering technological innovation and entrepreneurship, supported by government policies, financial investments, and resource integration. This creates abundant innovation resources and builds a favorable ecosystem for enterprise growth.

The data-driven resource allocation method of smart cities, when compared to traditional human judgment and empirical decision-making, significantly improves resource efficiency and utilization, profoundly impacting the optimization of the urban digital business environment. This is manifested in several ways: (1) Enhancing government service quality: Smart city construction accelerates the digital transformation of government services, improving efficiency and transparency. Through online processing, unified networks, and other service modes, it reduces business costs, boosts business satisfaction, and strongly supports the optimization of the city's digital business environment. (2) Promoting industrial upgrading and innovation: By optimizing resource allocation, smart cities attract high-tech enterprises and talent, promoting the development of emerging industries and the transformation of traditional ones. This fosters industrial agglomeration, enhances urban industries' competitiveness and innovation capacity, and drives continuous improvement in the digital business environment. (3) Strengthening social governance capacity: Smart cities leverage modern information technology to improve the intelligence and precision of social governance. Through real-time monitoring, early warning systems, and emergency response mechanisms, smart cities effectively address challenges in urban operations, ensuring stability and security, and providing a solid foundation for the ongoing optimization of the digital business environment.

On the other hand, smart city construction represents not just technological innovation, but also a profound transformation in urban governance and resource allocation. Throughout the construction process, the talent aggregation effect plays a key role in driving the optimization of the digital business environment. By offering high-quality living conditions, a robust innovation ecosystem, and efficient resource allocation, smart cities attract and retain high-end talent, injecting significant momentum into the optimization of the digital business environment. Smart city construction provides the foundation for this optimization by fostering a high-quality living and working environment and facilitating the concentration of skilled professionals. The gathering of top talent helps meet the growing demand for human resources, promoting social innovation and development, and thereby enhancing the digital business environment. Furthermore, a well-developed innovation ecosystem offers a broad platform for collaboration between enterprises, universities, and research institutions, fostering technological innovation and the transformation of achievements, while also opening up more development opportunities for market entities. Moreover, smart cities improve operational efficiency through intelligent infrastructure such as smart transportation and smart grids, reducing commuting times and living costs. Specifically, the unified data platform enables data sharing and openness, offering high-end professionals access to abundant market information and innovation resources. The widespread application of artificial intelligence further enhances the efficiency and accuracy of urban governance, creating a more stable and harmonious living environment. In summary, smart cities not only directly enhance the digital business environment but also indirectly contribute to its optimization by improving resource allocation and talent aggregation.

6. Conclusions

Based on the empirical analysis, the following policy recommendations are offered: (1) Strengthen digital infrastructure and improve support mechanisms. Efforts should be made to achieve intelligent upgrades of urban infrastructure. Advanced information network technologies should be actively employed to modernize existing public infrastructure, enhancing the completeness of the city's digital infrastructure.

This will improve public service convenience and align it with the digital business environment. Additionally, emerging smart infrastructures such as cloud computing platforms and urban data-sharing systems should be promoted. This will boost the city’s innovation competitiveness, attract talent, and enhance the efficiency and quality of resource allocation through technological advancement, providing robust support for the digital business environment. (2) Promote resource allocation optimization and strengthen the interaction between smart cities and the digital business environment. The design and objectives of smart city management platforms should be improved. Technologies like big data and cloud computing should be utilized for a comprehensive inventory and precise allocation of urban resources. Leverage big data technology to perform a comprehensive analysis of urban population, industry, and resource data, thereby clarifying the city's development positioning and the direction of its industrial layout. At the same time, interconnecting urban management platforms should be prioritized to facilitate data sharing, break down administrative barriers between cities, and ensure smooth resource flow across cities and departments. Drawing from the experience of the Pearl River Delta region in China with its integrated regional transportation management platform, the establishment of unified data interfaces standards and exchange protocols can facilitate data circulation between different city platforms. (3) Accelerate talent aggregation and support the digital business environment. Enhance efforts to cultivate and attract talent in the smart city domain, develop management protocols for special talent funds to ensure their rational allocation; institute a tracking service mechanism for entrepreneurial support to offer sustained aid to entrepreneurial talents; refine policies facilitating talent entry, exit, and residency, thereby providing robust living security for international talents; establish an evaluation framework for industry-academia-research collaboration outcomes, with incentives for exceptional achievements.

