Mathematical Biosciences and Engineering

MBE, 17(5): 4875–4890.
DOI: 10.3934/mbe.2020265
Received: 07 May 2020
Accepted: 09 July 2020
Published: 13 July 2020

http://www.aimspress.com/journal/MBE

Research article

Analyzing the effects of public interventions on reducing public gatherings in China during the COVID-19 epidemic via mobile terminals positioning data

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Abstract: At the beginning of 2020, the novel coronavirus disease (COVID-19) became an outbreak in China. On January 23, China raised its national public health response to the highest level. As part of the emergency response, a series of public social distancing interventions were implemented to reduce the transmission rate of COVID-19. In this article, we explored the feasibility of using mobile terminal positioning data to study the impact of some nonpharmaceutical public health interventions implemented by China. First, this article introduced a hybrid method for measuring the number of people in public places based on anonymized mobile terminal positioning data. Additionally, the difference-in-difference (DID) model was used to estimate the effect of the interventions on reducing public gatherings in different provinces and during different stages. The data-driven experimental results showed that the interventions that China implemented reduced the number of people in public places by approximately 60% between January 24 and February 28. Among the 31 provinces in the Chinese mainland, some provinces, such as Tianjin and Chongqing, were more affected by the interventions, while other provinces, such as Gansu, were less affected. In terms of the stages, the phase with the greatest intervention effect was from February 3 to 14, during which the number of daily confirmed cases in China showed a turning point. In conclusion, the interventions significantly reduced public gatherings, and the effects of interventions varied with provinces and time.

Keywords: COVID-19; effect evaluation; public gatherings; mobile terminals positioning data; difference-in-difference model

1. Introduction

In early 2020, the novel coronavirus disease (COVID-19) became an outbreak in China [1]. Due to its sudden infection rate and the lack of specific drugs, the World Health Organization (WHO) announced COVID-19 was a public health emergency of international concern on January 30, 2020.

Social distancing is a key nonpharmacologic control measure to reduce the transmission rate of infectious diseases; therefore, various preventive measures were implemented in response to the outbreak of this human-to-human transmission disease by the Chinese government. Some control measures were suggested to be effective. Several studies showed that the lockdown of Wuhan as well as the entire Hubei Province led to significant changes in the spread of COVID-19 cases [2,3], and travel and flight restrictions also mitigated the spread of COVID-19 in cities across China and even around the world [4,5]. However, in addition to population mobility between cities and countries, reducing population gathering inside cities also played an important role. Modeling results from Chinazzi et al. indicated that sustained 90% travel restrictions to and from the Chinese mainland only modestly affected the trajectory of the epidemic unless combined with a 50% or higher reduction of transmission in the community [6]. Pan et al. found that some nonpharmaceutical public health interventions, including cordon sanitaire, traffic restrictions, social distancing, and home quarantine, were temporally associated with improved control of the COVID-19 outbreak in Wuhan, China [7]. A study from Yang and colleagues showed that the prevention of family clustering transmission and preventive measures in public areas were crucial for the successful prevention of COVID-19 in Shenzhen, China [8]. Similar conclusions were also reached in an Italian study [9].

It is difficult to measure the flow and gathering of people in cities quickly and accurately by traditional methods, but mobility data, especially mobile terminals positioning data, can help solve this problem to a certain extent. Due to their large sample size and real-time features, mobility data are helpful for COVID-19 response research. These data can help refine interventions by providing nearly real-time information about changes in human movement [10]. Moreover, the mobility data may provide helpful insights to local governments and health authorities. A previous study used anonymized location data from mobile devices to understand the timing and potential impact of social distancing policies [11]. However, this study did not report the detailed data processing method and lacked a control group to prove the validity of the results.

In this work, we explored the feasibility of using mobile terminals positioning data to study the impact of some nonpharmaceutical public health interventions implemented by China. The following is a brief introduction of the interventions that the Chinese government took in public places before March during the COVID-19 epidemic.

On January 23, 2020, China raised its national public health response to the highest state to suppress the spread of COVID-19. As part of the response, a series of public policies were implemented to reduce public gatherings. Several important strategies are as follows.

- ***Strategy 1***: Starting from the Spring Festival, restaurants, movie theaters, shopping malls and some other facilities were gradually closed in many cities.
- ***Strategy 2***: The Spring Festival holiday was nationally extended by 3 days to February 2.
- ***Strategy 3***: On the basis of Strategy 2, more than 20 provinces postponed the resumption of work by 7 days to February 10 and encouraged companies to allow employees to work from home.
- ***Strategy 4***: After February 10, the conditions for offline resumption continued to be strictly limited.

- ***Strategy 5***: In the second half of February, when the epidemic was partly under control, the policy of "precision resumption and production by division and grading" started to be implemented.

The aim of this article is to evaluate the impact of interventions implemented by China, especially the above five strategies, on the number of people in public places by provinces and stages during the COVID-19 epidemic, with the hope of providing some insights about optimizing control strategies and contributing useful data to related research.

2. Materials and method

2.1. Experimental datasets introduction

To avoid leaking private information, we did not use any underlying data of mobile terminals throughout this study. Instead, we only used the number of mobile terminals with specific points of interest (POIs) as statistical results to measure the number of people in public places. The process of experimental dataset acquisition was divided into the following five steps:

The first step was POI sampling. With reference to the rankings from some famous websites in China such as Amap (www.amap.com) and Jobui (www.jobui.com), we first obtained a list of well-known enterprises, office buildings, and shopping malls in 31 provinces in the Chinese mainland, where enterprises and office buildings represent workplaces and shopping malls represent consumption places. Then, the judgment sampling method was adopted to sample 775 important workplaces and 279 famous consumption places from the above list.

