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A smart city is a less polluted city

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ABSTRACT

This study aims to examine the impact of smart city construction on the ecological environment quality (EEQ) of China. Due to the problems arising from urbanisation, local governments construct smart cities as inherent innovative advantages that can improve their level of science and technology, and efficiency in resource allocation, thereby reducing environmental pollution. Through this innovation-driven channel, shocks to the degree of city smartness can have a significant impact on the regional environment. In order to compute the sensitivity of urban pollution to the degree of city smartness in China both conceptually and empirically, we modify a theoretical model of classic land allocation decisions to demonstrate how local officials' responsibilities to protect the ecological environment and promote economic growth can lead to the long-run spatial expansion of smart cities, resulting in the improvement of EEQ. Using a difference-in-differences (DID) analysis, we find that from 2005 to 2017 period, smart city initiatives in China reduced industrial exhaust gas and industrial wastewater by approximately 20.7% and 12.2%, respectively, such that most of the reduction may be attributed to the technology effect and allocation effect of urban innovation.

1. Introduction

China has experienced a significant increase in its rural–urban migration with an expansion of cities and towns, influence of the drivers for dramatic growth and structural changes in its economy over a period of three decades (Yigitcanlar and Kamruzzaman, 2018). However, urbanisation has put significant stress on the environment (Lee and Lee, 2014). For example, many cities in central and eastern China are plagued by smog and haze, endangering the health of residents and causing a negative impact on the economic efficiency. According to the China Meteorological Administration, the average number of smog days in 2013 was 35.9, which was the highest since 1961 with some cities experiencing over 100 haze days. However, observations from the China Government Work Report of 2018 show that over the past 5 years, there has been a sign of gradual improvement in the ecological environment. The discharge of major pollutants has continued to decline, and the number of days of heavy pollution experienced in major cities has been reduced by half. Some reports have even suggested that China has entered 'the era of green development'.

Recently, a growing number of studies have been investigating the factors affecting ecological environment quality (Li et al., 2019; Munir and Ameer, 2018; Sun et al., 2019). For instance, Shapiro and Walker (2018) find that increasingly stringent environmental regulations and implicit pollution taxes that manufacturers must pay account for a major part of the reduction in emissions. Sapkota and Bastola (2017) argue that an increase in foreign direct investment (FDI) attracts clean and energy-efficient industries that could improve the ecological environment while enhancing the regional economy. In terms of empirical analysis, Yu and Zhang (2021) identify the causal effect of low-carbon city pilot policy on carbon emission efficiency, documenting that the policy has mitigated the average carbon dioxide emissions by approximately 8.37 million tons with 1% increase in the carbon emission efficiency. Existing studies have found that an increase in per capita gross domestic product (GDP) leads the rich to pay more attention to the environment; this acts as a driver for the structural change of an economy, leading to a reduction in ecological environmental degradation (Brajer et al., 2011; Xie et al., 2019). Yu et al. (2018) assert that China is experiencing a related dramatic change in its industrial structure; this is because economic development is more likely to have an influence on knowledge-intensive and service-based industries rather than energy-based and emissions-intensive-based manufacturing. Certain studies have demonstrated that urbanisation crossing the turning point

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may lead to a corresponding agglomeration effect as a result of the enlargement of urban scale characterised by their population and economic activities; this is conducive to a reduction in the emission intensity of industrial pollutants (Lin and Zhu, 2018; Wang et al., 2018). Although these factors are partly accountable for an the improvement in China's environmental quality, they cannot explain the overall change. We observe that only a limited number of studies have investigated the 'black box' regarding the environmental rationale behind urbanisation; however, most of these studies have demonstrated superficial environmental changes arising from economic transitions. One aspect of China's modernisation that could be the impetus to such changing norms is the development of smart city construction (SCC). In a smart city, previously intractable challenges in urban areas, such as social exclusion and environmental deterioration, are solved through the adoption and use of information and communication technologies (ICTs) (March and Ribera-Fumaz, 2016). Although China has historically adhered to factor-driven modes of economic development, its smart urban infrastructure has developed rapidly over the last 15 years. As of 2015, the urban smartness index (USI) is growing at an average annual rate of 50%, which could be a non-negligible factor affecting the ecological environment in a variety of ways (Gren et al., 2019).

Currently, smart city policies are being adopted globally. However, not only is there hardly any evidence that credibly estimates the causal effect of these policies on urban environmental quality, but also the mechanism behind them is unclear. The closest paper in this regard is Yu and Zhang (2019), which documents the importance of smart city policy for energy efficiency based on aggregated city-level data in China. Based on their seminal work, we further extend the research on the environmental effects of smart city policies by introducing a brand-new theoretical framework, expanding the scope of the analysis, and making substantial methodological improvements that allow for precise measurement. Smart city positively affects innovation. In agglomeration theory, these cities facilitate the production, diffusion, and accumulation of knowledge, naturally serving as knowledge hub (Camagni et al., 2016; Caragliu et al., 2016). Additionally, advanced face-to-face communication technology lowers the transaction costs in processing knowledge. In this regard, Angelidou (2017) shows that ICT is a positive factor for urban innovation. Taking advantage of city agglomeration and technologies, urban innovation can be enhanced by efficient smart city policies. Moreover, innovation processes can be upgraded through a general improvement in the local knowledge of production functions (Caragliu and Del Bo, 2018). Further, smart city boosts a city's stock of knowledge, stimulating its overall innovation in high technology, especially in the case of ICT and Internet of Things (loT) that act as the main drivers for green growth (Caragliu and Del Bo, 2019; Taylor Buck and While, 2017). Innovation, in turn, benefits the environment through the following channels: First, green technology is expected to be a key factor in supporting environmental management (Arenhardt et al., 2016; Chen et al., 2012; Yang et al., 2016). Empirical evidences have shown that SCC can mitigate the environmental degradation caused by unprecedented rapid urbanisation through an innovation-driven strategy (Cao et al., 2019; Contreras and Platania, 2019). Moreover, due to the comparative advantage experienced by smart cities in innovation (Shang et al. 2018), an increasing number of new green technologies are being merged into manufacturing chains, leading to an increase in productivity and decrease in environmental costs. Second, city administration can move forward to a new stage with the aid of the next generation of ICT. In terms of resource allocation, innovation enables smart cities to optimise industrial structure and scale efficiency in the operation of urban economies. Several studies have demonstrated that allocation in the context of innovation is an essential factor for smart city to achieve organisational efficiency, sustainable commuting patterns, and industrial upgradation (Schiavone et al., 2019; Yigitcanlar and Kamruzzaman, 2019). This is expected to transform both the traditional modes of pollution control and historically preconceived notions regarding urban development. Consequently, smart city policies may exert significant positive effects on environmental quality through the more effective promotion of technology, especially green technology, and efficient allocation of resources.

The following questions may arise in this context. Is SCC a new direction for urban initiatives, which is conducive to liveability, sustainability, and economic growth? How does it affect China's EEQ? However, until recently, such questions had not been broadly discussed in the literature of urban studies; there exists a controversy and lack in the quantitative analysis of the effects of urban smartness (US) on reduction of pollution. Hence, to fill this gap in existing literature, this paper conceptually and empirically examines the extent to which urban innovation enhanced by SCC has changed urban ecological environment in China. We begin with a brief introduction to the smart city initiatives in China and how it boosts technology and allocation effect of urban innovation to change the value of traditional land use. Then, we present a brand-new theoretical model of local officials' decisions on urban land allocation taking into account both environmental regulation and economic incentives. In other words, we model a substitution between traditional urban land and smart urban land driven by urban innovation. The model shows mandate for improved economic return from the central government and willingness to pay for better ecological environment from local residents incentivize local officials for converting the traditional city to smart city construction. The city conversion, in turn, reduces urban pollution and promotes economic performance. Furthermore, we test these conjectures using a panel data set of 287 prefecture-level cities in China for the period 2005 to 2017. We start by presenting OLS estimates. However, these may be biased due to omitted variables or reverse causality, so we also estimate difference-in-differences (and fixed effects) regressions to control for unobserved heterogeneity that affects smart city selection and pollution. We also discuss selection concerns, validating the identifying assumption that the trends are parallel for the smart city pilots' group and the control group which consist of cities absent the smart city initiative. Consistent with the theoretical analyses, the empirical results show, enhanced by smart city initiatives, that the dramatic changes in scientific and technological level and resource allocation efficiency exert a positive effect on EEQ and GDP in the city. Heterogeneity analysis shows that SSC has a stronger positive impact on EEQ in areas with a higher urban scale than lower urban scale. Additionally, urban EEQ has a U-shaped relationship with its urbanization rate. A variety of robustness checks also confirm our main findings. In summary, we find that smart city initiatives improve eco-environmental quality in Chinese cities. We perform a variety of robustness checks which confirm our main findings.

This study makes several important contributions. First, advancing the literature on the importance of smart city for different goals of sustainable urban development (Martin et al., 2018), we explore an equally vital outcome, namely urban ecological environment. In doing so, we focus our attention on the multi-dimensionality of influential mechanisms instead of treating it as separate. Second, we complement recent findings on urban innovation effect of smart city initiatives from the perspective of the agglomeration economies. Within the smart city paradigm, innovation processes are expected to be enhanced, mainly through a general improvement of local knowledge production functions (Caragliu and Del Bo, 2019), Furthermore, we demonstrate that urban innovation can be defined as a process that contributes to creating new production and technologies and augmenting resource efficiency with the aim of reducing environmental risks (Castellacci and Lie, 2017), thus adding to recent research on the interplay between urban innovation including green innovation and ecological environment based on the theory of Schumpi innovation. Finally, from an empirical standpoint, we pay special attention to a less-researched context (i.e. China) that provides a promising ground for examining the pollution reduction effects of smart city initiatives at work in less-developed and emerging economies.

To address these topics, this paper proceeds as follows. In Section 2, we build a theoretical framework. Section 3 presents a design of the variables and description of the data used in this study. Section 4 offers an empirical analysis of the data. Section 5 provides the concluding remarks.

