Environmental Science and Pollution Research (2023) 30:97233–97252
https://doi.org/10.1007/s11356-023-29225-x

RESEARCH ARTICLE

# Smart city construction and green technology innovation: evidence at China's city level

Yanan Tang[1] · Yong Qi[1] · Tingting Bai[1] · Chi Zhang[1]

Received: 30 September 2022 / Accepted: 2 August 2023 / Published online: 17 August 2023


**Abstract**
In the context of China's economic and social transformation, smart cities are becoming increasingly important for green development. Based on pilot smart cities and panel data from 274 prefecture-level cities in China from 2006 to 2018, this paper mainly evaluates the impact of smart city construction (SCC) on green technology innovation (GTI). To analyze SCC mechanisms and heterogeneity, we used China's smart city pilots as a quasi-natural experiment. In terms of the influencing mechanism, SCC can promote GTI by enhancing the digital economy level. Meanwhile, the optimization allocation of resources, including labor, land, and capital, can effectively foster the promoting effect of SCC on GTI. Moreover, SCC has a spatial diffusion effect; it will not only promote local GTI, but also improve the level of GTI in neighboring cities. In terms of the heterogeneity analysis, smart cities, which present a large scales, rich human capital, and high-level infrastructure, have a strongly positive effect on GTI. This study provides important empirical evidence for the development of SCC and GTI.

**Keywords** Smart city · Green technology innovation · Digital economy · Resource allocation · Difference-in-differences · Causal mediation analysis model

## Introduction

In the context of global green competition, green development is necessary for sustainable economic and social development. Green technology innovation (GTI) is an important method of effectively alleviating resource pressure and ecological threats and thus is attracting wide attention (Fei et al. 2016). Smart cities use the internet, big data, and spatial geographic information to generate new information technology, integrate city-wide large data, efficiently configure city resources, realize intelligent urban management operations, and promote the harmonious urban sustainable development of a new model and future development direction of the digital economy (Kandt and Batty 2021). An empirical analysis of Chinese urban data that did not consider the influencing mechanism showed that smart city construction (SCC) was important for preventing and controlling COVID-19 in the context of the global pandemic (Yang and Chong 2021). Studies have shown that SCC can improve the local ecological environment quality, local science and technology level, resource allocation efficiency, and informatization degree (Chu et al. 2021; Huang et al. 2020). Therefore, vigorously promoting SCC and accelerating the transformation of the economy from factor- to innovation-driven has important practical significance for the realization of GTI-driven transformation.

GTI improves manufacturing processes, optimizes resource allocation, reduces environmental pollution, and improves production efficiency (Li et al. 2017a, b). However, cities often lack resources and motivation to implement GTI, thus leading to widespread market failures (Shen et al. 2020). GTI requires government financial support (Wu et al. 2022), labor input (Liao and Li 2022), urban construction (Li et al. 2022a, b, c), and digital transformation (Rowan et al. 2022). Environmental regulation is another important factor, and Porter's hypothesis indicated that it can stimulate GTI (Porter and Linde 1995). As the costs and benefits of GTI are asymmetrical in the short term, enterprises lack the motivation to implement GTI based on their own development needs. Government policies play an extremely important role in the process of GTI (Acemoglu et al. 2012), such

Responsible Editor: Philippe Garrigues

Yanan Tang
tang1999yanan@163.com

[1] School of Business Administration, Northeastern University, Shenyang 110169, China

as through SCC (Yao et al. 2020a, b). Compared with cities that have not implemented SCC, regions that have implemented SCC will enjoy more comparative advantages, such as digital infrastructure development, and they are also able to provide companies with material infrastructure and tax incentives to achieve digital transformation and thus realize GTI (Jiang et al. 2021).

As a developing country, China has made significant progress in GTI in recent years. Figure 1 shows the ratio of the number of green patent applications to the total number of patents in China from 2006 to 2018, which indicates that the percent of green patents has been increasing annually. However, few core patents, low patent quality, and limited achievement conversion rate has been observed. These problems have led to a disconnect between the level of GTI and the actual demand, which has restricted the development of the green economy (Show et al. 2018). Based on this, this paper aims to determine whether SCC can promote the level of GTI, identify the mechanism underlying this promoting effect, and reveal the heterogeneity of SCC in GTI. These findings will provide a better understanding of the economic effects of SCC and promote research on the factors influencing GTI by providing new theoretical support for the popularization of smart cities using green technology.

The possible contributions are as follows.

First, in terms of research content, this paper focuses on the enabling effect of SCC in the field of GTI, explores the driving effect and mechanism of SCC on GTI from the perspectives of digital economy and resource allocation, and expands the theoretical analysis framework of SCC and GTI. On the one hand, previous studies have explored that SCC aims to build an intelligent nation by completing digital transformation (Kar et al. 2019); this study takes digital economy as the internal channel to investigate its mediating effect on SCC and GTI. On the other hand, SCC plays an important role in optimizing resource allocation and improving factor productivity (Ryzhenkov 2016; Xia et al. 2021); this study integrates SCC, resource allocation (land, labor, and capital), and GTI into a unified framework and examines the external regulatory effects of resource allocation on SCC and GTI.

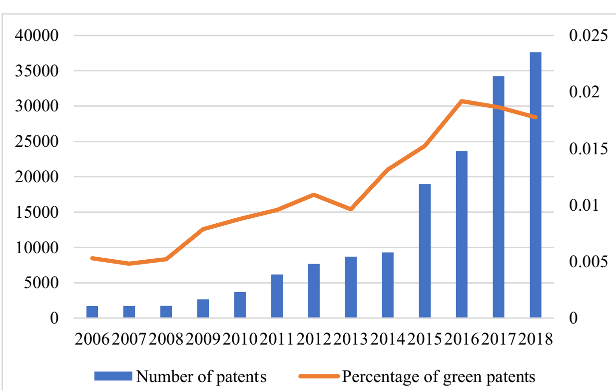


**Fig. 1** Trend chart of the number and proportion of green patent applications in China

Second, in terms of research methods, using the relatively exogenous event of SCC, this paper uses multiple robust methods such as different-in-difference model and instrumental variables to effectively identify the policy effect and mechanism of SCC on GTI. In addition, this paper uses the spatial difference-in-differences model to further investigate the "siphon effect" and "diffusion effect" of SCC on GTI in neighboring cities.

Finally, in terms of research sense, this study provides theoretical and empirical basis for further implementing SCC national strategy and stimulating the vitality of urban innovation. This paper determines the heterogeneity effect of SCC on GTI from the following aspects: city size and city characteristics (human, material and financial resources). It provides a new idea reference for discussing whether SCC, as a new urbanization model, can alleviate the "urban disease" problem brought by traditional urban construction and green development, so as to effectively solve the problem of unbalanced and uncoordinated regional economic development.

The remainder of the paper is organized as follows. Sect. "Institutional background and theoretical hypotheses" provides a literature review and presents the research hypotheses, which are based on a combination of previous literature results and research viewpoints. Sect. "Empirical strategy" describes the selection of the metrological model, index design, and data source description and expounds on the selection of the metrological model, research methods, and data structure. Sect. "Empirical results and discussion" provides the empirical test results and evaluation, an exploration of whether SCC can promote GTI, a discussion on the intermediary mechanism to explore the transmission mechanism between SCC and GTI, an analysis of the moderating effect and the influence mechanism between SCC and GTI, and the spatial spillover effect of SCC on GTI. Sect. "Heterogeneity analysis" presents the heterogeneity analysis and an exploration of the effect of heterogeneous of city sizes and characteristics. Sect. "Conclusions and policy implications"concludes the paper and provides policy suggestions. Sect. "Discussion and future" gives discussion and future of this study.

## Institutional background and theoretical hypotheses

### Institutional background

Since the early twenty-first century, the global economy and level of urbanization have increased rapidly. However, this development has brought some urban governance problems, such as resource shortages, environmental quality, and traffic congestion (Roscia et al. 2013). The United Nations launched the Sustainable Development Goals (SDGS) in 2015 to balance urban economic development with environmental protection, with an emphasis on environmentally sustainable, inclusive, and sustainable growth, which requires curbing pollution emissions while stimulating economic growth. As a result of the deep integration of urbanization and informatization, smart cities have become a model that combines environmental protection and sustainable economic development (Roscia et al. 2013).

With the rapid development of cloud technologies and big data, a global boom in the promotion of smart cities is witnessed; more than are 1000 smart cities are under construction worldwide. In 2004, South Korea launched the "UKorea" development strategy, which aims to build an environmentally friendly, digital, and seamlessly connected smart city based on information and communication technology. In 2006, many smart cities were launched in the UK, Ireland, Germany, and Europe. Japan launched the "I-Japan" strategy in 2009, and it focused on the intelligent management and operation of three public sectors: e-government, health, and education. Meanwhile, the USA established the first smart city that uses the Internet of Things to connect various public resources in the city and respond intelligently to residents' needs through analysis and integration of big data information. Similarly, China released the Interim Management Measures for the National Smart City Pilot program and the National Smart City Pilot Index System on December 5, 2012.

SCC in China has the following characteristics. First, it promotes the deep integration of the Internet, cloud computing, and big data. Its goal is to improve public information platforms and network infrastructure and promote a series of special applications, including smart transportation, smart logistics, smart communities, and smart finance. Second, it builds full mode and full response intelligent systems that "touches the whole body." Through the connection and integration of people, resources, government affairs, transportation, and communication in the city, the efficiency of resource allocation and urban management ability can be improved, while realizing high-quality urban development. Third, smart cities explore the priorities and development paths suitable for local SCC. The focus of the city construction and development of provinces' and cities' smart paths, that is the path used for smart city development, are not identical but are simultaneously promoted in the city master plan of action along with the local infrastructure construction, thus promoting smart education, healthcare, and traffic control for local SCC. After promulgating the smart city pilot policy, limited areas were included in the national smart city pilot list. Thus, this policy is equivalent to a "natural experiment" carried out in the economic field, and it presents obvious exogenous characteristics, thus providing a rare opportunity to effectively identify the impact of SCC on local GTI.

## Theoretical hypotheses

### Direct effect of SCC on GTI

As a new type of urbanization mode, smart cities have been widely recognized for their role in providing a feasible method of balancing economic growth and environmental protection. First, according to the Industrial Agglomeration Theory, SCC accelerates the popularization and penetration of digital technology; accelerates the agglomeration of economic factors such as talent, capital, and technology; and plays to the economic agglomeration effect to promote GTI (Wu et al. 2023).

Second, in the context of big data as a key factor of production, digital information technology in smart city pilot areas leads the development of industrial structure from the primary and secondary industries to tertiary industries with higher added value (Li et al. 2020; Pan et al. 2020), which contributes to the growth of green economy (Hao et al. 2023).