This study has made a preliminary exploration of the impact of smart city construction on the digital business environment and proposed relevant recommendations based on its findings. However, there are some limitations. First, the study focuses on smart city pilots in China, which are geographically detailed, and data access is a challenge. Regarding city selection, this paper uses only prefecture-level cities as research samples, excluding pilot areas such as counties, districts, and towns. Second, the digital business environment evaluation index is built using data from urban statistical yearbooks, urban databases, and the EPS data platform, with some system limitations. This paper primarily examines several Chinese cities as research samples, which is valuable for informing the construction of smart cities and the optimization of the digital business environment in China. However, the applicability and instructiveness of these findings for other countries and regions remain to be validated. Future research will adopt the methodologies of the World Bank and similar studies to analyze the impact of smart city pilot policies at the city, district, and county levels on the digital business environment, and to develop a more comprehensive evaluation index system. Additionally, smart city construction practices from other countries and regions will be used as references or benchmarks to provide a global perspective, enhance comparative analysis, and discuss the global positioning of China's smart city initiatives, thereby informing subsequent policy-making.

Author contributions

Conceptualization, D.Z.; methodology, D.Z. and Z.T.; software, Z.T.; validation, D.Z. and Z.T.; formal analysis, D.Z. and Z.T.; investigation, D.Z. and S.H.; resources, D.Z. and Z.T.; data curation, D.Z. and Z.T.; writing—original draft preparation, D.Z. and Z.T.; writing—review and editing, D.Z., Z.T. and S.H.; visualization, Z.T.; supervision, D.Z.; project administration, D.Z.; funding acquisition, D.Z.. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

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References

1. Sun L, Li F. Study on digital business environment in China: Outstanding problems and optimization measures. Journal of Northeast Normal University(Philosophy and Social Science Edition) 2023; (2): 116-124. doi:10.16164/j.cnki.22-1062/c.2023.02.014
2. Burgonov OV, Kruglov DV. Digital business environment: Prospects and challenges for the development of economic systems. Economics and Management 2020; 26(4): 407-414. doi:10.35854/1998-1627-2020-4-407-414
3. Wielgos DM, Homburg C, Kuehnl C. Digital business capability: Its impact on firm and customer performance. Journal of the Academy of Marketing Science 2021; 49(4): 762-789. doi:10.1007/s11747-021-00771-5
4. Pan S, Xu Y. Digital business environment and its evaluation. Zhejiang Social Sciences 2022; (11): 73-79, 72, 157, 158. doi:10.14167/j.zjss.2022.11.010
5. Xu H, Zhu Z, Zhang H, Guo Z. Theoretical logic, comparative analysis and policy recommendations for evaluating China's digital business environment. Economist 2022; (12): 106-115. doi:10.16158/j.cnki.51-1312/f.2022.12.002
6. Li Y, Zhong C. Influencing factors and generating paths of China's government's digital business environment construction performance. Finance and Accounting Monthly 2023; 44(11): 104-111. doi:10.19641/j.cnki.42-1290/f.2023.11.015
7. Zhao H, Wang W. Construction and empirical study of digital business environment evaluation index system. Statistics & Decision 2022; 38(23): 28-33. doi:10.13546/j.cnki.tjyjc.2022.23.005
8. Nilssen M. To the smart city and beyond? Developing a typology of smart urban innovation. Technological Forecasting and Social Change 2019; 142: 98-104. doi:10.1016/j.techfore.2018.07.060
9. Kourtit K, Nijkamp P, And Arribas D. Smart cities in perspective – a comparative European study by means of self-organizing maps. Innovation: The European Journal of Social Science Research 2012; 25(2): 229-246. doi:10.1080/13511610.2012.660330
10. Caragliu A, Bo CD, Nijkamp P. Smart cities in Europe. Journal of Urban Technology 2011; 18(2): 65-82. doi:10.1080/10630732.2011.601117
11. Yang H, Lee H. Smart city and remote services: The case of South Korea's national pilot smart cities. Telematics and Informatics 2023; 79: 101957. doi:10.1016/j.tele.2023.101957
12. Liu S, Li S. Smart city governance: Reshaping the supply mode of government public services. Journal of Social Sciences 2019; (1): 26-34. doi:10.13644/j.cnki.cn31-1112.2019.01.003
13. Song M, Xiao Y, Zhou Y. How does the smart city policy influence digital infrastructure? Spatial evidence from China. Land 2023; 12(7). doi:10.3390/land12071381
14. Guo Y, Tang Z, Guo J. Could a smart city ameliorate urban traffic congestion? A quasi-natural experiment based on a smart city pilot program in China. Sustainability 2020; 12(6). doi:10.3390/su12062291
15. Li C. The construction of smart city information service system in the era of big data. International Journal of Data Science 2023; 8(2): 104-123. doi:10.1504/IJDS.2023.131429
16. Marchesani F, Masciarelli F, Bikfalvi A. Smart city as a hub for talent and innovative companies: Exploring the (dis) advantages of digital technology implementation in cities. Technological Forecasting and Social Change 2023; 193: 122636. doi:10.1016/j.techfore.2023.122636
17. He Y, Li Z, Wang X, Chen X. Government investment, human capital flow, and urban innovation: Evidence from smart city construction in China. International Review of Financial Analysis 2025; 99: 103916. doi:10.1016/j.irfa.2025.103916
18. Li Z, Zhang S, Niu Z, et al. Theoretical logic, comparative analysis, and the countermeasures of doing business assessment in Chinese cities. Journal of Management World 2021; 37(5): 98-112, 8. doi:10.19744/j.cnki.11-1235/f.2021.0067
19. Ma X, Chang H. A qualitative comparative analysis of business environment and digital economy development. Modernization of Management 2021; 41(4): 51-54. doi:10.19634/j.cnki.11-1403/c.2021.04.010
20. Zhang S, Kang B, Zhang Z. Evaluation of doing business in Chinese provinces: Indicator system and quantitative analysis. Economic Management Journal 2020; 42(4): 5-19. doi:10.19616/j.cnki.bmj.2020.04.001
21. Zhang Q, Cao Y. Research on the construction and evaluation of China's business environment index system based on the reform of "Decentralization, Regulation and Service" - A case study of Shaanxi Province. Price Theory & Practice 2021; (9): 124-127, 203. doi:10.19851/j.cnki.CN11-1010/F.2021.09.294

