**RESEARCH ARTICLE**

# The effectiveness of smart city policy on pollution reduction in China: new evidence from a quasi-natural experiment

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## Abstract

Based on panel data of 285 prefecture-level and above cities in China from 2003 to 2020, this study has explored the impacts of smart city policy (SCP) on environmental pollution by utilizing the difference-in-differences (DID) model and its derived models. The results indicate that SCP can significantly reduce environmental pollution, and this conclusion still holds after passing numerous robustness tests, such as the propensity-score-matching difference-in-differences (PSM-DID) test, the placebo test, all independent variables lagging one period test, the policy interference test, and the instrument variable (IV) test. Moreover, the heterogeneity analysis shows that the effect of reducing environmental pollution of SCP is heterogeneous. Furthermore, the results of the spatial difference-in-differences (SDID) model show that SCP has a "beggar-thy-neighbor" effect among the pilot cities, and there is no spillover effect of SCP on pollution reduction in neighboring non-pilot cities. Finally, the analysis of moderating effect reflects that the government intervention plays a negative inhibition role in the process of SCP affecting environmental pollution, while the market competition plays a positive catalytic role in the process of SCP reducing environmental pollution.

## Introduction

Environmental pollution has become a global challenge, especially for developing countries like China, which are undergoing economic transition (Lin and Zhou 2022). Over the previous 43 years, China has witnessed rapid urbanization with the rate increasing from 17.92% in 1978 to 64.72% in 2021. However, there are a number of "urban diseases" appearing with urbanization (Zhang et al. 2017), such as traffic congestion, insufficient housing, and water supply, environmental pollution and skyrocketing house prices, among which, the environmental pollution is the gravest problem. In addition, as measured by the Global Environmental Performance Index Report 2021, China ranked 160th out of 180 countries and regions that participated in the assessment of

the ranking, which shows the seriousness of environmental pollution in China. Environmental pollution not only hinders China's economic development but also seriously damages the health and welfare of the citizens (Liao et al. 2021). Obviously, the environmental pollution caused by traditional extensive urban governance and development model can no longer be ignored. Against this background, the Chinese government is actively exploring more efficient and sustainable urban development models, of which the SCP is one such new urban development model. In this context, we attempt to answer the following questions: what is the effect of SCP on environmental pollution? Would it be able to be widely practiced as a new model of urban governance in China? Answering these questions is instructive for sustainable urban development in China.

SCP was conducted by the Chinese government in 2012 with the policy of applicability, economy, greenness, and esthetics, aiming to transform the crude management model and accelerate the construction of green cities. Currently, the effects of SCP have been empirically studied in a wide range of literature, including improving urban quality (Caragliu and Del Bo 2018; Meijer and Thaens 2018; Yigitcanlar

and Kamruzzaman 2018), promoting the upgrading of urban industrial structure (Cui et al. 2008; Zhao and Zhang 2020), and improving urban environmental pollution (Song et al. 2022). Regarding the effects of SCP on environmental pollution, part of the literature suggests that SCP can improve the efficiency of urban resources and it is beneficial to urban environment (Gao and Yuan 2022; Wang et al. 2022a), whereas some literature finds that the environmental effects of SCP are skeptical (Shelton et al. 2015; Huovila et al. 2019). Apparently, there is no consistent conclusion on the pollution reduction effect of SCP in the existing literature. Therefore, it is worth exploring how the effects of SCP on environmental pollution in China. Moreover, there are several shortages in current studies on the environmental impacts of SCP in China: first, most of the existing studies adopted the DID method to simply identify the policy effects of SCP, which ignored the spatial spillover effects. Second, studies on the environmental impacts of SCP have focused on the analysis of air pollution, and heterogeneity analysis is relatively homogeneous. Therefore, it is necessary to adopt more appropriate environmental pollution indicators to conduct more comprehensive heterogeneity analysis. In addition, the existing literature neglects the endogeneity problem brought by the self-selection in the evaluation of SCP, which can lead to biased estimation results. Last but not least, the construction of smart cities needs to define the relationship between the government and the market, however, the existing literature lack to explore the role of government and the market in SCP effects, so the moderating effects need to be explored in this study.

In this paper, industrial $SO_2$ and industrial wastewater are regarded as the proxies for environmental pollution to measure the effect of SCP on environmental pollution. Air pollution and water pollution are the most serious environmental pollutants in China, among which $SO_2$ is the main pollutant in air pollution and industrial wastewater is the most serious in wastewater pollution according to the Ministry of Ecology and Environment of China; therefore, $SO_2$ and wastewater are more representative than other pollutants. Moreover, China is a vast country and there are great differences in geographic location, resource endowment, city size, and administrative system in each region; thus, the heterogeneity of policy effects in different cities needs to be explored. In addition, the spatial spillover effect of SCP on surrounding cities is of great reference value, especially in policy evaluation, but it is mostly neglected in the existing literature. Furthermore, SCP is a platform that requires the participation of government and market; hence, investigating the mechanism and interaction between government and market can provide theoretical reference for the development of high-level smart cities.

Considering the above analysis, we explore the effect of SCP on environmental pollution by treating the SCP in China as a quasi-natural experiment. Specifically, this study first used a multi-period DID model based on panel data of 285 Chinese cities from 2003 to 2020 to measure the net effect of SCP on industrial $SO_2$ and wastewater emissions. Besides, the robustness of the empirical findings is tested by parallel trend test, PSM-DID model, placebo test, one-period lags of all independent variables test, policy interference test, and IV method. Secondly, a multidimensional heterogeneity analysis of cities with different regions, sizes, and resource endowments is conducted to explore the heterogeneous effects of SCP on environmental pollution, so as to draw more targeted conclusions and recommendations. Thirdly, the SDID model was employed to investigate the spatial spillover effects of SCP on the environmental pollution of neighboring non-pilot cities and pilot cities. Finally, inspired by Zhang and Huang (2022), this study also investigated the moderating role of government and market about SCP's impact on environmental pollution through a moderating effect model, so as to provide valuable suggestions on how the market and the government cooperate more effectively in the process of SCP implementation. To better understand the structure of this study, the detailed framework is illustrated in Fig. 1.

Given the limitations of existing studies, several potential contributions are presented as follows. Regarding the methodology, DID method, PSM-DID model, SDID method, and moderating effect model are adopted to explore the impacts of SCP on environmental pollution in a comprehensive manner, which is different from the single research method in the existing literature. Besides, the interaction term between the number of stagecoaches in the Ming Dynasty and the number of cabs is exploratively selected as an instrumental variable of the pilot smart city to mitigate the interference of endogeneity problems. Concerning the content, this study comprehensively explores the heterogeneity of SCP effects in terms of administrative level, regional location, resource endowment, and city scale based on the national city level. In addition, the existing literature lacks an analysis of the spatial and moderating effects of SCP, so we further discussed these two crucial effects that can provide more solid empirical support for joint regional environmental governance. For the practical sense, exploring the impacts of SCP on environmental pollution in China can provide valuable insights into the sustainable economic development of developing economies.

The rest of the paper is organized as follows. "Literature review" reviews the relevant literature. "Empirical strategy" outlines the empirical model and data. The main empirical outcomes and a series of robustness tests are reported in "Empirical analysis." "Further analysis" explores spatial heterogeneity and analyzes spatial spillover effects. Finally, the conclusions and policy implications are summarized in "Conclusions, policy implications, and research prospects."
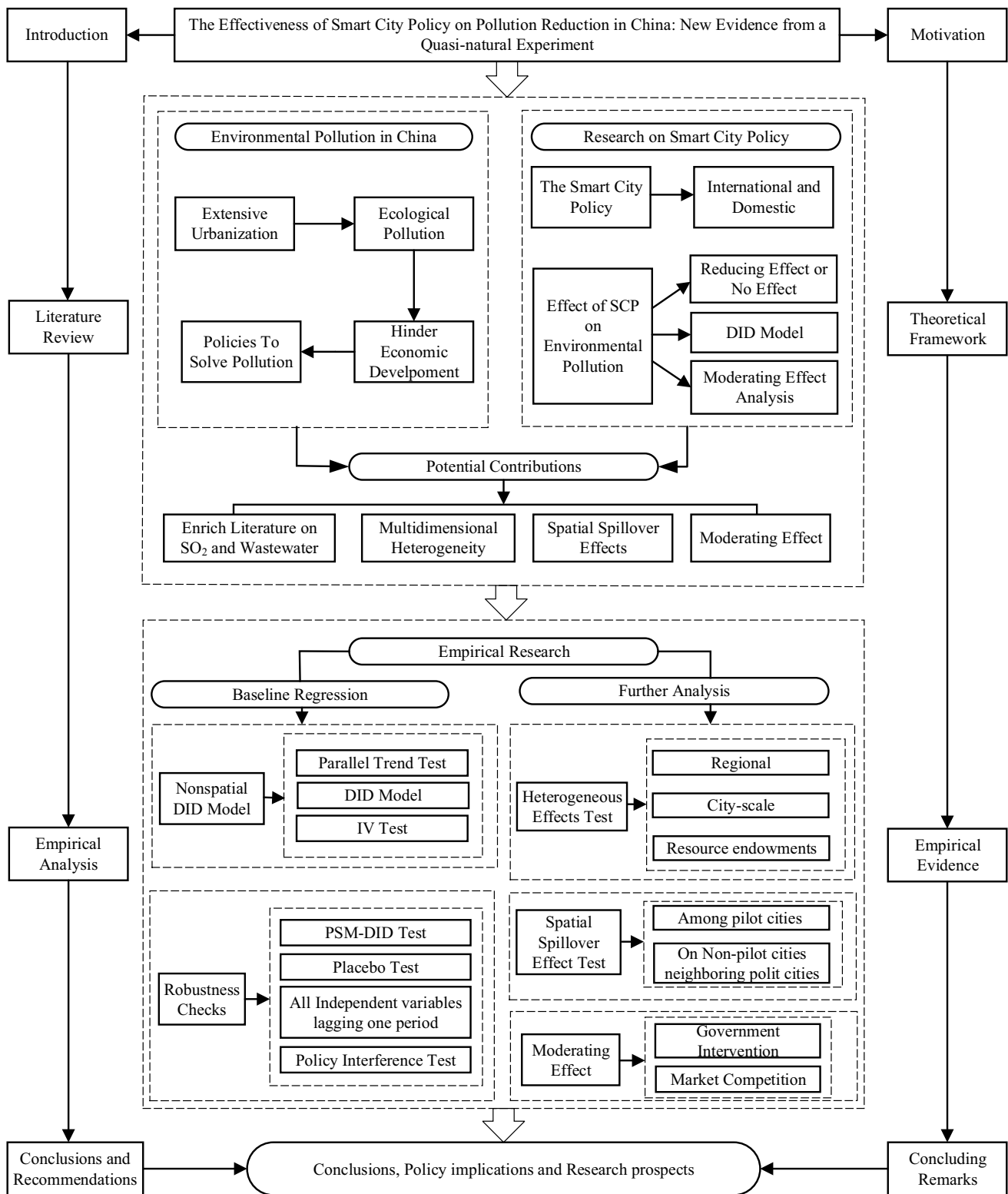
**Fig. 1** Flowchart of the research progress

