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Smart city projects against COVID-19: Quantitative evidence from China

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ABSTRACT

The outbreak of COVID-19 pandemic worldwide has brought huge challenges to urban governance. Whether the smart city projects play a significant role in the COVID-19 prevention and control process is a question worthy of attention. Based on the data of COVID-19 confirmed cases and the smart cities projects investment in China cities, our empirical results show that smart city projects have significantly reduced the number of COVID-19 confirmed cases. Specifically, for every 1 million yuan increase in smart city investment per 10,000 people, the number of COVID-19 confirmed cases per 10,000 people would decrease by 0.342. The heterogeneity analysis results show that the effect of the smart city projects on COVID-19 in the spread phase inside a city is stronger than that in the input phase. In addition, the effect differs for cities with different population sizes. This study provides quantitative evidence of the impact of smart city projects on COVID-19 prevention and control.

1. Introduction

The outbreak of COVID-19 pandemic has brought huge impact on the development and operation of cities around the world and people’s daily lives (Chakraborty & Maity, 2020; Chen, Yang, Yang, Wang, & Bärnighausen, 2020; Megahed & Ghoneim, 2020). With the rapid spread of COVID-19 around the world, the prevention and control of the pandemic has evolved into a major issue in social governance (Sonn, Kang, & Choi, 2020). The prevention and control of pandemic requires the coordination of policy implementation, management, new technology and other factors. Compared with the SARS (Severe Acute Respiratory Syndrome) that outbroke 17 years ago, the iteration of emerging technologies, especially the improvement and widespread use of portable devices, has brought many changes on how cities deal with the pandemic and the prevention and control methods (Mohammed, Syamsudin, Al-Zubaidi, Aks, & Yusuf, 2020). In COVID-19 pandemic prevention and control practice, related technologies and projects, samples, represented by “smart cities” have been applied to the pandemic prevention and control work (Inn, 2020).

Smart city refers to the use of various information technologies or innovative concepts to connect and integrate urban systems and services in the process of urban management and operation, so as to enhance the efficiency of resource utilization, optimize urban management and services, and improve the quality of life of citizens. Due to its role in urban management, travel reduction and information sharing, smart city projects have been seen as an important tool for effective pandemic prevention and control without implementing strict lockdown policy (Sonn & Lee, 2020; Sonn et al., 2020; Vega, 2020). Using smart city platforms for intelligent prevention, epidemic management, information screening, and medical resource matching in epidemic prevention and control has attracted policymakers and scholars’ attention (Adhikari et al., 2020; Allam & Jones, 2020a, 2020b; Allam, Dey, & Jones, 2020; Gasser, Iença, Scheibner, Sleigh, & Vayena, 2020; Gupta, Abdelsalam, & Mittal, 2020).

However, some scholars are skeptical whether the smart city projects, like intelligent transportation platform, have significantly reduced the risk of the spread of COVID-19 pandemic. For example, Allam and Jones (2020a, 2020b) argued that most smart city products can only be understood by service providers, and smart city products have the problem of information fragmentation. To what extent the city’s costly smart city projects have helped China’s COVID-19 prevention and control still lacks quantitative evidence. In practice, effective prevention and control of the pandemic cannot be achieved without relying on the basic measures implemented by the community to carry out prevention and control measures.

This paper attempts to quantitatively investigate the impact of smart city construction on COVID-19 pandemic prevention and control based on the data of confirmed cases and the smart cities projects investment in China cities. The main contributions of this paper mainly include the following contents. Using the quantitative research methods, we

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investigate the impact of smart city projects on the pandemic prevention and control of COVID-19. Our analysis explains what kinds of smart city projects help to prevent and control the pandemic and discusses the mechanism path of the influence. Besides, we further discuss the heterogeneous impact of smart cities on COVID-19 prevention and control from different phases and city population size. We believe the analysis is helpful to understand the role of smart cities in responding to public health emergency events and enrich this research field.

The rest of the paper is organized as follows. The second part is literature review, the third part introduces China’s COVID-19 pandemic prevention and control situation and the development of China’s smart city projects and their application scenarios in COVID-19 pandemic prevention and control. The fourth part introduces the data and research design; the fifth part discusses the empirical results. The final part concludes and discusses the policy implication and the future direction of smart city projects in pandemic prevention and control.