Finally, according to the signal theory, SCC helps local enterprises to release positive signals to external investors, introduce foreign economic activities, and enable local enterprises to have access to advanced green innovative technologies and apply them to their own green innovation research and development (Lee and Min 2015; Riillo 2017).

The first hypothesis for this study was proposed based on the above analysis:

*Hypotheses 1* SCC has a positive effect on GTI.

### SCC, digital economy, and GTI

Informatization and intelligent technologies are widely used in smart cities. Intelligent systems have penetrated traditional industries to realize smart medical care, smart homes, smart agriculture, and smart logistics. Due to the widespread use of the Internet, the renewal of products in traditional industries has been accelerated, the product structure and quality have been improved, and the efficiency of GTI has been improved in China (Yao et al. 2020b). Cities with new companies related to green and digital economy industries are more likely to be selected as smart city pilots, suggesting that smart cities could represent a policy to support local digital economy development (Manjon et al. 2022) .

In the era of the Internet, digital technology is the main force triggering a new round of scientific and technology revolution by facilitating information collection and increasing energy efficiency. Therefore, the important role of digital technology in the innovation and promotion of green technology must be recognized (Yao et al. 2020a, b). On the one hand, digital technology can be widely used in ecological environment information access, directly supporting ecological and environmental protection work; this is mainly reflected in the use of digital technology to increase the efficiency with which energy and resources are utilized, promote the use and development of renewable energy, and reduce the demand for energy and raw materials by allowing for virtual human interactions and communication (Qian et al. 2020). The trend of integration and innovation of the digital economy and green technology is obvious. Therefore, the digital economy is an important way to promote the green transformation of the global economy. China's green patents are mainly associated with "climate change mitigation" industries, which account for approximately 60% of the total green patents. The rapid increase in applications for information technology-based climate change mitigation patents, which accounted for 14.66% in 2016, reflects the increasing role of the digital economy in GTI development (Zhuang et al. 2020). SCC involves informatization, digitalization, and intelligentization of the whole society and thus plays an important role in promoting the degree of digitalization of cities and influences GTI.

The second hypothesis for this study was proposed based on the above analysis:

*Hypotheses 2* The digital economy is an important mechanism for transmitting the influence of SCC on GTI; that is, it plays an intermediary role in the influence of SCC on GTI.

### SCC, resource allocation, and GTI

Ensuring the necessary resources for realizing smart cities is an important challenge in the process of SCC (Angelidou 2017). The more optimized the allocation of resources, the more conducive the SCC to GTI. Starting with the three elements of land, labor, and capital at the city level, this paper explores the moderating role of resource allocation optimization on the effect of SCC on GTI.

**2.2.3.1. SCC, land resource allocation, and GTI** Previous studies have found that distorted land resource allocation modes will lead to over-investment in the industrial field and agglomeration of mid and low-end industries and hinder industrial upgrading and technology innovation (Zhou et al. 2022; Yu and Pan 2019). Therefore, land resource misallocation is not conducive to the construction and development of smart cities, which leads to low green incentive efficiency in the process of SCC. First, Chinese local governments take advantage of their monopoly position in the primary land market by selling a large amount of industrial land at low prices to attract investment and pursue high-speed economic growth while also selling less commercial service land at a high price, which hinders the green transformation of urban industries (Liu et al. 2021). Consequently, this creates an imbalance in land planning, which will hinder the planning and development of SCC. Second, in the process of land investment, local governments are mainly concerned about the scale of land investment rather than the quality (Yang et al. 2014), and they even deliberately introduce backward and highly polluting industries that can bring high output value at low prices (Huang and Du 2017). Therefore, when land resource misallocation is serious, local economic development often focuses on benefits but ignores the environment. It is difficult to drive local GTI only by relying on SCC. Based on the theoretical analysis, the following hypothesis is proposed:

*Hypotheses 3* With the increase of land resource mismatch, the inhibition effect of SSC on GTI will be strengthened.

**2.2.3.2. SCC, labor resource allocation, and GTI** Previous studies have found that when labor resource misallocation is serious, GTI activities in SCC cannot develop smoothly (Angelidou 2017) because labor resources are an important factor in innovation. If the allocation of labor resources is distorted in a city, it may lead to the loss and waste of talents, thus affecting the city's innovation ability (Benhabib and Spiegel 1994). In addition, when labor resource allocation is distorted, local research and development will be inhibited, resulting in a locking effect in terms of technology level (Zhang et al. 2011). Therefore, the implementation of SCC policies cannot be promoted, which impacts their influence on GTI. Based on the theoretical analysis, the following hypothesis is proposed:

*Hypotheses 4* With the increase of labor resource mismatch, the inhibition effect of SSC on GTI will be strengthened.

**2.2.3.3. SCC, capital resource allocation, and GTI** Previous studies have found that green innovation activities in SCC lack financial support when capital resource misallocation is serious. If capital allocation distortion is reduced, economic growth rate and green innovation efficiency can be improved with the same input (Ju et al. 2013) because capital resources can provide necessary financial support and input for GTI, including office space, equipment, and capital. The more capital that is accumulated, the more advanced the machinery equipment and technology level, which provides a good material foundation for the implementation of SCC. At this time, the government and local innovation subjects tend to increase R&D investment, thereby further improving the level of city's GTI. Moreover, when capital resource misallocation becomes larger, the financing cost and technology adjustment cost of local industry become higher, which restricts the sustainability of innovation investment of government and enterprises and ultimately inhibits the development of urban GTI activities (Ryzhenkov 2016). Based on the theoretical analysis, the following hypothesis is proposed:

*Hypotheses 5* With the increase of capital resource mismatch, the inhibition effect of SSC on GTI will be strengthened.

#### Spatial effects of SCC on the impact of GTI

Smart city is the development trend of new urbanization in the future, and non-pilot cities will also want to enter the list of SCC pilots through competition or imitation, so local governments will have a certain spatial correlation effect when formulating or implementing SCC (Wu et al. 2021). At the same time, interregional urban GTI has obvious spatial spillover effect, such as technology transfer and imitation effect (Peng et al. 2021; Qi et al. 2022). Therefore, it is necessary to study the influence of SCC on GTI from the perspective of spatial effect.

On the one hand, SCC has led to the rapid development of Internet information technology, accelerated the flow of innovation factors between regions, and further enabled the flow of innovation factors from regions with low marginal contribution rate to regions with high marginal contribution rate. This may lead to the tilt and concentration of resources towards the pilot cities, limiting the innovative development of surrounding cities, resulting in a "siphon effect" (Hu et al. 2023). On the other hand, the development of the Internet and digitization also speeds up the communication and collaborative innovation between cities. The establishment of pilot cities can exemplify the digital development of cities and provide corresponding technical support, thus generating a "diffusion effect" (Fang et al. 2022). Based on the theoretical analysis, the following hypothesis is proposed:

*Hypotheses 6.1* SCC have a siphon effect on GTI that causes a negative spatial overflow.

*Hypotheses 6.2* SCC have a diffusion effect on GTI that causes a positive spatial overflow.

## Empirical strategy

### Empirical method

#### Baseline model

This study takes the smart city pilot policy as the research object and conducts a quasi-natural experiment. From 2013 to 2015, China's Ministry of Housing and Urban–Rural Development officially announced three batches of SSC lists. Referring to the method of Bertrand and Mullainathan (2003), a continuous differential model was constructed as follows:

$$GTI_{it} = \beta_0 + \beta_1 treat \times post + \sum \lambda_j X_{it} + \mu_i + \nu_t + \varepsilon_{\mathrm{it}} \quad (1)$$

where $GTI_{it}$ is the dependent variable, which is defined as GTI in city $i$ in year $t$, and treat × post is the core independent variable, which represents the smart city pilot policy; its coefficient $\beta_1$ reflects the impact of SCC on GTI; $X_{it}$ represents the control variables affecting GTI, including regional industrialization degree, financial expenditure, population density, foreign direct investment level, and R&D investment; $\mu_i$ is the city fixed effect;$\nu_t$ is the time fixed effect; and $\varepsilon_{\mathrm{it}}$ is the random error term. The empirical analysis below was controlled at the city level to alleviate the error caused by the correlation between samples.

#### Parallel trend test for the difference-in-differences (DID) method

We need to ensure that the dependent variables have equal trends before the policy is enacted, but significantly different after the policy is enacted. This is an important premise for using the difference-in-differences (DID) estimation method. Considering this premise, we used the event research method of Jacobson et al. (1993) to formulate the estimation equation (Eq. 2):

$$GTI_{it} = \beta_0 + \sum_{2006}^{2018} \beta_t treat \times year + X_{it}\Phi + \mu_i + \nu_t + \varepsilon_{\mathrm{it}} \quad (2)$$

where $treat \times year$ is the core dummy variable, which is assigned a value of 1 if the city is a smart city pilot, and in the year in which the policy is implemented and beyond and a value of 0 otherwise, and $\beta_t$ reflects the differences in GTI between pilot cities and non-pilot cities before and after the smart city policy.

#### Causal mediation analysis model

This paper uses causal mediation analysis to analyze and test the mediation effect. Compared with traditional mediation effect analysis, causal mediation analysis, which is based on the potential outcome framework and the more general counterfactual framework (Holland 1986), provides general definitions and assumptions for determining causal effects in randomized and non-randomized studies. The regression model is constructed as follows:

$$digital_{it} = \delta_0 + \delta_1 T_i + \delta_2 treat \times post + \sum \phi_j X_{it} + \mu_i + \nu_t + \psi_{\mathrm{it}} \quad (3)$$

$$GTI_{it} = \theta_0 + \theta_1 T_i + \theta_2 treat \times post + \theta_3 digital_{it} + \sum \gamma_j X_{it} + \mu_i + \nu_t + \tau_{\mathrm{it}} \quad (4)$$

where digital is the intermediary variable. $\delta_1$, $\delta_2$, $\theta_1$, $\theta_2$, and $\theta_3$ are the parameters to be estimated. $T_i$ is the randomly generated treatment variable of a certain city in city $i$ in year $t$.

We performed a causal mediation analysis to study the mediating effect of the digital economy between SCC and GTI. On the one hand, it can solve the endogenous problem of mutual causation that may exist in traditional mediation analysis. On the other hand, we can measure how much of the causal effect of SCC on GTI is transmitted through the digital economy.