## Literature review

### Environmental pollution in China

The extensive urbanization in China has caused serious ecological pollution (Lin and Liu 2015, Liu et al. 2021; Lu et al. 2021; Wang et al. 2021). Currently, China has become one of the most polluted countries in the world (Jo et al. 2022). Industrial pollution from urban accounts for 70% of the total pollution in China (Kendy et al. 2004). Liu et al. (2022a) stated that air pollution is the greatest concern among environmental pollution in China, which was followed by water pollution and soil pollution. Besides, Liu et al. (2022b) proposed that serious air pollution has been brought about by massive energy consumption and $CO_2$ emissions, meanwhile China's $SO_2$ emissions already far exceed most countries, especially industrial $SO_2$ emissions (Chen and Lee 2020; Hao et al. 2020; Chen et al. 2021b). Wang et al. (2022b) pointed out that industrial $SO_2$ and wastewater emissions in Chinese cities accounted for 27.1% and 83.7%, respectively. Given the seriousness of industrial $SO_2$ and wastewater pollution, a large body of literature has selected industrial $SO_2$ and wastewater as proxies for environmental pollution (Jiang et al. 2014, 2021b; Chen et al. 2021a). Moreover, several literature also pointed out that environmental pollution caused by urbanization has seriously damaged the health of the residents (Huang et al. 2018; Guo et al. 2022a), the welfare of the residents and the social stability were also influenced (Chen and You 2021; Wu et al. 2021), which hinders China's economic development.

Undoubtedly, environmental pollution has emerged as an important barrier to sustainable and high-quality economic growth in China; therefore, the Chinese government has formulated many policies to address environmental pollution, but how effective are these policies? Lin and Xu (2022) empirically investigated that environmental decentralization in China can significantly exacerbate the corporations' pollution emissions based on the panel data from 2000 to 2012. Fan et al. (2021) pointed out that the environmental tax policy facilitates enterprises to invest more in pollution prevention, and its combination with the pollution control subsidy policy can further achieve a virtuous cycle of corporate governance, so as to accomplish the effect of pollution reduction and economic growth. Besides, Yuan et al. (2022) noted that a centralized environmental monitoring mechanism can significantly reduce the AQI based on a practical research design. Gao and Yuan (2022) confirmed that the national innovative city policy has the pollution emissions reduction effect and it is mainly accomplished by enhancing both the concentration of industrial elements and urban innovation levels.

### The smart city policy

The first smart city originated from the "Smart Island" project in Singapore in 1992 (Yuen 2018), and in 2010, the idea of "smart city" was formally proposed subsequently. At the beginning of the twenty-first century, the boom of the building smart city has become a common phenomenon throughout the world. Smart city is committed to promoting the integration of urbanization and information technology by using the web of things and cloud computation, which can enhance the efficiency and quality of urban management (Duygan et al. 2022). The smart city is an urban development strategy that incorporates user, open and collaborative innovation which is more sustainable (Wang and Deng 2022). Therefore, sustainable development is a critical connotation of the smart city (Caragliu et al. 2011). In 2012, the construction of 90 smart cities was launched after the "Notice on National Smart City Pilot Work" was published by China's Ministry of Housing and Urban–Rural Development, then the scale gradually expanded to 386 cities nationwide in 2013 and 2014, 100% of the cities at provincial-level, 74% of the cities at prefecture-level, and 32% of cities at county-level were covered (Yu and Zhang 2019). Figure 2 illustrates the pilot smart cities in China. The Deloitte statistics show that the market size of the smart city in China has maintained more than 30% growth in recent years and is expected to reach 25 trillion yuan by 2022.

The smart city is a comprehensive upgrade of urban systems, which involves the intelligence of various aspects, such as urban management, education, healthcare, real estate, transportation, utilities and public safety. China has also adopted a series of macro urban policies in the process of improving the environment, including low-carbon city pilot policies and innovation city pilot policies. However, scholars have pointed out that the spillover effects of SCP are more efficient than those of other policies (Guo et al. 2019), and smart cities can not only improve urban technology but also provide an impetus for the green development of cities (Zhang and Fan 2023). Smart cities have a huge positive impact on industrial development, resource allocation, and technological innovation (Zhang and Fan 2023), which is a feature that other policies do not have. The connotation of SCP in China already includes the concepts of intensification, low carbon, ecology, wisdom, and innovation. In consequence, the effect of smart cities on environmental pollution is more effective compared to other policies. Therefore, it has more practical significance to study the impact of SCP on environmental pollution, especially for economies in transition.

**Fig. 2** Geographical distribution of pilot cities
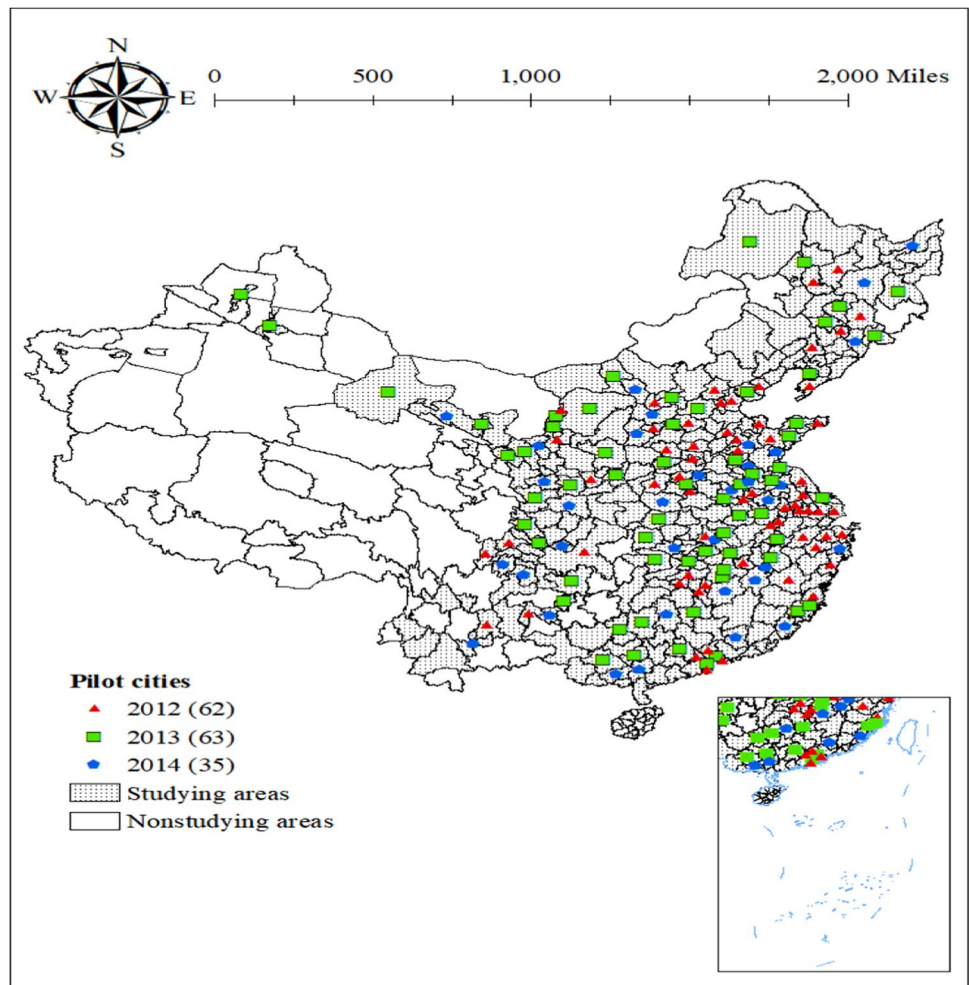


## Effect of SCP on environmental pollution

With the development of smart cities around the world, a series of issues about smart city have attracted increasing academic attention. Currently, there are three sorts of research on smart city approximately: the first category focuses on discussing the definition of smart city (Liu et al. 2019; Kirimtat et al. 2021), the second part concentrates on how to construct evaluation systems for smart city (Papastamatiou et al. 2017; Li et al. 2019), and the third type concentrates on analyzing the impacts of smart city on the environment and efficiency.