The second step was determining the time periods. Firstly, 10 days Chinese Spring Festival in 2020 were selected, because this festival always makes huge impact on public gathering, which means the same festival in 2019 should be selected as the control group. Secondly, 15 business days before the festival and 20 business days after the festival were included, because we were only authorized to use the data during these periods. Then, the same strategy was used to select the corresponding 45 days in 2019.

The third step was fence mapping of the sample POIs. The sample POIs were transformed into geographic ranges. To take into account the trade-off among accuracy, efficiency and timeliness, we designed the following two strategies:

- *Manual strategy.* The main processes included (1) searching and confirming the geographic location of the POI using online maps; (2) manually delineating the fence range based on the POI coverage of the map; (3) converting the fence range into 8-bit GeoHash codes; and (4) mapping the 8-bit GeoHash codes to the monitoring grid. This method required manual operations and was time-consuming but the results were relatively accurate, because we can draw irregular graphics to cover the geographic range of POIs with different shapes.
- *Automatic strategy.* The main process was divided into (1) automatically mapping the detailed text address of the POI according to the POI name; (2) determining the POI center point coordinates based on the text address; (3) setting the radius of the POI radiation range; and (4) using the circle drawn by the coordinates of the POI center point and its radiation radius as the POI fence range, which was further converted into a monitoring grid.

The fourth step was mobile terminal data acquisition. Once the monitoring grids were drawn, the mobile terminal data in these grids could be collected rapidly. In general, the time from determining the fence to acquiring data took less than 12 hours, which meant the time lag was low. In addition, to minimize errors, we only calculated the number of mobile terminals that remained longer than 2 hours in the monitoring grid area.

The fifth step was data cleaning. First, samples with missing values were removed, leaving 736 workplace samples and 248 consumption place samples. Then, the number of mobile terminals of all the provinces was summed daily.

Following these steps, we obtained two datasets that recorded the numbers of mobile terminal devices in workplaces and consumption places separately. It should be noted that we could not directly browse the original data during the whole process, and all of the data were anonymized. In addition, the extracted results were aggregated and did not include any private information. The format of the experimental datasets is shown in Table 1. In this article, the number of mobile terminals devices in the sample was used as a proxy measure for the number of people in public places, denoted as *Num.Ppl*. In addition, the number of daily confirmed cases (newly reported) of COVID-19 from the National Health Commission of China was used in the discussion section.

Table 1. Data format of the number of mobile terminal devices.

ID	***Date***	***Anhui Province***	**……**	***Zhejiang Province***	***All***
1	2019-01-16	*Num.Ppl*	……	*Num.Ppl*	*Num.Ppl*
……	……	……	……	……	……
90	2020-02-28	*Num.Ppl*	……	*Num.Ppl*	*Num.Ppl*

2.2. Data preprocessing

As mentioned above, in order to control the spread of COVID-19, the Chinese government has adopted different strategies during different phases to prevent people from gathering in public places. We labeled the data according to the date duration of some important strategies (shown in Table 2), based on which some new variables were added to the datasets.

- *Year.* When *Date* belonged to 2019, *Year* = 0. This indicated that the data in 2019 were used as the control group, which was not affected by the intervention. When *Date* belonged to 2020, *Year* = 1. This indicated that the data in 2020 were used as the treatment group.
- *Intervention.* Because the nationwide interventions in public places started during the Chinese Spring Festival, 15 business days before the festival were marked as *Invention* = 0. This indicated that interventions had not been implemented, and the other part of *Date* was marked as *Invention* = 1.
- *Phase.* Because interventions were implemented in stages, we added the variable *Phase* to subdivide the time period. First, the Chinese Spring Festival and the extended Chinese Spring Festival were labeled *Phase* = 1 and *Phase* = 2, respectively, which indicated the first 2 stages after the intervention. Then, we evenly divided the 20 business days after the extended Chinese Spring Festival into 4 groups, which were correspondingly labeled *Phase* = 3 to *Phase* = 6. In addition, the 15 business days before the Chinese Spring Festival were evenly divided into 3 groups, which were correspondingly labeled *Phase* = −2 to *Phase* = 0, and these 3 groups were used to test the model hypothesis. Finally, we converted *Phase* to the dummy variables $Phase_j$, where j corresponded to the value of *Phase*. For example, $Phase_{-2}$ = 1 if *Phase* = −2; otherwise, $Phase_{-2}$= 0.

Table 2. Coding table for new variables.