2. Literature review

The original intention of smart city construction is having a more convenient life of urban residents, a more efficient urban management, and a more advanced urban information system (Jones, Cook, & Dayot, 2017). The construction of smart cities includes e-government, medical services, smart community, geographic information system and other aspects of urban life (Mollao, Vahedi, & Rivera, 2020). In the past, the focus of discussion and research on smart cities was mainly on conceptual design framework, and the proposal and implementation of related policies are mainly driven by the government from top to bottom (Lan, Tseng, Yang, & Huisingh, 2020; Ojo, Curry, Janowski, & Dzhusupova, 2015; Schleicher et al., 2016). Some smart city projects can help to share information in real time, reduce face-to-face contact between people, and improve the efficiency of government response to the pandemic and the allocation of medical resources. Thus, in response to the urgent needs of COVID-19 pandemic prevention and control, smart city projects have been implemented in the work against COVID-19. 

Costa and Peixoto (2020) presented application scenarios of smart city projects in COVID-19 prevention and control, discussed possible solutions, and described feasible and promising trends using Singapore, New York, London as examples. Khan et al. (2021) analyzed the use of new technologies in COVID-19 control and prevention about computing large volumes of data, predicting infection threats, providing medical assistance, and analyzing diagnostic results. In addition, the advantages, disadvantages, opportunities and possible threats of the strict implementation of these technologies for COVID-19 outbreak control are described in their analysis. Das and Zhang (2020), Jaiswal, Agarwal, and Negi (2020) also introduce the application experience of smart city in COVID-19 prevention and control. However, there are few relevant quantitative analyses.

Although the wide spread of Covid-19 has made many scholars and government officials realize the importance of smart city projects, there are still some studies that argue that the expensive smart city projects are not working as they should be. Zhang (2020) believed that large-scale smart city projects perform poorly, failing to effectively achieve the transition from normal state to COVID-19 prevention and control state. Overall, a more comprehensive quantitative study is needed to further understand the impact of smart city projects on COVID-19 prevention and control.

How to measure “smart city level” is the first problem to be solved in the empirical analysis. In the existing literature, many studies used the 0–1 binary variable to reflect whether the city is the chosen pilot city, and employed difference-in-difference method to evaluate the impact of smart city construction (Xu, Luo, Yu, & Cao, 2020; Yao, Huang, & Zhao, 2020). However, this setting is not suitable for our analysis. The main reason is that most cities had smart city projects during the time period when COVID-19 pandemic broke out. Besides, the use of 0–1 binary variables cannot distinguish smart city level. The amount and density of investment in smart city projects is an important indicator reflecting the smart city level. Caragliu and Del Bo (2016) pointed out that the smart city level should be evaluated from the investment information of smart city projects.

Summarizing the existing studies, the prevention and control of COVID-19 has attracted the attention of many scholars, and some scholars have also discussed the application of smart city in the prevention and control of COVID-19. However, there is a lack of quantitative analysis on the effect of smart city on the prevention and control of COVID-19. This is a gap in existing research. Our study is based on this motivation to build an empirical analysis framework and strive to obtain quantitative evidence of smart city investment on the prevention and control of COVID-19.

3. Background

3.1. COVID-19 prevention and control practice in China

As a major public health emergency, COVID-19 pandemic has swept the world and become a pandemic disease. China government adopted a most comprehensive, strictest prevention and control measures. The number of daily new confirmed cases continues to decline after mid-February 2020. As of May 2020, the number of daily new cases in China has dropped to about 10 cases (see Fig. 1).

The spatial distribution of COVID-19 confirmed cases shows clear spatial differentiation characteristics (see Fig. 2). The cities with the largest number of COVID-19 confirmed cases are mainly Wuhan and its surrounding cities. Overall, COVID-19 confirmed cases are mainly distributed in central and eastern China, where have a high urbanization level and is also the gathering place of China cities.