To search for solutions to environmental pollution, SCP has been introduced as a new pattern of urban development (Shen et al. 2018). Li et al. (2020) demonstrated that SCP can significantly reduce air pollution and this reduction effect also has impacts on air quality around pilot cities. Feng and Hu (2022) concluded that the haze pollution in pilot cities was reduced by SCP and the spatial heterogeneity is distinct among cities at different administrative levels. Caragliu and Del Bo (2018) pointed out that technological

innovations generated by smart cities can promote the application of clean energy and clean technologies in production activities, which can further change the structure of energy use, and reduce energy consumption and pollution emissions. Moreover, Yao et al. (2020) proposed that smart monitoring systems in smart cities can enhance the real-time monitoring of polluting enterprises and thus enable more effective treatment of pollution sources. Guo et al. (2022b) showed that the per capita $CO_2$ emissions were significantly reduced by about 18.42 log percentage points with the smart city construction. By contrast, some scholars may hold opposite opinions on the effects of SCP. For instance, Shen et al. (2018) indicated that SCP has little impact on the environment. Liu and Peng (2014) argued that people, government, infrastructure, and economy were mainly emphasized when developing smart cities, while the smart environment is rarely mentioned. Besides, Haarstad and Wathne (2019) concluded that the sustainable development impact of SCP on cities is highly contingent and largely depends on the implementation of the smart city by local policymakers. Thus, it can be seen that there is currently a controversy in

the literature regarding exploration of the SCP effect on the environment.

Additionally, many pieces of literature have conducted heterogeneity analysis when investigating the impact of SCP on environmental pollution (Yu and Zhang 2019), nonetheless, their heterogeneity analysis is only limited to city size or resource endowment that cannot provide more valuable references. There is much previous literature adopted the DID model to evaluate the environmental pollution reduction effect of SCP (Chu et al. 2021; Jiang et al. 2021a), but most of them do not consider the spatial spillover effect of SCP that may lead to biased estimations (Chen et al. 2021b). Meanwhile, the significance of the spatial spillover effect for effective decision-making is also emphasized (Wang et al. 2022a). Moreover, numerous scholars have explored the moderating effects of government and market in high-quality economic development (Li 2003); nevertheless, there is still a lack of literature on the analysis of their moderating effects in the process of SCP affecting environmental quality.

## Empirical strategy

### Empirical framework

The concept of the smart city was first proposed by IBM (International Business Machine Corporation) in 2010, and then China began piloting SCP between 2012 and 2014 among 160 cities gradually. To measure the impact of SCP on pollution reduction, the policy is regarded as a set of quasi-natural experiments and the DID model was used to estimate. In this paper, the control group is the non-pilot cities and the pilot cities are designated as the test group. The multi-period DID model was used since the pilot was conducted in different three years. The multi-period DID model is formulated as Eq. (1).

Besides, since the DID model cannot solve the problem of sample-selection bias, we structured a PSM-DID model for robustness testing which can eliminate the sample-selection bias problem. The specific model is constructed as Eq. (2).

$$pollution_{it} = \alpha_0 + \alpha_1 DID_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$pollution_{it}^{PSM} = \alpha_0 + \alpha_1 DID_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where city and year are indicated by the subscripts $i$ and $t$. *pollution* is the level of pollution in each city. *DID* stands for dummy variable for the status of the policy piloting. $X$ is a series of control variables. $\mu_i$ denotes the year-fixed effect. $\lambda_t$ denotes the time-fixed effect. $\alpha_1$ is the policy factor, demonstrating the net effect of the pollution reduction effect of SCP. $\delta$ refer to the coefficients of control variables. $\varepsilon$ is the random disturbance term. $\alpha_0$ is the constant term.

This paper considers the correlation of regions while measuring the environmental impact of SCP. Chagas et al. (2016) pointed out that the spatial spillover effects of pilot cities affect both pilot and non-pilot cities, while the effects on non-pilot regions adjacent to pilot regions are often neglected in previous spatial studies. Therefore, we consider the influence of pilot cities on adjacent non-pilot cities when conducting the spatial spillover effect analysis. To further investigate the SCP's spatial spillover effects, the SDID model was also employed in this study, which is a spatially extended form of the DID model based on Eq. (1), and the model is shown as follows:

$$pollution_{it} = \alpha_0 + \alpha_1 DID_{it} + \delta X_{it} + \beta_1 \times W_{T,T} D_{it} + \beta_2 \times W_{NT,T} D_{it}$$
$$+ \beta_3 \times W \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where $W$ is the spatial weight matrix, including the first-order adjacency weight matrix and the spatial squared inverse distance weight matrix. $W_{T,T} D_{it}$ indicates the spatial spillover effects in pilot cities. $W_{NT,T} D_{it}$ indicates the spatial spillover effect of pilot cities on non-pilot cities which neighboring polit cities. $W \times X_{it}$ is the spillover effects of control variables, $\beta_1$, $\beta_2$, $\beta_3$ are the spatial coefficient of $W_{T,T} D_{it}$, $W_{NT,T} D_{it}$, and $W \times X_{it}$, respectively.

Considering the moderating roles of government and market in the way of SCP affecting environmental pollution, government intervention and market competition are introduced as moderating variables based on Eq. (1), respectively. Moreover, the interaction terms of government intervention and *DID* and the interaction terms of market competition and *DID* are also incorporated. Specifically, the Official Fan Gang market index measures market competitiveness, whereas the ratio of local fiscal expenditure to local GDP measures government intervention. The moderation effect models are constructed as follows:

$$pollution_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 Govern_{it}$$
$$+ \alpha_3 Govern_{it} * DID + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$pollution_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_4 Market_{it}$$
$$+ \alpha_5 Market_{it} * DID + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where $Govern_{it}$ represents the level of government intervention. $Govern_{it} * DID$ represents the interaction term for government intervention and *DID*. $Market_{it}$ stands for the degree of market competition. $Market_{it} * DID$ is the interaction term of market competition and *DID*. $\alpha_2$ $\alpha_3$ $\alpha_4$ $\alpha_5$ are the coefficients of $Govern_{it}$, $Govern_{it} * DID$, $Market_{it}$, and $Market_{it} * DID$, correspondingly.

## Data and variables

The sample data is a panel dataset from 2003 to 2020 that includes 285 cities in China at the prefecture level and above which is based on the China City Statistical Yearbook (2003–2020). And through the interpolation method, the missing city data were completed. Moreover, according to the China Urban Statistical Yearbook (2003–2020), we collect the data of the core explanatory variables and control variables. In addition, the pilot list of smart cities was collected from the Notice on the Annual Declaration of National Smart Cities published by the Ministry of Housing and Urban–Rural Development of China for each year from 2012–2014.

### Dependent variable

The level of environmental pollution is the dependent variable. Drawing on existing literature, environmental pollution is weighed by "three industrial wastes," i.e., industrial $SO_2$ ($SO_2$) emission, industrial wastewater (*wastewater*) emission, and industrial solid waste emission indexes. Since the industrial solid waste emissions are not counted in the dataset used in this paper, $SO_2$ and wastewater emissions are adopted to measure the level of environmental pollution in each city.

### Key independent variable

The key explanatory variable is the *DID* in the study, a proxy variable of the status of the pilot smart city. The first batch of 90 national smart cities was piloted in 2012 in China and based on the 2012 pilots, the second and third batches of smart city pilots were launched in 2013 and 2014, respectively. In this paper, the year in which the pilot cities were piloted and all subsequent years are set to 1, and 0 otherwise.

### Control variables

Based on the reference to existing literature, variables that may be relevant to the level of city pollution are controlled to avoid omitting variables. The main control variables are summarized as follows: (1) GDP per capita (*PGDP*) is evaluated by the logarithm of GDP per capita; (2) population density (*DENSITY*) is weighed by the logarithm of the ratio of the total population to the administrative area of the city; (3) financial decentralization (*FD*) is the proportion of financial expenditure to financial revenue; (4) industry upgrade (*IU*) is the proportion of secondary industrial output to GDP and tertiary industrial output to GDP; (5) urban ratio (*UR*) is weighed by the ratio of the urban population in a general population of the city; (6) foreign direct investment (*FDI*) is the proportion of foreign direct investment to GDP. Table 1 shows the descriptive statistics for each variable.

**Table 1** Descriptive statistics of key variables

| Variables | Observations | Mean | S.D | Min | Max |
|---|---|---|---|---|---|
| $SO_2$ | 5130 | 4.899 | 5.831 | 0.004 | 113.069 |
| *Wastewater* | 5130 | 0.692 | 0.969 | 0.000 | 15.118 |
| *DID* | 5130 | 0.255 | 0.436 | 0.000 | 1.000 |
| *lnPGDP* | 5130 | 10.251 | 0.837 | 7.545 | 13.056 |
| *lnDENSITY* | 5130 | 5.726 | 0.917 | 1.548 | 7.923 |
| *FD* | 5130 | 2.814 | 1.869 | 0.649 | 18.399 |
| *IU* | 5130 | 0.933 | 0.512 | 0.094 | 5.348 |
| *UR* | 5130 | 0.495 | 0.174 | 0.078 | 1.000 |
| *FDI* | 5130 | 0.022 | 0.025 | 0.000 | 0.376 |

## Empirical analysis

### The validity of parallel trend assumption

The parallel trend test needs to be satisfied when using the DID model, i.e., that urban pollution levels in pilot and non-pilot cities do not differ systematically over time. Referring to Bertrand et al. (2004), we employ a time-analytic research framework to examine the dynamic pollution reduction effects of SCP by constructing a series of temporal dummy variables. The coefficients of *DID* are statistically insignificant if the temporal trends of the pilot and non-pilot cities are similar before 2012. This paper constructed the following model:

$$pollution_{it} = \alpha_0 + \sum_{t=-5}^{8} \alpha_t D_t + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where $D$ is a dummy variable for several years before and after the implementation of SCP. $D_0$ represents a dummy variable for the year when the smart city started to be launched, and due to SCP was piloted in three batches, $D_0$ indicates different initial years for different cities. $D_{-t}$ is a dummy variable for t years before the SCP's implementation; $D_t$ is a dummy variable for t years after the implementation of SCP; other variables are set the same as Eq. (1). Referring to Kunrong and Gang (2020), more than four years before the implementation are omitted and take four years before the policy implementation as the benchmark in this paper.