Intervention	*Phase*	*Year*		**Remarks**
		Year = 0 (2019)	*Year* = 1 (2020)	
0	−2	Jan. 16–18, Jan. 21–22	Jan. 6–10	Before intervention
	−1	Jan. 23–25, Jan. 28–29	Jan. 13–17	
	0	Jan. 30–31, Feb. 1–3	Jan. 19–23	
1	1	Feb. 4–10	Jan. 24–30	Strategy 1
	2	Feb. 11–13	Jan. 31, Feb. 1–2	Strategy 1&2
	3	Feb. 14–15 18–20	Feb. 3–7	Strategy 1&3
	4	Feb. 21–22, Feb. 25–27	Feb. 10–14	Strategy 1&4
	5	Feb. 28, Mar. 1, Mar. 4–6	Feb. 17–21	Strategy 1&5
	6	Mar. 7–8, Mar. 11–13	Feb. 24–28	

Then, the data were scaled by Eq (1). *Num.Ppl.Scal.* denotes the scaled number of people in public places, and it is easy to determine that Eq (2) holds. The scaled data are shown in Figure 1.

$$Num.Ppl.Scal. = \frac{Num.Ppl.}{E(Num.Ppl. \mid Intervention = 0, Year = 1)} \tag{1}$$

$$E(Num.Ppl.Scal. \mid Intervention = 0, Year = 1) = 1 \tag{2}$$

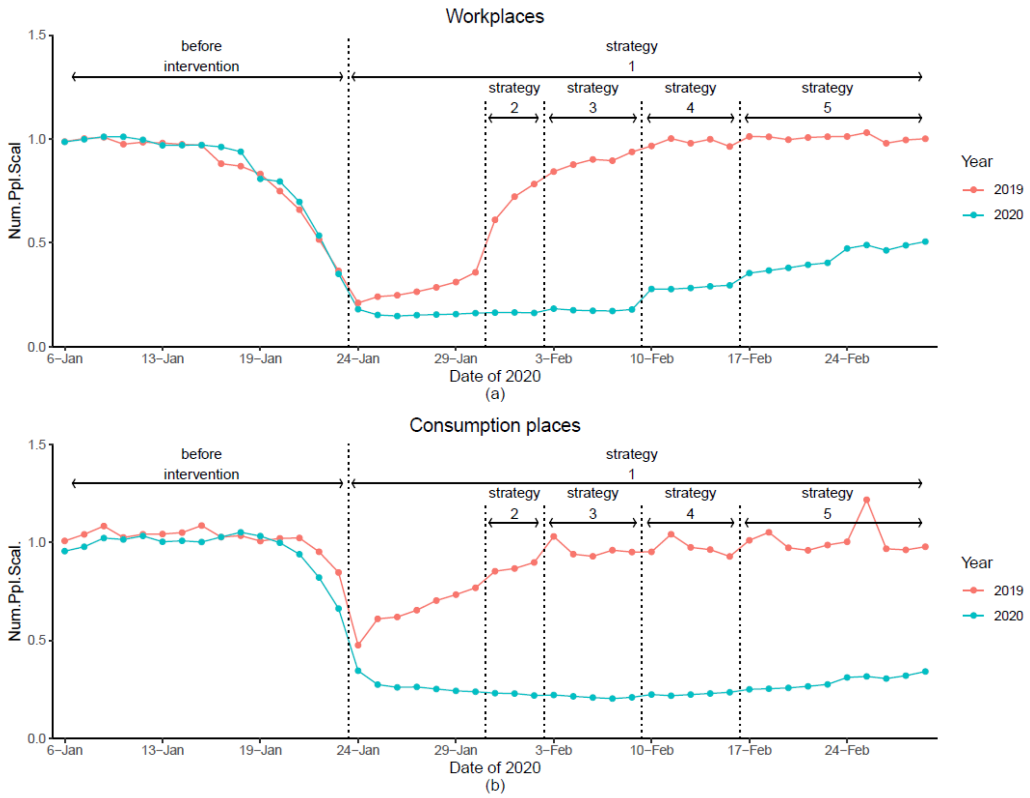

Figure 1. Num.Ppl.Scal. in workplaces and consumption places.

2.3. Model

The purpose of this work is to evaluate the impact of the interventions taken by the Chinese government on the number of people in public places, and the data used here are quasi-experimental, so the difference-in-difference (DID) model is adequate. The DID model is widely used in policy evaluation because it can control the systematic differences between treatment and control groups and can also isolate the different changes in the outcomes over time between samples that are and are not affected by the policy [12]. In essence, this is a regression model in which dummy variables and interactive terms are used, which is easily understood from the regression equation below, so it will not be discussed in detail here.

Equation (3) is used to evaluate the overall effect of all the interventions from January 24 to February 28, 2020. According to the DID model, the interaction term coefficient β_3 denotes the amount of change due to the influence of the intervention. Because of Eq (1), β_3 here denotes the proportion of the changed number of people in public places affected by the intervention.

$$Num.Ppl.Scal. = \beta_0 + \beta_1 \times Intervention + \beta_2 \times Year + \beta_3 \times Intervention \times Year + \varepsilon \quad (3)$$

The DID model is based on the parallel trend hypothesis, which means that if there is no intervention, then no systematic differences can be found between the treatment and control groups over time. We use Eq (4) to test the parallel trend hypothesis. If the interaction term coefficient of each phase does not become significant until interventions were implemented, then the data conform to the parallel trend hypothesis.

$$Num.Ppl.Scal. = \beta_0 + \sum_{i=1}^{8} (\beta_i \times Phase_{i-2}) + \beta_9 \times Year + \sum_{j=10}^{17} (\beta_j \times Phase_{j-11} \times Year) + \varepsilon \quad (4)$$

Based on Eq (4), Eq (5) removes $Phase_{-1}$ and $Phase_0$ so that *Invention* = 0 becomes the reference group of the dummy variables $Phase_1$ to $Phase_6$. Therefore, similar to Eq (3), the interaction term coefficients β_8 to β_{13} denote the proportion of the changed number of people in public places affected by the intervention in different phases.

$$Num.Ppl.Scal. = \beta_0 + \sum_{i=1}^{6} (\beta_i \times Phase_i) + \beta_7 \times Year + \sum_{j=8}^{13} (\beta_j \times Phase_{j-7} \times Year) + \varepsilon \quad (5)$$

The parameters in the above 3 equations are estimated using the least square method, in which a robust standard error is used [13,14].

