

Article

Smart Cities Policy and Corporate Total Factor Productivity: Evidence from China

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Abstract

The smart cities policy (SCP) is one of the key initiatives driving digital transformation in China, delivering a significant digital impact on enterprises within the region. This paper employs a multiple-period difference-in-differences (DID) model to systematically analyze the impact of the SCP on total factor productivity (TFP) of A-share listed companies in China. The results show that the SCP significantly enhances enterprise TFP. Heterogeneity analysis reveals that the policy has a more pronounced positive effect in regions with stronger intellectual property protection, as well as in non-manufacturing sectors and state-owned enterprises (SOEs). Furthermore, the SCP improves enterprise TFP through various dimensions, such as boosting innovation capacity, optimizing human capital structure, reducing operational costs, and improving investment efficiency. This study provides a solid theoretical foundation and policy recommendations for the further optimization and promotion of the SCP.

Keywords: smart cities policy; total factor productivity; cost rate; investment efficiency

1. Introduction

The industrial revolution fundamentally transformed human production and life-style patterns, accelerating the process of urbanization. As industrialization advanced, cities expanded continuously, but this process also brought numerous challenges [1]. Many cities around the world are plagued by “urban diseases” such as traffic congestion and smog. The swift advancement of cutting-edge digital technologies such as the Internet of Things, big data, and artificial intelligence has laid a strong foundation and offered essential support for the growth of smart cities [2]. IBM introduced the concept of “smart cities” in 2008 [3]. The United States was the first to experiment with smart cities. In 2009, Dubuque, Iowa, in collaboration with IBM, launched the first-ever smart city. The UK government also introduced the “Digital Britain” initiative in the same year. In 2011, the South Korean government launched the “Smart Seoul 2015” plan [4]. These initiatives aimed to upgrade and transform cities through information and digital technologies, with the goal of achieving urban digitalization, intelligence, and “smartness” [5]. As China’s reform enters a deeper phase, traditional production factors like capital and labor are no longer sufficient to drive sustained economic growth. The rapid evolution of information technology has made data a vital resource for production. The Chinese government has prioritized the potential of informatization and implemented an innovation-driven develop-

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ment strategy to foster structural transformation and economic upgrading, aiming for TFP [6]. In 2012, China's Ministry of Housing and Urban-Rural Development (MOHURD) issued the 'Notice on the Launch of National Smart City Pilot Work,' officially kicking off the country's smart city initiatives [7]. Between 2012 and 2014, 290 cities, districts, and counties were designated as pilot zones for the SCP.

The SCP integrates emerging digital technologies into traditional urban construction, creating a comprehensive technological ecosystem [8]. Smart cities evolve from the foundation of "digital cities" and are a more advanced form of urban development that continues the same trajectory, representing a higher stage of urban digitalization. Data is the core element of the SCP. These data sources are broad, spanning across natural, physical, economic, and social spaces, and they come in various forms [9]. The integration of these data sources provides a solid foundation for the development of a new SCP. By applying data analytics to mine these data, implicit information can be transformed into explicit knowledge, thereby improving the effectiveness of decision-making [10]. The core components of SCP primarily involve two aspects: first, the digital acquisition and widespread transmission of necessary information; and second, the timely, intelligent processing and extensive application of the acquired digital information [11]. The emergence of advanced digital technologies has made the construction of these core elements of smart cities possible [12].

The report from IDC shows that China's smart cities market expenditure grew from \$14.7 billion in 2016 to \$38.9 billion (projected) in 2023. In 2021, the total investment in China's SCP reached approximately 2.79 trillion RMB [13]. This demonstrates the substantial resources the Chinese government has invested in SCP [14]. Enterprises are crucial in the development of smart cities, as they not only propel the progress of the SCP but also stand to gain the most from its successful implementation [15]. So, can such large-scale funding achieve the expected TFP goals? Can the SCP promote the TFP of listed companies? Is the effect of the SCP model different across various types of enterprises? What are the pathways through which the SCP affects TFP [16]? Answering these questions will evaluate the current SCP's effectiveness and offer targeted recommendations for future smart city development.

Since the concept of smart cities was introduced, a significant amount of theoretical research has been conducted by scholars in this field. Hodson et al. (2023) offered a comprehensive analysis of the concept and driving forces behind smart cities, exploring the challenges encountered in their development and the possible directions for future growth [9]. Shamsuzzoha et al. (2021) employed grounded theory to perform a qualitative analysis comparing smart city projects in London, Singapore, and Helsinki [17]. They identified key shortcomings in addressing the complexity, conflicts, and interdependencies of smart cities, and advocated for a more comprehensive evaluation approach to measure their success. Nilssen (2019) constructed four dimensions of smart city innovation: technology, organization, collaboration, and experimentation, and proposed a smart city continuum to classify and analyze the multi-dimensional innovations of smart city projects [4]. Letaifa et al. (2015) answered how to formulate smart city strategies based on the SMART model [18]. De Jong et al. (2024) viewed smart cities as a typical representation of 21st-century capital accumulation, with six spatial forms, pointing out that financialization is the main driving force [19]. Artmann et al. (2019) introduced a structured framework that integrates smart growth with green infrastructure to promote the creation of compact, sustainable cities [20]. As smart city construction progresses, an increasing number of studies based on specific cases and data have evaluated the economic impacts of SCP. Prasad and Alizadeh (2020) analyzed the proposals of the first 20 cities in India's smart cities plan, revealing the prioritized and neglected smart dimensions and calling for further research on the nationwide implementation effect [21]. Cai et al. (2023) examined

the link between smart cities and urban sustainability in the United States, revealing that while smart cities excelled in economic sustainability, there was no notable connection to environmental or social sustainability [22]. Yigitcanlar et al. (2022) carried out a comprehensive geographical analysis of Twitter data to evaluate the awareness and adoption of smart city concepts and technologies across Australia [23]. Their findings highlighted innovation, sustainability, and governance as key themes.

China has emerged as the leading hub for the implementation and testing of SCP. A significant amount of research in China has concentrated on assessing the real-world effectiveness of the program. Most scholars examine the issue from a macro perspective, affirming that SCP has positively influenced urban innovation capacity and fostered green innovation, boosting employment and achieving green development. Guo and Zhong (2022) argued that SCP enhanced the innovation capacity of pilot cities [24]. Filiou et al. (2023) found that the policy promoted urban green innovation outputs [25]. Lv and Gao (2023) found that smart city development notably boosted urban employment and enhanced the employment structure [26]. Chen (2023) pointed out that SCP significantly reduced nitrogen dioxide concentrations in pilot cities, with the first round of pilot cities showing the most significant effects [27]. Shu et al. (2023) confirmed that SCP reduced carbon emissions in pilot cities [28]. Su et al. (2023) demonstrated that the development of smart cities was crucial in mitigating environmental pollution, promoting industrial transformation, enhancing pollution control technologies, and boosting urban greenery [29]. A small number of scholars, however, have explored the specific impacts of SCP on enterprises and households from a micro perspective. Yang et al. (2024) provided empirical evidence that SCP boosts enterprises' green innovation performance [7]. Wu (2022) confirmed that China's SCP significantly reduced indirect carbon emissions from households, particularly in the areas of transportation and education [30]. The broader international literature provides important theoretical grounding for our analysis. Albino et al. (2015) offer a foundational framework for understanding smart cities, defining them across six key dimensions—economy, people, governance, mobility, environment, and living—and documenting how digital infrastructure investments translate into measurable urban performance improvements [31]. Caragliu et al. (2013) further establish that smart city investment in European cities generates productivity and innovation spillovers, while Hollands (2020) cautions that genuine productivity gains depend on whether digital infrastructure translates into improvements in urban governance and firm competitiveness rather than merely serving as a technological showcase [32,33]. Kourtit and Nijkamp (2012) emphasize that smart cities function as engines of innovation-driven growth, attracting talent and stimulating entrepreneurial activity [34]. More recently, Marchesani et al. (2023) demonstrate that digital technology implementation in cities creates innovation-oriented ecosystems that lower barriers to firm creation and growth, while Contreras and Platania (2019) highlight the role of policy design quality in determining whether smart city initiatives deliver their intended economic outcomes [35,36]. Despite this growing international evidence, existing studies have predominantly focused on city-level or regional-level outcomes, leaving the firm-level productivity effects of smart city policy largely unexplored outside the Chinese context. This paper addresses this gap by providing micro-level causal evidence on how smart city policy transmits to enterprise TFP, using a quasi-experimental framework that draws on recent methodological advances in causal inference [37–40].