Figure 3 reports the estimated parameters of $SO_2$ and *wastewater* and their corresponding 95% confidence intervals, respectively. Besides, the horizontal axis indicates the years before and after the implementation of SCP and the vertical axis indicates the parameter $\alpha_t$. The subgraph (a) of Fig. 3 shows that the coefficients of *DID* are not significantly different from zero in the years before the smart city pilot, which indicates that there are at least five years that the time trends are similar between pilot and non-pilot

**Fig. 3** Parallel trend test



(a) *SO₂*

(b) *Wastewater*
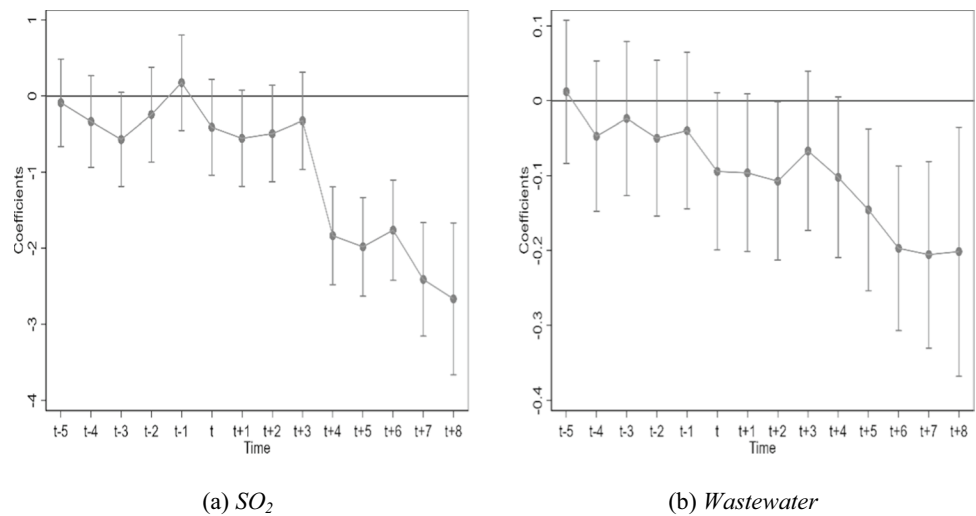
cities, proving that the study passes the parallel trend test. The estimated coefficients of *DID* are significantly negative three years after the implementation of smart city, indicating that there may be a lagged effect of SCP implementation, but the unchanging thing is that it reduces environmental pollution. Moreover, the results of subgraph (b) also reveal the same trend, which is also consistent with the parallel trend test. Hence, the parallel trend assumption is satisfied.

## Baseline results

Based on Eq. (1), the effect of SCP on reducing environmental pollution is estimated by DID model. Table 2 shows the baseline regression results. Columns 1 and 2 show the effects of SCP on $SO_2$ emissions and wastewater emissions, respectively. The coefficient of *DID* is significantly negative which indicates that SCP can reduce environmental

**Table 2** The baseline results based on the DID model

| Variables | All cities | | Excluding municipalities | | Prefecture-level cities | |
|---|---|---|---|---|---|---|
| | $SO_2$ | Wastewater | $SO_2$ | Wastewater | $SO_2$ | Wastewater |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *DID* | − 0.982*** | − 0.099* | − 1.028*** | − 0.100* | − 0.839** | − 0.047 |
| | (0.330) | (0.052) | (0.330) | (0.053) | (0.358) | (0.043) |
| *lnPGDP* | 3.364*** | 0.151** | 3.475*** | 0.146* | 3.523*** | 0.160** |
| | (0.533) | (0.077) | (0.530) | (0.077) | (0.543) | (0.073) |
| *lnDENSITY* | − 1.616 | − 0.228 | − 1.464 | − 0.232 | − 1.849 | − 0.372* |
| | (1.421) | (0.290) | (1.420) | (0.291) | (1.864) | (0.221) |
| *FD* | 0.040 | − 0.008 | 0.044 | − 0.009 | 0.010 | − 0.014* |
| | (0.059) | (0.008) | (0.058) | (0.008) | (0.058) | (0.008) |
| *IU* | − 0.117 | − 0.054 | − 0.083 | − 0.055 | 0.398 | 0.010 |
| | (0.409) | (0.061) | (0.411) | (0.062) | (0.419) | (0.038) |
| *UR* | 0.527 | 0.183 | 0.314 | 0.199 | 0.380 | 0.110 |
| | (1.261) | (0.164) | (1.254) | (0.165) | (1.256) | (0.142) |
| *FDI* | 0.861 | − 1.447** | − 0.930 | − 1.336** | − 2.264 | − 0.967* |
| | (3.769) | (0.616) | (3.521) | (0.601) | (3.814) | (0.544) |
| Constant | − 20.371** | 0.483 | − 22.482** | 0.520 | − 21.223* | 1.090 |
| | (9.286) | (1.571) | (9.221) | (1.573) | (10.849) | (1.202) |
| Observations | 5,130 | 5,130 | 5,058 | 5,058 | 4,500 | 4,500 |
| *R*-squared | 0.755 | 0.756 | 0.674 | 0.719 | 0.667 | 0.693 |

Robust standard errors in parentheses, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

pollution and this result remains significantly negative without controlling for control variables. The possible reason is that the smart city can optimize the energy structure through scientific city governance and improve the operational efficiency of various resources; thus, it is conducive to reducing pollution emissions.

For control variables, it is clear that the coefficient of *lnPGDP* is significantly positive, it demonstrates that economic development leads to further environmental pollution. Economic development on the one hand will improve the technology of optimizing the environment, but on the other hand, will increase energy consumption and consequently lead to environmental pollution. Besides, the coefficient of *lnDENSITY* is negative and non-significant, which reveals that an increase in population does not necessarily bring environmental pollution, the process of population increase is also the process of service industry development and continuous technological innovation, which are conducive to the reduction of urban pollution. Moreover, the coefficient of *FD* about $SO_2$ is positive, but the coefficient about *wastewater* is negative, demonstrating that the effect of *FD* on environment pollution is unstable. The negative but non-significant coefficient of *IU* reflects that industrial upgrading can reduce pollution emissions but the effect is not significant. Furthermore, the positive but non-significant coefficient of *UR* indicates that urbanization increases environmental pollution in cities. It can be explained by the fact that urbanization leads to more exploitation of urban resources and energy, a dramatic increase of transportation, and large agglomeration of industries thus leading to increased emissions of wastewater and $SO_2$.

Referring to the existing literature, the sensitivity analysis was also conducted in the baseline regression. Considering that the administrative level of municipalities is more complex than prefecture-level cities, four municipalities in China (namely Beijing, Shanghai, Tianjin, and Chongqing) have been removed in columns 3 and 4 of Table 2. It can be found that the estimated results of the main explanatory variables are significantly negative as in the baseline regression in columns 3 and 4. Moreover, columns 5 and 6 removed the provincial cities and municipalities as these cities have more economic and political resources than prefecture-level cities. The reported results show that the administrative level of the city does not affect the conclusion that SCP significantly reduces urban pollution levels.

## Results from the IV method

To accurately evaluate the effect of SCP, Eq. (1) should not only satisfy the parallel trend test, but the core explanatory variables also need to satisfy the homogeneity requirement (Zhang et al. 2022a). In detail, the core

explanatory variables are endogenous if the pilot smart cities are not randomly selected, which may lead to the biased estimations. To address the problem of endogeneity, the IV method is adopted in this subsection. Specifically, this paper constructs the *IV* by using the interaction term of the number of stagecoaches in the Ming Dynasty and the number of city cabs (Duranton and Turner 2012). The IV variable needs to satisfy the validity principles of correlation and homogeneity conditions. On the one hand, the number of stagecoaches in the Ming Dynasty can be viewed as the functional infrastructure that may exert the potential influence on the high-quality development of smart cities, namely it satisfies the correlation requirement. On the other hand, it is independent of the urban pollutant emissions and cannot pose underlying shocks on the influencing path of SCP on pollution reduction to some extent, which satisfies the exogenous requirement. Furthermore, because the number of stagecoaches in the Ming dynasty is a fixed value that cannot be directly adopted in the panel regression model, this paper constructs suitable and reasonable interaction term here. The results of the IV method are presented in Table 3.

As shown in column 1, the coefficient of *IV* is positive and significant at the 1% level, which indicates that if the number of stagecoaches in the Ming Dynasty and the number of city cabs in a city is higher, then the probability of that city becoming a pilot smart city is higher, which validate the relevance requirement of *IV*. Also, the first-stage *F* value is 43.616, which is greater than 10 indicating that there is no weak instrumental variable problem. In columns 2 and 3, it is obvious that the baseline regression results can be concluded again, namely the coefficients of $SO_2$ and *wastewater* are significantly negative at the 5% level. It demonstrates that SCP can still have the effect of pollution reduction after accounting for the endogeneity of the core explanatory variables, which in turn further validates the robustness of the above conclusions.

**Table 3** Estimation results for the IV method

| Variables | DID (1) | $SO_2$ (2) | Wastewater (3) |
|---|---|---|---|
| *DID* | | −42.914** | −4.357** |
| | | (−2.26) | (−2.47) |
| *IV* | 0.003*** | | |
| | (2.67) | | |
| First-stage *F* statistic value | 43.616 | | |
| Control variables | YES | YES | YES |
| Observations | 5130 | 5130 | 5130 |

Robust standard errors in parentheses, ** and *** indicate significance at the 1%, 5%, and 10% levels, respectively

## Robustness checks

### PSM-DID estimation

We employ the robustness test of PSM-DID method in this study. Before applying PSM-DID model, it is necessary to check whether the variables satisfy the common support hypothesis test, i.e., whether the variables become balanced after matching. If there is no significant difference in the matched variables, it justifies the use of PSM-DID model in this paper. The specific steps are employed in turn: first, the logit regression on the control variables was applied to obtain the propensity scores; second, the matching cities of smart cities are matched by the propensity scores; third, the DID model is applied to estimate the paired cities.