### Moderation effect model

To study the interaction effect caused by resource allocation between SCC and GTI, this study used the land resource misallocation (land), labor resource misallocation (*lab*), and capital resource misallocation (*cap*) indices to measure the rationality of resource allocation. The smaller the resource misallocation index, the bigger the resource allocation efficiency. The interaction terms of the three moderating and independent variables were plugged into model (5):

$$GTI_{it} = \alpha_0 + \alpha_1 treat \times post + \alpha_2 M_{it} + \alpha_3 treat \times post \times M_{it} + \sum \lambda_j X_{it} + \mu_i + \nu_t + \tau_{\mathrm{it}} \quad (5)$$

where $M_{it}$ is the moderating variable and $\alpha_3$ is the coefficient of the core interaction term. If $\alpha_3$ is significantly positive, then resource allocation negatively regulates the relationship between SCC and GTI and vice versa. To maintain consistency in the estimation of interaction terms in the regression model, all lower-order terms of the interaction terms need in the model. However, the model is heterogeneous timing DID, and individual fixed effect and time fixed effect have been controlled; *treat* $\times$ *post* cannot be divided into lower order.

### Spatial effect model

As a national project, does the green innovation-driven role of SCC have spatial spillover effect? If so, will it have a siphon effect that plunders innovation resources in neighboring regions, or a diffusion effect that accelerates the flow of information and innovation factors in neighboring regions? In order to further identify the spatial impact of SCC on GTI and the spillover effect of SCC, the Spatial Durbin model (SDM) is established as the initial model. Referring to Dubé et al. (2014), this paper constructs a spatial difference-in-differences model (SDID) for testing. The specific measurement model is set as follows:

$$GTI_{it} = \beta_0 + \left(\beta_1 + W\nu\right) \cdot treat \times post_{it} + \eta \mathrm{X} + W\eta\prime \mathrm{X} + \varepsilon_{it} \quad (6)$$

In model (6), $\beta_0$ is the intercept term. $W$ denotes spatial weight matrix, $W = I_t \otimes \overline{W}$, $I_t$ is a $T \times T$ dimensional matrix, and $\overline{W}$ is a $N \times N$ dimensional spatial weights matrix. If the two cities are adjacent, $W$ is 1; otherwise, $W$ is 0. $W\nu \cdot treat \times post$ represents the existence of spatial spillover effects. $\nu$ represents the size of the spillover effect. $\eta$ is the coefficient of control variables. $\eta\prime$ is the impact of other local exogenous variables on GTI in neighboring regions. $\varepsilon_{it}$ is the error term。

## Variable measurement

### Dependent variable (GTI)

In this paper, the dependent variable is the level of local GTI. For the GTI index, scholars have used R&D investment and the number of patents to measure R&D input and patent output (Bai et al. 2019; Li et al. 2018). However, the activities and production of R&D investment are characterized by a high failure rate and strong uncertainty. Compared with R&D investment, patent data can more directly reflect the innovation level of enterprises (Cornaggia et al. 2015). In addition, patent data are easy to obtain, and most existing studies use the number of patent filings and patents granted to measure the level of innovation. Following previous studies (Calel and Dechezleprêtre 2016), we use data on patent filings, instead of patents granted. The reason is that the granting of a patent requires an annual fee payment, and instability and lag are observed when using such data (Li and Zheng 2016); however, patent filing are less affected by human factors and more timely and thus can better reflect the innovation ability of a city (Xu et al. 2021).

Referring to Xu et al. (2021), we adopted the number of green patent applications in a city to represent the level of GTI in the city. Based on the International Patent Classification (IPC) code in the list of green patents issued by the World Intellectual Property Organization, this study obtained prefecture-level green patent data and measured the GTI level through patent retrieval by the State Intellectual Property Office (Tian et al. 2020).

**Table 1** Digital economy indicators constructed in this study

| System | Category | Indicator | Contribution |
|---|---|---|---|
| Digital economy | Internet development | Number of internet broadband access users per 100 people | Positive |
| | | Proportion of computer service and software employees in urban units | Positive |
| | | Total number of telecom services per capita | Positive |
| | | Number of mobile phone users per 100 people | Positive |
| | Digital financial inclusion | China Digital Inclusive Finance Index | Positive |

#### Key independent variable (smart city pilot policy)

Smart city pilot policies are a key independent variable used for the quasi-natural experiment. (1) The dummy variable treat was 1 for pilot city and 0 for non-pilot city. (2) The policy time dummy variable post was 0 before the establishment of the pilot and 1 following the establishment of the pilot. The smart city pilot list was obtained from China's Ministry of Housing and Urban–Rural Development. In early 2013, the country announced its first batch list, which included 90 national smart city pilots. In August 2013, the country announced 103 smart city pilots. In April 2015, the third batch of the national smart city pilot list was released, which included 84 cities. In this study, considering the problems of unbalanced regional development, this paper sampled cities using the following process: First, we considered the four municipalities belonging to the provincial administrative levels: Beijing, Shanghai, Tianjin, and Chongqing. The economic scale, resource endowment, and innovation ability in these municipalities are significantly higher than the ordinary level; therefore, samples from the four municipalities are excluded. Second, considering the problem of repeating treats, this paper excluded from the samples cities that only set up the pilot in a certain county or district of the prefecture-level city rather than the whole prefecture-level city. Finally, 274 prefecture-level city samples were selected for empirical analysis in this study.

#### Mediating variable (digital economy)

Following previous studies (Zhao et al. 2020; Zou and Deng 2022; Wang et al. 2022a, b), the digital economy is measured as a comprehensive indicator from the two aspects of internet development and digital financial inclusion. Using the method of Huang et al. (2019) as a reference, we measured internet development at the city level using four indicators: internet penetration rate (number of internet broadband access users per 100 people), relevant employees (proportion of computer service and software employees in urban units), relevant output (total number of telecom services per capita), and mobile phone penetration rate (number of mobile phone users per 100 people). The raw data for the above indicators were obtained from the China Urban Statistical Yearbook. Using the method of Guo et al. (2020) as a reference, we measure digital financial inclusion using the China Digital Inclusive Finance Index, which is jointly compiled by Peking University Digital Finance Research Center and Ant Financial Group. After standardizing the data of the above five indicators, the digital economy comprehensive development index obtained through dimension reduction processing via principal component analysis was denoted as digital. The specific digital economy is shown in Table 1.

#### Moderating variable

**(1) Land resource misallocation** This variable was measured by the ratio of commercial service land transfer price to industrial land transfer price according to Huang and Du (2017). The price of commercial and industrial land comes from China's land market network. Using the methods of Yu and Pan (2019) as a reference, this study used web crawler technology to obtain the market transaction data of commercial and industrial land for 274 prefectural-level cities from the China Land Market network and summed them to the city level according to the land use and transaction mode. The average prices of commercial and industrial land in prefecture-level cities were sorted.

**(2) Labor resource misallocation and capital resource misallocation** The labor resource mismatch index (*lab*) and capital resource mismatch index (*cap*) of each prefecture-level city were calculated using the methods of Chen and Hu (2011) and Ji and Zhu (2019), and the calculation formula is as follows:

$$lab = 1/\gamma_{Li} - 1 \tag{6}$$

$$cap = 1/\gamma_{Ki} - 1 \tag{7}$$

where $\gamma_{Li}$ and $\gamma_{Ki}$ are the labor and capital absolute distortion coefficients, respectively, and are calculated as follows:

$$\gamma_{Li} = \left(L_i/L\right)/(s_i\beta_{Li}/\beta_L) \tag{8}$$

$$\gamma_{Ki} = \left(K_i/K\right)/(s_i\beta_{Ki}/\beta_K) \tag{9}$$

**Table 2** Summary statistics of variables

| Variables | Definition | $N$ | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| treat × post | Smart city pilot | 3503 | 0.210 | 0.408 | 0 | 1 |
| *GTI* | GTI | 3503 | 0.0393 | 0.116 | 0 | 2.215 |
| digital | Digital economy | 2199 | 0. 9829 | 2.0514 | 0.0331 | 36.3392 |
| *lab* | Labor misallocation | 3503 | 3.436 | 1.947 | 0 | 23.67 |
| *cap* | Capital misallocation | 3503 | 0.853 | 0.821 | 0 | 6.790 |
| land | Land misallocation | 3426 | 8.962 | 45.84 | 0.00796 | 1481 |
| indus | industrialization level | 3503 | 48.44 | 10.62 | 0 | 85.64 |
| *gov* | Government intervention | 3503 | 0.209 | 0.228 | 0.0200 | 6.040 |
| *fdi* | FDI | 3503 | 0.0198 | 0.0263 | 0 | 0.780 |
| *den* | Population density | 3503 | 423.7 | 316.4 | 4.700 | 2648 |
| *sci* | R&D investment | 3503 | 1.371 | 1.379 | 0 | 20.68 |
| IV | Number of telephones in 1984 | 2764 | 10,156.1 | 15,252.4 | 525 | 108,166 |

where $s_i$ is the share of city $i$'s output among the total output, $L_i/L$ is the ratio of labor used in city $i$ among the total labor, $s_i\beta_{Li}/\beta_L$ is the proportion of labor used in city $i$ when labor is effectively allocated, $\beta_{Li}$ is the labor output elasticity of each city estimated using the Cobb–Douglas production function, and $\gamma_{Li}$ is the degree of misallocation of labor. $K_i/K$ is the ratio of capital used in the $i$ city to total capital, and $s_i\beta_{Ki}/\beta_K$ is the proportion of capital used in $i$ city when capital is effectively allocated. $\beta_{Ki}$ is the capital output elasticity of each city estimated using the Cobb–Douglas production function; $\gamma_{Ki}$ represents the degree of misallocation of capital. It is worth mentioning that this paper calculates the elasticity of labor and capital through Cobb–Douglas production function, which has a relatively solid theoretical foundation and is compared with other production functions, such as CES production function and ultra-logarithm production function, because it can minimize the estimation error of mean and variance (Cheng et al. 2001). The total output is the actual GDP of each city, labor input is expressed by the employment number of each city, and capital input is calculated using the perpetual inventory approach:

$$K_t = I_{it}/P_{it} + (1 - \delta_{it})K_{it-1} \tag{10}$$

where $I_{it}$ is the total social fixed asset investment of city $i$ in year $t$, $P_{it}$ is the fixed asset investment price index of city $i$ in year $t$, and $\delta_{it}$ is the depreciation rates, which references the commonly used value in extant literature (9.6%). The raw data for the above indicators are from China Urban Statistical Yearbook.