Existing studies have provided valuable evidence on the effects of smart city policy. Most of them focus on city-level outcomes, such as urban innovation, green innovation, employment, pollution reduction, carbon emissions, and public service improvement. These studies confirm that smart city construction can improve urban governance and promote sustainable urban development. However, this literature has paid limited atten-

tion to whether and how a city-level digital governance policy can be transmitted to firm-level production efficiency. This gap is important for both theoretical and policy reasons. Theoretically, firms are the key microeconomic agents that transform urban digital infrastructure, data platforms, smart logistics, digital government services, and information-sharing systems into real economic output. Without firm-level evidence, the productivity consequences of smart city construction remain insufficiently understood. From a policy perspective, smart city construction requires large-scale public investment. Therefore, evaluating whether this policy improves corporate total factor productivity is essential for assessing whether smart city construction generates real economic efficiency gains rather than only improving urban management indicators. To fill this gap, this paper treats China's smart cities policy as a quasi-natural experiment and examines its impact on the total factor productivity of A-share listed firms from 2007 to 2019. Compared with existing studies, this paper makes three main contributions. First, this paper extends the smart city literature from macro-level urban outcomes to micro-level firm productivity. Rather than only asking whether smart city construction improves urban performance, we examine whether and how a city-level digital governance shock is transmitted to firms' production efficiency. This provides firm-level evidence on the productivity consequences of urban digital transformation. Second, this paper develops a more structured theoretical framework linking smart city policy to corporate TFP. We argue that SCP affects firms not only through general digital infrastructure improvement, but more specifically through three resource-allocation channels: labor input upgrading, reduction in operational and transaction frictions, and improvement of capital allocation efficiency. Accordingly, the mechanism analysis focuses on human capital structure, enterprise cost, and investment efficiency. Third, this paper examines heterogeneous policy effects across institutional environments and firm characteristics, including intellectual property protection, ownership type, and industry category. These analyses help explain why the productivity effect of smart city policy differs across regions and firms, and provide more targeted policy implications for the design and implementation of future smart city programs. The research offers important strategic and policy recommendations for advancing smart city development. The research framework is shown in Figure 1.

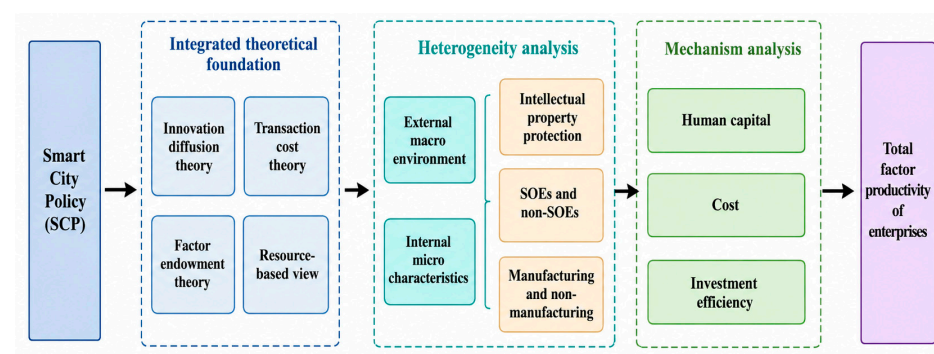


Figure 1. Research framework.

2. Theoretical Analysis and Research Hypotheses

Before developing the specific hypotheses, we clarify the integrated theoretical logic of this study. SCP is not merely an infrastructure construction program; it represents a city-level digital governance transformation that changes the external production environment faced by firms. The four theoretical perspectives used in this paper are not independent explanations, but complementary components of a unified analytical framework. Specifically, innovation diffusion theory explains how digital technologies, intelligent applications, and data-based services generated by SCP diffuse from the urban system to

firms. Transaction cost theory explains how smart transportation, smart logistics, digital government services, and information-sharing platforms reduce information search costs, coordination costs, and transaction frictions. Factor endowment theory explains how SCP improves the supply of new production factors, including digital infrastructure, data resources, and skilled labor. The resource-based view further explains how firms transform these external urban resources into internal capabilities, such as better human capital structure, lower operating costs, and more efficient investment decisions. Taken together, these theories form an integrated logic: SCP changes the external digital environment of firms; this change promotes technology diffusion, reduces transaction frictions, upgrades urban factor endowments, and helps firms reorganize internal resources; these processes ultimately improve corporate TFP. Therefore, innovation diffusion theory and factor endowment theory mainly support the baseline hypothesis that SCP improves corporate TFP, while transaction cost theory and the resource-based view provide the theoretical basis for the mechanism hypotheses related to cost reduction, human capital upgrading, and investment efficiency improvement.

2.1. SCP and TFP of Enterprises

The SCP, as an important strategy for new urbanization and digital transformation, aims to accelerate the widespread application of emerging technologies through the construction of next-generation digital infrastructure [7]. Smart cities are the practical application of the digital economy and an important part of the new infrastructure [41]. Through the penetration effect of new infrastructure and technologies, the SCP accelerates the process of industrial digitalization and intelligence, providing enterprises with a more adaptable and resource-efficient operating environment. The SCP is an important measure to address “urban diseases,” with core objectives including improving urban operational efficiency, optimizing resource allocation, reducing transaction costs, and promoting industrial upgrading [25].

First, the theory of innovation diffusion suggests that the popularization of new technologies can drive overall innovation in a system [42]. By developing digital infrastructure and fostering clusters of smart industries, the SCP offers enterprises advanced technological applications, driving innovation through data and intelligent technologies. Secondly, from the perspective of transaction cost theory [43], smart city development reduces the costs for enterprises in information search, communication coordination, and transaction supervision through digital platforms in smart transportation, logistics, and government services. Furthermore, the factor endowment theory highlights the importance of resource endowments in economic development [44]. Smart cities enhance urban factor endowments by introducing new production factors such as data, intelligent infrastructure, and high-end technical talent. Finally, the resource-based view further supports the positive impact of SCP on enterprise development. Smart cities build platforms for resource sharing and collaborative innovation by aggregating technology, talent, and information resources, providing enterprises with new channels for resource acquisition.

In conclusion, the SCP, through data-sharing platforms and collaborative interconnection networks, utilizes information technologies to reorganize and integrate data—an essential element—together with other production factors, helping cities and enterprises form intelligent collaborative networks [19]. These smart infrastructures not only enhance the intelligence of urban management but also provide solid support for TFP in enterprises.

Hypothesis 1. The SCP can promote the TFP of enterprises.

2.2. The Impact Mechanism of SCP on the TFP of Enterprises

2.2.1. Human Capital Mechanism

The SCP provides solid support for the TFP by optimizing the human capital structure. The SCP has led to a strong demand for highly skilled talent, especially in technology-intensive fields [45,46]. The application of these cutting-edge technologies relies on the support of a highly qualified workforce [47,48]. SCP not only attracts a large influx of highly skilled individuals by creating many high-skill job opportunities and offering a good living environment but also promotes the long-term accumulation of talent. The influx of such talent enables enterprises to better meet the high technical requirements of the smart city environment, driving progress in product innovation, research and development, and technological applications [19]. Simultaneously, the “learning by doing” in SCP motivates employees to continually update their knowledge and skills, enabling them to thrive in an information- and intelligence-driven work environment, thereby improving the quality of human capital in enterprises [49]. By enhancing employees’ skills and knowledge, enterprises can more effectively absorb and apply new knowledge, thereby strengthening their innovation capabilities. Moreover, the innovation collaboration platforms provided by SCP facilitate in-depth cooperation between enterprises, universities, and research institutions, offering employees high-quality learning and development opportunities [50]. Through the sharing and collaboration of these resources, the internal human capital structure of enterprises is continuously optimized, thereby supporting ongoing innovation and development. In summary, the SCP not only optimizes the human capital structure of enterprises by attracting high-quality talent but also promotes the updating of knowledge and skills within the enterprise, providing a strong human capital foundation for high-quality enterprise development [51].

Hypothesis 2a. The SCP promotes the TFP of enterprises by optimizing the human capital structure.

2.2.2. Cost Mechanism

The SCP helps lower business costs by facilitating the use of information technology and the development of smart management platforms. By utilizing technologies, the SCP helps enterprises optimize information transmission and resource allocation processes, effectively alleviating information asymmetry. This facilitates enterprises’ access to real-time market and supply chain data, which in turn minimizes unnecessary resource waste and costs [52]. Firstly, the SCP provides enterprises with efficient information-sharing and management platforms, optimizing resource allocation in procurement, production, and sales processes [53]. These intelligent systems help enterprises shorten information transmission cycles, allowing them to adjust production and inventory levels more quickly in response to changes in market demand, thus reducing inventory and management costs, ultimately lowering overall costs [54]. Furthermore, the smart city-driven infrastructure of intelligent transportation and smart logistics has made transportation and logistics management more convenient for enterprises, reducing both transportation time and costs. Through real-time monitoring and data feedback from smart transportation, enterprises can better plan logistics routes and optimize transportation processes, further reducing logistics expenses [55]. The e-commerce and smart payment systems under the SCP have also improved the efficiency of capital flow and reduced financial and transaction costs for enterprises. In summary, the SCP lowers enterprise costs by optimizing resource allocation, improving management efficiency, and reducing expenditures, thereby providing a solid foundation for the TFP of enterprises.

Hypothesis 2b. The SCP improves the TFP of enterprises by reducing enterprise costs.

2.2.3. Efficiency Mechanism

The implementation of the SCP optimizes resource allocation and improves information infrastructure, creating a favorable external environment for enterprise investment activities, which in turn enhances investment efficiency. Smart cities utilize information technologies to offer enterprises real-time insights into market trends, customer demands, and technological advancements, helping them make more informed investment decisions [48]. This integrated information and data-sharing environment lowers the costs associated with information retrieval and reduces uncertainty in investment decisions, thereby enhancing enterprise efficiency in resource allocation and investment strategy [56].