Table 4 presents the results of the PSM-DID model. It shows that the coefficient before *DID* remains negative regardless of whether considering the control variables, indicating that SCP significantly reduces pollution, which confirms the robustness of the above results.

## Placebo test

To exclude the possibility that the environmental pollution reduction effect of SCP may be confounded by omitted variables, referring to (Zhang et al. 2021), the baseline regression was conducted 1000 times in 285 cities, and we randomly select 160 cities as the treatment group for the placebo test. And Fig. 4 shows the kernel density distribution, with the *x*-axis showing the *t*-values of the policy coefficients and the *y*-axis representing the corresponding *p*-values. Figure 4 reports the distribution of regression coefficients for the explanatory variables $SO_2$ and *wastewater*, respectively. As can be seen from the figure, the absolute values of the *t*-values of the coefficients for most of the random samples are less than 2, and the corresponding *p*-values are higher than 0.1, which indicates that the policy effects of SCP on environmental pollution reduction are not disturbed by the omitted variables.

**Table 4** Parameter estimation results of the PSM-DID model

| Variables | PSM-DID | | | |
|---|---|---|---|---|
| | $SO_2$ | | Wastewater | |
| | (1) | (2) | (3) | (4) |
| *DID* | − 1.101*** | − 1.116*** | − 0.096*** | − 0.098*** |
| | (− 5.824) | (− 6.034) | (− 2.967) | (− 3.043) |
| Control variables | NO | YES | NO | YES |
| Observations | 4,369 | 4,369 | 4,369 | 4,369 |
| *R*-squared | 0.675 | 0.680 | 0.731 | 0.732 |

Robust *t*-statistics in parentheses, *** indicate significance at the 1%, 5%, and 10% levels, respectively

**Table 5** Results of the robustness test

| Variables | $SO_2$ | | Wastewater | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Lag.DID* | − 1.070*** | − 0.966*** | − 0.084* | − 0.081 |
| | (0.342) | (0.342) | (0.051) | (0.050) |
| Control variables | NO | YES | NO | YES |
| Observations | 4845 | 4845 | 4845 | 4845 |
| R-squared | 0.747 | 0.753 | 0.749 | 0.750 |

Robust standard errors in parentheses, * and *** indicate significance at the 1%, 5%, and 10% levels, respectively

**Fig. 4** Placebo test



(a)  $SO_2$

(b)  *Wastewater*
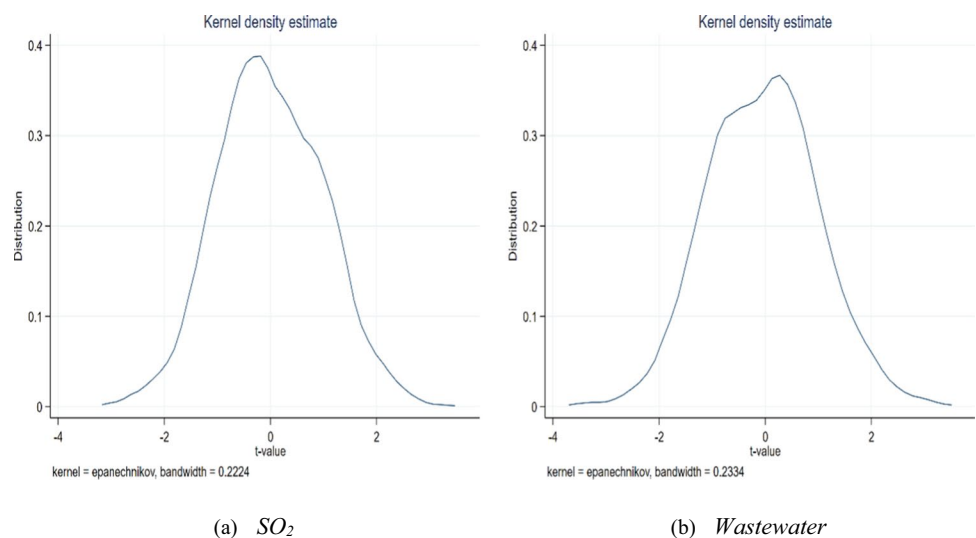
### All independent variables lagging one period

Given that the SCP may not have a direct impact and to avoid bias of the joint equation, the core explanatory variables and all control variables with a one-period lag were re-regressed in the study. The results in Table 5 illustrate that the core conclusions of this paper remain valid.

### Policy interference test

It is inevitable that there will be interference from other policies which may lead to overestimation or underestimation during the estimation of the impact of SCP on environmental pollution. Therefore, the policies related to SCP which were implemented in the years following the implementation of smart city are collected. Indeed, those relevant policies may have the potential to reduce environmental pollution emissions.

In 2013, the China Science and Technology Commission published the Notice on Supporting a New Group of Cities to Carry Out Innovative City Construction, which proposed to conduct pilot innovative city construction work in 57 cities in China. The policy called for creating an environment for innovation, which includes the need to improve the ecological environment through technology. Moreover, in 2015 and 2017, the second and third batches of the National Low-carbon City pilot work were announced by China's National Development and Reform Commission, respectively, the policy pointed out that scientific city planning is the first step to build a low-carbon city and proposed to protect the environment. Besides, in 2016, China's Ministry of Industrialization and Information promoted the construction of National Big Data Comprehensive plot zones among more than 50 cities, and the policy's main goal is to improve the operational efficiency of various resources through the use

and sharing of big data, which can also reduce environmental pollution to a certain extent. Presumably, these policies have also had an impact on the reduction of environmental pollution, so the above baseline regressions may overestimate the impact of smart city policies.

These policy dummy variables are added to the baseline model to make the estimation results more accurate. If the environmental pollution reduction effect of SCP is no longer significant after adding these policy dummy variables, which demonstrates that the above obtained conclusions are not robust; if it is still significant but the policy coefficients become smaller, which indicates that the above estimation results are robust and only overestimate this specific effect of SCP. Table 6 and Table 7 present the policy interference effects for $SO_2$ and *wastewater*, correspondingly. As shown in Table 6, it can be viewed that the coefficients of *DID* remain significantly negative regardless of whether these policies interfere individually or simultaneously, which indicates that SCP still significantly reduces environmental pollution. Most of the coefficients of *DID* in Table 7 are also significant, so the robustness of the empirical conclusions of this paper is verified.

## Further analysis

### Heterogeneous effects test

#### Regional heterogeneity analysis

The analysis mentioned above suggests that SCP can significantly reduce $SO_2$ and wastewater emissions, nevertheless, this analysis based on the total sample may ignore the effects of regional differences. Given that China is a vast country, namely different regions may differ in economic

**Table 6** Results of the policy interference test for $SO_2$

| Variables | $SO_2$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| DID | −0.894*** | −0.956*** | −0.914*** | −0.874*** | −0.825*** | −0.881*** | −0.799** |
| | (0.317) | (0.332) | (0.330) | (0.319) | (0.316) | (0.332) | (0.318) |
| IP1 | −0.772 | | | −0.745 | −0.782 | | −0.749 |
| | (0.513) | | | (0.515) | (0.514) | | (0.516) |
| IP2 | | −0.351 | | −0.310 | | −0.424 | −0.383 |
| | | (0.312) | | (0.313) | | (0.310) | (0.311) |
| IP3 | | | −2.874*** | | −2.879*** | −2.905*** | −2.907*** |
| | | | (0.660) | | (0.667) | (0.657) | (0.664) |
| Control Variables | YES | YES | YES | YES | YES | YES | YES |
| Observations | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 |
| R-squared | 0.756 | 0.755 | 0.759 | 0.756 | 0.759 | 0.759 | 0.759 |

Robust standard errors in parentheses, ** and *** indicate significance at the 1%, 5%, and 10% levels, respectively

**Table 7** Results of the policy interference test for *Wastewater*

| Variables | Wastewater | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| DID | − 0.087* | − 0.096* | − 0.096* | − 0.085 | − 0.083 | − 0.093* | − 0.081 |
| | (0.053) | (0.052) | (0.052) | (0.053) | (0.052) | (0.052) | (0.052) |
| IP1 | − 0.110 | | | − 0.107 | − 0.111 | | − 0.108 |
| | (0.097) | | | (0.095) | (0.097) | | (0.096) |
| IP2 | | − 0.039 | | − 0.033 | | − 0.043 | − 0.037 |
| | | (0.059) | | (0.057) | | (0.059) | (0.057) |
| IP3 | | | − 0.142** | | − 0.143** | − 0.145** | − 0.145** |
| | | | (0.072) | | (0.072) | (0.072) | (0.072) |
| Control Variables | YES | YES | YES | YES | YES | YES | YES |
| Observations | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 | 5,130 |
| R-squared | 0.757 | 0.756 | 0.756 | 0.757 | 0.757 | 0.757 | 0.757 |

Robust standard errors in parentheses, * and ** indicate significance at the 1%, 5%, and 10% levels, respectively

**Table 8** Regional heterogeneity results of the DID model

| Variables | Eastern | | Central | | Western | |
|---|---|---|---|---|---|---|
| | $SO_2$ | Wastewater | $SO_2$ | Wastewater | $SO_2$ | Wastewater |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| DID | − 0.811 | − 0.223* | − 0.829* | − 0.011 | − 1.308* | − 0.076 |
| | (0.513) | (0.134) | (0.484) | (0.041) | (0.785) | (0.084) |
| Control variables | YES | YES | YES | YES | YES | YES |
| Observations | 1,818 | 1,818 | 1,800 | 1,800 | 1,512 | 1,512 |
| R-squared | 0.834 | 0.720 | 0.655 | 0.725 | 0.741 | 0.794 |

Robust standard errors in parentheses, * indicate significance at the 1%, 5%, and 10% levels, respectively

scale, technology level, policy enforcement, and institutional arrangement, which may lead to heterogeneity in the impacts of smart city policies on environmental pollution in different regions. Therefore, we classified the sample into three subsamples: eastern, central, and western regions based on the criteria for dividing geographic regions published by the National Bureau of Statistics of China.