3. Results

3.1. Overall intervention effect

First, we used Eq (3) to separately evaluate the impact of the intervention adopted by the Chinese government on the number of people in workplaces and consumption places.

Table 3 shows that the series of control strategies effectively reduced the number of people in public places during the observation period. The coefficients of the interactive terms in the two models are −0.606 and −0.614 (both at 99% confidence level), respectively, which means that due to the intervention, the numbers of people in these two types of public places dropped by approximately

60%. Both models are significant at the 99% confidence level, and their adjusted R^2 values are 0.578 and 0.907, respectively.

Table 3. Experimental results of the overall intervention effect.

	Workplaces	Consumption places
Intervention	−0.079	−0.124 ***
	(0.086)	(0.034)
Year	0.019	−0.051*
	(0.082)	(0.031)
Intervention* Year	−0.606 ***	−0.614 ***
	(0.108)	(0.044)
(Intercept)	0.981 ***	1.051 ***
	(0.058)	(0.015)
N	90	90
F	74.05	947.5
Adj.R^2	0.578	0.907

Note: Values in parentheses denote standard errors. ***, **, and * denote that the coefficient is statistically significant at the 99%, 95%, and 90% confidence levels, respectively.

The data used above passed the parallel trend test. At the 95% confidence level, the coefficients of the interactive terms are not significant before the intervention but immediately become significant after the control strategies were used. This result indicates that there are no systematic differences between the treatment and control groups before the intervention. In addition, it can be found from Figure 2 that the effects of the interventions change with time, so the effects of different strategies need to be evaluated separately.

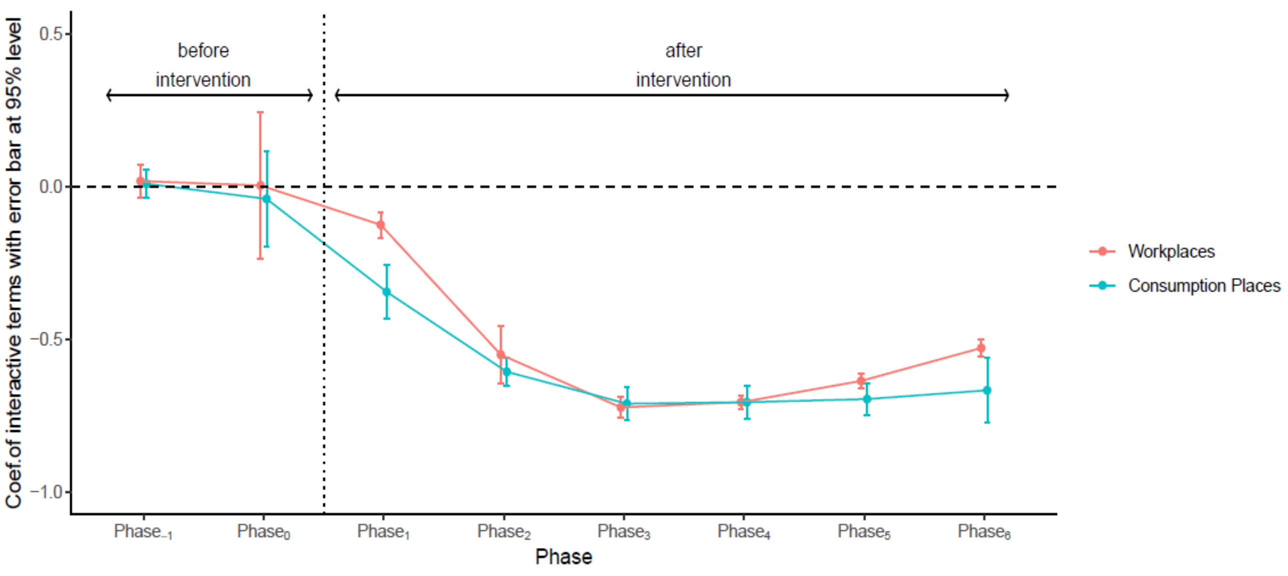

Figure 2. Result of the parallel trend test.

3.2. *Effect of the intervention by province*

Then, we used Eq (3) and the data by province to evaluate the impact of the intervention on the 31 provinces of the Chinese mainland. The aggregated results are as follows, and the detailed results are shown in the Supplementary section.

Table 4 shows that the impact of the intervention on workplaces in different provinces is quite different. First, all the coefficients of the interactive terms in Table 4 are greater than −0.8, while the coefficients in four provinces, including Zhejiang and Tianjin, are less than −0.7. Second, there are 9 provinces with a coefficient between −0.7 and −0.6, in which Hubei (the province most affected by COVID-19 in China) and Tibet (the province least affected by COVID-19 in China) are included. In addition, the coefficients of more than half of the provinces are distributed between −0.6 and −0.4. Gansu is least affected by the intervention, with a coefficient larger than −0.4.