3.2. Smart city construction and its application on the prevention and control of COVID-19

China has attached great importance to the construction of smart cities. In December 2012, China’s Ministry of Housing and Urban-Rural Development issued the “Notice on the Pilot Work of the National Smart City” and approved the first batch of 90 pilot cities in January 2013. After this, the pace of smart city construction continues to accelerate, and smart city projects are also more abundant. In August 2013, the second batch of 103 pilot cities was announced. In August 2014, the Ministry of Construction released the third batch of smart city pilots.

In the epidemic theory, reducing person-to-person communication, timely detection of the source of transmission, tracking the trajectory of virus transmission, and efficient medical care are the priorities of the government to control the spread of epidemic (Patten & Arboleda-Flores, 2004). Combining smart city concepts and detailed project characteristics, we find that smart city projects can help with COVID-19 prevention and control on the above perspectives (World Health Organization, 2020). Specifically, Smart Community, Smart Government, Smart Healthcare and Smart Information are most directly related to COVID pandemic prevention and control (Jin, 2020; Xu, Ding et al., 2020; Xu, Luo et al., 2020). The detailed information about the four categories smart city projects is listed in Fig. 3.

Smart Community, including “Zero contact service”, “High efficiency identification” and other smart community technologies, plays an active role in community emergency information collection, floating population management, and can reduce the unnecessary travel of citizens during the pandemic by providing e-commerce services in community. For example, the “micro-neighborhood” smart community platform in Wuhan enable people do “self-examination and report of pneumonia”, which assists the detection of potential patients in the community and thus effectively reduce COVID-19 virus cross-infection.

Smart Government improves the government’s governance and emergency response capabilities with the help of intelligent government affairs platform, and it is of great value in resource allocation and social
management. For example, Hangzhou “city brain” platform help policymakers see the number of confirmed cases in real time. This real-time dynamic data is invaluable to the government’s decision-making. Combining it with other data, the government will greatly increase the possibility of making correct and precise response measures. 

Smart Healthcare plays a huge role in the process of selecting patients, improves the speed of diagnosis and treatment, helps coordinate regional medical resources, and thus contributes to COVID-19 prevention and control. For example, henan provincial people’s hospital launches the COVID-19 online consultation service with the help of the online system of interconnected smart health service hospital. The service can not only help local patients, but also help patients in other cities.

**Fig. 1.** Daily changes in the number of newly confirmed cases of COVID-19 in China.
Note: The figure is drawn by the author using the data from the China Data Laboratory of Harvard University.

**Fig. 2.** Spatial distribution of cumulative number of confirmed cases in Chinese cities on May 10, 2020.
Note: The figure is drawn by the author. The original map and data are from the China Data Laboratory of Harvard University.
4. Empirical analysis model and data description

4.1. Model setting

Multiple regression analysis model is a classical model in quantitative analysis. To verify the above hypothesis we proposed, we designed the following regression analysis model.

\[
\text{confirm}_i = \beta_0 + \beta_1 \text{smart}_i + \beta_2 \text{Control}_i + \epsilon_i \tag{1}
\]

where \(\text{confirm}_i\) measures the severity of COVID-19 pandemic in city \(i\), and is represented using the number of confirmed cases per 10,000 people. We select the cumulative number of COVID-19 confirmed cases in each city on May 10 to calculate it. \(\text{smart}_i\) is our explanatory variable that reflects the development level of smart city projects in city \(i\).

\(\text{Control}_i\) is the control variables that may have an influence on city \(i\)'s COVID-19 confirmed cases. \(\text{Input}_i\) namely the number of population inflows from Wuhan to city \(i\) from December 1 to January 23, is introduced to control COVID-19 pandemic input risk. The more people coming from Wuhan, the greater the city’s COVID-19 input risk. Besides, we introduce GDP per capita (\(\text{gdpp}_i\)), the number of medical persons per 10,000 people (\(m_{\text{person}}\)) and the number of hospital beds per 10,000 people (\(m_{\text{bed}}\)) as the control variables. These variables reflect the economic and health care condition of city \(i\). We do not include Wuhan and other cities without COVID-19 confirmed cases in the empirical analysis, to avoid interference caused by extreme values.