Firstly, the SCP's intelligent information management systems enable enterprises to more effectively collect and process market dynamics, providing reliable support for identifying high-potential investment opportunities and making sound capital allocations. Through this data-driven resource allocation, enterprises can avoid inefficient and redundant investments, directing capital more precisely into promising areas such as technological upgrades, product innovation, and market expansion [57]. Secondly, the intelligent infrastructure under the SCP, such as smart transportation, smart logistics, and smart payment systems, reduces operational costs for enterprises during investment and expansion processes [58,59]. These intelligent infrastructures enhance resource utilization efficiency, enabling enterprises to minimize capital waste and achieve higher investment returns with lower costs, thus boosting investment efficiency [16]. In summary, the SCP provides enterprises with digital and intelligent support for optimizing investments, enabling them to allocate capital more flexibly and accurately in an uncertain market environment, thereby driving TFP.

Hypothesis 2c. The SCP enhances enterprise TFP by improving investment efficiency.

2.3. Heterogeneous Effects of SCP

The productivity effect of SCP may not be homogeneous across all firms and regions. Smart city construction is a city-level digital governance policy that changes the external production environment faced by firms. However, the extent to which firms can transform this policy shock into productivity improvement depends on regional institutional conditions, ownership characteristics, and industry attributes [60,61]. In regions with stronger institutions, firms are more capable of protecting and using digital resources, as robust intellectual property regimes reduce technology misappropriation risks and strengthen innovation incentives [29,62]; firms with stronger policy responsiveness—particularly SOEs with closer government ties—can more easily participate in government-led smart city projects and capture associated resource advantages [7,56]; and industries that rely more heavily on information flow and digital services may benefit more directly from smart city construction, as digital infrastructure reduces transaction frictions and improves service delivery efficiency more immediately in information-intensive sectors [47,48]. Therefore, this paper further develops three heterogeneity hypotheses from the perspectives of intellectual property protection, ownership type, and industry category.

Regional intellectual property protection may strengthen the productivity effect of SCP. Smart city construction relies heavily on digital technologies, data resources, knowledge-based services, and intelligent public platforms. These elements increase the importance of technological application and knowledge protection. In regions with stronger intellectual property protection, firms face lower risks of imitation, technology misappropriation, and data misuse. This institutional environment can strengthen firms' incentives to adopt, apply, and share new technologies. Existing studies also emphasize that intellectual property protection plays an important role in improving total factor

productivity by protecting innovation returns and promoting efficient technology diffusion [29]. In the context of SCP, stronger intellectual property protection can help firms better transform digital infrastructure, data resources, and smart city applications into productivity gains. In addition, the measurement method of city-level intellectual property protection adopted by Shen and Huang (2019) provides a basis for distinguishing regional institutional environments [62]. Smart city construction also relies on digital governance and natural resource management capacity, which makes the security and effective use of data resources more important [63]. Regions with stronger judicial and institutional capacity can provide better protection for firms' innovation activities and productivity improvement [64]. Therefore, we propose the following hypothesis:

Hypothesis 3a. The positive effect of SCP on corporate TFP is stronger in regions with stronger intellectual property protection.

Ownership type may influence firms' ability to benefit from SCP. SCP is a government-led policy program that involves digital infrastructure construction, public service platforms, smart transportation systems, urban governance modernization, and data-based public management. Compared with non-SOEs, SOEs usually have closer connections with local governments, stronger policy responsiveness, better access to public resources, and greater capacity to participate in infrastructure and public service projects. Existing studies suggest that smart city policy can promote enterprise digitalization and performance, but firms differ in their ability to obtain and transform policy resources [7,65]. SOEs are more likely to participate in smart city construction projects, receive financing support, and respond to government-led digital transformation strategies. In addition, SOEs usually have stronger risk-bearing capacity and more stable financing channels, which allow them to undertake long-term digital transformation and innovation activities under the SCP framework [66]. Non-SOEs, by contrast, are more constrained by profit pressure, financing limitations, and uncertainty in policy participation. Therefore, the productivity-enhancing effect of SCP is expected to be stronger for SOEs than for non-SOEs.

Hypothesis 3b. The positive effect of SCP on corporate TFP is stronger for SOEs than for non-SOEs.

Industry characteristics may affect the productivity effect of SCP. Non-manufacturing firms, especially those in service, finance, information, logistics, and platform-based sectors, are more directly connected to digital platforms, smart logistics, digital payment systems, information-sharing platforms, and intelligent public services. These firms rely heavily on information flow, transaction efficiency, customer matching, logistics coordination, and service delivery. Therefore, improvements in digital infrastructure and smart public services can be converted into productivity gains more quickly in the non-manufacturing sector. Existing studies show that smart city investment and digital governance can reshape urban economic activities and improve the efficiency of information transmission and service provision [58]. By contrast, manufacturing firms can also benefit from SCP, but their productivity improvement usually requires equipment upgrading, production-line transformation, smart manufacturing systems, and deeper integration of digital technologies into physical production processes. These changes involve higher fixed costs, longer implementation cycles, and more complex coordination between digital systems and production processes. Studies on smart manufacturing and supply-chain transformation also indicate that the digital transformation of manufacturing requires more systematic changes in production organization and supply-chain design [67,68]. In addition, productivity improvement in manufacturing is closely related to technological progress

and efficiency change, which often materialize over a longer time horizon [69,70]. Therefore, in the short and medium term, SCP is expected to have a stronger productivity effect on non-manufacturing firms.

Hypothesis 3c. The positive effect of SCP on corporate TFP is stronger for non-manufacturing firms than for manufacturing firms.

3. Study Design

3.1. The Model for Setting the Impact of SCP on the TFP of Enterprises

To examine the impact of SCP on the TFP of enterprises, we constructed model (1):

$$TFP_{i,t} = \beta_0 + \beta_1 SCP_{i,t} + \gamma Controls'_{it} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

where $TFP_{i,t}$ represents the TFP of the enterprise, which is used to measure the TFP of the enterprise. $SCP_{i,t}$ is the explanatory variable, and the magnitude and sign of its coefficient β_1 are our primary focus. $SCP_{i,t}$ reflects whether the city where the enterprise is located has implemented an SCP. If the region where enterprise i is located is a pilot city for SCP in year t , $SCP_{i,t}$ is assigned a value of 1; otherwise, it is assigned a value of 0. μ_i represents the enterprise fixed effect, and δ_t represents the time fixed effect. This study uses a two-way fixed effects panel model to design the SCP model. $Controls'_{it}$ are the control variables.

3.2. Selection of Variables and Data Sources

(1) Dependent Variable: TFP of Enterprises. TFP is a crucial indicator, often used for macro-level evaluations of cities, provinces, and regions, but it also provides insights into the development quality of individual enterprises. TFP integrates the effects of management optimization and structural adjustment, making it more comprehensive and information-rich than other methods. The measurement methods for enterprise TFP include OLS, fixed effects, GMM, OP method, and LP method. The OP and LP methods effectively address the endogeneity issues of OLS, and as such, they are widely used. The difference between the two lies in the selection of proxy variables: the OP method uses the firm's actual investment as a proxy, which requires investment to be greater than zero and has higher data requirements, potentially leading to sample omission. In contrast, the LP method uses intermediate inputs as proxies, which can effectively avoid the omission problem. Based on this, this study uses the LP method to estimate the TFP of China's listed companies, while the results from the other four methods are used for robustness checks.

The TFP of Chinese A-share listed companies showed an overall upward trend from 2007 to 2019, reflecting a positive trajectory of TFP. However, there were declines in 2009 and 2012: the decline in 2009 was primarily due to the global financial crisis of 2008. In response, the government implemented the four-trillion-yuan stimulus plan, which led to the entry of many firms with productivity below the average, thus lowering the overall mean. In 2012, TFP further decreased due to economic restructuring, a slowdown in exports, and overcapacity issues. TFP remained at a low growth rate from 2013 to 2015 (See Figure 2).

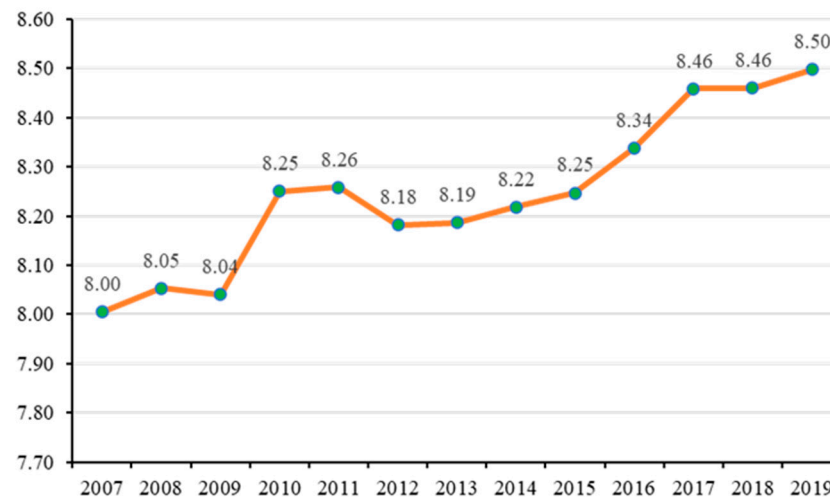


Figure 2. Time Trend of Enterprise TFP from 2007 to 2019.