Table 4. Aggregated results of the intervention effect on workplaces by province.

Coef. interval	Number	Provinces
[−0.8, 0.7)	4	Zhejiang, Tianjin, Shanghai, Chongqing
[−0.7, −0.6)	9	Guangdong, Tibet, Hubei, Henan, Xinjiang, Sichuan, Beijing, Hunan, Jiangsu
[−0.6, −0.5)	10	Fujian, Anhui, Hebei, Guangxi, Jiangxi, Guizhou, Shandong, Shaanxi, Heilongjiang, Liaoning
[−0.5, −0.4)	7	Shanxi, Qinghai, Yunnan, Jilin, Inner Mongolia, Hainan, Ningxia
[−0.4, −0.3)	1	Gansu

Note: Coef. interval denotes the interval to which the coefficient of the interactive term in the model belongs.

As shown in Table 5, the intervention effect on consumption places also varies with provinces, while the distribution is slightly different from that in Table 4. First, the consumption places in 6 provinces, including Hebei and Jiangxi, are the most affected by the intervention, and their coefficients of interactive terms are between −0.8 and −0.7. Second, the coefficients of approximately half of the provinces (including Hubei) are between −0.7 and −0.5. In addition, the coefficients of 10 provinces are more than −0.5, among which Tibet, Liaoning and Shanxi are the least affected by the intervention.

Table 5. Aggregated results of the intervention effect on consumption places by province.

Coef. interval	Number	Province
[−0.8, 0.7)	6	Hebei, Jiangxi, Tianjin, Henan, Chongqing, Jiangsu
[−0.7, −0.6)	7	Xinjiang, Zhejiang, Hunan, Fujian, Guangdong, Shaanxi, Shandong
[−0.6, −0.5)	8	Hubei, Ningxia, Hainan, Anhui, Heilongjiang, Beijing, Shanghai, Jilin
[−0.5, −0.4)	7	Inner Mongolia, Qinghai, Sichuan, Guangxi, Yunnan, Guizhou, Gansu
[−0.4, −0.3)	3	Tibet, Liaoning, Shanxi

Note: Coef. interval denotes the interval to which the coefficient of the interactive term in the model belongs.

3.3. Effect of the intervention by phase

Equation (5) was used to evaluate the effects of the interventions in different stages, and the results are shown in Table 6 and Table 7. The intervention effect varies with phase.

For workplaces, Table 6 shows that the effect in the first phase (the Chinese Spring Festival) after the intervention is significant at the 90% confidence level and that each stage thereafter is significant at the 99% confidence level, indicating that the intervention effect persists during the observation period. Compared with the two-stage model (see Table 3), the adjusted R^2 of the multistage model jumped from 0.578 to 0.87, which means that more variability is explained. The coefficients of the interactive terms drop rapidly in the first three stages after the intervention, from −0.153 to −0.844, and then start to rise, returning to −0.619 at the end of February.

Table 6. Results of the intervention effects on workplaces by phase.

	Coef.	Std. Error	t value	Pr (>|t|)
$Phase_1$	−0.666	0.065	−10.178	0.000
$Phase_2$	−0.167	0.081	−2.075	0.041
$Phase_3$	0.047	0.064	0.733	0.466
$Phase_4$	0.152	0.062	2.444	0.017
$Phase_5$	0.182	0.062	2.939	0.004
$Phase_6$	0.177	0.062	2.839	0.006
Year	0.019	0.088	0.216	0.829
$Phase_1$* Year	−0.153	0.090	−1.695	0.094
$Phase_2$* Year	−0.645	0.102	−6.334	0.000
$Phase_3$* Year	−0.844	0.089	−9.450	0.000
$Phase_4$* Year	−0.825	0.088	−9.356	0.000
$Phase_5$* Year	−0.744	0.088	−8.434	0.000
$Phase_6$* Year	−0.619	0.088	−6.999	0.000
(Intercept)	0.981	0.062	15.895	0.000

Adj.R^2=0.87, F-statistic: 8854 on 13 and 76 DF, p-value: <2.2e-16

For consumption places, the intervention effects also persist during the observation period, with significance at the 99% confidence level (shown in Table 7). Compared with the two-stage model (see Table 3), the adjusted R^2 of the multistage model rises from 0.907 to 0.965. Similar to the results regarding workplaces, in the first three stages after the intervention, the coefficients of the interactive terms decline gradually, from −0.345 to −0.724. However, the difference is that the intervention effect on consumption places did not rebound significantly after the fourth stage and remained at −0.678 at the end of February.

Table 7. Results of the intervention effects on consumption places by phase.

	Estimate	Std. Error	t value	Pr (>|t|)
Phase$_1$	−0.379	0.041	−9.138	0.000
Phase$_2$	−0.151	0.020	−7.524	0.000
Phase$_3$	−0.059	0.024	−2.442	0.017
Phase$_4$	−0.049	0.025	−1.954	0.054
Phase$_5$	−0.024	0.023	−1.037	0.303
Phase$_6$	0.007	0.051	0.131	0.897
Year	−0.051	0.033	−1.553	0.125
Phase$_1$* Year	−0.345	0.052	−6.609	0.000
Phase$_2$* Year	−0.616	0.035	−17.579	0.000
Phase$_3$* Year	−0.724	0.037	−19.339	0.000
Phase$_4$* Year	−0.719	0.038	−18.928	0.000
Phase$_5$* Year	−0.708	0.037	−19.251	0.000
Phase$_6$* Year	−0.678	0.059	−11.496	0.000
(Intercept)	1.051	0.016	65.501	0.000

Adj.R^2 = 0.965 F-statistic: 921.4 on 13 and 76 DF, p-value: <2.2e-16

4. Discussion

In this section, we discuss the abovementioned experimental results with the number of newly confirmed cases in China (see Figure 3). It should be noted that the intervention effect is the comprehensive result of many strategies, in which the five strategies discussed below are just a more important part.