2. Theoretical framework

2.1. Brief description of the smart cities in China

The concept of smart city was first proposed by International Business Machines Corporation (IBM) in 2008 as a solution to the 'smart earth' strategy. Smart city is an application of the IoT system that connects public resources, such as power grids, highways, and water supply systems via various types of embedded smart sensors. This system dynamically retrieves the key information from the sensors, thus, the analysis and integration of the data resources generated in city operations might be performed to achieve refined resources and efficient configuration, which would facilitate intelligent governance and the operation of production activities leading to a sustainable development of the city. The concept of smart city is prevalent worldwide. Globally, more than 1,000 smart cities are under construction, and the number of smart cities is expected to increase at the rate of 20%. In this context, Europe is focusing on the aspects of transportation, energy, public services and infrastructure. The United Kingdom, Ireland and Germany have launched the 'Digital Britain' plan, 'T-CITY' experiment and 'Smart Bay' project, respectively. In Asia, Korea initiated the 'U-Korea' project, striving to build a smart city with environmental protection, digitalisation, and seamless mobile connectivity. Singapore started the 'smart country 2015' plan, which intends to integrate government, enterprises, individuals and infrastructure. Japan launched the 'I-Japan' strategy, concentrating on the operation of e-government, healthcare, and education. In North America, the United States established its first smart city in Dubuque with assistance from IBM, using the IoT system to connect various public resources which can be intelligently responsible to the residents.

China was never an outsider in the aspect of SCC. Since 2010, the Chinese central government has been continuously introducing relevant policies to guide and encourage the construction of smart cities, considering all the relevant aspects from advanced designs to specific applications. In 2012, 90 cities from the prefecture to township levels were selected as pilot national smart cites by the Chinese Ministry of Housing and Urban-Rural Development among which 37 cities belonged to the prefecture-level, 50 cities were at the district or county level, and 3 cities were at the township level. In 2015, 'Guiding Opinions on the Construction and Application of Smart City Standard System and Evaluation Index System' was implemented to accelerate the development of relevant standards; smart city standardisation was officially put on the national agenda, and government work report was presented in terms of the development of SCC. More than 85% of cities in China were undertaking smart city construction, and a total number of 290 smart city pilots (SCP) have been launched by the end of 2015. In 2017, the Nineteenth National Congress of the Communist Party of China reported that the investment in smart cities would exceed 500 billion yuan, while 100 more cities would be organised for its promotion. According to the report, China would enter the era of smart city 2.0 by 2021. It can be predicted that the construction of smart cities will have a significant and far-reaching impact on all the aspects of China's economic development.

In the early stages of urbanisation, urban development is primarily based on an extensive mode that places GDP under its foremost consideration. Through the requisition of a selected amount of land, local government officials convert the use of agricultural lands to that of traditional urban practices. This mode of development has the following distinct characteristics. Since the level of science and technology is relatively low and urban infrastructure is backward, this system decreases the probability of building a smart city. However, the central government assesses local governments in the context of GDP and taxes that act as the indicators of total economic development but lack strong environmental regulations. In addition, the public's awareness of environmental protection is weak. In this case, local governments sell urban lands at low prices to attract traditional investment, leading to inefficient land uses and substantial environmental damage. Hence, we can assume that, a local government's economic incentives from the construction of traditional cities, represented by $R_1(m_1)$, is increasing and strictly concave in the amount of land leasedand, that is, m_1; however, $P_1(m_1)$, representing the waste disposal costs incurred by the a local government from the construction of traditional cities, is increasing and strictly convex in the amount of land leased, namely, that is, m_1. Therefore, $R_1'(m_1) > 0, R_1''(m_1) < 0, P_1'(m_1) > 0, P_1''(m_1) > 0$.

A smart city is a new and urban form of traditional cities. Local government officials choose the amount of land to convert their use from traditional urbans to smart urban practices by renovating traditional urban land. To better link the rather generic literature on smart cities and the impact we expect from the smart city initiatives on urban ecological environment, these underlying micro foundations are further dug deeper as follow. First, smart city projects play an important role in fostering urban innovation. Because of a more concentrated and denser structure of consumption and production, urban areas lower transaction costs in production and consumption, thus potentially attracting locations for producers and consumers. However, the externality described by classical economics has changed, at least in advanced economies. Because of a more standardized traditional traded goods for decades now, manufacturing activities have been relocating in peripheral locations with lower rents (O'Donoghue, 2014). However, contrary to Marshallian framework, city size keeps expanding. A possible explanation can be identified in the nature of cities as knowledge hubs (i.e., the increasing importance of urban areas as innovation cradles) (Caragliu et al., 2016). In this case, smart city initiatives can facilitate these effects, and innovation processes are expected to be enhanced, mainly through a general improvement of local knowledge production functions. Second, urban innovation, especially green innovation, can direct organizations and communities towards achieving sustainable competitive advantages (Hur et al., 2013). According to the theory of Schumpi innovation, urban innovation can be defined as a process that contributes to creating the new technologies and production to meet the demands of customers in terms of environment protection (Guerlek and Tuna, 2018). More specifically, urban innovation can be divided into process innovation and service/product innovation. The ultimate goal of service/product innovation is to promote the functioning of services and products for clients and customers. The innovation process has resulted in diminishing pollution rates (Amore and Bennedsen, 2016), giving a lift to recycling (Aid et al., 2017), saving energy (Corrocher and Solito, 2017), designing and producing eco-friendly products or services (green product design) (Arenhardt et al., 2016), as well as creating new opportunities for environmentally friendly practices (Amore and Bennedsen, 2016). Within this framework, urban innovation efficiency in the operation of smart cities can be improved by continuously increasing scientific research on information technologies such as the cloud computing, Internet of Things (IoT), and big data. An increasing number of companies have accelerated the optimisation and upgradation of their production systems, resulting in the development of new technologies and products; this has directly helped in improving the scientific and technological level in cities through technology innovation. Additionally, the change of enterprise management pattern to smart governance, and the transform of industry structure to smart production have indirectly improved the efficiency of resource allocation at the enterprise and industry levels in cities through allocation innovation. Hence, we assume that $R_2(m_2)$, is a local government's economic incentives from SCC, which is increasing and strictly convex in the amount of land renewedand, that is, m_2; $P_2(m_2)$, representing the waste disposal costs incurred by the local government from SCC, is increasing and strictly concave in the amount of land leased, namely, that is, m_2. Hence $R_2'(m_2) > 0$, $R_2''(m_2) > 0$, $P_2'(m_2) > 0$, and $P_2''(m_2) < 0$.

2.2. Model of local officials' land allocation decisions

Considering the decentralisation of government and fiscal system reforms the mid-1990s in China, the following conceptual model formalises environmental regulations and economic incentives simultaneously, which puts local Chinese officials in the position of land developers. In addition, SCC can be simplified as the smart transformation of traditional cities depends on governments' land allocation, based on the urban renewal theory. We adopt a dynamic model of aggregate land use based on Hartwick et al. (2001) and Turnbull (2004); the model is essentially the same as that proposed by Lichtenberg and Ding (2009) and Wang and Tang (2019), which is used to study transition dynamics under urban growth boundaries. Moreover, it is modified to investigate the extent to which the spatial expansion of smart cities has been shaping China's EEQ.

For simplicity, we consider a region based on two sectors, that is, the agricultural and urban sectors. Extension to the case of multiple urban patterns in the urban sector is complicated but facilitates the analysis by adding insights into the impact of SCC on EEQ. We divide the total area of land in the region according to their agricultural, traditional urban and smart urban uses. For simplicity, we normalise the total area of land to 1. Let $E_1(t)$, $E_2(t)$ and $E_3(t)$ denote the share of land in the region devoted to traditional urban uses, SCC, and agricultural uses, respectively, during period t.The changes in the stock of traditional urban land and smart urban land at any time t are separately

$$\dot{E}_1(t) = m_1(t) - m_2(t), \dot{E}_2(t) = m_2(t), \tag{2.1}$$

where $m_1(t)$ is the amount of land converted from agricultural to traditional urban uses during period t, and $m_2(t)$ is the amount of land converted from traditional urban to smart urban uses during period t. The negative values of $m_1(t)$ and $m_2(t)$ denote a conversion from urban to agricultural uses and from smart urban to traditional urban uses, respectively.

In general, the social benefit and social cost arising from various externalities remain unprized in the private market. However, similar to land developers, local officials not only consider the central government's provision of economic incentives and implementation of environmental regulations but also consider residents' willingness to pay for the sustenance of ecological environment. Thus, they choose land conversions $m_1(t)$ and $m_2(t)$ at each point in time to maximise the present value of ecological bonus and net economic returns.

$$\max_{\{m_1, m_2\}} W = \int_0^{\infty}\left\{\int_0^{E_1(t)+m_1(t)-m_2(t)} r_1(x) - \pi_1(x)dx + \int_0^{E_2(t)+m_2(t)} r_2(x) - \pi_2(x)dx + \int_0^{1-E_1(t)-E_2(t)-m_1(t)} \tau(x)q(x)dx\right\}e^{-\rho t}dt \tag{2.2}$$
$$s.t.\ \dot{E}_1(t) = m_1(t) - m_2(t), \dot{E}_2(t) = m_2(t);\ E_1(0) = E_{10},\ E_2(0) = E_{20},$$

where $r_1 = R_1^{'}$, $r_2 = R_2^{'}$, $\pi_1 = P_1^{'}$, $\pi_2 = P_2^{'}$, and $\tau q = Q^{'}$. Let q denote the unit regional EEQ for agricultural land use, and τ represent the unit value for regional EEQ. A fall in the willingness to pay for the improvement of ecological environment suggests that the unit ecological environmental value is decreasing in the stock of agricultural land, that is, $\tau^{'} < 0$. Here, ρ represents the discount rate of time preference for obtaining results from local officials' activities. Moreover, we assume that $\frac{\rho+1}{\rho}[r_2(0) - \pi_2(0) - \tau(1)q(1)]\rangle 0$, $\frac{\rho+1}{\rho}[r_2(1) - \pi_2(1) - \tau(0)q(0)] < 0$, and $r_2^{'} - \pi_2^{'} + \tau^{'} q < 0$ to ensure that there remains a certain amount of land in the region that can be allocated for both agricultural and urban uses in the long-run.