(2) Explanatory Variable: SCP Dummy Variable. If the enterprise is located in a city designated as a smart city pilot, the explanatory variable is coded as 1; otherwise, it is coded as 0. The coefficient of this variable indicates the effect of the SCP on the TFP of enterprises in pilot cities. The SCP was implemented in stages in 2012, 2013, and 2014. To visually display the regional distribution of smart cities, we have marked the areas where the SCP has been implemented in red on the map, as shown in Figures 3–5. The first batch designated 42 prefecture-level cities across 22 provinces, municipalities, and autonomous regions. The pilot cities include: Beijing, Tianjin, Shanghai, Chongqing, Shijiazhuang, Langfang, Handan, Qinhuangdao (Hebei), Taiyuan, Changzhi (Shanxi), Wuhai (Inner Mongolia), Liaoyuan (Jilin), Dezhou, Weihai, Dongying (Shandong), Wuxi, Changzhou, Zhenjiang, Taizhou (Jiangsu), Wuhu, Huainan, Tongling, Bengbu (Anhui), Wenzhou, Jinhua (Zhejiang), Nanping (Fujian), Pingxiang (Jiangxi), Zhengzhou, Hebi, Luohe (Henan), Wuhan (Hubei), Zhuzhou (Hunan), Zhuhai, Guangzhou, Shenzhen, Foshan (Guangdong), Tongren, Liupanshui (Guizhou), Ya'an (Sichuan), Lhasa (Tibet), Xianyang (Shaanxi), and Wuzhong (Ningxia) (See Figure 3).

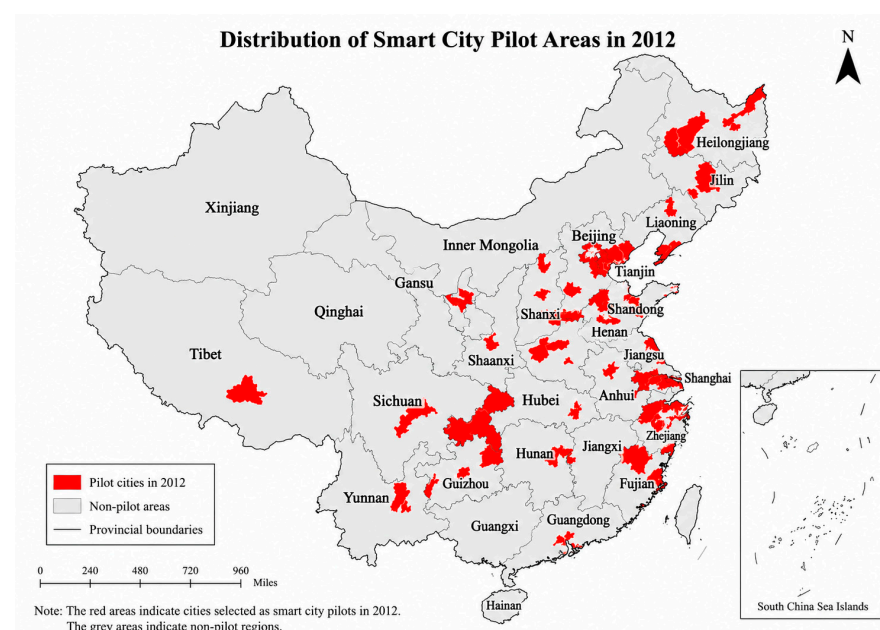


Figure 3. Distribution of smart cities in 2012.

The second batch added 48 new prefecture-level cities. The newly designated cities include: Yangquan, Datong, Jincheng (Shanxi), Hulunbuir, Ordos, Baotou (Inner Mongolia), Qiqihar, Mudanjiang (Heilongjiang), Siping (Jilin), Yingkou (Liaoning), Yantai (Shandong), Nantong, Suqian (Jiangsu), Fuyang, Huangshan, Huaibei (Anhui), Hangzhou, Ningbo (Zhejiang), Putian (Fujian), Xinyu (Jiangxi), Xuchang (Henan), Huanggang, Xianning, Yichang, Xiangyang (Hubei), Yueyang (Hunan), Zhaoqing, Dongguan (Guangdong), Nanning, Liuzhou, Guilin, Guigang (Guangxi), Guiyang, Zunyi, Bijie (Guizhou), Mianyang, Suining (Sichuan), Baoji, Weinan, Yan'an (Shaanxi), Lanzhou, Jinchang, Baiyin, Longnan (Gansu), Yinchuan, Shizuishan (Ningxia), Urumqi, Karamay (Xinjiang) (See Figure 4).

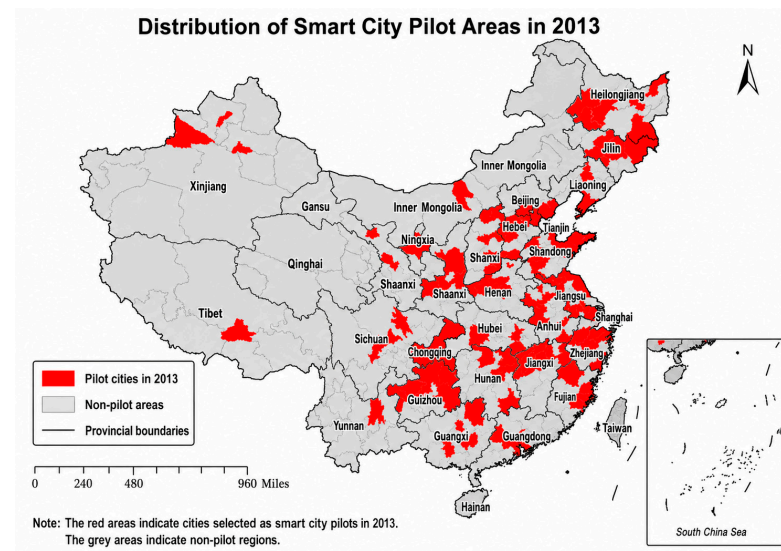


Figure 4. Distribution of smart cities in 2013.

The third batch added 28 new prefecture-level cities. The newly designated cities include: Tangshan (Hebei), Xinzhou (Shanxi), Hohhot (Inner Mongolia), Jiamusi (Heilongjiang), Tonghua (Jilin), Laiwu (Shandong), Xuzhou (Jiangsu), Suzhou, Bozhou, Chuzhou (Anhui), Quanzhou (Fujian), Yingtan, Ji'an (Jiangxi), Kaifeng, Nanyang (Henan), Jingzhou (Hubei), Changde (Hunan), Qinzhou, Yulin (Guangxi), Dali, Yuxi (Yunnan), Guang'an, Luzhou, Leshan (Sichuan), Hanzhong (Shaanxi), Zhangye, Tianshui (Gansu), Zhongwei (Ningxia) (See Figure 5).

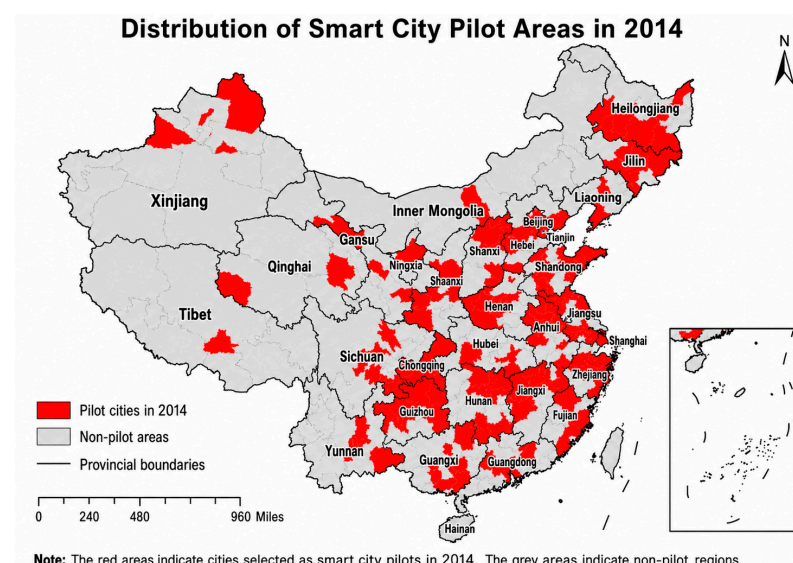


Figure 5. Distribution of smart cities in 2014.

(3) Control variables. The enterprise-level control variables include enterprise age (AGE), size (SIZE), debt-to-asset ratio (LEV), fixed asset ratio (FAR), equity concentration (TOP10), operating income growth rate (ORG), current ratio (DUAL) and proportion of independent directors (INDE). The macro-level control variables include population density (PD), industrial structure (INDS), government intervention (GOV), economic development level (RGDP) and financial development (FINA).

The ST, ST*, financial companies, and companies with significant missing data were removed one by one, resulting in a final total of 3346 listed companies and 27,672 samples. Patent data comes from the CNDRS database, and other data at the enterprise level are from Wind and the CSMAR database. We obtained the list of SCP from the official website of the Ministry of Housing and Urban-Rural Development and constructed explanatory variables based on them. The data of control variables at the macro level are all from the China City Statistical Yearbook. The descriptive statistical results of the data are shown in Table 1.