### Control variables

Based on the factors influencing GTI (Choi 2010; Chun et al. 2015; Duggal et al. Saltzman and Klein, 2007), this paper selected the following control variables:

(1) Industrial level (*indus*). This variable is the ratio of the added value of the secondary industry to GDP.
(2) Foreign direct investment (*fdi*). This variable is the proportion of the total foreign direct investment actually used in each city's GDP (Peng 2020).
(3) Population density (*den*). This variable is the log of the population per unit of administrative area at the end of the year.
(4) Government intervention (*gov*). This variable is the ratio of government fiscal expenditure to regional GDP (Dong et al. 2020).
(5) R&D investment (*sci*). This variable is determined by multiplying the ratio of GDP of prefectures and provinces by the amount of R&D investment in the provinces (Wang and Shi 2019).

Table 2 shows descriptive statistics of the variables. All nominal variables were analyzed based on the constant price in 2000. To eliminate the dimension effect, the value of GTI was divided by 10,000 based on the raw data and measured by the number of green patents.

## Data

This study used prefecture-level data from 2006 to 2018 for analysis. Urban data for the basic regression in the sample are from the China Urban Statistical Yearbook. The data in the mediation effect model are from China Urban Statistical Yearbook and China Digital Financial Inclusion Index. The data in the moderation effect model are from the China Urban Statistical Yearbook and China Land Market Network. To eliminate the error caused by uneven development among prefecture-level cities, cities with incomplete data and the four major municipalities were excluded. Subsequently, we obtained 3503 observations in 274 cities.

**Table 3** Baseline regression results

| Variables | (1) *GTI* | (2) *GTI* | (3) *GTI* | (4) *GTI* | (5) *GTI* | (6) *GTI* |
|---|---|---|---|---|---|---|
| treat × post | 0.0537*** (0.0115) | 0.0473*** (0.0101) | 0.0410*** (0.0087) | 0.0415*** (0.0087) | 0.0400*** (0.0085) | 0.0392*** (0.0083) |
| *den* | | 0.0010*** (0.0003) | 0.0010*** (0.0002) | 0.0009*** (0.0002) | 0.0009*** (0.0002) | 0.0009*** (0.0002) |
| *sci* | | | 0.0272*** (0.0078) | 0.0271*** (0.0077) | 0.0266*** (0.0076) | 0.0269*** (0.0077) |
| *fdi* | | | | −0.3512** (0.1600) | −0.3009* (0.1574) | −0.3076** (0.1485) |
| *gov* | | | | | 0.0379*** (0.0123) | 0.0383*** (0.0134) |
| indus | | | | | | 0.0011*** (0.0004) |
| Constants | 0.0017 (0.0048) | 0.4107*** (0.1032) | 0.3887*** (0.0920) | 0.3792*** (0.0915) | 0.3740*** (0.0918) | 0.3225*** (0.0951) |
| YearFE | YES | YES | YES | YES | YES | YES |
| City*FE* | YES | YES | YES | YES | YES | YES |
| Observations | 3503 | 3503 | 3503 | 3503 | 3503 | 3503 |
| $R^2$ | 0.2004 | 0.3726 | 0.4389 | 0.4460 | 0.4512 | 0.4548 |
| Adjusted$R^2$ | 0.1974 | 0.3701 | 0.4365 | 0.4435 | 0.4485 | 0.4519 |

***, **, and * represent $p<0.01$, $p<0.05$, and $p<0.1$, respectively. Numbers in parentheses represent robust standard errors. The empirical results are clustered at the city level. These values are the same in the tables below and will not be repeated.

## Empirical results and discussion

### Impact of SCC on GTI

#### Baseline results

The baseline regression was obtained from model (1), and the results are listed in Table 3. Time and individual fixed effects were controlled for in the model, and all regressions adopted the standard error clustered at the city level. In Column (1), the coefficient before treat × post is 0.0537 at the 1% significance level, which only contains the core variable. This demonstrates that SCC improve GTI at the prefectural level, which is consistent with Hypothesis 1. This indicates that SCC is conducive to innovation, which is consistent with the findings of Caragliu and Del Bo (2019). After the control variables of population density (*den*), R&D investment (*sci*), foreign direct investment (*fdi*), government intervention (*gov*), and industrialization level (indus) were added to Columns (2) to (6), the coefficients of the core independent variables were still credible at the 1% significance level, which indicates that SCC promote GTI.

#### Influence of SCC on different types of GTI

GTI can be divided into green invention innovation (GII) and green utility innovation (GUI). To further investigate the impact of SSC on different GTI, the empirical results of the two types of patents were taken as independent variables. In Table 4, Columns (1) to (2) show the regression results of SSC on GII, while Columns (3) to (4) show the regression results of SSC on GUI. Columns (1) and (3) show only the core independent variables, while Columns (2) and (4) show the results after adding control variables. The coefficients in columns (1) and (3) are 0.0227 and 0.0165 at the 1% significance level, respectively, which indicates that SSC plays an important role in promoting GII and GUI. Therefore, the following discussion no longer classifies GTI.

#### Parallel trend test results

Based on Model (2), the parallel trend test result is shown in Fig. 2. The parallel dynamic trend indicates that before SCC, the change trends of the experimental and control groups were consistent and there was no significant difference. However, one year after SCC, the regression coefficient of the experimental group was significantly positive and gradually deviated from the zero axis, indicating that the SCC significantly improves the level of GTI in the region. Meanwhile, the results in the last two years of the event study are not significant, indicating that the government needs to strengthen supervision, promote SCC comprehensively, and maintain its influence.

**Table 4** Regression results of different types of GTI

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | GII | GII | GUI | GUI |
| treat × post | 0.0309*** (0.0068) | 0.0227*** (0.0050) | 0.0228*** (0.0050) | 0.0165*** (0.0035) |
| *den* | | 0.0005*** (0.0001) | | 0.0005*** (0.0001) |
| *gov* | | −0.0216*** (0.0078) | | −0.0168*** (0.0057) |
| indus | | −0.0005** (0.0002) | | −0.0005*** (0.0002) |
| *fdi* | | −0.1725** (0.0838) | | −0.1351** (0.0655) |
| *sci* | | 0.0163*** (0.0047) | | 0.0105*** (0.0030) |
| Constants | 0.0008 (0.0027) | −0.1689*** (0.0501) | 0.0009 (0.0022) | −0.1536*** (0.0453) |
| YearFE | YES | YES | YES | YES |
| City*FE* | YES | YES | YES | YES |
| Observations | 3503 | 3503 | 3503 | 3503 |
| $R^2$ | 0.1776 | 0.4104 | 0.2156 | 0.4808 |
| Adjusted$R^2$ | 0.1746 | 0.4073 | 0.2127 | 0.4781 |

## Robustness tests

### IV estimation

Although the potential variables affecting GTI were controlled in this study, the problem of missing variables may not have been solved completely. Therefore, we need to rule out possible endogenous problems in the model to ensure the credibility of empirical conclusions. Referring to Cai et al. (2016), we use instrumental variable (IV) estimation as a robust test to solve the policy endogeneity problem. Good instrumental variables must be exogenous and correlated. Basic information infrastructure is essential for the construction of smart cities. Telephone wire dial-up access was the most basic method for constructing network infrastructure at the beginning of smart city creation. In general, cities with high telephone penetration have better digital economy development and are more likely to be included in the smart city pilot. A direct relationship was not observed between telephones in 1984 and local GTI, which met the requirements of instrumental variables. Therefore, we select the number of telephones in 1984 as the instrumental variable for SCC. To test the promotion effect of SCC on GTI, we adopted the two-stage least squares method. The number of telephones in 1984 represents sectional data and thus does not change with time. To determine that the selected instrumental variables have dynamic characteristics, the interaction term between the number and time trend of telephones in 1983 was constructed as the instrumental variable (Nunn and Qian 2014).

Table 5 shows the results. The coefficient of regression of the instrumental variable in the first stage was 0.0078 at the 1% significance level. The regression coefficient of treat × post in the second stage was 0.6861, which was also positive at the 1% significance level. This indicates that SSC still plays an important role in promoting GTI after excluding the interference of endogeneity. The *F* value of the regression of instrumental variables was 21.38 in the first stage, which is much higher than 10, thus showing that the weak instrumental variable test has been passed. Therefore, the conclusion that SSC can promote GTI is robust.

**Fig. 2** Parallel trend test

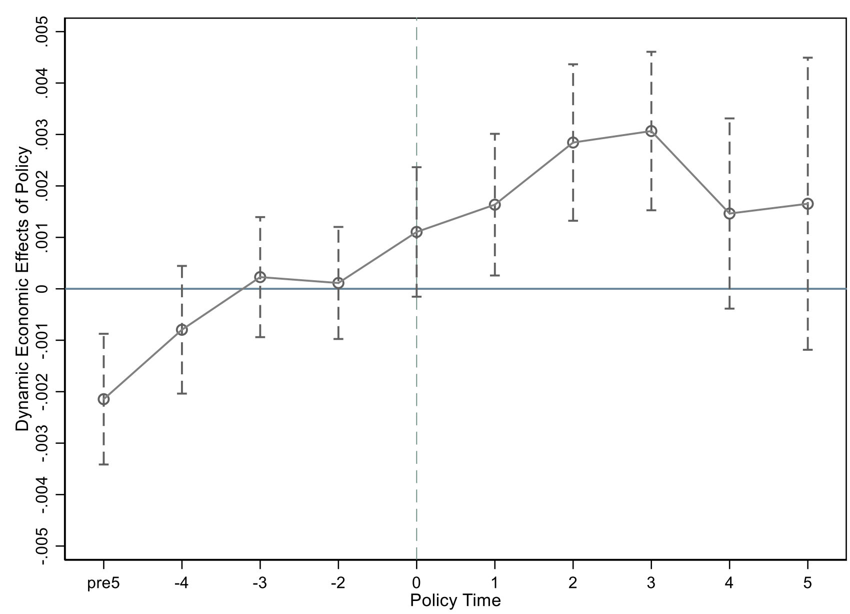

**Table 5** Instrumental variable regression results

| Dependent variable | First-stage regression | Second-stage regression |
|---|---|---|
| | treat × post | *GTI* |
| IV: Fixed-line penetration in 1984 | 0.0078***<br>(0.0019) | |
| treat × post | | 0.6861***<br>(0.2179) |
| Constants | −0.1175<br>(0.1649) | −0.2962*<br>(0.1239) |
| Control variables | YES | YES |
| YearFE | YES | YES |
| City*FE* | YES | YES |
| *F v*alue | 21.38 | - |
| Observations | 2764 | 2764 |
| $R^2$ | 0.5231 | 0.3110 |

### Post-propensity score matching DID estimation

The sample selection bias of smart cities, in which SSC may be influenced by the regional differences of economic and infrastructure, was also considered. To correct sample selection bias, this paper uses the Propensity Score Matching-DID (PSM-DID) method. Before performing PSM, it is necessary to test whether the variables satisfy the common support hypothesis. The inspection results are shown in Table 6, and they reveal that significant difference is not observed after matching, thereby indicating that PSM-DID is feasible.