Let λ_1(t) and λ_2(t), respectively, denote the shadow prices of traditional urban and smart urban lands at time t separately. Here, we drop the time argument to simplify the exposition. The necessary conditions for maximisation are as follows.

$$r_1(E_1 + m_1 - m_2) - \pi_1(E_1 + m_1 - m_2) - \tau(E_3 - m_1)q(E_3 - m_1) + \lambda_1 = 0, \tag{2.3}$$

$$r_2(E_2 + m_2) - \pi_2(E_2 + m_2) - \tau(E_3 - m_1)q(E_3 - m_1) + \lambda_2 = 0, \tag{2.4}$$

$$\rho\lambda_1 - r_1(E_1 + m_1 - m_2) + \pi_1(E_1 + m_1 - m_2) + \tau(E_3 - m_1)q(E_3 - m_1) = \dot{\lambda}_1, \tag{2.5}$$

$$\rho\lambda_2 - r_2(E_2 + m_2) + \pi_2(E_2 + m_2) + \tau(E_3 - m_1)q(E_3 - m_1) = \dot{\lambda}_2. \tag{2.6}$$

Further, we can obtain an insight into the nature of the long-run value of the stock of urban land for Chinese local government officials from an explicit representation of the shadow price of urban land, derived by integrating the costate Eq. (2.5) and Eq. (2.6).

$$\lambda_1 = \int_t^{\infty}[r_1(E_1+m_1-m_2) - \pi_1(E_1+m_1-m_2) - \tau(E_3-m_1)q(E_3-m_1)]e^{-\rho(y-t)}dy, \tag{2.7}$$

$$\lambda_2 = \int_t^{\infty}[r_2(E_2 + m_2) - \pi_2(E_2 + m_2) - \tau(E_3 - m_1)q(E_3 - m_1)]e^{-\rho(y-t)}dy. \tag{2.8}$$

The shadow price of the stock of urban land at any point in time has two components: (a) its contribution to achieving future economic incentives $r_1(E_1 + m_1 - m_2)$ and $r_2(E_2 + m_2)$; and (b) its repression to alleviating future environmental pressure $\pi_1(E_1 + m_1 - m_2) + \tau(E_3 - m_1)q(E_3 - m_1)$ and $\pi_2(E_2 + m_2) + \tau(E_3 - m_1)q(E_3 - m_1)$. Therefore, Eqs. (2.7) and (2.8) indicate that local officials' land conversion decisions are determined by both economic incentives as well as ecological environmental pressure.

Combining Eqs. (2.3), (2.4), (2.7), and (2.8), we obtain a single equation that defines optimal land conversion conditional on the stock of urban land at any point in time. Differentiating the resulting equation (see the Appendix A for a formal derivation) yields the following predictions about the factors influencing environmental quality.

Result 1. Dramatic changes in the scientific and technological level and resource allocation
efficiency resulting from smart urban innovation exert a positive effect on EEQ. Therefore,
EEQ is higher in areas where the US is higher.
Result 2. Smart urban construction has a stronger positive impact on EEQ in areas with a
higher urban scale than lower urban scale.
Result 3. Urban EEQ has a U-shaped relationship with its urbanisation rate.
In the following section, we empirically examine whether the changes in urban EEQ are consistent with these results.

Although there has been a tremendous leap in China's urban development, the initial stock of traditional urban land is less likely to be higher than the long-run equilibrium amount, or that of the smart urban land, that is, $E_{20} \ll E_{10}$ (Au and Henderson, 2006). Urban land conversions are constrained by ecological environmental pressure. Hence, SCC based on the new generation of information technology will greatly

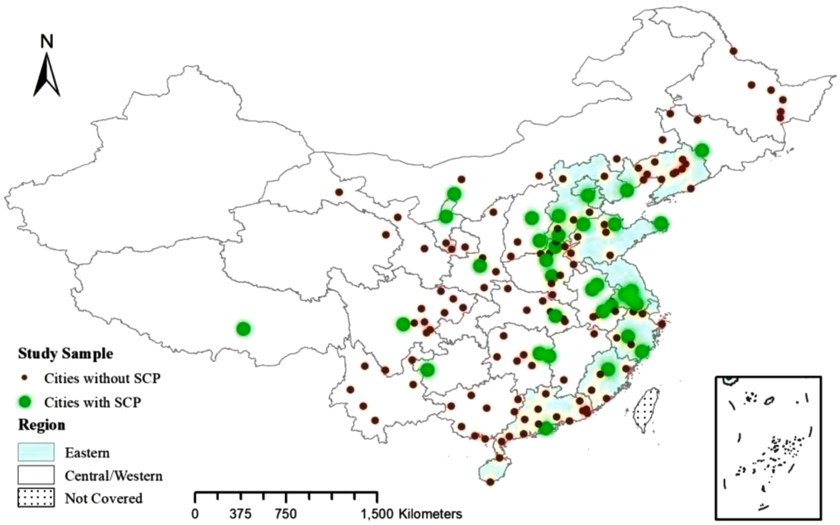

Fig. 1. Geographical distribution of the data sample.

improve science, technology, and resource allocation efficiency, alleviating the ecological environmental pressure on traditional urban construction to a certain extent. Thus, traditional urban lands would be gradually replaced by smart urban lands until they reach a steady state, that is, $E_1^* = 0$ and $E_2^* \neq 0$. In the long-run equilibrium, when $\dot{E}_1(t) = m_1 - m_2 = 0$ and $\dot{\lambda}_1 = \dot{\lambda}_2 = E_1 = 0$, the shadow price of smart urban land will be given by

$$\lambda_2^* = \frac{r_2(E_2) - \pi_2(E_2) - \tau(1-E_2)q(1-E_2)}{\rho}, \tag{2.9}$$

and the amount of land in urban use is defined by

$$F(E_2) \equiv \frac{\rho+1}{\rho}[r_2(E_2) - \pi_2(E_2) - \tau(1-E_2)q(1-E_2)] = 0. \tag{2.10}$$

$F(E_2)$ is monotonically decreasing in E_2 ($F'(E_2) = (\rho+1)(r_2' - \pi_2' + \tau' q)/\rho < 0$); thus, if $F_2(0) > 0$ and $F_2(1) < 0$, as per our assumption, there exists a unique long-run equilibrium stock of smart urban E_2^*, which is stable (see Appendix).

The results are in accordance with the intuition that the land allocations are influenced by land values in a manner similar to those characterising the long-run equilibrium in markets with completely private land ownership, even when primary land allocation remains in the hands of government officials nominally subjected to bureaucratic constraints on decision-making. A major difference lies in the role of greenspace externality. Local officials value land for its cost of pollution control and opportunity cost to lose greenspace externality in the long-run. In contrast, for private developers, an unassessed greenspace externality increases their estimate of returns to land conversion rather than decreasing them. Thus, greenspace externality plays a key role in the expansion of smart urban land and urban growth controls. The result is neither novel nor surprising; however, we explain it in this paper to establish the benchmarks required to derive the aforementioned predictions on urban spatial expansion influencing EEQ in the short run.

3. Data and variables

In this section, we describe the data sample and present descriptive graphs on pollutant growth and GDP growth in line with the empirical estimations presented in the next section. With reference to empirical studies that have explored the effect of SCC on EEQ, we sort the data for twelve variables, including two outcome variables, one core explanatory variable, four mediating variables, and five control variables. Considering the consistency in the collection and availability of data, we restrict the sample for period of 2005 to 2017 to reflect on the rapidly developing stage of China's SCC since it was first proposed by the government in 2009. Additionally, a small portion of missing data was supplemented by using the average growth rate method. We finally obtain a panel data set of 287 prefecture-level cities in China, which were extracted from the *China Urban Statistics Yearbook* (2006-2018), *China Regional Economic Statistics Yearbook* (2006-2018), and *EPS* database.

3.1. Outcome variables

The outcome variable, EEQ, can be measured through the forward processing of urban pollution level by including three industrial wastes. In the absence of data on solid waste discharge in certain cities, we consider two independent measures from different sources, that is, the amount of sulphur dioxide (SO_2) emission in air pollution per unit land (ASO; unit: kg/km^2) and the amount of chemical oxygen demand discharge in water pollution per unit land (ACOD; unit: 10^5 kg/km^2), such that the latter can be used to check the robustness of basic results.