Table 1. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
TFP	27,671	8.2898	1.0520	5.9463	11.0565
SCP	27,671	0.2993	0.4580	0.0000	1.0000
LEV	27,671	0.4420	0.2072	0.0552	0.9060
AGE	27,671	2.7254	0.3809	1.3863	3.4012
SIZE	27,671	8.2627	1.2676	5.8982	12.2381
FAR	27,671	0.2243	0.1659	0.0021	0.7136
TOP10	27,671	57.5764	15.2812	22.2000	90.0800
ORG	27,671	0.1906	0.4547	−0.5872	2.9656
CR	27,671	2.2820	2.3299	0.2876	15.3754
INDE	27,671	37.3345	5.3424	30.7700	57.1400
PD	25,946	872.1534	611.6195	4.8200	2759.1390
INDS	25,946	1.4398	0.9640	0.0943	5.1683
FINA	25,946	1.5197	0.6530	0.0753	7.4502
GOV	25,946	0.1524	0.0575	0.0437	1.0268
RGDP	25,946	11.2393	0.6131	8.3770	13.0557

4. Empirical Results Analysis

4.1. Parallel Trend Test

Figure 6 reports the event-study estimates used to examine the parallel trends assumption. The horizontal axis represents the relative year to the implementation of the smart city policy, with the year immediately before policy implementation used as the omitted benchmark period. The vertical axis reports the estimated coefficients of the relative-time indicators, and the vertical bars represent the 95% confidence intervals. The results show that the estimated coefficients before policy implementation are statistically insignificant. Specifically, the coefficient of pre3 is −0.0145 with a p -value of 0.381, and the coefficient of pre2 is 0.0049 with a p -value of 0.756. More importantly, we further conduct a formal joint significance test for the pre-treatment coefficients. The F-test fails to reject the null hypothesis that the pre-treatment coefficients are jointly equal to zero, with $F(2, 22,707) = 0.55$ and p -value = 0.5766. This provides statistical evidence that there was no significant difference in pre-treatment trends between the treatment and control groups. After the implementation of the smart city policy, the estimated coefficients become positive. The contemporaneous effect is 0.0283 and is marginally significant, while the post-treatment coefficients are generally positive and statistically significant. For example, the coefficients of post1, post3, post4, post5, post6, and post7 are significantly positive. These

results suggest that the productivity-enhancing effect of the smart city policy gradually emerges after policy implementation and persists over time. Therefore, the DID model satisfies the parallel trends assumption.

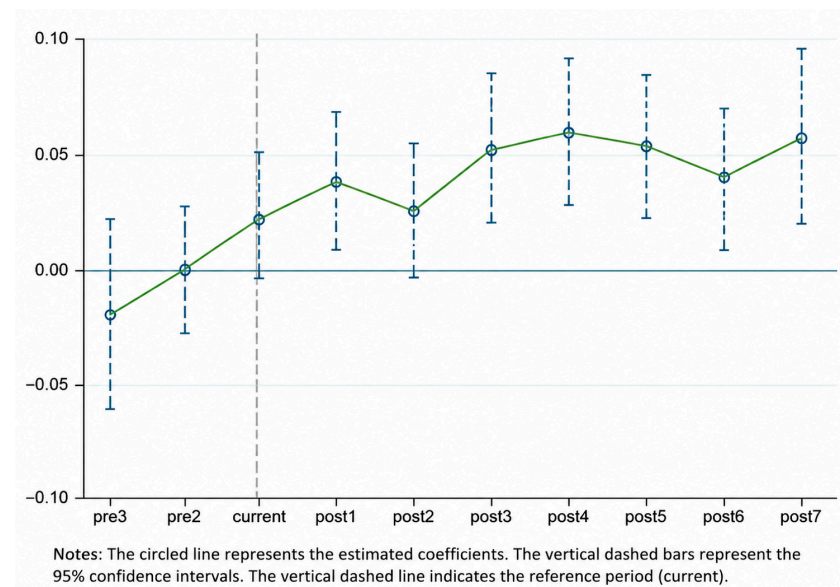


Figure 6. Parallel trend test.

4.2. Benchmark Regression Analysis

Column 1 of Table 2 presents the regression results accounting for both individual and time fixed effects, excluding macro-level control variables. The results show that the SCP coefficient is significantly positive at the 1% level. Column (2) includes both individual and time fixed effects, along with control variables at the enterprise and macro levels. The coefficient of SCP remains significantly positive, confirming that the SCP has enhanced the TFP of enterprises in pilot cities, thus contributing to the TFP of enterprises [58]. Columns (3) and (4) show the results after controlling for industry and city fixed effects, with the SCP coefficient still significantly positive. In Column (5), we control for individual, time, city, and industry fixed effects, while also including enterprise and macro-level control variables. The SCP coefficient remains significantly positive, reinforcing the conclusion that the SCP has successfully promoted the TFP of enterprises. China has made significant strides in implementing the SCP, with substantial government investment yielding effective returns without major resource waste [59]. The improved information infrastructure in pilot cities has enhanced their livability [60], benefiting enterprise innovation, investment efficiency, human capital optimization, cost reduction, and ultimately, TFP improvement.

Table 2. The impact of SCP on TFP of enterprises.

	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP
SCP	0.0289 *** (3.25)	0.0454 *** (2.64)	0.0435 *** (2.59)	0.0497 *** (2.91)	0.0465 *** (2.78)
LEV	0.1339 *** (5.72)	0.1325 ** (2.32)	0.1303 ** (2.31)	0.1194 ** (2.12)	0.1210 ** (2.16)
AGE	0.2362 *** (8.33)	0.2315 *** (4.06)	0.2270 *** (4.11)	0.2085 *** (3.71)	0.2092 *** (3.82)
SIZE	0.4771 *** (93.21)	0.4823 *** (34.62)	0.4736 *** (35.58)	0.4837 *** (35.42)	0.4740 *** (36.03)

FAR	−1.2266 *** (−46.14)	−1.2578 *** (−19.00)	−1.2484 *** (−20.29)	−1.2636 *** (−19.05)	−1.2503 *** (−20.18)
TOP10	0.0001 (0.28)	0.0001 (0.18)	0.0000 (0.08)	−0.0000 (−0.08)	−0.0001 (−0.15)
ORG	0.2056 *** (43.90)	0.2064 *** (26.51)	0.2079 *** (26.79)	0.2072 *** (26.40)	0.2080 *** (26.78)
CR	−0.0146 *** (−8.92)	−0.0157 *** (−5.01)	−0.0157 *** (−5.30)	−0.0162 *** (−5.25)	−0.0162 *** (−5.51)
INDE	−0.0003 (−0.46)	−0.0002 (−0.20)	0.0000 (0.04)	−0.0002 (−0.20)	0.0000 (0.03)
ROE	0.3802 *** (22.62)	0.3718 *** (10.52)	0.3823 *** (11.30)	0.3784 *** (10.85)	0.3894 *** (11.68)
PD		0.0001 ** (2.19)	0.0001* (1.83)	0.0001 ** (2.07)	0.0001 * (1.93)
INDS		−0.0244 (−1.28)	−0.0181 (−1.02)	−0.0273 (−1.42)	−0.0199 (−1.07)
FINA		−0.0054 (−0.30)	−0.0032 (−0.18)	−0.0353 ** (−2.09)	−0.0295 * (−1.83)
GOV		0.0339 (0.16)	0.0632 (0.31)	0.2495 (1.38)	0.2656 (1.48)
RGDP		0.0282 (1.17)	0.0324 (1.39)	0.0190 (0.85)	0.0245 (1.14)
Constant	3.9260 *** (50.00)	3.5795 *** (11.57)	3.4508 *** (9.68)	4.0520 *** (11.27)	3.8726 *** (9.77)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	N	N	Y	N	Y
City FE	N	N	N	Y	Y
N	27,671	25,946	25,946	25,946	25,946
R ²	0.6055	0.6058	0.6190	0.6185	0.6308

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included; N indicates that it is not included.

4.3. Robustness Test

① To test the robustness of the conclusions, we use four different methods (OLS, fixed effects, GMM, and OP) to calculate TFP, and each method's results are used as the dependent variable (See Table 3). ② Excluding municipalities such as Beijing, Tianjin, Shanghai, and Chongqing, which differ from other cities in infrastructure, institutional development, and economic scale. These cities are also all included in the smart city pilot program. Analyzing these municipalities alongside other cities could potentially lead to inaccurate estimates of the effect of the SCP. Therefore, we exclude the listed companies in these four municipalities (Beijing, Tianjin, Shanghai, and Chongqing) from our sample. ③ Shortening the sample period: Similarly, we shortened the sample period for robustness checks. Considering the significant impact of the 2008 financial crisis on China's A-shares and the operations of listed companies, we shortened the sample period by two years and retained data from 2009 to 2017. ④ Using PSM-DID as an alternative estimation approach, we first apply Propensity Score Matching (PSM) to identify a control group with comparable characteristics, and then implement the DID model. ⑤ Adjusting the clustering level: In Model (1), the standard errors are clustered at the individual level. We adjust the clustering level to the industry-time dimension to account for industry-specific factors and time-varying influences. The results from these five robustness checks show

that the coefficient of SCP remains significantly positive in all cases, confirming that our empirical results are robust. ⑥ To address the concern that the binary SCP indicator may not fully capture differences in implementation intensity across pilot cities, we further add a robustness test based on digital infrastructure intensity. Specifically, we introduce the digital infrastructure indicator and its interaction with SCP into the regression. This specification allows us to examine whether the productivity-enhancing effect of SCP varies with the level of urban digital infrastructure. The results are reported in Column (5) of Table 4. The coefficient of the interaction term between SCP and digital infrastructure is significantly positive at the 5% level. This indicates that the effect of SCP on corporate TFP is stronger in cities with better digital infrastructure. Therefore, the impact of smart city policy depends not only on whether a city is selected as a pilot city, but also on the city's digital foundation and implementation conditions. This finding suggests that the baseline conclusion is not solely driven by the binary policy indicator, but is further supported by evidence based on smart city construction intensity.