Table 8 reports the heterogeneous effects of the SCP in each region. Based on columns 1, 3, and 5, it can be found that the coefficients of *DID* for all three regions are negative, indicating that SCP reduces $SO_2$ emissions in all three regions. Whereas the coefficient of *DID* for the eastern sample is not significant, the possible explanation is that the eastern region has a well-developed economy, a large industrial scale, and a concentration of industries, which may cause emitting more $SO_2$, namely this may lead to insignificant pollution reduction effects of SCP. Moreover, it also can be observed that the pollution reduction effects of SCP on $SO_2$ in the three regions are in the sequence of western, central, and eastern. Referring to (Deng et al. 2021), it can be explained by the fact that the western region has a weak "lock-in effect" on pollution emissions because of

the relatively backward economic level, and thus responding more quickly to SCP. By contrast, the eastern region has a large amount of pollution emissions caused by industrial agglomeration and crowded transportation, so the "lock-in effect" of pollution emissions is greater and the effect of SCP is smaller. In terms of wastewater emission, the coefficient of *DID* is still negative for the three regions, but it is insignificant for the central and western cities.

### City-scale heterogeneity analysis

Whether the environmental pollution reduction effects of SCP are different under cities of different sizes is explored in this part. Cities of different sizes may have different economic agglomeration and congestion effects. Generally, cities with larger size may have a greater economic agglomeration effect and more efficient use of resources, which can reduce environmental pollution. However, there may also have a greater congestion effect and bring more environmental pollution in the larger cities. Referring to the Notice on Adjusting the Criteria of City Size Classification published by the State Council of China, the sample cities are classified

**Table 9** City-scale heterogeneity results of the DID model

| Variables | Small | | Medium | | Large | |
|---|---|---|---|---|---|---|
| | $SO_2$ | Wastewater | $SO_2$ | Wastewater | $SO_2$ | Wastewater |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| DID | −0.478 | −0.033 | −1.130* | −0.020 | −0.505 | −0.057 |
| | (0.858) | (0.046) | (0.623) | (0.042) | (0.554) | (0.123) |
| Control variables | YES | YES | YES | YES | YES | YES |
| Observations | 896 | 896 | 1801 | 1801 | 2397 | 2397 |
| R-squared | 0.505 | 0.781 | 0.704 | 0.640 | 0.874 | 0.812 |

Robust standard errors in parentheses, * indicate significance at the 1%, 5%, and 10% levels, respectively

into three categories: if the population of the city is less than 500,000 in urban areas, that is the small city (Xi and Mei 2022); if the population of the city is more than 500,000 and less than 1 million in urban areas, that is the medium city; and if the population of the city is more than 1 million in urban areas, that is the large city (Bao et al. 2022).

The estimation results are reported in Table 9. Generally, the coefficients of *DID* are all negative, which reveals that the implementation of SCP reduces environmental pollution in cities of different sizes. Specifically, for $SO_2$ emission reduction, the coefficient of *DID* is significantly negative in medium-sized cities, while it is not significant in small and large size cities, illustrating that the effect of reducing environmental pollution of SCP is more obvious in medium-sized cities. This phenomenon lies in the fact that medium-sized cities are relatively less polluting than large-sized cities, but relatively more technologically advanced than small-sized cities, so its pollution reduction effect is more reactive and obvious to SCP than both small and large cities. As for wastewater emissions, the environmental pollution reduction effect of big cities is greater probably because of the advanced information technology, so smart city construction can reduce wastewater pollution through the good use of these specific advantages for urban wastewater pollution management. The above findings also illustrate that the correlation between city size and the pollution reduction effect of smart cities is not very high.

### Resource endowments heterogeneity analysis

Cities with different resource endowments may also differ in the environmental pollution reduction effect of SCP. In general, resource-intensive cities may have more exploitation of fossil energy and wastewater resources, which may accelerate more wastewater and $SO_2$ emissions, and lead to more serious environmental pollution. Hence, we classify the sample into resource-intensive and non-resource-intensive cities, based on the National Sustainable Development Plan for Resource-based Cities published by the Chinese State Council in 2013.

**Table 10** Resource endowments heterogeneity results of the DID model

| Variables | Resource intensive | | Non-resource intensive | |
|---|---|---|---|---|
| | $SO_2$ | Wastewater | $SO_2$ | Wastewater |
| | (1) | (2) | (3) | (4) |
| DID | −1.034* | −0.028 | −0.696* | −0.136 |
| | (0.605) | (0.046) | (0.370) | (0.083) |
| Control variables | YES | YES | YES | YES |
| Observations | 2,070 | 2,070 | 3,060 | 3,060 |
| R-squared | 0.803 | 0.695 | 0.745 | 0.757 |

Robust standard errors in parentheses, * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 10 shows the results. In columns 1 and 3, the coefficients of *DID* about $SO_2$ emission are significantly negative, demonstrating that SCP can achieve pollution reduction in both types of cities. Contrary to the expected results, it is viewed that the effect is more obvious in resource-intensive cities than in non-resource-intensive cities. The possible reasons for this fact are that the early exploitation of resources in resource-intensive cities has already caused a large amount of environmental pollution; thus, the implementation of SCP precisely makes these cities better use information technology for environmental management and improves the efficiency of extraction and utilization of various resources. However, the non-resource-intensive cities have fewer industries and less total pollution due to the lack of resources, which makes the policy effect relatively less significant. Moreover, the coefficients of *DID* about wastewater emission are negative but insignificant, indicating that there is a trend of pollution reduction but it is not obvious.

### Spatial spillover effect test

There may be a spatial correlation of environmental pollution among cities, and ignoring this spatial correlation may lead to inaccurate conclusions and deteriorating model performance. Therefore, the SDID model is employed in this

**Table 11** Results of the SDID model

| Variables | $SO_2$ | | Wastewater | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *DID* | − 0.565 | − 0.284 | − 0.193** | − 0.179** |
| | (0.559) | (0.536) | (0.086) | (0.081) |
| $W_{T,T}D$ | − 0.449 | − 0.454 | 0.342** | 0.336** |
| | (0.896) | (0.846) | (0.146) | (0.142) |
| $W_{NT,T}D$ | 0.594 | 0.977 | 0.152 | 0.169 |
| | (0.689) | (0.667) | (0.120) | (0.119) |
| Control Variables | NO | YES | NO | YES |
| Observations | 5,130 | 5,130 | 5,130 | 5,130 |
| *R*-squared | 0.749 | 0.756 | 0.756 | 0.758 |

Robust standard errors in parentheses, ** indicate significance at the 1%, 5%, and 10% levels, respectively

**Table 12** Results for moderating effect

| Variables | $SO_2$ | | Wastewater | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *DID* | − 1.415*** | − 0.856*** | − 0.129*** | − 0.028 |
| | (− 8.469) | (− 2.928) | (− 4.253) | (− 0.645) |
| *Govern* | 4.923*** | | 0.424*** | |
| | (2.629) | | (2.839) | |
| *Govern * DID* | 9.231*** | | 1.158*** | |
| | (2.666) | | (5.510) | |
| *Market* | | − 0.086 | | − 0.020 |
| | | (− 1.008) | | (− 1.543) |
| *Market * DID* | | − 0.244*** | | − 0.043*** |
| | | (− 2.930) | | (− 3.450) |
| Control variables | YES | YES | YES | |
| Observations | 5130 | 5130 | 5130 | 5130 |
| *R*-squared | 0.692 | 0.688 | 0.729 | 0.728 |

Robust standard errors in parentheses, *** indicate significance at the 1%, 5%, and 10% levels, respectively

paper considering the spatial dependence of environmental pollution and the spatial spillover effect of SCP pilot based on Eq. (3). Table 11 presents the result. The spillover effects of SCP on $SO_2$ emissions are reported in columns 1 and 2, and we can find that the coefficients are not significant which indicates that the results may be divergent. Besides, columns 3 and 4 report the SCP's spillover effects on wastewater emissions, it can be found that the coefficients of *DID* are significantly negative regardless of the consideration of control variables, indicating that smart cities can directly reduce wastewater pollution when spatial spillover effects are considered in the model, so as to confirm the SCP's pollution reduction effect. Moreover, the coefficients of $W_{T,T}D$ are significantly positive at the 5% confidence level, revealing that the spatial spillover effect of the SCP exacerbates wastewater pollution in the neighboring pilot cities and there is a "beggar-thy-neighbor" effect (Zhang et al. 2021). In addition, the positive but insignificant coefficient of $W_{NT,T}D$ reflects that among the neighboring non-pilot cities, there is no spillover effect of SCP on environmental pollution reduction, which may be explained by the different administrative systems and economic situations of the pilot cities and non-pilot cities, thus leading to different directions of policy implementation.

## Moderating effects analysis

This section explores the moderating effect of the government and the market in the process of SCP in relieving environmental pollution from the perspective of their coordination and interaction. As a socialist market economy with special characteristics, how do the government and the market each play a catalytic role in regulating the pollution reduction effect of SCP?