4.2. Measurement issues

We use the investment amount of four categories smart city projects per 10,000 people to measure \(\text{smart}_i\) (million yuan per 10,000 people). According to the categories of smart city projects related to pandemic prevention and control listed in Fig. 3, we counted the related smart city projects investment that have been completed before December 2019. Information on these projects is collected through the official website of the Ministry of Housing and Urban-Rural Development of China, the official website of Municipal Housing Authority and China smart city information network website (https://www.zhihuichengshi.cn/). The information includes project name, project content, project completion time, and project investment amount. Fig. 4 shows the spatial distribution of investment in the four categories of smart city projects. The spatial distribution is overall consistent with the three batches of smart city pilot cities, and is similar with the smart city development evaluation rankings issued by the Information Research Center of the Chinese Academy of Social Sciences and GuoMat Internet Information Consulting Co., Ltd. This supports the reliability of our investment data that used in the measure of \(\text{smart}_i\). The smart city projects mentioned in the following part refer to the specific four types of smart community projects: \(\text{Smart Community}, \text{Smart Government}, \text{Smart Healthcare} \) and \(\text{Smart Information}\).

In addition to the measurement indicators of smart cities, the relevant data of COVID-19 used in this paper comes from the China Data Laboratory of Harvard University. The number of population inflows from Wuhan to city \(i\) in our study period can be obtained using the human mobility big data from Baidu (Kraemer et al., 2020).

For the cities other than Wuhan, the number of migrants from Wuhan before January 23 is the main potential source of pandemic input. The spatial distribution of outflow population from Wuhan is shown in Fig. 5. Overall, the spatial distribution is uneven, showing a radial decreasing distribution centered on Wuhan. The cities in Hubei Province adjacent to Wuhan are the main destinations of Wuhan’s population flow.

In addition to the above variables, \(\text{gdpp}_i, m_{\text{person}}, m_{\text{bed}}\) can be obtained from the public city statistical yearbook. The descriptive statistics of the variables involved in the empirical analysis are shown in

![Smart City Projects](image-url)
5. Empirical results

5.1. The impact of smart city projects on COVID-19 control and prevention

Table 2 shows the empirical results of examining the impact of smart city projects on cities’ COVID-19 control and prevention. The column 1 of Table 2 shows the regression results when no control variables are added. The regression coefficient of our explanatory variable $smart_i$ is significantly negative, meaning that the increase of investment in smart city projects in city $i$ would reduce the number of COVID-19 confirmed cases per 10,000 people.

Following this, the control variable $input_i$ and other control variables are added respectively. The regression results are shown in the column 2 and column 3 of Table 2. After these control variables are added, the regression coefficients of our explanatory variable $smart_i$ remain significantly negative. In addition, the coefficients of $input_i$ that reflects the input pressure of COVID-19 virus from Wuhan stay significantly positive, indicating that the greater the input risk of COVID-19 virus, the greater the number of local confirmed cases. The column 4 of Table 2 is the regression result under the robust standard error. Under this result, the coefficients of $smart_i$ is still significantly negative, which verifies the reliability of our benchmark regression results. The coefficient of $smart_i$ is $-0.342$, meaning that for every additional unit of investment in smart city projects (million yuan per 10,000 people), the number of confirmed COVID-19 cases per 10,000 people will fall by 0.342 units. Finally, we select a control group of cities with no smart projects developed, but with migration from Wuhan as robust test. The coefficient of $smart_i$ in column 5 stays significantly negative, which further verifies the robustness of the effect. Overall, our analysis suggests that investments in smart city projects contribute to cities’ COVID-19 prevention and control.

5.2. Heterogeneity effects at different phases of COVID-19 transmission

Considering that Wuhan announced the “lockdown of the city” on January 23, 2020, and the incubation period of COVID-19 virus is about 14 days, the confirmed cases of COVID-19 reported by the Centers for Disease Control of non-Wuhan cities before February 6, 2020 are mainly imported cases (World Health Organization, 2020). The confirmed cases before February 6, 2020 generally have a history of Wuhan residence or travel before January 23. For the cases after February 6, 2020, they come into contact with COVID-19 virus carriers mainly within the city. Therefore, the phase before February 16 corresponds to “input phase”, and the phase after February 16 corresponds to “intra-city transmission phase”.