Table 3. Robustness test—replacement of explained variables.

	(1) TFP_OLS	(2) TFP_FE	(3) TFP_OP	(4) TFP_GMM
SCP	0.0372 ** (2.20)	0.0360 ** (2.11)	0.0398 ** (2.06)	0.0476 ** (2.34)
LEV	0.0822 (1.46)	0.0718 (1.25)	0.1357 ** (2.41)	0.2137 *** (3.51)
AGE	0.2527 *** (4.47)	0.2538 *** (4.42)	0.2445 *** (4.18)	0.1953 *** (3.09)
SIZE	0.7004 *** (48.76)	0.7486 *** (50.97)	0.3378 *** (23.21)	0.0973 *** (6.31)
FAR	−0.1624 ** (−2.54)	−0.0012 (−0.02)	−0.9917 *** (−14.90)	−2.4301 *** (−30.90)
TOP10	−0.0002 (−0.37)	−0.0003 (−0.47)	0.0003 (0.46)	0.0006 (0.92)
ORG	0.1990 *** (25.55)	0.1986 *** (25.22)	0.2021 *** (24.56)	0.2059 *** (23.99)
CR	−0.0202 *** (−6.24)	−0.0215 *** (−6.47)	−0.0093 *** (−2.98)	−0.0041 (−1.24)
INDE	−0.0007 (−0.66)	−0.0008 (−0.76)	−0.0001 (−0.12)	0.0006 (0.48)
ROE	0.3700 *** (10.60)	0.3705 *** (10.53)	0.3696 *** (10.40)	0.3783 *** (10.30)
PD	0.0001 *** (2.66)	0.0001 *** (2.72)	0.0001 * (1.78)	0.0001 (1.31)
INDS	−0.0418 ** (−2.18)	−0.0423 ** (−2.17)	−0.0560 *** (−2.76)	−0.0332 (−1.51)
FINA	−0.0026 (−0.14)	−0.0038 (−0.21)	0.0181 (0.96)	0.0115 (0.59)
GOV	0.1370 (0.64)	0.1166 (0.53)	0.4234 * (1.95)	0.2741 (1.23)
RGDP	0.0377 (1.57)	0.0366 (1.51)	0.0548 ** (2.10)	0.0322 (1.25)
Constant	3.9336 *** (12.63)	4.0742 *** (12.88)	2.6243 *** (8.00)	2.3468 *** (6.97)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

N	25,946	25,946	25,946	25,946
R ²	0.7148	0.7304	0.4838	0.3800

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included.

Table 4. Robustness test.

	(1) Excluding Munic- ipalities TFP	(2) Shorten the Sample Period TFP	(3) PSM-DID TFP	(4) Industry-Time Di- mension Clustering TFP	(5) Digital Infrastructure Intensity TFP
SCP	0.0350 *** (3.18)	0.0349 ** (2.32)	0.0450 *** (2.62)	0.0454 *** (4.24)	0.0129 (0.90)
SCP × Digital infra- structure					0.2616 ** (2.48)
Digital infrastruc- ture					−0.0522 (−1.03)
Controls	Y	Y	Y	Y	Y
Constant	3.6627 *** (16.52)	3.9937 *** (13.25)	3.5773 *** (11.63)	3.5157 *** (15.24)	3.4711 *** (18.88)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	18,900	17,827	25,928	25,850	25,946
R ²	0.6116	0.5738	0.6058	0.9225	0.6188

Note: t-statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included.

⑥ Placebo test. To ensure that changes in enterprise TFP are attributable to the SCP and not random factors, we conducted a placebo test using a randomly assigned fictitious treatment group [61]. From the 3446 sample companies, we randomly selected 1409 listed companies as the pseudo-treatment group, assuming they were affected by the SCP. The results indicate that most estimated coefficients are close to 0, with the majority of p -values exceeding 0.1. This suggests that the observed increase in TFP is driven by the SCP, not by unobserved factors.

⑦ To address potential bias from staggered adoption, we implement the Sun & Abraham (2021) interaction-weighted estimator, which separately estimates treatment effects for each pilot cohort using only never-treated firms as controls [38]. As reported in Table 5, the weighted average ATT is 0.037 ($p < 0.05$), slightly smaller than but directionally consistent with the TWFE baseline (0.045, $p < 0.05$ from Table 2). All three cohorts yield positive estimates (2012: 0.035; 2013: 0.024; 2014: 0.096), with no sign reversal across waves. These results confirm that our baseline finding is robust to heterogeneous treatment effects across pilot cohorts.

Table 5. Robustness test.

	(1) TWFE (Baseline)	(2) Sun-Abraham (2021) (Heterogeneity-Robust)
Panel A: Overall Average Treatment Effect (ATT)		
Smart City Pilot SCP)	0.0454 ** (2.64)	0.0366 ** (2.11)
Control Variables	Y	Y
Firm Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
Control Group	All untreated	Never-treated only
Observations	25,946	25,946
R-squared	0.6058	0.5108
Panel B: Sun-Abraham (2021)—ATT by Pilot Cohort		
2012 Cohort (n =1040 firms)		0.0353 (0.0220)
2013 Cohort (n =306 firms)		0.0241 (0.0268)
2014 Cohort (n =87 firms)		0.0958 * (0.0558)
Weighted Average ATT		0.0366 ** (0.0174)

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included.

⑧ To address potential selection bias in pilot city designation, we implement two formal tests for selection on unobservables, complementing the PSM-DID check in Table 4. First, following Oster (2019), we compute the coefficient stability statistic δ [40]. The restricted regression (DID only, without controls) yields $\beta = 0.1282$ with $R^2 = 0.0047$, while the full specification yields $\beta = 0.0454$ with $R^2 = 0.5142$. Under the conservative assumption of $R^2_{\max} = 1.3 \times R^2_{\text{full}}$, we obtain $\delta = 11.17$, far exceeding the threshold of 1. This implies that unobservable factors would need to be more than 11 times stronger than all observable controls combined to nullify our finding—an implausible scenario given the richness of our control set. Second, as shown in Panel B of Table 4, the PSM-DID estimate (0.0454, $p < 0.01$, Table 4 Col. 3) is virtually identical to the baseline TWFE estimate (0.045, $p < 0.05$, Table 2 Col. 2), with a difference of only 0.0004, confirming that observable selection bias does not drive the main result. Together, these tests establish that neither observable nor unobservable selection bias constitutes a viable threat to the internal validity of our findings (See Table 6).

Table 6. Robustness test.

	Restricted Model (DID Only, No Controls)	Full Model (+14 Controls)	Bias-Corrected Coefficient (β^*)
SCP Coefficient (β)	0.1282	0.0454 ** (2.64)	—
R-squared	0.0047	0.5142	—
$R^2_{\max}$ ($1.3 \times R^2_{\text{full}}$)	—	0.6685	—
δ (key statistic)	—	—	11.17
Threshold for robustness	—	—	$\delta > 1 \checkmark$

Interpretation: $\delta = 11.17 \gg 1$. Unobservable factors would need to be 11× stronger than all observable controls combined to nullify the treatment effect—an implausible scenario. t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$. $\checkmark$ indicates that the robustness criterion is satisfied.

4.4. Heterogeneity Analysis

On the one hand, cities in different regions have different factor endowments and external policy environments, which will affect the implementation effect of SCP. This paper employs grouped regression for heterogeneity analysis to identify issues within the current SCP and provide targeted recommendations for improving smart city development.

4.4.1. Intellectual Property Protection

The impact of SCP may be influenced by other local institutions and policies. The effectiveness of implementing SCP in cities with varying levels of intellectual property (IP) protection might differ. Adopting the method of Shen and Huang (2019), model (2) was constructed [62]. Given that the size of a city can affect the reliability of this indicator, it is necessary to adjust for city size.

$$IPP_{jt} = \frac{IPPCourt_{jt}/GDP_{jt}}{IPPCourt_{ct}/GDP_{ct}} \quad (2)$$

where IPP_{jt} , $IPPCourt_{jt}$, and GDP_{jt} represent the intellectual property protection level, the number of intellectual property cases concluded by courts, and the GDP of city j in year t , respectively. $IPPCourt_{ct}$ and GDP_{ct} represent the total number of intellectual property cases concluded by courts and national GDP in year t , respectively. The results show that the minimum, maximum, mean, and standard deviation of IPP are 0, 0.0255, 0.0034, and 0.0052, respectively. If a city's level of intellectual property protection is above the median, it is assigned a value of 1; otherwise, it is assigned a value of 0.

We find that the stronger the intellectual property protection (IPP) in pilot cities, the more effectively SCP can promote the TFP of enterprises. The development of smart cities relies on advanced technologies. High-tech innovations often involve significant R&D costs and long development cycles. If intellectual property is easily stolen or replicated, and innovators' rights are not adequately protected, it can undermine their incentives and interests. Furthermore, the construction and operation of smart cities rely heavily on big data analysis, with data becoming an increasingly important production factor [63]. Strong intellectual property protection is essential to safeguard its security and exclusivity. Only with such protection can data be effectively transformed into productive resources [29]. Furthermore, enterprises located in areas with strong intellectual property protection are more willing to share technology. This allows other enterprises in smart cities with strong IP protection to also use advanced technologies to improve their own production efficiency. Finally, regions with strong intellectual property protection can attract more domestic and foreign investment. This not only provides ample funding for SCP but also brings advanced technologies [64]. To formally test whether the SCP effect differs significantly between high- and low-IP protection cities, we conduct a between-group coefficient difference test. The result shows a significant difference ($\chi^2 = 3.04$, $p < 0.05$), confirming that the productivity-enhancing effect of SCP is significantly stronger in cities with stronger intellectual property protection.

