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The Effects of Stringent and Mild Interventions for Coronavirus Pandemic

Ting Tian*[a], Jianbin Tan*[a], Wenxiang Luo*[a], Yukang Jiang*[a], Minqiong Chen[a], Songpan Yang[a], Canhong Wen[b], Wenliang Pan[a], and Xueqin Wang[b]

[a]School of Mathematics, Sun Yat-sen University, Guangzhou, China; [b]Department of Statistics and Finance/International Institute of Finance, School of Management, University of Science and Technology of China, Hefei, China

ABSTRACT
The pandemic of COVID-19 has caused severe public health consequences around the world. Many interventions of COVID-19 have been implemented. It is of great public health and social importance to evaluate the effects of interventions in the pandemic of COVID-19. With the help of a synthetic control method, the regression discontinuity, and a state-space compartmental model, we evaluated the treatment and stagewise effects of the intervention policies. We found statistically significant treatment effects of broad stringent interventions in Wenzhou and mild interventions in Shanghai to subdue the epidemic's spread. If those reduction effects were not activated, the expected number of positive individuals would increase by 2.18 times on February 5, 2020, for Wenzhou and 7.69 times on February 4, 2020, for Shanghai, respectively. Alternatively, regression discontinuity elegantly identified the stringent (p-value: <0.001) and mild interventions (p-value: 0.024) lowered the severity of the epidemic. Under the compartmental modeling for different interventions, we understood the importance of implementing the interventions. The highest level alert to COVID-19 was practical and crucial at the early stage of the epidemic. Furthermore, the physical/social distancing policy was necessary once the spread of COVID-19 continued. If appropriate control measures were implemented, then epidemic would be under control effectively and early. Supplementary materials for this article, including a standardized description of the materials available for reproducing the work, are available as an online supplement.

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Compartmental model; Counterfactual; COVID-19; Synthetic control method; Treatment effect

1. Introduction

The novel coronavirus disease (COVID-19) as an acute infection has rapidly spread over 200 countries in the world since December 2019. There were 750,178 reported positive individuals and 36,398 total deaths around the world, 82,545 and 140,640 positive individuals, and 3314 and 2398 total deaths from China and from the United States until March 31, 2020, respectively (National Health Commission of the People's Republic of China 2020). These numbers are rapidly arising daily. Generally, the coronavirus family includes the virus that caused Severe Acute Respiratory Syndrome (SARS) in 2003. Early positive individuals of COVID-19 suggested that it might not be as severe as SARS-CoV, but the rapid increase in positive individuals and the evidence of human-to-human transmission indicated that this coronavirus was more contagious (Wang, Horby et al. 2020; Guan et al. 2020).

Compared with the SARS outbreak, the Chinese government rapidly mounted responses to contain COVID-19 by reducing personal exposure and transmission (Tu et al. 2020). Wenzhou was the city with the largest number of positive individuals in Zhejiang province, which activated the first-level public health emergency response on January 23, 2020 (Zhejiang Online News Website 2020). Strict control measures were implemented across Wenzhou, where one family member was assigned to go out for each household's necessary purchase every two days since February 1, 2020 (Guangming Daily 2020). It also had suspended all city shuttle and chartered buses (Wenzhou Municipal People's Government 2020a). Thus, Wenzhou had adopted the broad stringent intervention policies to intensively prevent and control the epidemic situation of COVID-19, including both traffic blockade inside and outside the city, and the community strictly closed management (i.e., implementing physical/social distancing) (Wenzhou Municipal People's Government 2020b). Besides, as an industrial city of a first ranking city in the contribution of real gross domestic product (GDP) during the first season of 2020 in China, Shanghai also activated the first-level public health emergency response on January 24, 2020 (Shanghai Municipal Health Commission 2020). It adopted closely following the close contact of the positive individuals and isolating them at the same time (Shanghai Municipal Health Commission 2020). Comparatively, Shanghai implemented relatively mild and targeted community management interventions (Shanghai Observer 2020). Figure 1 shows the timeline of policies and the number of newly positive individuals in the two cities.

However, during the first season of 2020, all areas of China implemented interventions to subdue the transmission of COVID-19, and the nationwide residents were recommended to stay at home except for essential needs. There was substantial economic loss compared with the same duration of 2019.