To reveal the heterogeneity effects at different phases of COVID-19 transmission, we discuss the impact of the smart city projects on the cumulative number of confirmed cases before February 16, and the number of confirmed cases between February 16 and May 10. In addition, in order to more thoroughly investigate the differential impact of different pandemic phases, we also analyze the impact of the smart city project on the cumulative number of confirmed cases on February 10, which is the day with the largest number of new cases in a single day.

Table 3 shows the regression results of heterogeneity effects at different phases of COVID-19 transmission. The three column regression results show that the explanatory variable $smart_i$ has a stable significantly negative effect on the outcome variable confirm at different time points. However, there is a clear difference in the magnitude of the effect of $smart_i$ at different time points. Among them, the coefficient value of
Fig. 5. Spatial distribution of relevant outflow population intensity from Wuhan.
Note: The figure is drawn by the author. The original map and data are from the China Data Laboratory of Harvard University.

Table 2
Regression results.

| Variables | Obs | Mean | Std  | Min   | Max  |
|-----------|-----|------|------|-------|------|
| smarti    | 245 | 0.13 | 0.261| 0      | 2.393|
| inputi    | 245 | 31.513| 137.792| 0   | 1189.66|
| gdppi     | 245 | 58110.28| 34740.62| 11516.7| 249137|
| m_personi | 245 | 25.125| 12.073| 8.295 | 93.661|
| m_bedi    | 245 | 45.703| 19.288| 13.204| 155.402|

Note: T-statistics in parentheses for Column (1), (2), (3) and robust t-statistics in parentheses for Column (4). *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 3
Results of heterogeneity effects at different phases.

| VARIABLES | (1) COVID-19 cumulative confirmed cases before 16th February | (2) COVID-19 cumulative confirmed cases between 17th February and 10th May | (3) COVID-19 cumulative confirmed cases before 12th February |
|-----------|-------------------------------------------------------------|---------------------------------------------------------------------|----------------------------------------------------------|
| smarti    | 0.178*** (-3.21)                                           | 0.285*** (-2.96)                                                  | 0.164** (-2.30)                                           |
| inputi    | 0.275*** (5.6)                                             | 0.426*** (4.35)                                                   | 0.233*** (2.73)                                           |
| gdppi     | -0.003 (-0.05)                                             | 0.015 (0.14)                                                     | 0.054 (0.63)                                              |
| m_personi | 0.008 (-0.11)                                              | -0.032 (-0.24)                                                   | -0.082 (-0.74)                                            |
| m_bedi    | -0.040 (-1.51)                                             | -0.047 (-1.41)                                                   | -0.009 (-0.59)                                            |
| Constant  | -0.138 (-0.28)                                             | -0.355 (-0.38)                                                   | -0.564 (-0.77)                                            |
| Observations | 245 245 245 245 245 245 245 245 245 245 245 245 245 245 245 |                                                                 |                                                          |

Note: Robust T-statistics in parentheses for Column (1), (2), (3). *** p < 0.01, ** p < 0.05, * p < 0.1.

smarti in the column 2 is the largest (-0.285), indicating that the smart city project has the most prominent role in the prevention and control of COVID-19 from 17th February to 10th May. As mentioned above, this phase corresponds to the prevention and control of intra-city transmission of COVID-19. The heterogeneity analysis means that the smart city project has a larger effect during the “intra-city transmission phase”.

Table 1
Summary statistics of the variables.

| Variables | Obs | Mean | Std  | Min   | Max  |
|-----------|-----|------|------|-------|------|
| confirmi  | 245 | 0.281| 1.04 | 0.004 | 12.577|
| smarti    | 245 | 0.13 | 0.261| 0      | 2.393|
| inputi    | 245 | 31.513| 137.792| 0   | 1189.66|
| gdppi     | 245 | 58110.28| 34740.62| 11516.7| 249137|
| m_personi | 245 | 25.125| 12.073| 8.295 | 93.661|
| m_bedi    | 245 | 45.703| 19.288| 13.204| 155.402|

Note: T-statistics in parentheses for Column (1), (2), (3) and robust t-statistics in parentheses for Column (4). *** p < 0.01, ** p < 0.05, * p < 0.1.
5.3. Heterogeneity effects for city population size

The pressure to prevent and control infectious diseases will increase exponentially with the size of urban population. Cities with different population sizes may also have different degrees of application of smart city technologies in COVID-19 prevention and control. The population size of Chinese cities varies greatly, as can be seen in Fig. 6. Thus, for cities with different population sizes, the effect of smart city projects on COVID-19 pandemic prevention and control may be different.