4.4.2. Nature of Property Rights

During the SCP implementation, enterprises with different ownership types exhibit notable variations in participation and benefits. Based on ownership and control rights, the full sample is divided into two groups: SOEs and non-SOEs. The regression results reveal that for the SOE group, the SCP coefficient is significantly positive, while for the non-SOE group, it is positive but not statistically significant. This indicates that the SCP has a significant impact on the TFP of SOEs, but its effect on non-SOEs is less pronounced. First, SOEs can prioritize access to the substantial resources and policy benefits associated

with SCP. The implementation of SCP requires strong government support and resource investment. SOEs, with their close ties to the government, can gain priority access to R&D funding and investment opportunities for smart city projects. Moreover, SCP requires the construction of significant infrastructure and public services, areas in which SOEs have a considerable advantage and market competitiveness. In bidding processes, SOEs are more likely to win contracts based on their inherent competitive strength [7]. Second, the development strategies of SOEs are often aligned with government plans. During the implementation of SCP, SOEs actively respond to government calls, engaging in initiatives for digitalization, automation, smart technologies, and green transformations. In contrast, the development strategies of non-SOEs are generally driven by profit maximization. Faced with resource constraints and uncertain future prospects, non-SOEs are less likely to undergo transformation or upgrades [65]. Third, SOEs have a stronger capacity to bear risks and possess higher innovation capabilities. On the one hand, SOEs often operate in monopolistic markets, and with the backing of the government, they face lower business risks. On the other hand, SOEs have stable sources of funding. Therefore, under the SCP framework, SOEs are more proactive in innovation, which in turn helps improve their TFP [66]. The between-group difference test confirms that the SCP coefficients for SOEs and non-SOEs differ significantly ($\chi^2 = 0.031$, $p < 0.05$), supporting the conclusion that SCP has a significantly stronger effect on SOEs than on non-SOEs.

4.4.3. Manufacturing and Non-Manufacturing

There are significant differences in product, service and technology dependence among different industries. This will also affect the implementation effect of SCP. We classify the entire sample into manufacturing and non-manufacturing sectors to further explore the efficiency-enhancing effects of the SCP on different types of enterprises. The results show that SCP significantly boosts TFP in both manufacturing and non-manufacturing industries, with a more pronounced effect in the non-manufacturing sector. The core technologies of SCP have broader and more immediate application potential in non-manufacturing industries, especially in finance, information services, logistics, retail, and other service-oriented sectors. These industries rely more heavily on information transmission, customer matching, transaction efficiency, and digital service delivery. Therefore, digital infrastructure, smart logistics, big data analytics, blockchain applications, and digital payment systems can be quickly embedded into their business processes, thereby improving operational efficiency and productivity. Manufacturing firms can also benefit from SCP, but the productivity effect is relatively smaller in the short and medium term. Manufacturing productivity improvement usually requires equipment upgrading, production-line transformation, and deeper integration of digital technologies into physical production processes. These changes involve higher fixed costs and longer adjustment cycles [67]. In addition, manufacturing firms have long received industrial policy support and often already possess a certain level of automation and informatization, so the marginal effect of SCP may be smaller than that for non-manufacturing firms [68–70]. Finally, SCP can generate more immediate benefits for non-manufacturing firms through improvements in information flow and service efficiency, whereas its effect on manufacturing firms may appear with a longer lag [48]. Therefore, the productivity-enhancing effect of SCP is more pronounced in the non-manufacturing sector. The between-group difference test confirms that the SCP coefficients differ significantly between manufacturing and non-manufacturing firms ($\chi^2 = 0.060$, $p < 0.01$). Consistent with this, the coefficient for non-manufacturing firms (0.079) is significantly larger than that for manufacturing firms (0.029), indicating that the productivity-enhancing effect of SCP is significantly more pronounced in the non-manufacturing sector (See Table 7).

Table 7. Heterogeneity analysis.

	(1) Strong Intellectual Property Protection TFP	(2) Weak Intellectual Property Protection TFP	(3) SOEs TFP	(4) Non-SOEs TFP	(5) Manufactur- ing TFP	(6) Non-Manu- facturing TFP
SCP	0.0658 ** (2.48)	0.0350 (1.45)	0.0390 * (1.65)	0.0306 (1.24)	0.0290 *** (2.81)	0.0793 *** (4.43)
LEV	0.1535 * (1.80)	0.1007 (1.35)	0.1328 (1.42)	0.1129 (1.55)	0.1110 *** (3.98)	0.0824 * (1.80)
AGE	0.2868 *** (3.72)	0.1356 (1.56)	0.1952 ** (2.04)	0.1839 ** (2.53)	0.1812 *** (5.58)	0.3180 *** (5.79)
SIZE	0.4814 *** (22.19)	0.4794 *** (26.30)	0.4566 *** (19.33)	0.4705 *** (26.32)	0.4488 *** (71.27)	0.4801 *** (48.22)
FAR	−1.4519 *** (−13.43)	−1.1014 *** (−13.08)	−1.0876 *** (−11.58)	−1.4353 *** (−15.91)	−1.0685 *** (−33.35)	−1.3582 *** (−25.99)
TOP10	−0.0009 (−1.03)	0.0008 (0.87)	−0.0007 (−0.73)	0.0007 (0.77)	−0.0011 *** (−3.23)	0.0005 (0.99)
ORG	0.2112 *** (19.44)	0.2061 *** (18.61)	0.1884 *** (15.01)	0.2159 *** (21.24)	0.1960 *** (32.92)	0.2270 *** (28.90)
CR	−0.0166 *** (−3.59)	−0.0129 *** (−3.07)	−0.0150* (−1.80)	−0.0160 *** (−4.66)	−0.0117 *** (−6.48)	−0.0227 *** (−6.91)
INDE	0.0003 (0.19)	−0.0007 (−0.49)	0.0006 (0.42)	−0.0001 (−0.09)	−0.0011 * (−1.71)	0.0008 (0.68)
ROE	0.3736 *** (7.33)	0.3685 *** (7.75)	0.4924 *** (10.76)	0.2962 *** (6.06)	0.4137 *** (21.50)	0.3737 *** (11.25)
PD	0.0001 (1.59)	0.0001 (0.65)	0.00002 (0.31)	0.0001 ** (2.39)	0.0000 (1.07)	0.0002 *** (5.82)
INDS	−0.0305 (−1.01)	−0.0176 (−0.56)	0.0119 (0.46)	−0.0143 (−0.53)	−0.0084 (−0.72)	−0.0382 ** (−2.36)
FINA	−0.0163 (−0.37)	−0.0112 (−0.56)	−0.0137 (−0.53)	0.0156 (0.60)	−0.0297 *** (−2.61)	0.0177 (0.81)
GOV	0.3001 (0.80)	−0.1140 (−0.46)	−0.0561 (−0.17)	0.0869 (0.33)	0.1697 (1.42)	−0.5441 ** (−2.25)
RGDP	0.0259 (0.90)	0.0350 (0.69)	0.0557 (1.47)	0.0206 (0.64)	0.0246 (1.63)	0.0782 *** (2.88)
Constant	3.5882 *** (8.35)	3.6628 *** (6.45)	3.6701 *** (7.35)	3.7444 *** (9.07)	4.0745 *** (22.12)	2.8238 *** (8.40)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Differences be- tween groups	3.0408 ** ($p < 0.05$)		0.0308 ** ($p < 0.05$)		−0.0603 *** ($p < 0.01$)	
N	13,143	12,803	10,590	14,994	16,431	9515
R ²	0.5975	0.6098	0.5770	0.6190	0.6180	0.5474

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included.

5. Mechanism Analysis

To further identify the channels through which the smart city policy affects corporate total factor productivity, this section conducts a formal mediation analysis. The previous mechanism regressions only examined whether the smart city policy affected the proposed mediating variables, which captured the first stage of the mechanism but did not

directly test the indirect effects. In response to this limitation, we adopt a more complete mediation framework. Following the Baron–Kenny approach, we examine whether each mediating variable affects corporate TFP after controlling for SCP and other covariates. More importantly, we calculate the indirect effect as the product of the coefficient from SCP to the mediator and the coefficient from the mediator to TFP. Bootstrap procedures with 5000 replications are used to obtain the standard errors, *z*-statistics, *p*-values, and 95% confidence intervals of the indirect effects, thereby providing a more rigorous statistical test of the mediation mechanisms.

In addition, the selection of the mechanism variables is grounded in a unified theoretical framework. Smart city construction fundamentally reshapes the urban economic environment through digital infrastructure, information integration, and governance modernization. These changes primarily affect firms through three core dimensions: factor allocation, cost structure, and investment decision-making. Specifically, human capital structure captures the reallocation and upgrading of labor inputs; enterprise cost reflects the reduction in transaction and operational frictions; and investment efficiency represents improvements in capital allocation under reduced information asymmetry. These channels jointly constitute the most direct and economically meaningful pathways through which smart city policies influence firm-level productivity [71].

Table 8 reports the formal mediation test results. Panel A presents the Baron–Kenny regression results, while Panel B reports the bootstrapped indirect effects. The results show that human capital structure, enterprise cost, and investment efficiency all constitute significant mediating channels through which the smart city policy improves corporate TFP. The 95% bootstrap confidence intervals of all three indirect effects exclude zero, indicating that the corresponding mediation effects are statistically significant.