New regression results were obtained after re-matching the samples. A comparison of the treatment and control groups showed that the different variables with mean differences were not significant at the 1% level, which indicated that the treatment and control groups were consistent. We selected the regional industrialization degree, fiscal expenditure, population density, level of foreign direct investment, R&D investment, and per capita real GDP as the matching variables according to the 1:1 nearest neighbor matching method with back sampling. The treatment groups were matched year by year. Columns (1) and (2) in Table 7 show the regression results of the new samples matched using the PSM method. The independent variable is the amount of GTI. In addition, we change the matching method to indicate that the results are robust. Columns (3) and (4) show the radius matching results, while columns (5) and (6) show the kernel matching results. The results show that the coefficients of SCC are all significant. Thus, SCC still significantly promotes GTI after considering the sample selection bias.

### Eliminating the impact of traditional city construction

To ensure the robustness of the regression results, we discuss city policies that may affect GTI. Before the smart city pilot was launched, urban development was driven by urbanization. The higher the urbanization level, the better economic development in the city. Urbanization is a powerful driving force for sustainable economic growth and inevitable trend in social development. Technology innovation and urbanization levels interact with each other in the process of rapid urbanization. Therefore, the effect of interference by traditional city construction on GTI must be considered. The urbanization rate (urban) is an important indicator that reflects the level and process of urbanization. This study measured the proportion of the city's permanent urban population to the total urban population. The results show that the coefficients of the core independent variables were always positive and significant in Table 8. This means that traditional urban construction did not influence the significance level of the baseline regression results, thus excluding the interference of other policies and verifying the robust of the baseline regression results.

## Causal mediation effect analysis

Using the causal mediation analysis method, this paper tests whether SCC has a mediating effect on GTI through the digital economy. Referring to Hicks and Tingley (2011), we used Stata software to generate treatment variable T and then randomly generated data into experimental group and control group, where 1 represented the experimental group and 0 represented the control group. The "medeff" command was used to test the causal mediation effect, and the regression results were shown in Table 9. Column (1) shows that the coefficient of treat × post is significantly positive at the 1%

**Table 6** PSM-DID method suitability test (common support hypothesis)

| Variable | Mean of the experimental group | Mean of the experimental group | Difference | *T* value | *P* value |
|---|---|---|---|---|---|
| *den* | 403.202 | 381.814 | 21.388 | 0.65 | 0.5145 |
| *sci* | 1.257 | 1.317 | 0.061 | 0.41 | 0.6813 |
| *fdi* | 0.015 | 0.016 | 0.001 | 0.59 | 0.5551 |
| *gov* | 0.474 | 0.476 | 0.002 | 0.03 | 0.9739 |
| indus | 3.006 | 3.104 | 0.098 | 0.64 | 0.5245 |

**Table 7** PSM-DID estimation results

| | Nearest neighbor matching | | Radius matching | | Kernel matching | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *GTI* | *GTI* | *GTI* | *GTI* | *GTI* | *GTI* |
| treat × post | 0.0129**<br>(0.0051) | 0.0107**<br>(0.0052) | 0.0122**<br>(2.3812) | 0.0103**<br>(1.9851) | 0.0153**<br>(2.5096) | 0.0113*<br>(1.8757) |
| *den* | | 0.0014***<br>(0.0004) | | 0.0014***<br>(3.3759) | | 0.0014***<br>(3.9277) |
| *gov* | | 0.0391***<br>(0.0087) | | −0.0432***<br>(−3.9346) | | −0.0577***<br>(−5.1982) |
| indus | | 0.0001<br>(0.0003) | | 0.0001<br>(0.3294) | | 0.0002<br>(0.6098) |
| *fdi* | | −0.0804<br>(0.0651) | | −0.0754<br>(−1.1809) | | −0.1766*<br>(−1.6672) |
| *sci* | | 0.0171**<br>(0.0080) | | 0.0170**<br>(2.1352) | | 0.0148**<br>(2.1671) |
| YearFE | YES | YES | YES | YES | YES | YES |
| City*FE* | YES | YES | YES | YES | YES | YES |
| Constants | 0.0336***<br>(0.0043) | 0.5699***<br>(0.1727) | 0.0348***<br>(7.9268) | −0.5785***<br>(−3.2864) | 0.0449***<br>(8.4816) | −0.6072***<br>(−3.6836) |
| Observations | 1614 | 1614 | 1614 | 1614 | 1614 | 1614 |
| $R^2$ | 0.1553 | 0.4235 | 0.1580 | 0.4253 | 0.1526 | 0.3647 |
| Adjusted$R^2$ | 0.1521 | 0.4195 | 0.1548 | 0.4213 | 0.1495 | 0.3605 |

**Table 8** Eliminating the impact of other policies

| | (1) *GTI* | (2) *GTI* | (3) *GTI* | (4) *GTI* | (5) *GTI* | (6) *GTI* |
|---|---|---|---|---|---|---|
| treat × post | 0.0464*** (0.0118) | 0.0446*** (0.0111) | 0.0423*** (0.0103) | 0.0428*** (0.0104) | 0.0416*** (0.0101) | 0.0409*** (0.0101) |
| urban | 0.0002 (0.0005) | 0.0003 (0.0005) | 0.0002 (0.0004) | 0.0002 (0.0004) | 0.0002 (0.0004) | 0.0002 (0.0004) |
| *den* | | 0.0011*** (0.0004) | 0.0010*** (0.0003) | 0.0010*** (0.0003) | 0.0010*** (0.0003) | 0.0010*** (0.0003) |
| *sci* | | | 0.0219*** (0.0083) | 0.0220*** (0.0083) | 0.0216*** (0.0082) | 0.0217*** (0.0082) |
| *fdi* | | | | −0.2130* (0.1157) | −0.1330 (0.1049) | −0.1480 (0.1046) |
| *gov* | | | | | 0.0498*** (0.0120) | 0.0514*** (0.0115) |
| indus | | | | | | −0.0007 (0.0005) |
| _cons | 0.0966*** (0.0275) | 0.5777*** (0.1685) | 0.5324*** (0.1550) | 0.5230*** (0.1546) | 0.5155*** (0.1541) | 0.4831*** (0.1562) |
| YearFE | YES | YES | YES | YES | YES | YES |
| City*FE* | YES | YES | YES | YES | YES | YES |
| Observations | 2083 | 2083 | 2083 | 2083 | 2083 | 2083 |
| $R^2$ | 0.2734 | 0.4198 | 0.4586 | 0.4609 | 0.4672 | 0.4680 |
| Adjusted$R^2$ | 0.2685 | 0.4156 | 0.4544 | 0.4565 | 0.4625 | 0.4631 |

level, indicating that SCC plays a positive role in promoting the digital economy. Column (2) shows that the coefficients for treat × post and digital are both significantly positive at the 1% level. In addition, the mediating effect value of digital economy is 0.0014, and the ratio of mediating effect to total effect is 28.04%. These findings indicate that digital economy plays a partial intermediary role in the process of SCC promoting GTI, thereby verifying hypothesis H2.

## Moderating effect analysis

Referring to the mainstream regulatory effect test method, we included control variables, independent variables, moderating variables, and interaction terms between independent variables and moderating variables in the model to determine their coefficients and significance changes. Table 10 shows the test results of the resource allocation adjustment effect of the three categories (land, labor, and capital). The variables land,*lab*, and *cap* represent the land resource misallocation, labor resource misallocation, and capital resource misallocation indices, respectively. Columns (1) to (3) show the moderating effects of land, labor, and capital misallocation on SCC and GTI. Table 10 shows that compared with the coefficient of treat × post in the baseline regression (Table 3), the coefficient before treat × post in the moderating regression result becomes negatively significant, small or insignificant, indicating that the effect of treat × post is absorbed by the added interaction term. In the analysis of moderating effects, we only focus on the coefficient of the interaction term.

In Column (1), the coefficient before treat × post is − 0.0212, which is negative significantly. The coefficient before treat × post × land is 0.0084, which is positive significantly at the 1% level. After comparing the results, we found that land resource optimization plays a significantly

**Table 9** Causal mediating effect of SCC on GTI through the digital economy

| variables | (1) digital | (2) *GTI* |
|---|---|---|
| T | 0.0282 (0.0517) | -0.0008 (0.0030) |
| treat × post | 0.4484*** (0.1147) | 0.0270*** (0.0051) |
| digital | | 0.0810*** (0.0031) |
| Controls | YES | YES |
| Constant | − 0. 8745*** (0.2418) | − 0.0467*** (0.0088) |
| ACME | | 0.0021 |
| Direct effect | | − 0.0007 |
| Total effect | | 0.0014 |
| Proportion of mediating effect | | 0.2804 |
| Observations | 2199 | 2199 |
| $R^2$ | 0.2236 | 0.8281 |

**Table 10** Regression analysis of the moderating effect of resource allocation

| | (1) *GTI* | (2) *GTI* | (3) *GTI* |
|---|---|---|---|
| treat × post | −0.0212* (0.0112) | 0.1235*** (0.0274) | −0.0112 (0.0115) |
| land | 0.0000 (0.0000) | | |
| treat × post × land | 0.0084*** (0.0019) | | |
| *lab* | | 0.0039* (0.0023) | |
| treat × post × *lab* | | −0.0298*** (0.0077) | |
| *cap* | | | 0.0083 (0.0065) |
| treat × post × *cap* | | | 0.0967*** (0.0262) |
| *den* | 0.0010*** (0.0003) | 0.0009*** (0.0002) | 0.0008*** (0.0002) |
| *gov* | −0.0361*** (0.0123) | −0.0406*** (0.0134) | −0.0375*** (0.0130) |
| indus | −0.0010*** (0.0004) | −0.0007** (0.0003) | −0.0005* (0.0003) |
| *fdi* | −0.3164** (0.1478) | −0.2263* (0.1188) | −0.2262** (0.1095) |
| *sci* | 0.0221*** (0.0068) | 0.0250*** (0.0071) | 0.0246*** (0.0069) |
| Constants | −0.3397*** (0.1066) | −0.3527*** (0.0912) | −0.2971*** (0.0761) |
| YearFE | YES | YES | YES |
| City*FE* | YES | YES | YES |
| Observations | 3415 | 3503 | 3503 |
| $R^2$ | 0.4996 | 0.4930 | 0.5184 |
| Adjusted$R^2$ | 0.4966 | 0.4901 | 0.5157 |

negative regulatory role between SCC and GTI, which violates Hypothesis 3. This may be because the inefficient allocation of land resources is usually manifested in the fact that the price of industrial land is much lower than that of commercial land, which is beneficial to the development of industry, whereas the patents of GTI are mostly in the field of industrial production (Hua et al. 2020).