In order to identify the heterogeneous impact of smart city projects on COVID-19 prevention and control under different population sizes, we divide the research sample into three groups according to the quantile of population size. Then, we perform regression analysis on each group according to Eq. (1). The regression results are shown in Table 4.

The results show that the population size of large cities and small cities is quite different. The coefficients of $\text{smart}_i$ in the column 1 and column 3 of Table 4 are significantly negative, and the coefficient of $\text{smart}_i$ in the column 2 fails the significance test. This means that the smart city project is effective for the prevention and control of COVID-19 pandemic in large cities with the top 30 % of population scale and small cities with the last 30 % of population scale. For medium-sized cities, this effect is not significant. Judging from the magnitude of the effect, smart city projects have the greatest impact on the prevention and control of COVID-19 in small cities with the coefficient value of −0.601.

The reason for this result may be due to that the per capita investment of smart city projects in medium-sized cities is lower than that in small cities and large cities. Smart city project investment is easier to make a difference for cities with small populations. For large cities, their smart city projects are more mature and diverse. Large cities can develop more effective and wide-ranging smart city initiatives to improve the processing and sharing of critical data, leading to improved detection and mitigation of outbreaks, as well as reduced execution time for critical actions. As stated earlier in this article, smart cities will require different technological solutions to work, which are more likely to be adopted by larger cities. Hence, it is also likely to leverage the synergy of different smart city projects and help pandemic prevention and control in large cities.

### Table 4

Results of heterogeneity effects for city population size.

|                  | (1) Cities with the top 1/3 of the population | (2) Cities with the medium 1/3 of the population | (3) Cities with the last 1/3 of the population |
|------------------|---------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| $\text{smart}_i$ | $-0.601^*$                                   | $-0.154$                                      | $-0.198^{**}$                                 |
|                  | ($-1.91$)                                    | ($-1.28$)                                     | ($-2.58$)                                     |
| $\text{input}_i$| $0.748^{***}$                                | $0.252^{***}$                                 | $0.607^{***}$                                 |
|                  | ($2.79$)                                     | ($4.05$)                                      | ($3.67$)                                      |
| $\text{gdp}_i$  | $-0.110$                                     | $0.119$                                       | $-0.084$                                      |
|                  | ($-0.49$)                                    | ($1.56$)                                      | ($-0.41$)                                     |
| $m_{\text{person}}$ | $-0.241$                                   | $-0.015$                                      | $0.156$                                       |
|                  | ($-0.74$)                                    | ($-0.13$)                                     | ($0.50$)                                      |
| $m_{\text{bed}}_i$ | 0.088                                       | $-0.061$                                      | $-0.031$                                      |
|                  | ($0.96$)                                     | ($1.51$)                                      | ($0.29$)                                      |
| Constant         | 1.112                                        | $-1.242^*$                                    | $-0.529$                                      |
|                  | ($0.57$)                                     | ($-1.90$)                                     | ($-0.35$)                                     |
| Observations     | 81                                           | 82                                            | 82                                            |

Note: Robust T-statistics in parentheses for Column (1), (2), (3). $^{***} p < 0.01$, $^{**} p < 0.05$, $^* p < 0.1$. 

Fig. 6. Map of China cities’ population size.

Note: The figure is drawn by the author. The original map and data are from the China Data Laboratory of Harvard University.
6. Conclusions and policy implications

This paper quantitatively investigates the impact of smart city projects on COVID-19 prevention and control. Compared with the existing studies, this paper provides quantitative evidence for the impact of smart cities on COVID-19. We sort out the smart city projects into four categories that are closely related to COVID-19 prevention and control, including Smart Community, Smart Government, Smart Healthcare and Smart Information. Our empirical analysis results show that China’s smart city project has significantly helped the prevention and control of COVID-19 pandemic. For every 1 million yuan increase in smart city investment per 10,000 people, the number of COVID-19 confirmed cases per 10,000 people will decrease by 0.342. The heterogeneity analysis results show that the effect of the smart city projects is stronger in the period that COVID-19 virus spreads within the city than the input results show that the effect of the smart city project is significant for large cities. The central government should play a leading role.