3.2. Explanatory variables

At present, there is no consensus on the development of an evaluation index system for smart cities or the existence of complete historical statistical data for relevant indicators because this concept is newly emerging. Accordingly, we consider an appropriate proxy indicator for SCC, the core explanatory variable, in our quantitative research process. In 2012, the Chinese Ministry of Housing and Urban-Rural Development (MOHURD) announced the project of SCP, a list including 90 cities as the pioneers of SCC. Additionally, 163 cities were selected for the project in the following years. In this study, we use the SCP project as a quasi-natural experiment; therefore, a DID method is used to evaluate the environmental performance of SCC. Due to data availability, the following constraints are applied to refine the sample. First, since our study lies between the period of 2005 and 2017, we exclude the cities from our dataset that were not mentioned in the pioneers list announced in 2012 in order to construct a five-year experiment period for a better DID analysis. Second, since it is difficult to collect effective data at the county and town levels, this study focuses on the pilot cities at the prefecture-level. Our final sample includes 34 cities included in the SCP project and 122 cities that were not included in it. Therefore, we consider SCC to be a dummy variable that takes the value of one if a city was included in the SCP project in 2012, and zero otherwise. Fig. 1 also differentiates our data sample by groups, that is, in accordance to cities

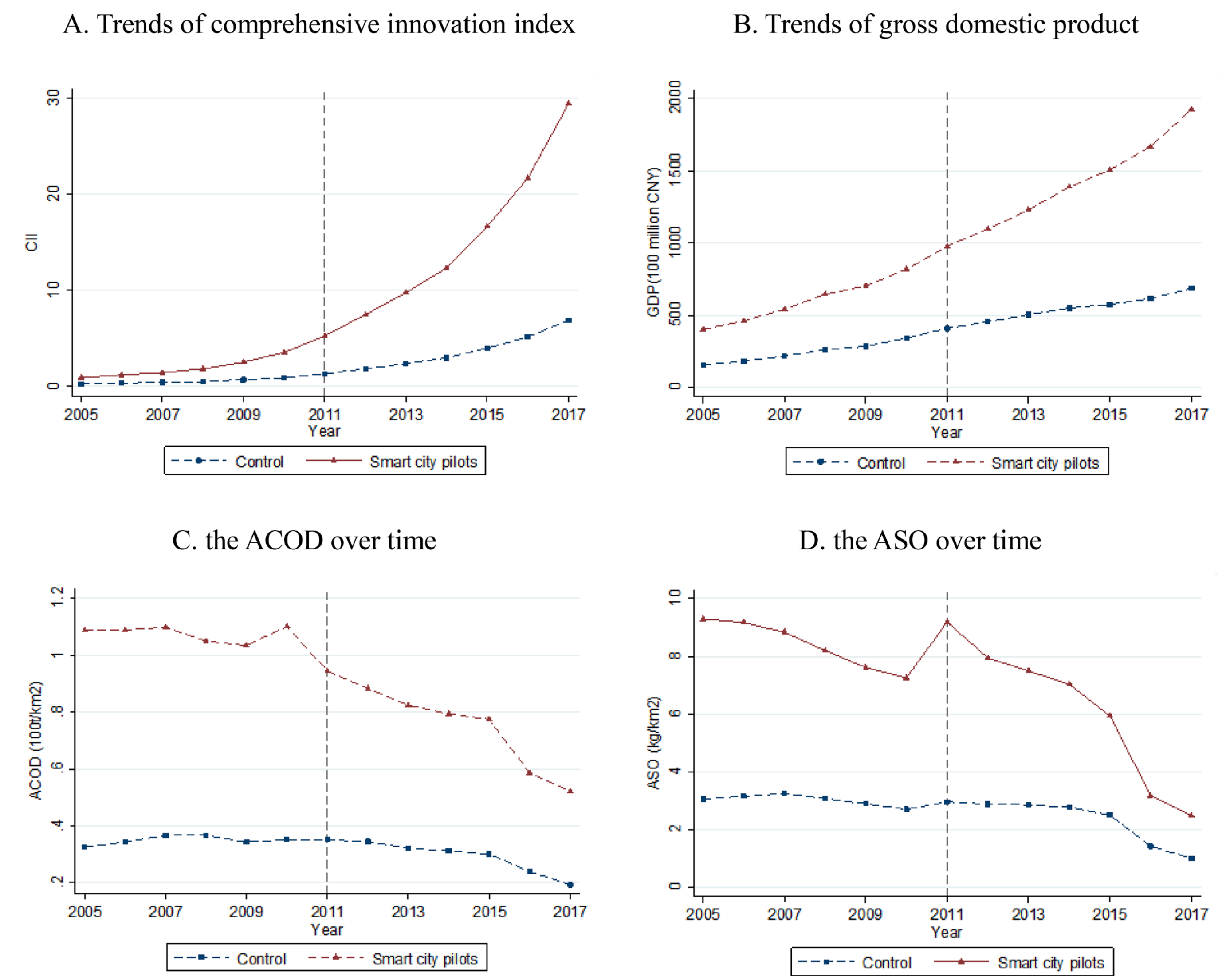

Fig. 2. Comparison of ACOD and ASO over time.

that were included in or excluded from the SCP project.

3.3. Control variables

We account for possible confounding factors with the help of control variables. First, urbanisation ratio (Urbar; unit: %), that is the share of urban built-up area, measures the process of transforming agricultural activities into non-agricultural ones from the perspective of land use (Yu and Li, 2014)[1]. Guided by prior studies, the influence of urbanisation level on EEQ may be positive or negative. We include the population density (Densi; unit: 10^4 individuals/km^2), as measured by the ratio of total population to land area at the end of the year, because areas that are more agglomerative may result in damaging the environment. Moreover, we control for the industrial structure (Instr; unit: %), the proportion of added value of the secondary industry in GDP, because of the varying industry advantages across cities and years. As Sapkota and Bastola (2017) pointed out, the increasing FDI attracts clean and energy-efficient industries that could improve ecological environment while enhancing the regional economy. Opening-up level (Openl; unit: %), the proportion of total export-import volume in GDP, is also included. In addition, we include the natural logarithm of real per capita GDP (Lpgdp; unit: CNY) to reveal how economic development affects EEQ based on the environmental Kuznets curve.

Fig. 2A and B illustrate the trends of the prefecture-level comprehensive innovation index (CII)[2] and GDP. The main implication suggests that both groups had started with very low levels of CII and GDP. Although the SCP group grew faster, it took a certain amount of time for the difference in the levels of CII and GDP to become significant. Fig. 2C and D plot ACOD and ASO since 2005. The SCP group did not decrease faster than the control group before it was included under the SCP project. However, divergence sets in after the establishment of SCP in 2012. Thus, we empirically explore whether there is a connection between them in Section 4.

4. Empirical analysis

In this section, we analyse the impact of SCC on environmental quality. Our aim is to provide an estimate of the effect of a reduction in

[1] In the absence of statistical data distinguishing agricultural and urban population in China, the urbanisation ratio cannot be measured by the share of urban population from the perspective of population distribution.

[2] This indicator can comprehensively reflect all aspects of urban innovation, which has been derived from the industrial development center of Fudan University, China's urban and industrial innovation report.

pollution in a smart city, that is the extent of growth difference in SCP in terms of EEQ at the city level, and the reason of its occurrence.

4.1. Model specification

Since cities with better EEQ are more likely to attach importance to green development, the degree of USI can reflect such behaviour. In addition, there may be an existence of USI measurement errors and unobserved confounding factors that do not change over time, causing serious endogeneity problems. To avoid biased results in the estimation of the effects of a reduction in pollution following smart city initiatives, we adopt a standard DID strategy to improve the robustness of the results. The model specification is given by

$$UPL_{it} = \beta_0 + \beta_1 SCP_{it} + \sum\nolimits_{j=2}^{n} \beta_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.1}$$

where UPL_{it} represents the urban pollution level measured by ASO in city i and at year t. We focus on the effects of SCP_{it}, whether a city implemented the smart city initiative in 2012, and we hypothesise that β_1 is lower than zero. We denote SCP_{it} as $treated_i \times period_t$, where $treated_i$ indicates the city's smart city (SC) status. Specifically, $treated_i = 1$ if city i is a SCP, and 0 otherwise. Here, $period_t$ is a post-treatment indicator, taking a value of 1 if $t \geq 2012$ and 0 otherwise. Vector $\boldsymbol{X}_{it}$ denotes control variables, that is, the urbanisation ratio, level of science and technology, industrial structure, opening-up level, and natural logarithm of real per capita GDP. The remaining empirical analyses are based on the fixed effects log-linear model. The error term, ε_{it}, is clustered at the city–year level. μ_i and γ_t denote city and year fixed effects.

Urban scale is a vital factor affecting EEQ. Studies have found that urban scale plays a critical role in explaining how to strengthen or weaken SCC. Thus, this study explores the mechanism of the potential impact of SCC on EEQ by introducing the interactions between SCP and urban scale. The following model is employed to analyse this mechanism:

$$UPL_{it} = \gamma_0 + \gamma_1 SCP_{it} + \gamma_2 SCP_{it} \times dum\_Scale_{it} + \sum\nolimits_{j=3}^{n} \gamma_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.2}$$

where we include dum_Scale_{it} as a dummy variable that is equal to one if a city belongs to the category of a high level of population.[3] We represent the interactions between USI and urban scale by $USI_{it} \times dum\_Scale_{it}$, which is our variable of interest. We hypothesise that γ_2 is greater than zero. Vector $\boldsymbol{X}_{it}$ d includes the control variables.

Although most studies have reached a consensus that urban EEQ has a U-shaped relationship with urbanisation rate, there are different explanations for this phenomenon. The urbanisation process can be seen as a staggered combination of both SCC and traditional urban construction, such that the structural changes would likely result in to the potential nonlinear impact of urbanisation rate on EEQ. From this perspective, this study provides new evidence on this debate by introducing the square term of urbanisation rate. The model is constructed as follows:

$$UPL_{it} = \gamma_0 + \gamma_1 SCP_{it} + \gamma_2 Urbar_{it} + \gamma_3 Urbar_{it}^2 + \sum\nolimits_{j=4}^{n} \gamma_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.3}$$

where $Urbar_{it}$ is a threshold variable explaining the effect of urbanisation rate on pollution, and $Urbar_{it}^2$ represents the square term associated with urbanisation rate. In this model, the variable of interest is the squared term; we hypothesise that γ_3 is lower than zero. Vector $\boldsymbol{X}_{it}$ denotes the control variables.