In Column (2), the coefficient before treat × post is 0.1235, which is positive significantly at the 1% level. The coefficient before treat × post × *lab* is − 0.0298, which is significant at the 1% level, indicating that labor resource optimization positively regulates the relationship between SCC and GTI, which supports Hypothesis 4. This indicates that cities with mismatched labor resources will not foster the promoting effect of SCC on GTI because the improper allocation of labor resources reduces the total factor productivity and innovation output, which is consistent with the conclusions of Hsieh and Klenow's (2008).

In Column (3), the coefficient before treat × post is − 0.0112. The coefficient before treat × post × *cap* is 0.0967, which is significant at the 1% level, indicating that capital resource optimization plays a significant negative regulatory role between SCC and GTI, which indicates that Hypothesis 5 is not valid. This may be because the capital input is too high in traditional production fields (Rong and Gu 2016), while GTI mostly occurs in traditional production industries, such as heavy industries and pollution. Therefore, the higher the mismatch of capital resources, the stronger the promotion effect of SCC on GTI.

This finding does not mean that the mismatch of land and capital resources is favorable, which is due to the current low quality of China's industrial development and the actual conditions of extensive development. The misallocation of resources beneficial to industrial development promotes technology innovation in industry. China is also trying to improve the situation by upgrading and rationalizing its industry and improving the efficiency of resource allocation by upgrading its industrial structure.

## Further analysis: spatial spillover effect

### Spatial correlation and model suitability test

Although the above analysis has explained the positive effect of SCC on GTI, the estimation results may be biased because the spatial correlation among regions is ignored, which violates the Stable Unit Treatment Value Assumption. Therefore, the impact of SCC on GTI based on DID investigation needs to be further expanded. In this paper, spatial DID was introduced to test the impact of environmental protection interview on local and neighboring areas, namely, the spillover effect of GTI in the implementation of SCC. Before spatial regression, the variables should be spatially correlated. The test results of the Moran index in this paper are shown in Table 11. From 2006 to 2018, the Moran index is all greater than zero, and the *P* value test results are all less than 0.1, indicating that there is an obvious spatial positive correlation in SCC and GTI as a whole.

In addition, to verify the applicability of the spatial Durbin model, LR and Wald tests were carried out, and $P < 0.01$, showing that Spatial Durbin model (SDM) was rejected to degenerate into the spatial lag model and spatial error model. Combined with the Hausman test, the SDM with fixed effects is used to estimate the spillover effect of SCC on GTI. The specific results are presented in Table 12.

**Table 11** Distribution of Moran's I of GTI

| Year | Moran's I | *P* value |
|---|---|---|
| 2006 | 0.070 | 0.049 |
| 2007 | 0.107 | 0.003 |
| 2008 | 0.144 | 0.000 |
| 2009 | 0.146 | 0.000 |
| 2010 | 0.223 | 0.000 |
| 2011 | 0.215 | 0.000 |
| 2012 | 0.203 | 0.000 |
| 2013 | 0.179 | 0.000 |
| 2014 | 0.192 | 0.000 |
| 2015 | 0.215 | 0.000 |
| 2016 | 0.205 | 0.000 |
| 2017 | 0.215 | 0.000 |
| 2018 | 0.211 | 0.000 |

**Table 12** Suitability results of Spatial Durbin model

| Models | *T* value | *P* value |
|---|---|---|
| LR spatial lag | 106.82 | 0.000 |
| Wald spatial lag | 91.78 | 0.009 |
| LR spatial error | 103.81 | 0.000 |
| Wald spatial error | 119.76 | 0.000 |
| Hausman test | −227.64 | - |

The result of the Hausman test is negative; the basic assumptions of the RE model (Corr(x_it, u_i) = 0) cannot be satisfied. Therefore, FE should be used

### SDID results

Table 13 shows the estimated results of the Spatial Durbin model. The coefficients of treat × post are the spatial direct effect, and the coefficients of Wtreat × post are the spatial spillover effect of SCC on GTI. Rho is positive and passes the significance test, showing a significant spatial effect of SCC on GTI. In column (3), city fixed effect and time fixed effect have been controlled. And the coefficient of direct effect and spatial spillover effect of SCC on GTI is significantly positive. This indicates that local SCC will not only promote local GTI, but also improve the level of GTI in neighboring cities. This conclusion is in agreement with the conclusion of Hu et al. (2023) that SCC policy plays an exemplary role in neighboring cities and has positive spatial spillover effect. It is easy to form imitation effect between regions and has positive spatial spillover effect. Therefore, Hypothesis 6.2 is established; SCC have a diffusion effect on GTI that causes a positive spatial overflow.

**Table 13** SDID regression results

| | *GTI* (1) | *GTI* (2) | *GTI* (3) |
|---|---|---|---|
| treat × post | 0.033*** (0.004) | 0.047*** (0.004) | 0.036*** (0.004) |
| Wtreat × post | 0.014** (0.007) | 0.001 (0.010) | 0.023** (0.010) |
| rho | 0.343*** (0.020) | 0.171*** (0.023) | 0.273*** (0.021) |
| Control | YES | YES | YES |
| YearFE | NO | YES | YES |
| City*FE* | YES | NO | YES |
| Log likelihood | 5091.107 | 3764.593 | 5153.928 |
| Observations | 3562 | 3562 | 3562 |
| $R^2$ | 0.439 | 0.274 | 0.406 |

## Heterogeneity analysis

### Differences in city size

The analysis above shows that SCC can effectively promote GTI. However, it is important to explore whether heterogeneity occurs in the GTI effect for cities of different scales. Large-scale cities act as resource siphons and agglomeration centers and present higher allocation efficiency of GTI factors, which are beneficial for promoting GTI. However, most large cities face urban problems such as resource shortages, environmental pollution, and traffic congestion, which severely restrict the green development of the social economy (Wang and Zhou 2021).

The latest standards in the Notice on Adjusting the Standards for Classifying Cities issued by the State Council in 2014 were used to delimit the cities. These standards classify cities into three types, namely, small and medium-sized cities, big cities, and megacities (Sun et al. 2018; Li et al 2022a, b, c; Qi et al. 2022), and the classification standard is based on the number of permanent residents in urban areas: Cities with less than 1 million residents are classified as small and medium-sized cities, cities with more than 1 million residents and less than 5 million residents are classified as big cities, and cities with more than 5 million residents are classified as megacities. In this study, the samples are divided into different sizes to test heterogeneity, and the results are presented in Table 14. SCC in big cities and megacities had significant positive effects on GTI, whereas SCC in small and medium-sized cities did not have significant effects on GTI. These differences can be explained as follows. In small and medium-sized cities, SCC has not yet played a role as catalyst, which may be due to the fact that these cities have

**Table 14** Test results of heterogeneity of city size

| | (1) | (2) | (3) |
|---|---|---|---|
| | Cities with the last 1/3 of the population | Cities with the medium 1/3 of the population | Cities with the top 1/3 of the population |
| | *GTI* | *GTI* | *GTI* |
| treat × post | −0.0016 | 0.0423*** | 0.3856* |
| | (−0.4532) | (4.3370) | (1.9811) |
| *den* | −0.0001 | 0.0009*** | 0.0029* |
| | (−0.9638) | (3.1930) | (2.0130) |
| *sci* | 0.0034 | 0.0241*** | 0.0315 |
| | (1.6448) | (2.9393) | (0.7648) |
| *fdi* | 0.0352 | −0.7650*** | 1.7028 |
| | (1.1402) | (-3.1007) | (0.7695) |
| *gov* | −0.0058*** | −0.0545** | 1.3215 |
| | (−2.7962) | (−2.4357) | (0.9448) |
| indus | 0.0001 | −0.0016*** | 0.0016 |
| | (0.9163) | (−2.6190) | (0.3326) |
| Constants | 0.0156 | −0.3316** | −2.9426* |
| | (0.7702) | (−2.2720) | (−1.9411) |
| YearFE | YES | YES | YES |
| City*FE* | YES | YES | YES |
| Observations | 1553 | 1829 | 182 |
| $R^2$ | 0.2848 | 0.5604 | 0.6655 |
| Adjusted$R^2$ | 0.2764 | 0.5561 | 0.6285 |

relatively extensive economic development models and face greater downward pressure on the economy than large cities, and economic transformation and upgrading by SCC have not been observed in these cities (Cheng et al. 2022). Compared with small and medium-sized cities, large-scale cities present higher human capital and innovation capabilities and have stronger communication infrastructure and economic foundations, which are more conducive to SCC. The empirical results further confirm the heterogeneity of SCC on GTI according to the city size.

## Differences in city characteristics

Whether the impacts of urban characteristics differ based on different resource endowments among cities has significant practical significance and policy value. Starting with the human, material, and financial resources necessary for urban development, this study verifies whether heterogeneity occurs in the effect of GTI on cities of different characteristics. Based on Sun et al. (2018) and Li et al. (2022a, b, c) are referenced, the proportion of the number of students in regional institutions of higher learning in the total population at the end of the year was used to represent the level of urban human capital (*h*), the per capita road area of the region was used to represent the level of urban material resources (*inf*), and the proportion of local government's financial expenditure was used to represent the level of urban financial resources (*fis*). These three indicators were divided into two groups according to their average values. The value of the high-level group was set to 1, and the value of the low-level group was set to 0. This study compared the differences between the two groups using triple differences to determine the impact of different urban characteristics.

The results are presented in Table 15. In column (1), treat × post × hhigh is the triple difference interaction term between the high human resource level group and SCC, and it has a coefficient of 0.1036 and a significantly positive value at the 1% level, indicating that SSC has a more obvious promoting effect on GTI in cities with higher human capital levels. The level of human capital is an important support for SCC and GTI. If the level of human capital is low, then support for city construction and green innovation will be low (Li et al. 2022a, b, c).

Similarly, Column (2) represents the triple-difference empirical results for the group with high material resource levels. The results show that the promotion effect of the SCC on GTI in cities with high material resource levels was significantly improved by 12.94% compared with that in cities with low material resource levels. This indicates that the human capital level and traditional infrastructure construction are both important resource elements supporting SCC. In addition to information infrastructure, traditional infrastructure such as roads, railways, shipping, and airports plays a supporting role in SCC (Guo and Zhong 2022).