5.1. Human Capital Structure

Columns (1) and (2) of Table 8 report the mediation test results for human capital structure. HC is measured by the proportion of employees with a bachelor's degree or higher. Column (1) shows that the coefficient of SCP is significantly positive when HC is used as the dependent variable. This indicates that the smart city policy significantly increases the share of highly educated employees within enterprises. Column (2) further shows that HC has a significantly positive effect on corporate TFP after controlling for SCP and other covariates. Therefore, the optimization of human capital structure is an important transmission channel through which the smart city policy improves corporate productivity.

The bootstrap results in Panel B further confirm this mediating mechanism. The estimated indirect effect of SCP on TFP through HC is 0.0015, with a bootstrap standard error of 0.0006. The *z*-statistic is 2.56, and the *p*-value is 0.010. The 95% bootstrap confidence interval is [0.0004, 0.0027], which excludes zero. This indicates that the human capital channel is statistically significant. In terms of economic magnitude, the mediating effect of HC accounts for 3.3% of the total effect. Therefore, Hypothesis 2b is supported.

This finding is consistent with the logic that smart city construction increases enterprises' demand for highly skilled labor. The development of smart cities promotes the expansion of emerging sectors such as information technology, intelligent manufacturing, and new energy vehicles, all of which require a more educated and technically capable workforce [72]. Meanwhile, smart city construction improves urban livability and public service quality, thereby enhancing the ability of cities to attract and retain skilled workers [73]. The accumulation of highly educated employees strengthens firms' knowledge absorption capacity, innovation capacity, and management efficiency, ultimately contributing to higher corporate TFP [74–76].

5.2. Cost Effect

Columns (3) and (4) of Table 8 report the mediation test results for enterprise cost. CER is measured by the cost-to-expense ratio, which reflects the cost burden faced by enterprises. Column (3) shows that the coefficient of SCP is significantly negative when CER is used as the dependent variable. This indicates that the smart city policy significantly reduces the cost-to-expense ratio of enterprises. Column (4) further shows that CER has a significantly negative effect on corporate TFP after controlling for SCP and other covariates. This means that a higher cost-to-expense ratio reduces enterprise productivity, while cost reduction contributes to the improvement of TFP.

The bootstrap results in Panel B confirm the existence of a significant cost-based mediating effect. The estimated indirect effect of SCP on TFP through CER is 0.0067, with a bootstrap standard error of 0.0023. The *z*-statistic is 2.84, and the *p*-value is 0.004. The 95% bootstrap confidence interval is [0.0021, 0.0113], which excludes zero. This indicates that cost reduction is a statistically significant channel through which the smart city policy improves corporate TFP. The mediating effect of CER accounts for 17.4% of the total effect, suggesting that the cost channel has relatively strong explanatory power among the tested mechanisms. Therefore, Hypothesis 2c is supported.

Economically, this result means that the smart city policy improves enterprise productivity partly by reducing operational frictions. Smart transportation, smart logistics, digital government services, and information-sharing systems enable firms to obtain market, production, and supply chain information more efficiently. These improvements reduce unnecessary resource consumption and lower the costs associated with procurement, production, logistics, and management [77]. Since excessive cost burdens constrain resource allocation efficiency and weaken productivity performance [78–80], the cost-reducing effect of smart city construction becomes an important pathway for improving corporate TFP.

5.3. Enterprise Investment Efficiency

Columns (5) and (6) of Table 8 report the mediation test results for enterprise investment efficiency. EIE measures the degree of inefficient investment, with a higher value indicating more serious investment inefficiency. Column (5) shows that the coefficient of SCP is significantly negative when EIE is used as the dependent variable. This indicates that the smart city policy significantly reduces inefficient investment and improves firms' investment efficiency. Column (6) further shows that EIE has a significantly negative effect on corporate TFP after controlling for SCP and other covariates. This means that inefficient investment reduces productivity, while the improvement of investment efficiency contributes to higher TFP.

The bootstrap results in Panel B further confirm this mediating mechanism. The estimated indirect effect of SCP on TFP through EIE is 0.0029, with a bootstrap standard error of 0.0012. The *z*-statistic is 2.37, and the *p*-value is 0.018. The 95% bootstrap confidence interval is [0.0005, 0.0053], which excludes zero. This indicates that the investment efficiency channel is statistically significant. The mediating effect of EIE accounts for 6.1% of the total effect. Therefore, Hypothesis 2d is supported.

This finding suggests that smart city construction improves corporate TFP by enhancing the quality of investment decisions. Through digital infrastructure, public data platforms, smart governance systems, and more efficient information transmission, smart cities reduce information asymmetry and uncertainty faced by enterprises. As a result, firms can identify investment opportunities more accurately and allocate capital more efficiently. By reducing inefficient investment and improving resource allocation efficiency, the smart city policy ultimately contributes to the improvement of corporate TFP [81,82].

Table 8. Mechanism analysis.

	(1) HC	(2) TFP	(3) CER	(4) TFP	(5) EIE	(6) TFP
Panel A: Baron–Kenny Regression Results						
SCP	0.0117 *** (3.92)	0.0453 *** (4.85)	−0.0076 *** (−3.14)	0.0384 *** (4.22)	−0.0038 ** (−2.42)	0.0474 *** (4.76)
HC		0.1324 *** (6.31)				
CER				−0.8795 *** (−35.42)		
EIE						−0.7597 *** (−16.97)
Control	Y	Y	Y	Y	Y	Y
Constant	0.1429 *** (2.64)	3.5228 *** (20.81)	1.0508 *** (23.90)	4.5092 26.95	0.1271 *** (4.50)	3.7595 *** (21.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	25,368	25,368	25,944	25,944	23,164	23,164
R ²	0.4973	0.6109	0.3273	0.6261	0.0807	0.6081
Panel B: Bootstrap Indirect Effects (5000 replications)						
Indirect Effect (SCP → M → TFP)	0.0015 **		0.0067		0.0029	
Bootstrap SE	(0.0006)		0.0023		0.0012	
z-statistic	2.56		2.84		2.37	
p-value	0.010		0.004		0.018	
95% Bootstrap CI	[0.0004, 0.0027]		[0.0021, 0.0113]		[0.0005, 0.0053]	
Percentage of Total Effect	3.3%		17.4%		6.1%	

Note: t-statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$. The same notation applies to the following tables. Y indicates that the variable/fixed effect is included.

6. Conclusion and Policy Implications

This paper treats the SCP as a quasi-natural experiment, using data from Chinese A-share listed companies and prefecture-level cities from 2007 to 2019. A DID model is constructed to examine the impact of SCP on the TFP of listed firms. In addition, we analyze the heterogeneity of this effect from both external macro-environmental and internal micro-characteristics perspectives. The results lead to the following conclusions. First, SCP significantly promotes the TFP of A-share listed firms located in pilot cities. Second, the heterogeneity analysis shows that the effect of SCP is stronger in regions with stronger intellectual property protection, as well as among SOEs and non-manufacturing listed firms. Third, the mechanism analysis shows that SCP improves corporate TFP mainly by optimizing human capital structure, reducing enterprise costs, and improving investment efficiency. These findings are consistent with the integrated theoretical framework developed in this paper. The positive baseline effect indicates that SCP improves the external technological and factor environment faced by firms, which is consistent with innovation diffusion theory and factor endowment theory. The cost-reduction channel is consistent with transaction cost theory, while the human capital and investment efficiency channels show how firms transform external digital resources into internal productivity-enhancing capabilities, which is related to the resource-based view. The heterogeneity results further

suggest that the effect of SCP depends on institutional conditions, ownership characteristics, and industry attributes.

Based on these conclusions, the following policy recommendations are proposed. First, the government should continue to strengthen the promotion and implementation of SCP. Since SCP significantly improves the TFP of listed firms in pilot cities, continued investment in smart city infrastructure, digital government services, smart transportation, and data-sharing platforms can help improve the external operating environment for firms. Second, intellectual property protection should be strengthened. The results show that intellectual property protection is an important condition for maximizing the effectiveness of SCP. Therefore, local governments should improve legislation and enforcement related to IP protection, especially in smart city pilot areas, to provide a more secure institutional environment for technology application and digital resource use. Third, differentiated policy support should be provided for different types of firms. Since SCP has a stronger effect on SOEs and non-manufacturing listed firms, governments should consider the differentiated needs of firms when designing policies. For non-SOEs, targeted support such as special subsidies, tax incentives, financing assistance, and access to public digital platforms could be provided to reduce barriers to participation in SCP. Fourth, smart city construction should be combined with human capital development. Local governments should continue to improve public services and living conditions through smart city construction, attract high-quality talent, and further enhance the human capital quality of firms.

It should be noted that the empirical analysis in this paper is based on Chinese A-share listed firms. Therefore, the conclusions mainly apply to listed companies. The effect of SCP on SMEs, non-listed firms, and ordinary private firms may differ because these firms may face stronger financing constraints, weaker access to policy resources, and lower digital transformation capacity. Future research can further examine whether the productivity effect of SCP also exists among non-listed firms and SMEs.

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Abbreviations

The following abbreviations are used in this manuscript:

SCP	Smart cities policy
TFP	Total factor productivity
DID	Difference-in-differences
SOEs	State-owned enterprises

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