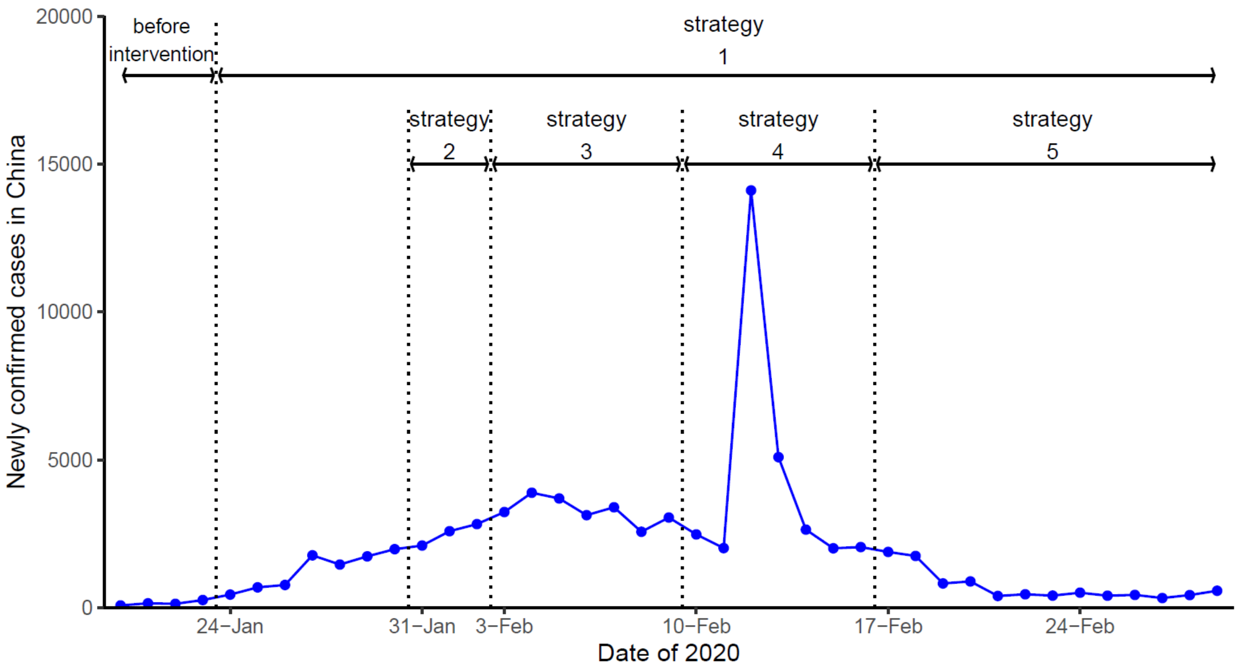

Figure 3. Number of newly confirmed cases in China.

4.1. Strategy 1

The Spring Festival is the most important traditional festival in China. On the one hand, people usually buy a large amount of food and daily necessities before this festival, most people do not go to their workplaces during the festival, and many restaurants and shops are closed, which is conducive to social distancing. On the other hand, some consumption places, such as famous restaurants and shopping malls, attract a large number of customers during this period, which is not conducive to epidemic prevention and control. Figure 1 shows that during the Chinese Spring Festival of 2019, the decrease in the number of people in consumption places was much lower than that in workplaces. Therefore, it is more important to control the flow of people in consumption places in this phase.

During the Chinese Spring Festival of 2020, restaurants, movie theaters, shopping malls and other consumption places in many cities in China were closed because of public interventions, reducing the number of people in these places by approximately two-thirds, which was conducive to social distancing. After this festival, if there was no intervention, the number of people in consumption places would quickly return to the preholiday level (as shown in Figure 1(b)). To continue to suppress public gatherings, restrictions on consumption places were not lifted immediately after this festival; therefore, the intervention effect quickly dropped to approximately −0.7 and remained stable at this level to the end of February (as shown in Table 7). Because most people do not work during the Chinese Spring Festival, the number of people in workplaces, compared with that in consumption places, was less affected during this phase.

4.2. Strategy 2

Under normal circumstances, the Chinese Spring Festival holiday of 2020 would have ended on January 30, which was the seventh day after the lockdown of Wuhan. As shown in Figure 1, if there was no intervention, the number of people in public places would quickly return to approximately 80% of the preholiday level in the first 3 days after the Spring Festival. Because COVID-19 was still spreading rapidly and the number of newly confirmed cases remained at a high level before this phase, public interventions were still necessary.

In the early morning of January 27, China announced a nationwide extension of the Spring Festival by 3 days to February 2. During these three days, the intervention effect on the numbers of people in workplaces and consumption places were −0.645 and −0.616, respectively, which indicates that the interventions effectively prevented people from gathering in public places.