Our research uses the quantitative analysis method to reveal the impact of smart city projects on the prevention and control of COVID-19 pandemic. Our limitations mainly lie on that we don’t introduce detailed smart city projects and analyze their role in the prevention and control of COVID-19 pandemic through case analysis, which may have more specific findings. Nevertheless, our analysis gives evidence about the significant effect of smart city projects and highlights its role in the prevention and control of COVID-19 pandemic that still spreads in many countries.

A key factor in predicting and controlling a pandemic like COVID-19 is “technology”. As discussed in this study, smart cities can integrate data from different sources to improve the city’s ability to respond to major outbreaks and effectively reduce the spread of outbreaks, especially for large cities. The central government should play a leading role in the rules of data sharing between cities and budgets affairs. For policymakers and academic researchers, they should rethink the role of smart city projects in future public health emergency events like COVID-19. Relevant research and discussion should be enriched regarding the role of smart city projects in public health emergency events. In terms of urban governance, smart city projects should work better with management factors and other infrastructure and better serve the pandemic prevention and control when a pandemic appears in the future. Besides, how to attract citizen’s buy-in to smart city projects and increase citizen’s understanding on smart city projects are also worthy of attention.

Author contributions

All authors contributed equally in the preparation of this manuscript.

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Availability of data and material

The data will be available when requested.

Code availability

The code will be available when requested.

Declaration of Competing Interest

The authors report no declarations of interest.

Appendix A. The cities included in our empirical analysis

| Beijing  | Jixi  | Xiamen  | Zhumadian | Qinzhou  | Guiyang  |
|---|---|---|---|---|---|
| Tianjin | Hegang | Putian | Huangshi | Qinzhou | Guiyang |
| Shijiazhuang | Shuangyashan | Sanming | Shiyang | Yulin | |
| Tangshan | Daqing | Quanzhou | Yichang | Haikou | |
| Qinhuangdao | Yichun | Zhangzhou | Enzhou | Sanya | |
| Handan | Jiamusi | Nanping | Jingmen | Chengdu | |
| Xingtai | Qitaib | Longyan | Xiaogan | Zigong | |
| Baoding | Mudanjiang | Ningde | Jingzhou | Panzhihua | |
| Zhangjiakou | Heihe | Nanchang | Huanggang | Luzhou | |
| Chengde | Suizhong | Jingdezhen | Xianming | Deyang | |
| Cangzhou | Nanjing | Pingxiang | Suizhou | Mianyang | |
| Langfang | Wuxi | Jiujian | Changsha | Guangzhou | |
| Hengshui | Xuzhou | Xinyu | Zhuzhou | Suning | |
| Taiyuan | Changzhou | Yingtian | Xiangtan | Neijiang | |
| Datong | Suzhou | Ganzhou | Hengyang | Leshan | |
| Yangquan | Nantong | Jian | Shaoxing | Nanchong | |
| Changzhi | Lianyungang | Yichun | Yueyang | Meishan | |
| Jinzheng | Yancheng | Fuyang | Changde | Yibin | |
| Shuozhou | Yangzhou | Shangrao | Zhangjiajie | Guanqian | |
| Jinzhong | Zhenjiang | Xinan | Yiyang | Dazhou | |
| Yuncheng | Taizhou | Qingdao | Chenzhou | Yan | |
| Xinzhou | Suzian | Zibo | Yibin | Guizhou | |
| Linfen | Hangzhou | Zaozhuang | Huaihua | Ziyang | |
| Hubeiaoke | Ningbo | Yantai | Ludi | Guiyang | |
| Baotou | Wenzhou | Weifang | Guangzhou | Liupanshui | |
| Wuhan | Jiaxing | Jining | Shaoquan | Zunyi | |
| Chifeng | Huizhou | Tai'an | Shenzhen | Anshan | |
| Tongliao | Shaoxing | Weihai | Zhuhai | Kunming | |
| Shenyang | Jinhua | Rizhao | Shantou | Yuxi | |
| Dalian | Quzhou | Linyi | Foshan | Lasa | |

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