**Table 15** Test results of city characteristic heterogeneity analysis

| | (1) *GTI* | (2) *GTI* | (3) *GTI* |
|---|---|---|---|
| treat × post × hhigh | 0.1036***<br>(0.0180) | | |
| treat × post × *inf*high | | 0.1294***<br>(0.0196) | |
| treat × post × fishigh | | | −0.0329***<br>(0.0067) |
| *den* | 0.0009***<br>(0.0002) | 0.0008***<br>(0.0002) | 0.0009***<br>(0.0002) |
| *gov* | −0.0311***<br>(0.0106) | −0.0294***<br>(0.0102) | −0.0395***<br>(0.0133) |
| indus | −0.0006*<br>(0.0003) | −0.0008**<br>(0.0003) | −0.0011***<br>(0.0004) |
| *fdi* | −0.2209*<br>(0.1173) | −0.1979*<br>(0.1029) | −0.2729**<br>(0.1315) |
| *sci* | 0.0250***<br>(0.0071) | 0.0244***<br>(0.0068) | 0.0280***<br>(0.0080) |
| Constants | −0.3199***<br>(0.0949) | −0.2980***<br>(0.0944) | −0.3248***<br>(0.0969) |
| Observations | 3503 | 3503 | 3503 |
| $R^2$ | 0.5049 | 0.5336 | 0.4438 |
| Adjusted$R^2$ | 0.5024 | 0.5312 | 0.4409 |

In Column (3), the independent variable is the triple interaction term between the group with high financial resources and SCC, and its coefficient is – 0.0329, which is significant at the 1% level. This finding may be because the financial resources of local governments are primarily used for productive expenditures, such as capital construction, including the improvement of transportation infrastructure. Information infrastructure is still in its early stages, and the digitalization level is too low. At this time, smart cities should aim to construct and improve information infrastructure. Therefore, cities with high fiscal support are conducive for further improving the infrastructure for science, education, culture, health, and transportation, thus providing a guarantee for GTI (Li et al. 2021). The empirical results confirm the heterogeneous effect of SCC on GTI in terms of city characteristics.

## Conclusions and policy implications

This study used data from 274 prefecture-level cities in China from 2006 to 2018 as the sample, adopted SSC as a quasi-natural experiment, empirically tested the impact of SCC on GTI. The findings explained the heterogeneity of GTI effects and provided an empirical basis for developing smart cities worldwide, especially China, and accelerating the process of SCC. The results showed that SCC significantly promotes GTI in cities. This conclusion remained robust even after various endogenous treatments and robustness tests. Second, a causal mediation effect analysis revealed that SCC can promote local GTI by improving the digital economy level. Third, the moderating effect analysis revealed that labor resource mismatches have a negative moderating effect on the relationship between SCC and GTI. Fourth, the spatial spillover effect analysis revealed that SCC has policy spillover effects that can promote GTI in both local and neighboring cities. Finally, the heterogeneity analysis revealed that the impact of SCC on GTI is more obvious in cities with a larger size and higher level of human and material resources.

The following policy implications were drawn based on the conclusions of this study:

First, SCC can improve GTI, and the digital economy is an important mechanism. Therefore, to promote urban GTI, the government should vigorously promote SCC and improve the digital economy development level in cities. On the one hand, we should accelerate the high-quality development of information infrastructure; expand fiber broadband penetration, 5 g coverage, IPV6, and internet access; construct other new generation communication infrastructure; and improve the quality of communication network coverage and service. On the other hand, we should promote the deep integration of the digital economy with the real economy, accelerate the digital transformation of traditional manufacturing, and promote the deep integration of digital technology with manufacturing to foster high-quality GTI.

Second, regions with optimized factor resource allocation foster the promoting effect of SCC on GTI. Therefore, the government needs to focus on and guide rational resource allocation to stimulate the vitality of GTI. Based on the findings, the following suggestions are provided. (1) Promote the shift from government-led land allocation to market-led land allocation, establish a mechanism to coordinate the transfer prices of industrial and commercial land, and optimize the land transfer structure. (2) Strengthen labor force education and training, improve labor force skills and quality, and provide conditions for labor force transfer to under-allocated areas. At the same time, the whole society should accelerate the construction of information transmission channels and reduce the friction of employment information to facilitate the full free matching of labor and jobs within the whole society. (3) Preferential governmental policies should be developed, investment environment construction should be promoted, attraction of local capital should be enhanced, and optimization of capital resource allocation should be promoted through inter-regional cooperation and coordination.

Third, the spatial spillover effect of SCC on GTI has been demonstrated. To further exert the positive externalities, the policy support for the establishment of SCC pilots should be further strengthened, and the spatial diffusion effect of GTI should be strengthened both in time and space. At the same time, strengthen the development of digital technology in pilot cities; ensure the smooth flow of innovation elements such as data, knowledge, information, patents, funds, and talents; and promote the radiation of innovation factors to surrounding areas, forming a development trend of first mover driving late.

Finally, in view of the heterogeneity of the smart city scale and characteristics, cities should gradually implement policy guidance that matches the local resource systems. The implementation process of SCC should be flexible and adjusted for local conditions. For cities with a small size with low human, material, and financial resources, the government should (1) establish the perfect talented person mechanism invest in education, which can effectively enrich the regional talent reserve and improve the level of scientific research; (2) improve the city's infrastructure, such as traffic, accommodation, and communication; (3) and adjust the structure of fiscal expenditure to meet the needs of SCC and green economic development. However, for large-scale cities with abundant human, material, and financial resources, the transformation of scientific and technology achievements in pilot cities should be actively guided, and smart city pilot policies should be utilized to build an urban innovation ecosystem to promote high-quality urban development.

## Discussion and future

Large-scale cities have abundant innovation resources, such as skilled labor, capital, and technology, which facilitate the development of digital technologies and realization of green innovation through economic agglomeration effect (Zhu et al. 2019). However, can the impact of SCC on GTI be achieved in cities with small size, low human capital, and relatively low level of urban construction? The answer is no. Lopes and Oliveira (2017) researched SCC in Portugal and showed that small and medium-sized cities can also implement SCC policies by making personalized smart city plans that match local economic capabilities and development conditions, and they ultimately achieved sustainable development.

Because of available data limitations, knowledge reserves, and time constraints, this paper cannot discuss how smart cities may promote green innovation with an undominant external environment. However, cities with small-scale, low human capital, and relatively low level of urban construction will be taken as the research object of our next paper. Perhaps the government should focus on three aspects: improving traditional infrastructure, increasing financial support, and setting up policies to attract talent. In the future, we will discuss how talent subsidy policies in different locations affect the green innovation effect of smart cities.

**Author contribution** Yanan Tang: writing, reviewing, methodology, and editing.

Yong Qi: conceptualization, supervision, and funding acquisition.

Tingting Bai: data curation and software.

Chi Zhang: data curation.

**Funding** This study was supported by National Nature Science Foundation of China (no. 71873027), Humanities and Social Science Foundation of the Ministry of Education of China (no. 18YJA790063), and China Association for Science and Technology High-end Science and Technology Innovation Think Tank Youth Project (no.2121ZZZFLZB1207095).

**Data availability** The data used to support the findings of this study are available from the corresponding author upon request.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** All authors have given their consent to publish this research article.

**Conflict of interest** The authors declare no competing interests.

## References

Acemoglu D, Aghion P, Bursztyn L, Hemous D (2012) The environment and directed technical change. Am Econ Rev 102(1):131–166

Ahvenniemi H, Huovila A, Pinto-Seppä I, Airaksinen M (2017) What are the differences between sustainable and smart cities? Cities 60:234–245

Angelidou M (2017) The role of smart city characteristics in the plans of fifteen cities. J Urban Technol 24(4):3–28

Bai Y, Song S, Jiao J, Yang Y (2019) The impacts of government R&D subsidies on green innovation: evidence from Chinese energy-intensive firms. J Clean Prod 233:819–829

Benhabib J, Spiegel MM (1994) The role of human capital in economic development evidence from aggregate cross-country data. J Monet Econ 34(2):143–173

Bertrand M, Mullainathan S (2003) Enjoying the quiet life? Corporate governance and managerial preferences. J Polit Econ 111(5):1043–1075

Cai X, Lu Y, Wu M, Yu L (2016) Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. J Dev Econ 123:73–85

Calel R, Dechezleprêtre A (2016) Environmental policy and directed technological change: evidence from the European carbon market. Rev Econ Stat 98(1):173–191

Caragliu A, Del Bo CF (2019) Smart innovative cities: the impact of Smart City policies on urban innovation. Technol Forecast Soc Chang 142:373–383

Chen Y, Hu W (2011) Distortions, misallocation and losses: theory and application. China Econ Q 10(04):1401–1422 (in Chinese)

Cheng B, Liu S, Wu X (2001) An important property of the C-D production function. J Quant Technol 07:78–80 (in Chinese)

Cheng Z, Wang L, Zhang Y (2022) Does smart city policy promote urban green and low-carbon development? J Clean Prod 379:134780

Choi C (2010) The effect of the Internet on service trade. Econ Lett 109(2):102–104

Chu Z, Cheng M, Yu N N (2021) A smart city is a less polluted city. Technol Forecast Soc Chang, 172.