4.3. Strategy 3

As shown in Figure 3, at the end of January, the number of newly confirmed cases in China was still rising. Considering that the incubation period of COVID-19 may be more than 10 days [15], China was still in the critical stage of epidemic prevention and control in early February. A key issue at that time was how to strike a balance between restoring production and epidemic control. Against this background, China did not continue to extend the holiday nationwide but took different measures in different provinces in accordance with the characteristics of different provinces. More than 20 provinces, such as Shanghai and Zhejiang, postponed the resumption of business until February 10. Although some other provinces, including Beijing, allowed enterprises to resume production, they strictly restricted the working conditions. For example, enterprises had to provide employees with adequate protective equipment and limit the minimum distance between employees. At the same time, enterprises were encouraged to allow employees to work from home.

Due to the severe restrictions on the conditions for resumption of work, between February 3 and 7, the number of people in workplaces only increased slightly (see Figure 1(a)). At the same time, the effect of interventions did not decrease but rather increased. As shown in Table 6, the intervention effect on the number of people in workplaces in $Phase_3$ was −0.844, which was the lowest value among all the phases. From a retrospective perspective, if the extreme value of February 12 is not taken into account, as Figure 3 shows, China's newly confirmed cases would also have had an inflection point at this stage.

4.4. Strategy 4

Although newly confirmed cases in China began to decline on February 4, the government still imposed very strict restrictions on the conditions for resumption of business in the days after February 10. For example, some cities required that people from other cities had to be isolated for 14 days before returning to work, everyone was required wear a mask in public places, and offices needed to be sufficiently spacious, ventilated, and clean.

In Phase_4, because many people were still in isolation and many companies' workplaces and protective equipment could not meet the policy requirements, only some employees of some companies had returned to their workplaces, and a large number of employees were working from home. As shown in Table 6, even if all the provinces had ended their holidays, the intervention effect on the number of people in workplaces remained above 0.8 in Phase_4, which shows that the restriction on the conditions for the resumption of public gatherings may play an effective role.

4.5. Strategy 5

With the continuation of the downward trend in newly confirmed cases, China began to gradually promote "precision resumption and production by division and grading". "By division and grading" meant that places outside Hubei and Beijing were divided into three categories of low-risk areas, medium-risk areas and high-risk areas based on the severity of the epidemic. For low-risk areas, local governments were not allowed to set conditions for enterprises to resume production and open businesses, the order of production strove for full restoration, and the local governments were required to help enterprises resume production. For medium-risk areas, the local governments guided enterprises to strictly implement requirements, such as disinfection, ventilation and temperature measurement, and helped them resume production as soon as possible. Affected by these policies, the impact of interventions on the number of people in workplaces began to weaken rapidly in Phase_5, from −0.825 to −0.619, within two weeks.

4.6. Provincial differences

Although all the sample provinces adopted a series of measures to limit public gatherings, the results of Section 3.2 show that the intervention effects in different provinces were quite different. First, provinces such as Zhejiang, Chongqing, and Henan, which are closer to Hubei and had a higher risk of virus transmission than other provinces, demonstrated better policy intervention effects. Second, some provinces, such as Xinjiang and Tibet, which had a relatively small number of confirmed cases, also took strict measures to limit public gatherings. In addition, Hubei Province was not the most affected by the intervention. This may be because many companies in Hubei worked overtime to provide epidemic prevention and control services, and at the same time, there were a large number of people stranded in or assisting Hubei, which meant more consumption places were needed to provide services for them.

5. Conclusion

At different stages of the spread of COVID-19, China has taken corresponding measures to reduce public gatherings. In this work, based on mobile terminal data, we used the DID model to measure the impact of various strategies used by China. From a retrospective viewpoint, these strategies reduced the number of people in public places by approximately 60% between January 24 and February 28. At the same time, these measures fitted well with the needs of COVID-19 prevention and control during the different stages and in different provinces.

Although this article is a retrospective study, the data and methods used here can play a role in the process of epidemic prevention and control. The mobile terminal data acquisition method used in this paper can be used to quickly and accurately ascertain the number of people in public places, which is useful to formulate prevention and control strategies. Moreover, the method we used can dynamically assess the effectiveness of public interventions and help to optimize those prevention and control strategies.

There are some limitations in this work. First, the intervention effect may be overestimated because personal willingness is not considered in the model, although personal willingness is also affected by public policy. Second, because the samples used are well-known enterprises and shopping malls, the results may not reflect the intervention effect in rural areas. In addition, although mobile terminal data can approximately measure the number of people, there may be some errors.

In this work, we did not use these data to further quantify the relationship between interventions and COVID-19 transmission. However, the research here can provide more data for professionals, and a retrospective analysis of China's interventions can also provide some reference for the treatment of similar situations. Next, we will further study how to use big data to better optimize epidemic prevention and control strategies.

Acknowledgments

This work was supported by the National Social Science Foundation of China (Youth Program) under Grant No. 18CSH018 and the Key Laboratory of Evidence Based Medicine and Knowledge Translation of Gansu Province under Grant No. GSEBMKT-2020YJ04. We would like to thank the reviewers for their detailed reviews and insightful comments, which have helped to improve the quality of this article.

Conflict of interest

The authors declare that they have no competing interests.

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Supplementary

Table 8. The detailed results of intervention effect on workplaces by province.