SCC greatly promotes urban innovation (Fig. 1). In the past ten years, CII has been increasing at an annual rate of approximately 30%. Therefore, Smart city policies may exert significant positive impacts on environment quality through the more effective improvement of technology, especially the green technology, and more efficient resources allocation. As outlined in the theoretical framework, these underlying micro foundations are mainly divided into two stages. First, smart city projects are of importance to fostering urban innovation. Second, urban innovation, especially green innovation, can direct organizations and communities towards achieving sustainable competitive advantages.We use the mediation channel variable method to address this concern (Baron and Kenny, 1986). The mechanism model can be set as follows,

First stage: channels through which SCC promotes urban innovation

$$CII_{it} = \theta_0 + \theta_1 SCP_{it} + \sum\nolimits_{j=2}^{n} \theta_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.4}$$

$$Chann_{it}^k(Scite_{it}, Alloc_{it}) = \alpha_0 + \alpha_1^k SCP_{it} + \sum\nolimits_{j=2}^{n} \alpha_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.5}$$

$$Chann_{it}^k(Scite_{it}, Alloc_{it}) = \varphi_0 + \varphi_1 SCP_{it} + \varphi_2^k CII + \sum\nolimits_{j=3}^{n} \varphi_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.6}$$

Second stage: channels through which SCC improves EEQ

$$Chann_{it}^k(Scite_{it}, Alloc_{it}) = \alpha_0 + \alpha_1^k SCP_{it} + \sum\nolimits_{j=2}^{n} \alpha_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.7}$$

$$UPL_{it} = \beta_0 + \beta_1 SCP_{it} + \sum\nolimits_{j=2}^{n} \beta_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.8}$$

$$UPL_{it} = \gamma_0 + \gamma_1 SCP_{it} + \gamma_2^k Chann_{it}^k(Scite_{it}, Alloc_{it}) + \sum\nolimits_{j=3}^{n} \gamma_j \boldsymbol{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}. \tag{4.9}$$

We also examine the credibility and explanatory power of the aforementioned two mechanisms in a manner similar to Gelbach (2014):

$$UPL_{it} = \delta_0 + \delta_1 SCP_{it} + \sum\nolimits_{k=1}^{2} \delta_2^k Chann_{it}^k + \sum\nolimits_{j=3}^{n} \delta_j \boldsymbol{X}_{it} + \nu_i + \eta_t + \theta_{it}, \tag{4.10}$$

$$\widehat{\beta}_1 = \widehat{\delta}_1 + \sum\nolimits_{k=1}^{2} \widehat{\alpha}_1^k \widehat{\gamma}_2^k, \tag{4.11}$$

$$\psi_k = \widehat{\alpha}_1^k \widehat{\gamma}_2^k \Big/ \widehat{\beta}_1, \tag{4.12}$$

where our mediating variable of interest is $Chann_{it}^k$, including $Scite_{it}$ and $Alloc_{it}$, representing the scientific and technological level and efficiency of resource allocation respectively. Here, ψ_k represents the proportion of the kth mediating effect in the total effect., We include the level of science and technology (Scite; unit: item/10^4 individuals), as measured by the number of patents per capita, because areas that are more creative may offer more treatment plans for protecting the environment. Due to data availability, it is challenging to measure resource allocation efficiency at the prefecture city level (Ren et al., 2019). To measure comprehensively how efficient the resources allocation are in smart city, this paper adopts two measurement strategies. First, following Xu et al. (2018), we use the total factor productivity (Alloc1) as a proxy variable for resource allocation efficiency. Since TFP is a comprehensive Solow residual value, it includes both the effect of resource allocation and the technological progress. After controlling for the number of patent applications in our mechanism model, the technological progress effects of TFP is eliminated so as to better analyze the remaining resource allocation effects of smart city construction. Second, draw on the method of Shi et al. (2018), industrial structure (Alloc2) is used as a proxy variable of resource allocation efficiency to test the impact of smart city construction on the ecological environment.

4.2. Main results

SCC affects urban pollution level (UPL). In this context, we present

[3] In the main results as shown in Table 3, we define $dum\_Scale_{it} = 1$ if a city's population level is above 50 percentile among all the cities in the sample.

Table 1
Impact of SCC on urban pollution.

	OLS ASO (1)	Log(ASO) (2)	DID ASO (3)	(4)	(5)	Log(ASO) (6)	(7)	(8)
SCP	0.579	0.106	-3.213***	-2.569***	-2.993***	-0.220***	-0.224***	-0.207***
	(0.708)	(0.094)	(0.447)	(0.511)	(0.477)	(0.054)	(0.045)	(0.042)
Urbar	1.766***	0.203***		-1.290***	-1.200***		-0.069**	-0.056**
	(0.242)	(0.025)		(0.362)	(0.387)		(0.032)	(0.026)
Densi	7.257***	3.740***		0.699	0.327		-0.031	-0.057
	(1.711)	(0.270)		(1.750)	(1.620)		(0.230)	(0.248)
Instr	0.209***	0.056***		0.069***	0.039***		0.013***	0.008***
	(0.015)	(0.002)		(0.015)	(0.013)		(0.003)	(0.003)
Openl	-0.005**	0.77e-4		-0.005***	-0.005***		-0.001***	-0.001***
	(0.002)	(0.000)		(0.002)	(0.001)		(0.000)	(0.000)
Lpgdp	-0.652**	-0.059		0.433	0.359		0.109**	0.102**
	(0.257)	(0.048)		(0.286)	(0.319)		(0.045)	(0.045)
Constant	-0.384	-1.760***	7.718***	0.148	3.548	1.125***	-0.494	-0.203
	(2.455)	(0.442)	(0.293)	(2.845)	(2.909)	(0.040)	(0.443)	(0.429)
Year fixed effect	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Province-year fixed effect	No	No	No	Yes	No	No	Yes	No
City fixed effect	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	2028	2028	2028	2028	2028
R^2	0.304	0.431	0.267	0.467	0.306	0.367	0.599	0.382

Note: The values represent the regression coefficients of explanatory variables; t-statistics are in parentheses; standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2
Robustness checks.

	Log(ASO) (1)	(2)	(3)	lag (4)	PSM-DID (5)	Log(ACOD) (6)	(7)
SCP		-0.204***	-0.207***	-0.172***	-0.183***		-0.122***
		(0.055)	(0.054)	(0.0417)	(0.0684)		(0.038)
dum_Y2013			-1.104***				
			(0.098)				
Four or more periods before	0.091					-0.043	
	(0.097)					(0.081)	
Three periods before	-0.045					-0.0332	
	(0.119)					(0.099)	
Two periods before	-0.052					-0.054	
	(0.097)					(0.081)	
Initiative period	-0.056					-0.173*	
	(0.118)					(0.099)	
One period after	-0.110					-0.178*	
	(0.118)					(0.099)	
Two periods after	-0.140					-0.191*	
	(0.118)					(0.099)	
Three periods after	-0.235**					-0.221**	
	(0.119)					(0.099)	
Four or more periods after	-0.338***					-0.081	
	(0.097)					(0.081)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	1872	1720	2028	2028
R^2	0.386	0.389	0.382	0.425	0.335	0.243	0.241

Note: Columns (3) and (6) introduce a series of 'environmental regulation' policies implemented nationwide since 2013 on the basis of Eq. (4.1). The values represent the regression coefficients of explanatory variables; t-statistics are in parentheses; standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the ordinary least squares (OLS) and DID specifications in Table 1. The estimated coefficients of the SCC indicator in the DID method are negative and statistically significant at the 1% level. We expect the OLS coefficient on SCC to be biased upward if the SCP group has a better policy support than cities in the control group. A DID strategy employing city and year fixed effects reduces the SCC effect on ASO from 0.579 to -2.993, which is equivalent to a 617% reduction in the SCC effect. Such a huge fluctuation in the coefficient implies that there may be a potential bias caused by the extreme values of ASO and their differences before policy implementation. Consequently, the corresponding estimates using their logarithms as the dependent variables under a DID strategy are presented in the following tables.

From column (8) we observe that SCC significantly reduces the ASO in China. In the case of SCP, a coefficient of -0.207 can be interpreted as a difference in the SO_2 emission per unit land of the SCP group relative to the control group, indicating that the ASO of the SCP group reduced by 20.7% in response to the establishment of SCP. Column (6) excludes all control variables, and column (7) further employs a DID strategy by including province and year fixed effects. The coefficient and significance of SCC almost remain unchanged in this case. Therefore, these analyses support Result 1, that is, SCC significantly increased China's EEQ. The growth of SCC has been a contributing factor in the

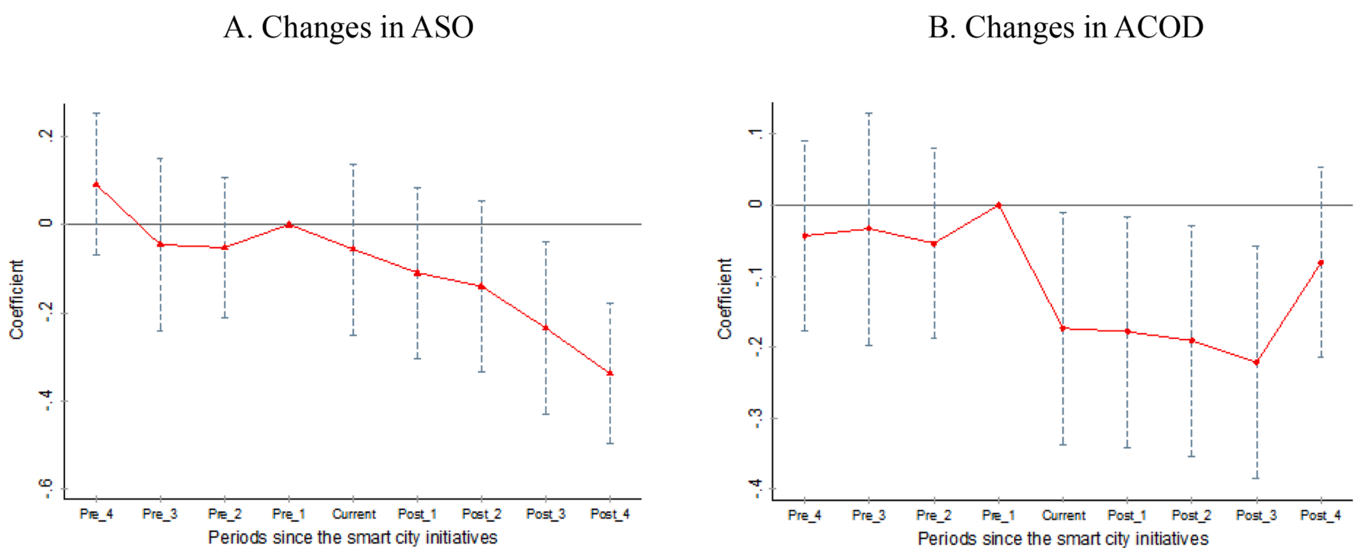

Fig. 3. Dynamics of the urban pollution level before and after the smart city initiatives were undertaken. Note: The horizontal axis measures periods since the SCP initiative was undertaken. The average length of one period is approximately two years. The points connected by the solid line indicate changes in urban pollution of the SCP group (relative to the control group) compared to one period before the initiatives were undertaken, which is displayed as an effect of zero to aid the visual analysis. See columns (1) and (4) in Table 2 for the numbers of these point estimates. The bounds are given by the 90% confidence intervals.

improvement of EEQ in China. In addition, the regression results for the control variables conform to the economic intuition: the industrial structure and natural logarithm of real per capita GDP decrease China's EEQ. The urbanisation ratio, population density, and opening-up level exert a significant positive impact on China's EEQ, such that their effects tend to be statistically significant.