Based on Eq. (4) and Eq. (5), Table 12 reports the relevant results. In columns 1 and 3, it can be found that SCP

significantly reduces $SO_2$ emissions and wastewater emissions, which is consistent with the previous conclusions. The coefficients of government intervention are all significantly positive, revealing that government intervention exacerbates pollution to some extent. Besides, the interaction term of government intervention and *DID* are both positive at the 1% significance level, which demonstrates that government intervention stimulates $SO_2$ emissions and wastewater emissions in the pilot smart cities, namely exacerbating environmental pollution. The possible reason is that government intervention leads to distortion of market mechanisms, thus increasing the degree of green resource mismatch within smart cities and hindering the pollution reduction effect of SCP. In addition, columns 2 and 4 demonstrate the moderating role of the market. It can be observed that SCP significantly reduces $SO_2$ emissions, nonetheless, the coefficients of *DID* for wastewater and market competition are both negative but insignificant. Moreover, the interaction term of market competition and *DID* are both negative at the 1% significance level, which illustrate that the competition of the market reduces $SO_2$ emissions and wastewater emissions, namely the pressure of environmental pollution in the pilot smart cities can be released to some extent. The possible explanation is that the market functions an important role in resource allocation (Zhang et al. 2022b), and market competition is conducive to breaking the local market segmentation and enabling the price mechanism to truly reflect the market potential and opportunities. Meanwhile, it also accelerates the flow and accumulation of green factors in smart cities and thus has a positive effect on optimizing green resource allocation and further reducing pollution.

# Conclusions, policy implications, and research prospects

## Conclusions

Does SCP reduce environmental pollution in cities? The answer to this question has practical implications for promoting SCP in China as well as the world. Therefore, based on a panel data of 285 prefecture-level and above cities in China scanning from 2003 to 2020, this study has explored the impacts of SCP on environmental pollution by utilizing the DID model and its derived models. The results indicate that SCP can significantly reduce environmental pollution, and this conclusion still holds after passing numerous robustness tests, such as the PSM-DID test, the placebo test, all independent variables lagging one period test, the policy interference test, and the IV test. Moreover, the heterogeneity analysis shows that the effect of reducing environmental pollution of SCP is heterogeneous. Especially, for $SO_2$ emissions, the positive effect is more significant in western cities, medium-sized cities, and resource-intensive cities; for wastewater emissions, the eastern cities and non-resource-intensive cities are where the positive effect is most significant. Furthermore, the results of the SDID model show that SCP has a "beggar-thy-neighbor" effect among the pilot cities, and there is no spillover effect of SCP on pollution reduction in neighboring non-pilot cities. Finally, the analysis of moderating effect reflects that government intervention plays a negative inhibition role in the process of SCP affecting environmental pollution, while market competition plays a positive catalytic role in the process of SCP reducing the environmental pollution.

## Policy implications

There are several policy implications based on the abovementioned conclusions. First, SCP can balance the relationship between economic development and environment quality; thus, the government should energetically promote the construction of smart cities, especially in developing countries like China that face a similar environmental governance problem during urbanization. Therefore, SCP should be elevated to the national strategic status. Second, the key problem of smart city construction does not lie in the influence of region, scale, and resource endowment; therefore, the government ought to take priority application and development of smart projects adapted to the city to improve the quality of smart city construction. Actually, the government should actively introduce advanced smart technologies and further enhance the efficiency of smart city construction by applying smart construction to all aspects of city construction, enterprise production, and the lives of residents. In addition, some of the economically backward cities in the west can take advantage of the dividends of SCP to improve the operation and governance efficiency of the city. Meanwhile, the large-scale cities, resource-intensive cities and other areas with more serious environmental pollution can utilize smart city construction to improve energy efficiency and make good planning for pollution emissions to alleviate or even eliminate urban diseases. Thirdly, for the spatial spillover effect between pilot cities, local government should minimize the impact of the "beggar-thy-neighbor" effect during the construction of the smart city. Specifically, the central government should make top-level planning to build a community of regional interests and responsibilities, so as to eliminate the phenomenon of pollution transfer. In response to the spatial spillover effect of pilot cities on neighboring non-pilot cities, the phenomenon of "one size fits all" must be prevented during the development of the smart city as the administrative system and environmental pollution of each city is different, and the government should adopt the differentiated policies for each city instead of copying the original smart city pilot experience. Finally, it is essential to define the relationship between the government and the market during the construction of smart city, the government should play a guiding role to let the market become the protagonist of smart city construction. For instance, the government can provide financial support, technical support, cutting-edge technologies, and innovative resources for the smart city, so as to stimulate the vitality of various market participants in smart cities.

## Research prospects

Indeed, future research needs to be further expanded. First, this study only adopts industrial $SO_2$ emissions and industrial wastewater emissions as the proxy indicators of environmental pollution; therefore, it is possible to incorporate more pollution indicators into the measurement of environmental pollution for a more comprehensive analysis, such as industrial solid waste pollution and soil pollution. In addition, the mediating effect analysis was not conducted in this study due to technical limitations, so the results of this study can be more complete if reasonable mediating variables could be analyzed.

**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** Not applicable.

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

## References

Bao Z, Zhou X, Li G (2022) Does the Internet Promote Green Total Factor Productivity? Empirical Evidence from China. Pol J Environ Stud 31:1037–1048. https://doi.org/10.15244/pjoes/141806

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? Quart J Econ 119:249–275. https://doi.org/10.1162/003355304772839588

Caragliu A, Del Bo CF (2018) The economics of smart city policies. Scienze Regionali 17:81–104. https://doi.org/10.14650/88818

Caragliu A, Del Bo C, Nijkamp P (2011) Smart cities in Europe. J Urban Technol 18:65–82. https://doi.org/10.1080/10630732.2011.601117

Chagas ALS, Azzoni CR, Almeida AN (2016) A spatial difference-in-differences analysis of the impact of sugarcane production on respiratory diseases. Reg Sci Urban Econ 59:24–36. https://doi.org/10.1016/j.regsciurbeco.2016.04.002

Chen L, Li K, Chen S, Wang X, Tang L (2021a) Industrial activity, energy structure, and environmental pollution in China. Energy Econ 104:105633. https://doi.org/10.1016/j.eneco.2021.105633

Chen Y, Lee C-C (2020) Does technological innovation reduce $CO_2$ emissions? Cross-country evidence. J Clean Prod 263. https://doi.org/10.1016/j.jclepro.2020.121550

Chen L, Yu Y (2021) How does environmental pollution erode political trust in China? A multilevel analysis. Environ Impact Assess Rev 88. https://doi.org/10.1016/j.eiar.2021.106553

Chen Y, Cheng L, Lee C-C, Wang-S (2021b) The impact of regional banks on environmental pollution: evidence from China's city commercial banks. Energy Econ 102. https://doi.org/10.1016/j.eneco.2021.105492

Chu Z, Cheng M, Yu NN (2021) A smart city is a less polluted city. Technol Forecast Soc Change 172. https://doi.org/10.1016/j.techfore.2021.121037

Cui N, Hao H, Wang G, Wang W, Wang Y (2008) Orthogonal design-directed optimization of an LC method for fingerprinting Mai-Luo-Ning injection, and validation of the method. Chromatographia 68:33–39. https://doi.org/10.1365/s10337-008-0650-2

Deng Z, Liu Y, Zhu Z, Luo D, Gu C, Zhou L, Xie G, Li W (2021) Ultra-precise optical phase-locking approach for ultralow noise frequency comb generation". Optics Laser Technol 138:106906. https://doi.org/10.1016/j.optlastec.2020.106906

Duranton G, Turner MA (2012) Urban growth and transportation. Rev Econ Stud 79:1407–1440. https://doi.org/10.1093/restud/rds010

Duygan M, Fischer M, Pärli R, Ingold K (2022) Where do Smart Cities grow? The spatial and socio-economic configurations of smart city development. Sustain Cities Soc 77. https://doi.org/10.1016/j.scs.2021.103578

Fan Q, Qiao Y, Zhang T, Huang K (2021) Environmental regulation policy, corporate pollution control and economic growth effect: evidence from China. Environ Challenges 5. https://doi.org/10.1016/j.envc.2021.100244

Feng Y, Hu S (2022) The effect of smart city policy on urban haze pollution in China: empirical evidence from a quasi-natural experiment. Pol J Environ Stud 31:2083–2092. https://doi.org/10.15244/pjoes/143775

Gao K, Yuan Y (2022) Is the sky of smart city bluer? Evidence from satellite monitoring data. J Environ Manag 317:115483. https://doi.org/10.1016/j.jenvman.2022.115483

Guo K, Cao Y, Wang Z, Li Z (2022a) Urban and industrial environmental pollution control in China: an analysis of capital input, efficiency and influencing factors. J Environ Manag 316:115198. https://doi.org/10.1016/j.jenvman.2022.115198

Guo W, Yexi Z, Xinghua F, Jianxin L (2019) County-level highway network centrality of urban agglomerations and its influencing factors in the middle reaches of the Yangtze River

Guo Q, Wang Y, Dong X (2022b) Effects of smart city construction on energy saving and $CO_2$ emission reduction: Evidence from China. Appl Energy 313. https://doi.org/10.1016/j.apenergy.2022.118879

Haarstad H, Wathne MW (2019) Are smart city projects catalyzing urban energy sustainability? Energy Policy 129:918–925. https://doi.org/10.1016/j.enpol.2019.03.001

Hao Y, Ling-Ou W, Chien-Chiang L (2020) Financial development, energy consumption and China's economic growth: new evidence from provincial panel data. Int Rev Econ Financ 69:1132–1151. https://doi.org/10.1016/j.iref.2018.12.006

Huang J, Pan X, Guo X, Li G (2018) Health impact of China's Air Pollution Prevention and Control Action Plan: an analysis of national air quality monitoring and mortality data. Lancet Planet Health 2:e313–e323. https://doi.org/10.1016/s2542-5196(18)30141-4