22. Ma Y, Gao T. Digital economic business environment: International indicator framework and policy direction. Development Research 2020; (11): 45-50. doi:10.3969/j.issn.1003-0670.2020.11.007
23. Shi D, Ding H, Wei P, Liu J. Can smart city construction reduce environmental pollution? China Industrial Economics 2018; (6): 117-135. doi:10.19581/j.cnki.ciejournal.2018.06.008
24. Callaway B, Sant'Anna PHC. Difference-in-Differences with multiple time periods. Journal of Econometrics 2021; 225(2): 200-230. doi:10.1016/j.jeconom.2020.12.001
25. Roth J, Sant'Anna PHC, Bilinski A, Poe J. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. Journal of Econometrics 2023; 235(2): 2218-2244. doi:10.1016/j.jeconom.2023.03.008
26. Bertrand M, Mullainathan S. Enjoying the quiet life? Corporate governance and managerial preferences. Journal of Political Economy 2003; 111(5): 1043-1075. doi:10.1086/376950
27. Wen Z, Ye B. Analyses of mediating effects: The Development of methods and models. Advances in Psychological Science 2014; 22(5): 731-745. doi:10.3724/SP.J.1042.2014.00731
28. Bertrand M, Duflo E, Mullainathan S. How much should we trust differences-in-differences estimates? The Quarterly Journal of Economics 2004; 119(1): 249-275. doi:10.1162/003355304772839588
29. Liu C, Ma Q. Research on the influence of network infrastructure construction on total factor productivity growth: A quasi-natural experiment of "Broadband China" pilot policy. Chinese Journal of Population Science 2020; (3): 75-88, 127, 128.
30. Liu C, Hu Y, Li H, Zhang N. The impact of Smart City pilot policies on the quality of urban development in China: Based on the perspective of resilient development. Urban Problems 2021; (11): 79-89. doi:10.13239/j.bjsshkxy.cswt.211109