4.3. Robustness checks

To verify the robustness of the relationship between SCC and UPL, we conduct a series of robustness tests (Table 2). First, although quasi-natural experimental methods can effectively make up for a shortage in the relatively small sample size and difficulty in capturing long-term effects with the help of a randomised controlled experimental trial, we need to discuss selection concerns and our strategies to deal with them. To validate the identifying assumption that the trends are parallel in the case of the SCP group, while the control group does not consider the smart city initiative, we employ a strategy similar to the event study as follows:

$$UPL_{i,t} = \alpha_0 + \sum_{k \in K} \beta_k D_{i,k} + \sum\nolimits_{j=1}^{n} \gamma_j X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{4.13}$$

where $D_{i,k}$ is a set of eight dummy variables that take the value of one if k periods have passed since the implement of i, such that $\boldsymbol{K} = \{-4, -3, -2, 0, 1, 2, 3, 4\}$, and the values -4,-3,-2,-1,0,1,2,3, and 4 refer to $t \in \{2005, 2006, 2007\}$, $t \in \{2008, 2009\}$, $t \in \{2010, 2011\}$, $t \in \{2012\}$, $t \in \{2013\}$, $t \in \{2014\}$, $t \in \{2015\}$, and $t \in \{2016, 2017\}$, respectively. One period before the smart city initiatives is left as the comparison group. If the coefficients β_{-4}, β_{-3} and β_{-2} are not significantly different from zero, the assumption of parallel trends is likely to hold.

The results are presented in Table 2. Columns (1) and (4) show the results with different proxy indicators for the dependent variable, which are also shown in Fig. 3. It can be observed that the growth rates of the two groups did not differ before the smart city initiatives were undertaken; the divergence took place after their implementation. It takes time for the effect to become significant. Another key issue in the comparison lies in the identification of the process of assigning SCP. If these pilots were randomly assigned, it would be easy to compare their development paths. However, this might not be true since there were indeed strategic considerations in choosing SCP. To alleviate the potential estimation bias caused by the non-random selection of the experimental and control groups, we adopt the following general framework by introducing the interactions between urban inherent characteristics and time linear trend on the basis of Eq. (4.1). The interactions in year t are denoted by $Z_{i,t} \times trend_t$, where $Z_{i,t}$ represents the urban inherent characteristics, such as whether the city was a pilot city for 'two control areas' in 1998, it is a special economic zone, it is a provincial capital city, or it is a northern city. Here, $trend_t$ represents time linear trend. Column (2) shows that the results remain robust after considering the potential impact of inherent inter-regional differences. These results alleviate our concerns of potential endogeneity problems. Second, a series of 'environmental regulation' policies implemented nationwide since 2013, resulted in an increase in environmental awareness. Hence, some individuals and enterprises reduced pollution emissions to avoid punishment from the government. However, one concern is that this might generate data that confounds the hypothesised relationship, which overestimates SCC's effect of reducing pollution. To account for this concern, we examine the policy effects by adding dum_Y2013_{it} as a dummy variable that takes the value of one during the period of 2013 to 2015. Column (3) reveals that the estimated coefficient of the policy dummy variable is negative and statistically significant at the 1% level, which indicates that the environmental protection policy implemented by the new government is effective. Hence, cities with environmental protection policies reduce on an average of 110.4% more on the ASO than cities without them. Since the coefficient and significance of SCP after controlling a policy variable remain qualitatively unchanged, we further conclude that the suspected overestimates in the SCP results should not lead to the problem of biased results.

Third, different measures of UPL are available; thus, ACOD can be adopted as a second outcome variable in Column (7) of Table 2. Again, SCP is significantly negative regardless of whether the control variables are introduced or not. This indicates that implementing the SCP from 2012 exerts a positive effect on the level of EEQ. More specifically, the SCP has significantly reduced the ACOD by approximately 10.6% without control variables and nearly 12.2% with all control variables. Taking advantage of both DID and PSM, PSM-DID solves the endogeneity problem and sample selection bias effectively. In our study, we can estimate the impact of smart city policy on eco-environment quality more reliably through PSM-DID. We further use lags in control variables

Table 3
Heterogeneous responses.

	ASO		Log (ASO)			
	(1)	(2)	(3)	(4)	(5)	(6)
SCP	-2.187***	-3.363***	-0.108**	-0.230***	-0.126**	-0.229***
	(0.678)	(0.477)	(0.053)	(0.043)	(0.053)	(0.043)
SCP × dum_Scale	-1.624**		-0.221***		-0.164***	
	(0.816)		(0.058)		(0.060)	
Urbar	-1.142***	1.199**		0.075	-0.050*	0.084*
	(0.398)	(0.473)		(0.050)	(0.028)	(0.050)
Urbar × Urbar		-0.139***		-0.008***		-0.008***
		(0.020)		(0.002)		(0.002)
Control variables	Yes	Yes	No	No	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	2028	2028	2028
R^2	0.309	0.353	0.369	0.369	0.383	0.388

Note: The values represent the regression coefficients of explanatory variables; t-statistics are in parentheses; standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Channels: first stage.

	CII	Scite		Alloc	
	(1)	(2)	(3)	(4)	(5)
SCP	6.305***	15.28***	9.267***	1.46e-3***	6.26e-4*
	(0.890)	(2.170)	(2.178)	(0.000)	(0.000)
CII			0.954***		1.93e-4***
			(0.191)		(0.000)
Scite				8.45e-5***	5.97e-5***
				(0.000)	(0.000)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	0.543	48.64**	48.12**	0.106***	0.107***
	(7.843)	(20.31)	(19.10)	(0.005)	(0.004)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	1716	1716	1716	1716	1716
R^2	0.305	0.388	0.463	0.919	0.928

Note: The values represent the regression coefficients of explanatory variables; t-statistics are in parentheses; standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

for one year, which alleviates potential simultaneity between smart city policies and urban pollution. The estimated coefficients for PSM-DID and lag term are reported in Columns (4) and (5) respectively, and each of them remains significantly negative. In summary, these robustness checks further support the basic conclusions.

4.4. Heterogeneous responses: urban scale and urbanization rate

Columns (1), (3), and (5) in Table 3 further introduce the interactions between SCP and the dummy for urban scale above the median. Here, we can observe that the impact of SCP on ASO is negative and marginally significant, but the interaction between SCP and large-scale dummy exerts significant negative impact (at the 5% level) on the ASO. Column (3) provides robustness checks by removing all control variables, such that the results are qualitatively similar. The regression results suggest that SCC has a stronger positive impact on environmental quality in areas with a large urban scale. Urban size disparities are attributed to different policies and capital endowment, including human capital and physical capital. First, large-scale cities more easily achieve favourable economic policies during SCC. For example, economic zones with a larger scale provide investors with preferential tax treatments and can be selected as the first pilot projects for smart cities and 5G cities by the government. Second, the agglomeration of abundant economic factors provides stronger support for the realisation of a reduction in the pollution of smart cities, just as the human body requires the coordinated operation of various organs. We examine the effect of SCC using different urban scales to provide new evidences for this debate, which implies that an appropriate expansion of urban scale within reasonable urban boundaries positively affects environmental quality by promoting SCC.

Columns (2), (4), and (6) introduce the urbanisation rate that is used as a threshold variable affecting pollution. We observe that a single threshold effect is significant, such that the effect of urbanisation rate on ASO changes slightly. This finding implies that the urbanisation rate exerts a nonlinear impact on EEQ. Furthermore, considering the regression on primary and quadratic terms of urbanisation rate with respect to ASO, the estimated coefficients in columns (2), (4), and (6) are significant at the 1% significance level, which indicates a stable inverted U-shaped relationship between the urbanisation rate and urban pollution. From the first-order condition of the urbanisation rate, we observe that the turning point of urbanisation rate is 5.25%, while the actual average urbanisation rate was 2.13% in 2017. Thus, the existing urbanisation rate is on the left side of the inverted U-shaped curve. Hence an increase in urbanisation rate increases urban pollution. This result occurs because the scientific and technological level and resource allocation efficiency that are influenced by SCC do not reach the threshold for improving EEQ for most cities; the high effect of emission of traditional urban construction remains the primary factor. Therefore, an increase in urbanisation rate helps to increase the speed of smart urban construction, promoting new urbanisation. Subsequently, the urbanisation rate will cross the inflection point of the inverted U-shaped curve, increasing the roles of the scientific and technological level and resource allocation efficiency, thereby reducing urban pollution.

4.5. A balance between the sustainable development goals: innovation driven channels

There has been a growing importance for sustainable development; however, in the developing countries it implies a serious conflict of interest considering the sustainable development goals (SDGs)[4]. In the case of SCC, it is a challenge to manage the trade-off between environmental protection and economic development. In this section, we present some suggestive evidences on the channels for the long-run impact.