Huovila A, Bosch P, Airaksinen M (2019) Comparative analysis of standardized indicators for Smart sustainable cities: what indicators and standards to use and when? Cities 89:141–153. https://doi.org/10.1016/j.cities.2019.01.029

Jiang L, Lin C, Lin P (2014) The determinants of pollution levels: Firm-level evidence from Chinese manufacturing. J Comp Econ 42:118–142. https://doi.org/10.1016/j.jce.2013.07.007

Jiang L, He S, Zhou H, Kong H, Wang J, Cui Y, Wang L (2021b) Coordination between sulfur dioxide pollution control and rapid economic growth in China: evidence from satellite observations and spatial econometric models. Struct Chang Econ Dyn 57:279–291. https://doi.org/10.1016/j.strueco.2021.04.001

Jiang H, Jiang P, Wang D, Wu J (2021a) Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. Sustaina Cities Soc 69. https://doi.org/10.1016/j.scs.2021.102809

Jo H, Kim H-E, Sim M (2022) Environmental preference, air pollution, and fund flows in China. Pacif-Basin Financ J 72. https://doi.org/10.1016/j.pacfin.2022.101723

Kendy E, Zhang Y, Liu C, Wang J, Steenhuis T (2004) Groundwater recharge from irrigated cropland in the North China Plain: case study of Luancheng County, Hebei Province, 1949–2000. Hydrol Process 18:2289–2302. https://doi.org/10.1002/hyp.5529

Kirimtat A, Krejcar O, Tasgetiren MF, Herrera-Viedma E (2021) Multi-performance based computational model for the cuboid open traveling salesman problem in a smart floating city. Build Environ 196. https://doi.org/10.1016/j.buildenv.2021.107721

Kunrong S, Gang J (2020) The Policy effects of the environmental governance of Chinese local governments: a study based on the progress of the river chief system. Social Sci China 41:87–105. https://doi.org/10.1080/02529203.2020.1806475

Li JS (2003) Relation-based versus rule-based governance: an explanation of the East Asian miracle and Asian crisis. Rev Int Econ 11(4):651–673. https://doi.org/10.1111/1467-9396.00409

Li X, Fong PSW, Dai S, Li Y (2019) Towards sustainable smart cities: an empirical comparative assessment and development pattern optimization in China. J Clean Prod 215:730–743. https://doi.org/10.1016/j.jclepro.2019.01.046

Li L, Zheng Y, Zheng S, Ke H (2020) The new smart city programme: evaluating the effect of the internet of energy on air quality in China. Sci Total Environ 714:136380. https://doi.org/10.1016/j.scitotenv.2019.136380

Liao L, Du M, Chen Z (2021) Air pollution, health care use and medical costs: evidence from China. Energy Econ 95. https://doi.org/10.1016/j.eneco.2021.105132

Lin B, Liu H (2015) China's building energy efficiency and urbanization. Energy Build 86:356–365. https://doi.org/10.1016/j.enbuild.2014.09.069

Lin B, Xu C (2022) Does environmental decentralization aggravate pollution emissions? Microscopic evidence from Chinese industrial enterprises. Sci Total Environ 829:154640. https://doi.org/10.1016/j.scitotenv.2022.154640

Lin B, Zhou Y (2022) Understanding the institutional logic of urban environmental pollution in China: evidence from fiscal autonomy. Process Saf Environ Prot 164:57–66. https://doi.org/10.1016/j.psep.2022.06.005

Liu P, Peng Z (2014) China's smart city pilots: a progress report. Computer 47:72–81. https://doi.org/10.1109/MC.2013.149

Liu F, Zhang Y, Li H, Zhang C, Deng W, Shi Y (2019) Meta-analysis of peer effects on smart cities. Procedia Comput Sci 162:873–877. https://doi.org/10.1016/j.procs.2019.12.062

Liu S, Liu C, Yang M (2021) The effects of national environmental information disclosure program on the upgradation of regional industrial structure: Evidence from 286 prefecture-level cities in China. Struct Chang Econ Dyn 58:552–561. https://doi.org/10.1016/j.strueco.2021.07.006

Liu H, Liu H, Cheng Y (2022a) Illustrating the multi-stakeholder perceptions of environmental pollution based on big data: lessons from China. Reg Sustain 3:12–26. https://doi.org/10.1016/j.regsus.2022.03.003

Liu X, Zhong S, Li S, Yang M (2022b) Evaluating the impact of central environmental protection inspection on air pollution: an empirical research in China. Process Saf Environ Prot 160:563–572. https://doi.org/10.1016/j.psep.2022.02.048

Lu W, Wu H, Geng S (2021) Heterogeneity and threshold effects of environmental regulation on health expenditure: considering the mediating role of environmental pollution. J Environ Manag 297:113276. https://doi.org/10.1016/j.jenvman.2021.113276

Meijer A, Thaens M (2018) Urban technological innovation: developing and testing a sociotechnical framework for studying smart city projects. Urban Affairs Rev 54:363–387. https://doi.org/10.1177/1078087416670274

Papastamatiou I, Marinakis V, Doukas H, Psarras J (2017) A decision support framework for smart cities energy assessment and optimization. Energy Procedia 111:800–809. https://doi.org/10.1016/j.egypro.2017.03.242

Shelton T, Zook M, Wiig A (2015) The 'actually existing smart city.' Camb J Reg Econ Soc 8:13–25. https://doi.org/10.1093/cjres/rsu026

Shen L, Huang Z, Wong Siu W, Liao S, Lou Y (2018) A holistic evaluation of smart city performance in the context of China. J Clean Prod 200:667–679. https://doi.org/10.1016/j.jclepro.2018.07.281

Song M, Tan KH, Wang J, Shen Z (2022) Modeling and evaluating economic and ecological operation efficiency of smart city pilots. Cities 124. https://doi.org/10.1016/j.cities.2022.103575

Wang J, Deng K (2022) Impact and mechanism analysis of smart city policy on urban innovation: evidence from China. Econ Anal Policy 73:574–587. https://doi.org/10.1016/j.eap.2021.12.006

Wang Q, Tang J, Choi G (2021) A two-stage eco-efficiency evaluation of China's industrial sectors: a dynamic network data envelopment analysis (DNDEA) approach. Process Saf Environ Prot 148:879–892. https://doi.org/10.1016/j.psep.2021.02.005

Wang Y, Duan X, Wang L, Zou H (2022b) Spatial temporal patterns and driving factors of industrial pollution and structures in the Yangtze River Economic Belt. Chemosphere 303:134996. https://doi.org/10.1016/j.chemosphere.2022.134996

Wang K-L, Pang S-Q, Zhang F-Q, Miao Z, Sun H-P (2022a) The impact assessment of smart city policy on urban green total-factor productivity: evidence from China. Environ Impact Assess Rev 94. https://doi.org/10.1016/j.eiar.2022.106756

Wu H, Xia Y, Yang X, Yu H, Ren S (2021) Does environmental pollution promote China's crime rate? A new perspective through government official corruption. Struct Chang Econ Dyn 57:292–307. https://doi.org/10.1016/j.strueco.2021.04.006

Xi Q, Mei L (2022) How did development zones affect China's land transfers? The scale, marketization, and resource allocation effect. Land Use Policy 119:106181. https://doi.org/10.1016/j.landusepol.2022.106181

Yao T, Huang Z, Zhao W (2020) Are smart cities more ecologically efficient? Evidence from China. Sustain Cities Soc 60. https://doi.org/10.1016/j.scs.2019.102008

Yigitcanlar T, Kamruzzaman Md (2018) Does smart city policy lead to sustainability of cities? Land Use Policy 73:49–58. https://doi.org/10.1016/j.landusepol.2018.01.034

Yu Y, Zhang N (2019) Does smart city policy improve energy efficiency? Evidence from a quasi-natural experiment in China. J Clean Prod 229:501–512. https://doi.org/10.1016/j.jclepro.2019.04.316

Yuan F, Zhai Y, Sun X, Dong Y (2022) Air pollution mitigation: Evidence from China's central environmental inspection. Environ Impact Assess Rev 96. https://doi.org/10.1016/j.eiar.2022.106835

Yuen B (2018) Singapore: smart city, smart state. J Southeast Asian Stud 49:349–351. https://doi.org/10.1017/s0022463418000152

Zhang X, Fan D (2023) Collaborative emission reduction research on dual-pilot policies of the low-carbon city and smart city from the perspective of multiple innovations". Urban Climate 47:101364. https://doi.org/10.1016/j.uclim.2022.101364

Zhang L, Huang S (2022) Social capital and regional innovation efficiency: the moderating effect of governance quality. Struct Chang Econ Dyn 62:343–359. https://doi.org/10.1016/j.strueco.2022.05.013

Zhang Xu, Ou X, Yang X, Qi T, Nam K, Zhang D, Zhang X (2017) Socioeconomic burden of air pollution in China: province-level analysis based on energy economic model. Energy Econ 68:478–489. https://doi.org/10.1016/j.eneco.2017.10.013

Zhang W, Li G, Guo F (2022) Does carbon emissions trading promote green technology innovation in China? Appl Energy 315:119012. https://doi.org/10.1016/j.apenergy.2022.119012

Zhang Z, Zhang J, Feng Y (2021) Assessment of the carbon emission reduction effect of the air pollution prevention and control action plan in China. Int J Environ Res Public Health 18. https://doi.org/10.3390/ijerph182413307

Zhang H, Xu T, Feng C (2022a) Does public participation promote environmental efficiency? Evidence from a quasi-natural experiment of environmental information disclosure in China. Energy Econ

Zhao Z, Zhang Y (2020) Impact of smart city planning and construction on economic and social benefits based on big data analysis. Complexity 2020:8879132. https://doi.org/10.1155/2020/8879132