Chun H, Kim JW, Lee J (2015) How does information technology improve aggregate productivity? A new channel of productivity dispersion and reallocation. Res Policy 44(5):999–1016

Cornaggia J, Mao Y, Tian X, Brian W (2015) Does banking competition affect innovation? J Financ Econ 115(1):189–209

Dong Z, He Y, Wang H, Wang L (2020) Is there a ripple effect in environmental regulation in China?–Evidence from the local-neighborhood green technology innovation perspective. Ecol Indic 118:106773

Dubé J, Legros D, Thériault M et al (2014) A spatial difference-in-differences estimator to evaluate the effect of change in public mass transit systems on house prices. Transp Res Part b: Methodol 64:24–40

Duggal VG, Saltzman C, Klein LR (2007) Infrastructure and productivity: an extension to private infrastructure and it productivity. J Econ 140(2):485–502

Fang Z, Razzaq A, Mohsin M et al (2022) Spatial spillovers and threshold effects of internet development and entrepreneurship on green innovation efficiency in China. Technol Soc 68:101844

Fei J, Wang Y, Yang Y, Chen S, Zhi Q (2016) Towards eco-city: the role of green innovation. Energy Procedia 104:165–170 (in Chinese)

Guo Q, Zhong J (2022) The effect of urban innovation performance of smart city construction policies: Evaluate by using a multiple period difference-in-differences model. Technol Forecast Soc Chang 184:122003

Guo F, Wang J, Wang F, Kong T, Zhang X, Cheng Z (2020) Measuring China's digital financial inclusion: index compilation and spatial characteristics. China Economic Quarterly 19(04):1401–1418 (in Chinese)

Hao X, Li Y, Ren S et al (2023) The role of digitalization on green economic growth: does industrial structure optimization and green innovation matter? J Environ Manage 325:116504

Hicks R, Tingley D (2011) Causal Mediation Analysis. The Stata Journal 11(4):605–619

Holland PW (1986) Statistics and causal inference. J Am Stat Assoc 81(396):945–960

Hsieh CT, Klenow PJ (2009) Misallocation and manufacturing TFP in China and India. Quart J Econ 124(4):1403–1448

Hu J, Hu M, Zhang H (2023) Has the construction of ecological civilization promoted green technology innovation? Environ Technol Innov 29:102960

Hua L, Zhang T, Wang J, Liu Y (2020) Analysis of innovation evolution and layout characteristics in patents for Global Green technology. Sci Manag Res 38(06):149–158 (in Chinese)

Huang Z, Du X (2017) Government intervention and land misallocation: evidence from China. Cities 60:323–332

Huang Q, Yu Y, Zhang S (2019) Internet development and productivity growth in manufacturing industry: internal mechanism and China experiences. China Ind Econ 08:5–23 (in Chinese)

Huang H, Zhang M, Yu K, Gao Y, Liu J (2020) Construction of complex network of green infrastructure in smart city under spatial differentiation of landscape. Comput Commun 154:380–389

Jacobson LS, LaLonde RJ, Sullivan DG (1993) Earnings losses of displaced workers. Am Econ Rev 685–709

Ji S, Zhu Y (2019) Research on industrial agglomeration, environmental pollution and resource mismatch. Economist 06:33–43 (in Chinese)

Jiang X, Fu W, Li G (2020) Can the improvement of living environment stimulate urban innovation?——analysis of high-quality innovative talents and foreign direct investment spillover effect mechanism. J Clean Prod 255:1–12

Jiang H, Jiang P, Wang D, Wu J (2021) Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. Sustain Cities Soc 69:102809

Ju X, Lu D, Yu Y (2013) Financing constraints, working capital management and enterprise innovation sustainability. Econ Res J 1:4–16 (in Chinese)

Kandt J, Batty M (2021) Smart cities, big data and urban policy: towards urban analytics for the long run. Cities 109:102992

Kar AK, Ilavarasan V, Gupta MP, Janssen M, Kothari R (2019) Moving beyond smart cities: digital nations for social innovation & sustainability. Inf Syst Front 21(3):495–501

Lee KH, Min B (2015) Green R&D for eco-innovation and its impact on carbon emissions and firm performance. J Clean Prod 108:534–542

Li W, Zheng M (2016) Is it substantive innovation or strategic innovation? Impact of Macroeconomic Policies on Micro-enterprises' Innovation. Econ Res J 51(04):60–73

Li D, Zheng M, Cao C, Chen X, Ren S, Huang M (2017a) The impact of legitimacy pressure and corporate profitability on green innovation: evidence from China top 100. J Clean Prod 141:41–49

Li J, Nan Y, Liu XH (2017b) China's economic growth stabilizing conundrum, misallocation of human capital and solutions. Econ Res J 52(3):18–31 (in Chinese)

Li H, Zhang J, Wang C, Wang Y, Vaughan C (2018) An evaluation of the impact of environmental regulation on the efficiency of technology innovation using the combined DEA model: A case study of Xi'an, China. Sustain Cities Soc 42:355–369

Li L, Zheng Y, Zheng S et al (2020) The new smart city programme: evaluating the effect of the internet of energy on air quality in China[J]. Sci Total Environ 714:136380

Li T, Ma J, Li T, Ma J (2021) Does digital finance benefit the income of rural residents? A case study on China. Quant Financ Econ 5:664–688

Li L, Li M, Ma S, Zheng Y, Pan C (2022a) Does the construction of innovative cities promote urban green innovation? J Environ Manage 318:115605

Li X, Shao X, Chang T, Albu LL (2022b) Does digital finance promote the green innovation of China's listed companies? Energy Economics 114:106254

Li Z, Bai T, Tang C (2022c) How does the low-carbon city pilot policy affect the synergistic governance efficiency of carbon and smog? Quasi-experimental evidence from China. Journal of Clean Production 373:133809

Liao B, Li L (2022) Spatial division of labor, specialization of green technology innovation process and urban coordinated green development: evidence from China. Sustain Cities Soc 80:103778

Liu J, Jiang Z, Chen W (2021) Land misallocation and urban air quality in China. Environ Sci Pollut Res 28:58387–58404

Lopes IM, Oliveira P (2017) Can a small city be considered a smart city? Procedia Comput Sci 121:617–624

Manjon M, Aouni Z, Crutzen N (2022) Green and digital entrepreneurship in smart cities. Ann Reg Sci 68(2):429–462

Nunn N, Qian N (2014) US food aid and civil conflict. Am Econ Rev 104(6):1630–1666

Pan X, Guo S, Han C et al (2020) Influence of FDI quality on energy efficiency in China based on seemingly unrelated regression method. Energy 192:116463

Peng X (2020) Strategic interaction of environmental regulation and green productivity growth in China: green innovation or pollution refuge? Sci Total Environ 732:139200

Peng W, Yin Y, Kuang C et al (2021) Spatial spillover effect of green innovation on economic development quality in China: evidence from a panel data of 270 prefecture-level and above cities. Sustain Cities Soc 69:102863

Porter M E, Linde C (1995) Toward a new conception of the environment-competitiveness relationship. J Econ Perspect 24(4): 3–28, 97–118.

Qi Y, Bai T, Tang Y (2022) Central environmental protection inspection and green technology innovation: Empirical analysis based on the mechanism and spatial spillover effects. Environ Sci Pollut Res 29(57):86616–86633

Qian L, Fang Q, Lu Z (2020) Research on the synergy of green economy and digital economy in stimulus. Southwest Finance 12:3–13 (in Chinese)

Riillo CAF (2017) Beyond the question "Does it pay to be green?": How much green? and when? J Clean Prod 141:626–640

Rong J, Gu H (2016) Analysis of influencing factors on the status of the division of labor in global value chains——based on the comparison of trade value added among countries. J Int Econ Cooperation 05:39–46 (in Chinese)

Roscia M, Longo M, Lazaroiu G C (2013) Smart city by multi-agent systems. Int Conference Renew Energy Res App (ICRERA), IEEE 2013: 371–376

Rowan N J, Murray N, Qiao Y, et al (2022) Digital transformation of peatland eco-innovations ('Paludiculture'): Enabling a paradigm shift towards the real-time sustainable production of 'green-friendly' products and services. Sci Total Environ 156328

Ryzhenkov M (2016) Resource misallocation and manufacturing productivity: the case of Ukraine. J Comp Econ 44(1):41–55

Shen C, Li S, Wang X, Liao Z (2020) The effect of environmental policy tools on regional green innovation: Evidence from China. J Clean Prod 254:120122

Show PL, Lau PL, Foo DCY (2018) Green technologies: innovations, challenges, and prospects. Clean Technol Environ Policy 20(9):1939–1939

Sun C, Luo Y, Li J (2018) Urban traffic infrastructure investment and air pollution: Evidence from the 83 cities in China. J Clean Prod 172:488–496

Tian B, Yu B, Chen S, Ye J (2020) Tax incentive, R&D investment and firm innovation: evidence from China. J Asian Econ 71

Wang H, Shi D (2019) Does new urbanization help to alleviate smog Pollution? Empirical evidence from low-carbon city construction. J Shanxi Univ Finance Econ 41(10):15–27 (in Chinese)

Wang KL, Pang SQ, Zhang FQ, Miao Z, Sun HP (2022a) The impact assessment of smart city policy on urban green total-factor productivity: evidence from China. Environ Impact Assess Rev 94:106756

Wang L, Chen L, Li Y (2022b) Digital economy and urban low-carbon sustainable development: the role of innovation factor mobility in China. Environ Sci Pollut Res 29(32):48539–48557

Wang X, Zhou D (2021) Exploring the nonlinear impact of urbanization on pollutant emissions: a spatial approach. Atmospheric Pollution Research 12(11).

Wu G, Xu Q, Niu X, Tao L (2022) How does government policy improve green technology innovation: an empirical study in China. Front Environ Sci 9:723

Wu D, Xie Y, Lyu S (2023) Disentangling the complex impacts of urban digital transformation and environmental pollution: evidence from smart city pilots in China. Sustain Cities Soc 88:104266

Wu L, Yang M, Wang C (2021). Strategic interaction of environmental regulation and its influencing mechanism: evidence of spatial effects among Chinese cities. J Cleaner Prod 127668

Xia X, Wu X, Balamurugan S, Karuppiah M. (2021) Effect of environmental and social responsibility in energy-efficient management models for smart cities infrastructure. Sustain Energy Technol Assessments, 47

Xu L, Fan M, Yang L, Shao S (2021) Heterogeneous green innovations and carbon emission performance: evidence at China's city level. Energy Economics 99:105269

Yang Q, Zhuo P, Yang J (2014) Industrial land transfer and bottom line competition of investment quality—an empirical study based on the panel data of China's prefecture level cities from 2007 to 2011. J Manag World 11:24–34 (in Chinese)

Yang S S, Chong Z (2021) Smart city projects against COVID-19: quantitative evidence from China. Sustainable Cities & Society: 70.

Yao T, Huang Z, Zhao W (2020b) Are smart cities more ecologically efficient? Evidence from China. Sustain Cities Soc 60:102008

Yao J, Li H, Shang D (2020a) The literature review and future prospects of sustainable technology innovation. Ecological Economy 36(08): 49–56 + 113. (in Chinese)

Yu Y, Pan Y (2019) The mysterious coexistence of rapid economic growth and a lag in the service industry's upgrade in China: an interpretation based on the economic growth target constraints perspective. Econ Res J 3:150–165 (in Chinese)

Zhao T, Zhang Z, Liang S (2020) Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. Manage World 36(10):65–76 (in Chinese)

Zhou D, Huang Q, Chong Z (2022) Analysis on the effect and mechanism of land misallocation on carbon emissions efficiency: evidence from China. Land Use Policy 121:106336

Zhu L, Hao Y, Lu ZN, Wu H, Ran Q (2019) Do economic activities cause air pollution? Evidence from China's major cities. Sustain Cities Soc 49:101593

Zhuang Q, Wu B, Hong Q (2020) Market-oriented green technology innovation system: theoretical connotation, practical exploration and promotion strategy. Economist 11:29–38 (in Chinese)

Zou J, Deng X (2022) To inhibit or to promote: how does the digital economy affect urban migrant integration in China? Technol Forecast Soc Chang 179:121647