[4] SDGs stand for seventeen global development goals formulated by the United Nations, which aim to solve the development problems of social, economic and environmental dimensions comprehensively from 2015 to 2030, and turn to the path of sustainable development. In this study, it represents economic development and environmental protection.

Table 5
Channels: second stage.

Panel A: Dependent variable is Log (ASO)						
		Technology effect	Allocation effect		Total effect	
	(1)	(2)	(3)	(4)	(5)	(6)
SCP	-0.143***	-0.114***	-0.109***	-0.138***	-0.099***	-0.114***
	(0.038)	(0.038)	(0.037)	(0.039)	(0.037)	(0.038)
Scite		-0.002***			-0.001*	-0.002***
		(0.001)			(0.001)	(0.001)
Alloc1			-12.41***		-10.74**	
			(4.750)		(4.954)	
Alloc2				-0.221***		-0.214**
				(0.084)		(0.084)
Observations	1716	1716	1716	1672	1716	1672
R^2	0.065	0.049	0.121	0.092	0.116	0.077
Panel B: Dependent variable is Log (ACOD)						
	(7)	(8)	(9)	(10)	(11)	(12)
SCP	-0.151***	-0.122***	-0.150***	-0.140***	-0.127***	-0.112***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)
Scite		-0.002***			-0.002***	-0.002***
		(0.001)			(0.001)	(0.001)
Alloc1			-0.334		3.500	
			(3.779)		(3.992)	
Alloc2				0.003		0.010
				(0.051)		(0.051)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1716	1716	1716	1672	1716	1672
R^2	0.227	0.168	0.166	0.204	0.333	0.141

Note: The values represent the regression coefficients of explanatory variables; t-statistics are in parentheses; standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Explaining the long-run impact on GDP.

Panel A: Log (Agriculture/Industry/ Commerce)	Log(GDP)		Log(Agriculture)	Log(Industry)	Log(Commerce)
	(1)	(2)	(3)	(4)	(5)
SCP	0.077***	0.057***	0.069**	0.059**	0.042**
	(0.019)	(0.020)	(0.031)	(0.027)	(0.017)
Observations	2028	2028	1976	1976	1976
R^2	0.871	0.887	0.772	0.774	0.918
Panel B: Agriculture / Industry/ Commerce	GDP		Agriculture	Industry	Commerce
SCP	519.2***	116.3***	-3.634**	71.67***	50.61***
	(61.78)	(31.79)	(1.441)	(17.32)	(15.40)
Control variables	No	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2028	2028	1989	1989	1989
R^2	0.349	0.811	0.663	0.730	0.834

Notes: The values represent regression coefficients of explanatory variables; t-statistics are in parenthese. standard errors (in parentheses) are clustered at the city–year level; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Cost-benefit analysis: environmental pollution and medical expenses.

	Panel A					Panel B
	PM_{10}			Log (PM_{10})		Log (Pcs)
	(1)	(2)	(3)	(4)	(5)	(6)
ASO	1.148***	1.242***	0.376***	0.004***	0.003**	
	(0.249)	(0.227)	(0.145)	(0.001)	(0.001)	
PM_{10} (10ug/m^3)						0.00467***
						(0.001)
Control variables	No	Yes	Yes	No	Yes	Yes
Two-way fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	760	760	760	756	756	191964
R^2	0.057	0.214	0.436	0.506	0.516	0.626

Note: Panel A shows the results from a 2005 to 2017 panel data set of 287 prefecture level cities in China. Panel B shows the results from medical insurance patient management data of different levels of hospitals in Shanghai (sampling ratio is 5%). The values represent the regression coefficients of explanatory variables; standard errors (in parentheses) are clustered at the city–year level; additionally, *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

First, to understand the long-run impact on EEQ, we examine the technology and allocation effects separately. Second, to explain its long run impact on GDP, we examine different sectors over time.

In Table 4, columns (1) to (5) show that the gaining importance of SCC has significantly (at 1% significant level) promoted urban innovations, namely, technology innovation and allocation innovation. Columns (2), (3), (8), and (9) of Table 5 examine the mediating effects of urban innovations. Compared with the results in columns (1) and (7), all the absolute values of the coefficients of the SCP become smaller or insignificant, which indicates that SCC significantly reduces urban pollution by strengthening technology innovation and allocation innovation through the effects of technology and allocation.

These results have two explanations. First, the improvement in urban innovation has transformed the modes of urban development from an extensive to intensive development. Technology innovation has updated plant machinery and equipment and advanced the production process of enterprises. This has significantly increased productivity and decreased the cost of pollution control. Second, the information characteristics of allocation innovation increase the convenience of resource flow. In such a city, enterprises can predict market supply and demand on time, allocate resources to optimise production, capital flow, and information flow, such that they can be released from the limitations of traditional logistics to a certain extent. In addition, the upgradation of industrial structure driven by innovation accelerates the transformation of the economic structure into a high-quality development. This significantly promotes resource utilisation. In summary, urban innovation caused by SCC results in energy conservation that may ultimately lead to reduction in pollution.

In columns (1) and (7), the coefficients of SCP are all negative and significant, but their absolute values differ in columns (5) and (11), indicating that the direct impact of SCP on air pollution is greater than its counterpart in the case of water pollution. In addition, the range of variation in the coefficients of SCP in columns (2), (3), (8), and (9) indicate that the mediating effects from allocation innovation are larger to some extent,that is, the technology effect accounts for 10.23%, and the allocation effect accounts for 10.97%. This finding suggests that the effects of the SCP on UPL are operating through the improvement in urban innovation.

We propose two possible interpretations for these phenomena. First, the characteristic of a rapid diffusion of exhaust gas can form severe smog, causing a wide range of respiratory diseases under certain natural conditions; this has a more direct impact on the health of residents. However, the negative impact of wastewater can be alleviated by the supply of tap water to a certain extent. Regarding environmental governance, SCC focuses on eliminating exhaust gases in the short-run. Second, allocation innovation is a new innovative form of a deep integration of the new generation of information technology and traditional industries, which can complete the economic transformation by optimising production factors, updating business systems, and reconstructing business models. Although SCC can help in producing the latest scientific and technological achievements (technology innovation), it has a relatively slow effect when it is applied to production and society. In the context of millions of enterprises requiring transformation and upgrading, the wave of 'Internet +' has been launched in China. For example, the use of taxi-hailing software, online purchase of train and airline tickets, and travel navigation systems in the field of transportation have greatly improved individuals' travel experiences, increased the utilisation rate of vehicles, and rapidly reduced urban pollution emissions.

To explain the difference in economic activities that has led to the observed GDP, we run a similar regression as in Eq. (4.1) for different sectors. We focus on the outcomes of the three sectors: the primary sector (agriculture, forestry, and fishing), secondary sector (light industry and heavy industry), and tertiary sector (commerce and service), and employ a fixed-effects model similar to the specification in Eq. (4.1). The results are presented in Table 6. Panel A shows the results for the logarithm of output for each sector, whereas Panel B shows the results for levels of output per. The main drivers for economic development advantage of the SCP group come from the light and heavy industry sectors. Since this sector has been transforming from a labour-intensive to technology-intensive one, it creates demand for urban innovation, this finding is also consistent with the previous finding on environmental protection through innovation driven channels in SCP. This finding also suggests that the results on economic opportunities divergence are due to a potential reallocation of industrial proportion between the SCP and control groups. Overall, the development of smart cities promotes both economic growth and environmental protection, while playing a significant role in maintaining the balance of China's economy.

4.6. Potential cost savings or gains from smart city initiatives

EEQ is obviously an important determinant of city life. Urban pollution causes severe health problems, most notably strokes, heart diseases, chronic obstructive pulmonary disease, and respiratory infections. According to the 2011 report of the Chinese Academy of Environmental Sciences, more than one fifth of the medical expenditure of Chinese residents is spent on the prevention and treatment of diseases caused by environmental pollution. Therefore, we further construct the following empirical model to estimate the potential cost savings or gains of smart city initiatives from the perspective of medical health. Using a two-way fixed effects model, the parameters of interest are identified solely based on a within-city time variation that differs from global time variation. The variable of interest is $Pollution_{it}$ that is employed as the proxy of PM_{10}, and; we hypothesise that φ_1 is higher than zero.

$$Pcs_{it} = \varphi_0 + \varphi_1 Pollution_{it} + \sum\nolimits_{j=2}^{n} \beta_j \boldsymbol{Z}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4.14}$$

where Pcs_{it} represents the medical expenses in hospital $i$and at day t;. ε_{it} is the random disturbance term; and μ_i and γ_t denote hospital and day fixed effects. A series of control variables $\boldsymbol{Z}_{it}$ are incorporated into Eq. (4.14) in order to accommodate the characteristics of local weather.

As estimated in column (6) of Table 7 following Song et al. (2019), PM_{10} significantly increases the medical expenses. Its coefficient of 0.00467 implies that every time it increases by 10 μg/m^3, a 0.47% increase occurs in the medical expenses. Since information related to PM_{10} is not available before 2013 to match the results of benchmark regression, we focus on the relationship between PM_{10} and ASO and employ a fixed-effects model similar to the specification in Eq. (4.1). ASO affects PM_{10}; the OLS and fixed effects specifications are presented in columns (1) to (5). All the estimated coefficients of the ASO indicator are positive and statistically significant at the 1% level. Hence, it can be exhibitedthat the medical expenditure of Shanghai due to the construction of smart cities has decreased by approximately 8.69 million yuan[5]. By using the weighting of the number of medical beds in different regions, we can calculate that the medical expenditure from SCP would be reduced by approximately 2.676 billion yuan during the period of 2012 to 2017. It is noted that the income estimated here only comes from the aspect of medical treatment, and does not take into account the income of other dimensions, such as the economic income resulting from an increase in labour productivity, and decrease of crime rate. Hence, it can be regarded as the lower boundary of the income. In conclusion, cities can realise more potential cost savings or gains through the implementation of smart city initiatives compared with traditional construction.