	Coefficient of the interactive term				Model	
Province	**Estimate**	**Std.Error**	**tvalue**	**Pr(>|t|)**	**Pr(>|t|)**	**Adj.R2**
Zhejiang	−0.761	0.123	−6.184	0.000	0.000	0.579
Tianjin	−0.736	0.127	−5.797	0.000	0.000	0.600
Shanghai	−0.718	0.106	−6.772	0.000	0.000	0.635
Chongqing	−0.717	0.110	−6.542	0.000	0.000	0.677
Guangdong	−0.670	0.147	−4.551	0.000	0.000	0.454
Tibet	−0.667	0.160	−4.156	0.000	0.000	0.468
Hubei	−0.660	0.088	−7.535	0.000	0.000	0.747
Henan	−0.651	0.107	−6.074	0.000	0.000	0.631
Xinjiang	−0.651	0.065	−10.019	0.000	0.000	0.795
Sichuan	−0.647	0.093	−6.958	0.000	0.000	0.673
Beijing	−0.646	0.108	−6.011	0.000	0.000	0.468
Hunan	−0.644	0.132	−4.879	0.000	0.000	0.506
Jiangsu	−0.600	0.111	−5.414	0.000	0.000	0.532
Fujian	−0.595	0.109	−5.471	0.000	0.000	0.565
Anhui	−0.586	0.103	−5.707	0.000	0.000	0.523
Hebei	−0.572	0.109	−5.223	0.000	0.000	0.559
Guangxi	−0.570	0.101	−5.629	0.000	0.000	0.662
Jiangxi	−0.567	0.105	−5.385	0.000	0.000	0.616
Guizhou	−0.542	0.100	−5.395	0.000	0.000	0.635
Shandong	−0.519	0.096	−5.435	0.000	0.000	0.591
Shaanxi	−0.515	0.121	−4.274	0.000	0.000	0.484
Heilongjiang	−0.509	0.071	−7.153	0.000	0.000	0.677
Liaoning	−0.506	0.090	−5.643	0.000	0.000	0.623
Shanxi	−0.497	0.085	−5.880	0.000	0.000	0.711
Qinghai	−0.489	0.091	−5.349	0.000	0.000	0.651
Yunnan	−0.471	0.100	−4.688	0.000	0.000	0.590
Jilin	−0.471	0.112	−4.192	0.000	0.000	0.461
Inner Mongolia	−0.468	0.093	−5.055	0.000	0.000	0.553
Hainan	−0.446	0.091	−4.887	0.000	0.000	0.547
Ningxia	−0.408	0.069	−5.935	0.000	0.000	0.583
Gansu	−0.387	0.098	−3.942	0.000	0.000	0.589

Table 9. The detailed results of intervention effect on consumption places by province.

	Coefficient of interactive term				Model	
Province	**Estimate**	**Std.Error**	**tvalue**	**Pr(>|t|)**	**Pr(>|t|)**	**Adj.R2**
Hebei	−0.769	0.076	−10.167	0.000	0.000	0.747
Jiangxi	−0.763	0.040	−18.881	0.000	0.000	0.911
Tianjin	−0.761	0.051	−14.976	0.000	0.000	0.920
Henan	−0.758	0.039	−19.196	0.000	0.000	0.948
Chongqing	−0.752	0.074	−10.142	0.000	0.000	0.856
Jiangsu	−0.709	0.056	−12.651	0.000	0.000	0.881
Xinjiang	−0.689	0.043	−15.866	0.000	0.000	0.882
Zhejiang	−0.688	0.050	−13.819	0.000	0.000	0.915
Hunan	−0.681	0.083	−8.158	0.000	0.000	0.746
Fujian	−0.655	0.100	−6.572	0.000	0.000	0.747
Guangdong	−0.647	0.064	−10.166	0.000	0.000	0.822
Shaanxi	−0.630	0.057	−11.041	0.000	0.000	0.861
Shandong	−0.602	0.056	−10.668	0.000	0.000	0.801
Hubei	−0.588	0.043	−13.798	0.000	0.000	0.932
Ningxia	−0.572	0.055	−10.370	0.000	0.000	0.880
Hainan	−0.571	0.074	−7.761	0.000	0.000	0.765
Anhui	−0.564	0.062	−9.155	0.000	0.000	0.760
Heilongjiang	−0.549	0.036	−15.344	0.000	0.000	0.935
Beijing	−0.548	0.034	−16.000	0.000	0.000	0.924
Shanghai	−0.528	0.070	−7.597	0.000	0.000	0.794
Jilin	−0.515	0.043	−11.972	0.000	0.000	0.896
Inner Mongolia	−0.498	0.045	−10.973	0.000	0.000	0.869
Qinghai	−0.487	0.111	−4.406	0.000	0.000	0.734
Sichuan	−0.484	0.031	−15.698	0.000	0.000	0.951
Guangxi	−0.478	0.075	−6.332	0.000	0.000	0.717
Yunnan	−0.446	0.036	−12.258	0.000	0.000	0.883
Guizhou	−0.433	0.058	−7.481	0.000	0.000	0.803
Gansu	−0.431	0.025	−16.964	0.000	0.000	0.942
Tibet	−0.356	0.037	−9.719	0.000	0.000	0.893
Liaoning	−0.341	0.038	−8.863	0.000	0.000	0.762
Shanxi	−0.317	0.061	−5.194	0.000	0.000	0.835