[5] Combing the sample data from Panel B (the average total amount of medical expenses per day is 2.32 million yuan) and the estimated coefficient in Column (5) of Table 1 (-2.993 kg/km^2), the medical expenditure of Shanghai is expressed as 2.993×0.376×0.000467×2320000×365/0.05=8687614.

5. Summary and conclusion

In order to understand the factors that have helped China experience a continuous rise in EEQ in recent years, this study conceptually and empirically investigates how the spread of smart city initiatives affects the capacity to reduce pollution in China. We adopt a theoretical model of classic land allocation decisions to demonstrate how local officials' responsibilities to protect the ecological environment and promote economic growth can lead to smart urban spatial expansion in the long-run, and respond to land values in a manner similar to that of competing land markets. These land conversion decisions improve the ecological environment in China from the perspective of innovation-driven advantages. Our study of 287 prefecture- level cities in China finds that SCC significantly reduces the discharge of urban pollution in a manner that is consistent with our theoretical model.

The main conclusions may be outlined as follows. First, the popularity of SCC is innovative, which helps to support 'a society of information'. Technology innovation and allocation innovation decrease the cost of pollution control and improve the efficiency of resource utilisation, resulting in energy conservation that ultimately leads to a reduction in pollution in China. In addition, the development of smart city promotes both economic growth and environmental protection, while playing a significant role in maintaining the balance of China's economy. Second, SCC has a stronger positive impact on environmental quality in areas with a large urban scale, suggesting that the expansion of urban size is likely to constitute effective supports, provided that the expansion is limited to a reasonable urban boundary by the individual making primary land allocation decisions. Third, our results demonstrate that urban EEQ has a U-shaped relationship with urbanisation rate during the period of a rapid construction of smart cities in China. This finding further indicates that the changes in urban structure introduced by SCC improve urbanisation quality and lead to a decrease in urban pollution. Finally, this study analyses the regional potential cost savings or gains from smart city programs, which is crucial for evaluating market-based policy and promoting national economic transformation and growth.

There are several policy implications based on our findings. First, the SCC, a new direction for urban initiatives, could balance the quality of the ecological environment and economic development to promote a high-quality growth, especially for developing countries like China. Governments should consider the SCC in their economic development policies. Second, our findings suggest that the innovation-driven technology advancement fuels the positive environmental effects of smart city. Therefore, the policy maker should promote the pro-innovation policies such as infrastructure construction project and university funding program so as to further exploit the potential of the urban innovation. Finally, the smart city policy enriches the theory of sustainable urban development. the smart city alleviates negative side effects caused by urban expansion (e.g. pollution) while making it possible for cities to efficiently allocate resources. It would be wise for local government to take into account the smart city construction in their urban development plans. Further analysis of smart city on urban eco-environment that connects macro estimates offered by this paper to the underlying micro impact of smart city initiatives on corporate or resident behavior remains an exciting area for future research.

CRediT authorship contribution statement

Zhen Chu: Conceptualization, Methodology, Software, Writing – review & editing, Writing – original draft. **Mingwang Cheng:** Data curation, Validation, Supervision. **Ning Neil Yu:** Visualization, Investigation.

Declaration of Competing Interest

None.

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Appendix A. Short run comparative statics, long run equilibrium, and transition dynamics

We derive Results (1)–(3) by integrating Eqs. (2.3), (2.4), (2.7) and (2.8) to obtain two equations defining optimal traditional urban land conversion traditional $m_2(t)$ and smart urban land conversion $m_2(t)$ at a given point in time.

$$G \equiv r_1(E_1+m_1-m_2)-\pi_1(E_1+m_1-m_2)-\tau(E_3-m_1)q(E_3-m_1)$$
$$+\int_T^{\infty}[r_1(E_1+m_1-m_2)-\pi_1(E_1+m_1-m_2)-\tau(E_3-m_1)q(E_3-m_1)]e^{-\rho(y-t)}dy=0. \tag{A1}$$

$$H \equiv r_2(E_2+m_2)-\pi_2(E_2+m_2)-\tau(E_3-m_1)q(E_3-m_1)$$
$$+\int_t^{\infty}[r_2(E_2+m_2)-\pi_2(E_2+m_2)-\tau(E_3-m_1)q(E_3-m_1)]e^{-\rho(y-t)}dy=0. \tag{A2}$$

Differentiating the resulting equation yields $H_{m_2}=r_2'-\pi_2'+\int_t^{\infty}(r_2'-\pi_2')e^{-\rho(y-t)}dy$ and $H_q=-\tau+\int_t^{\infty}-\tau e^{-\rho(y-t)}dy=-\tau-\frac{\tau}{\rho}$, So if $r_2'>0,\ \pi_2'<0$, as assumed above; then,

$$\frac{\partial q}{\partial m_2}=-\frac{H_{m_2}}{H_q}=\frac{r_2'-\pi_2'+\int_t^{\infty}(r_2'-\pi_2')e^{-\rho(y-t)}dy}{\tau+\frac{\tau}{\rho}}>0. \tag{A3}$$

Dramatic changes in scientific and technological level and resource allocation efficiency brought from smart urban innovation exert a positive effect on EEQ. That is, EEQ is higher in areas where the US is higher (Result 1); differentiating Eq. (A3) yields

$$\frac{\partial^2 q}{\partial m_2 \partial E_3}=\left(r_2'-\pi_2'+\int_T^{\infty}(r_2'-\pi_2')e^{-\rho(y-t)}dy\right)\cdot\frac{-\tau'}{\left(\tau+\frac{\tau}{\rho}\right)^2}<0. \tag{A4}$$

Smart urban construction has a stronger positive impact on EEQ in areas with a higher urban scale (Result 2); and differentiating Eq. (A1)

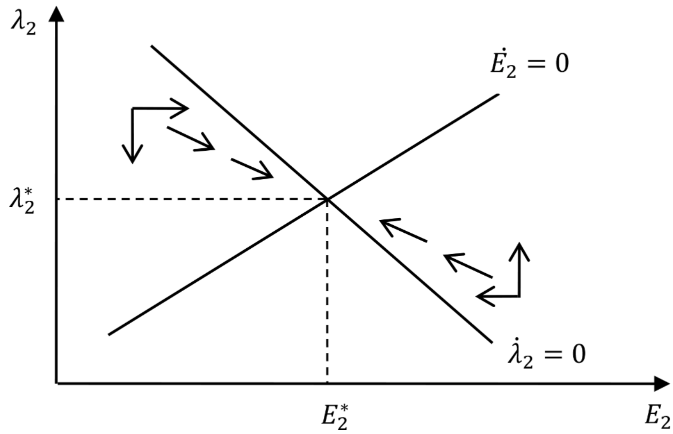

Fig. A1. Phase plane analysis of transition dynamics.

yields $G_{m_1} = r_1' - \pi_1' + \tau'\varepsilon + \int_t^\infty (r_1' - \pi_1' + \tau' q)e^{-\rho(y-t)}dy$ and $G_q = -\tau + \int_t^\infty -\tau e^{-\rho(y-t)}dy = -\tau - \frac{\tau}{\rho}$. Thus, if $r_1'\langle 0,\ \pi_1'\rangle 0$ and $\tau' < 0$, as assumed above,

$$\frac{\partial q}{\partial m_1} = -\frac{G_{m_1}}{G_q} = \frac{r_1' - \pi_1' + \tau' q + \int_t^\infty (r_1' - \pi_1' + \tau' q)e^{-\rho(y-t)}dy}{\tau + \frac{\tau}{\rho}} < 0. \tag{A5}$$

In general, SCC is faster than traditional construction in areas with a higher urbanization rate. Combined with Eqs. (A4) and (A5), we propose Result 3, that is, urban EEQ has a U-shaped relationship with its urbanisation rate.

We analyse the transition to the long-run equilibrium allocation of land between traditional urban and smart urban uses with a phase plane analysis in (E_2,λ_2). Eq. (2.8) implicitly defines land conversion m_2 as a function $m_2(E_2,\lambda_2)$ that is decreasing in the stock of smart urban land ($\frac{\partial m_2}{\partial E_2} = -1 < 0$) and increasing in the shadow price of smart urban land ($\frac{\partial m_2}{\partial \lambda_2} = -\frac{1}{r_2' - \pi_2' + \tau' q} > 0$). The long-run equilibrium is thus defined as the solution to the equations:

$$\dot{E}_2 = m_2(E_2,\lambda_2) = 0, \tag{A6}$$

$$\dot{\lambda}_2 = \rho\lambda_2 - r_2(E_2 + m_2) + \pi_2(E_2 + m_2) + \tau(E_3 - m_2)q(E_3 - m_2) = 0. \tag{A7}$$

The slope of $\dot{E}_2 = 0$ is

$$\left.\frac{d\lambda_2}{dE_2}\right|_{\dot{E}_2=0} = -\left(r_2' - \pi_2' + \tau' q\right) > 0. \tag{A8}$$

We observe from Eq. (A6) that E_2 is increasing at points above $\dot{E}_2$ and decreasing at points below it.

The slope of $\dot{\lambda}_2 = 0$ can be written as

$$\left.\frac{d\lambda_2}{dE_2}\right|_{\dot{\lambda}_2=0} = -\left(r_2' - \pi_2' + \tau' q\right) > 0. \tag{A9}$$

We observe from Eq. (A7) that λ_2 is increasing at points above $\dot{\lambda}_2 = 0$ and decreasing at points below it.

Fig. A1 depicts a phase diagram summarising the results. Under the given assumptions, we can verify the existence of an interior solution, such that the long-run equilibrium (E_2^*, λ_2^*) is a unique saddle point and is therefore stable. Land conversion m_2 will be positive, that is land will be converted from agricultural to smart urban use, in a region that is initially under smart urbanisation$(E_2 < E_2^*)$. Land conversion will be negative, that is land will be reverted from smart urban to agricultural use, in a region that is initially under smart urbanisation $(E_2 > E_2^*)$. In either case, the rate of land conversion decreases gradually in absolute value over time.

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