CONTACT Xueqin Wang wangxq20@ustc.edu.cn Department of Statistics and Finance/International Institute of Finance, School of Management, University of Science and Technology of China, Hefei 230052, China.
*Ting Tian, Jianbin Tan, Wenxiang Luo, and Yukang Jiang contributed equally to this article.
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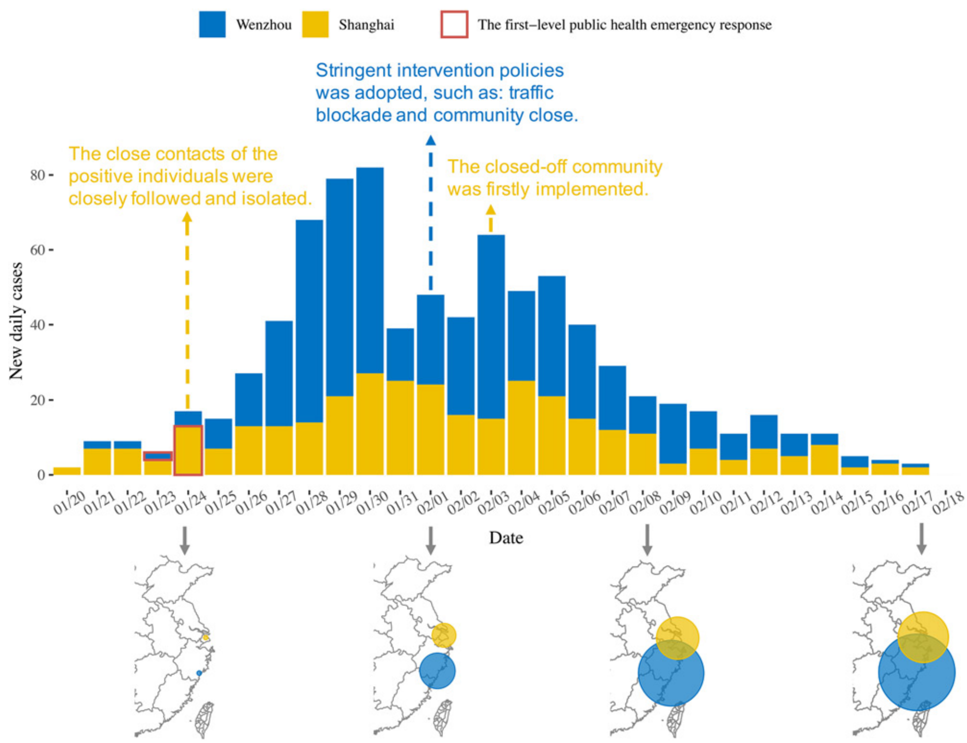

Figure 1. The timeline of the implementation of intervention policies. The histogram above represents the newly positive individuals every day from January 20, to February 18, 2020. The maps below the histogram present the positive individuals on the corresponding date (The more the positive individuals are, the larger the circles become on the maps).

Table A.1 in the supplementary materials, Section A summarized the GDP values and total retail sales of consumer goods (TRSCG) for Wenzhou (Wenzhou Bureau of Statistics 2020) and Shanghai (Shanghai Bureau of Statistics 2020) and corresponding increase year-on-year. Comparatively, Wenzhou implemented the broad stringent interventions to the prevention and control of COVID-19 at the more expense of the economic loss, where its seasonal GDP decreased by 8.2% to the same period of the year (Table A1). By March 31, 2020, the numbers of the positive individuals were 504 in Wenzhou and 339 in Shanghai, respectively (National Health Commission of the People's Republic of China 2020). As the economic important and the severe infected cities of Wenzhou and Shanghai, it is valuable to assess their interventions' effects on mitigating COVID-19.

Researchers (Lai et al. 2020; Ruan et al. 2020) stated that without the interventions in an infected area of China, the likely outcomes of the positive individuals would expect greatly increase to several fold using epidemiological compartmental models. For evaluating the intervention effects, whether these policies possess statistical significance to subdue the spread is also as important as the simulated hypothetical outcomes. In this article, we modified a technique of causal effects (Abadie, Diamond, and Hainmueller 2010) to assess the influence of these interventions, which was frequently used in social sciences (Abadie, Diamond, and Hainmueller 2015; Castillo et al. 2017) but rarely studied on the evaluation of the epidemic. The synthetic control method (SCM) was modified (Abadie, Diamond, and Hainmueller 2010; Abadie 2020) to construct a "synthetic" control trajectory by combining a number of time series of the untreated regions. We used the United States counties without official interventions as the control areas for Wenzhou and Shanghai. The placebo test was proposed (Abadie, Diamond, and Hainmueller 2010) for statistically evaluating the treatment effects by the comparison of the "synthetic" and original trajectories of the target cities. Besides, we also provided the vertical inference for the intervention effects before and after the implementation of the interventions in Wenzhou (and Shanghai) through regression discontinuous (RD) (Hahn, Todd, and Van der Klaauw 2001; Imbens and Lemieux 2008). This kind of vertical self-comparison would be an auxiliary for the horizontal comparison of the treatment effects between "treated regions" and their corresponding control regions.

In addition, we assessed the stagewise effects of the interventions by the effective reproduction numbers of a suitable compartmental model for COVID-19. To reflect the presymptomatic and asymptomatic transmission of COVID-19 (Gao and Li 2020; Furukawa, Brooks, and Sobel 2020), we divided the total population into four compartments: susceptible class (S), infectious class (I), self-healing class (H) and COVID-19-positive class (P) (Wang, Zhou et al. 2020; Tian, Tan, et al. 2021; Tan et al. 2020). We proposed a state-space SIHP model and modified the effective reproduction numbers to visualize the delay and stagewise effects of interventions. Additional simulations were also presented to illustrate the effects of the interventions of Wenzhou and Shanghai for the outbreak of COVID-19 outside China. Consequently, we could provide an example to build awareness of various interventions that control COVID-19 and support policymakers working to understand the effects of interventions.

In summary, this article concentrates on the broad strict intervention policies and relatively mild interventions of

COVID-19 in Wenzhou and Shanghai by the modified SCM and RD, respectively, providing insights into the effects of different interventions. We also selected two specific timings of the implementation of interventions and assessed what happened in both Wenzhou and Shanghai if these interventions were delayed by 3 and 5 days, and if the latter individual intervention or all interventions were not implemented instead. We accomplished these through the simulations using the state-space SIHP model. The next section describes the classical causal effects methods and the transmission models of COVID-19 in detail. The corresponding analysis for Wenzhou and Shanghai are illustrated in Section 3. In the end, Section 4 would discuss the effects of interventions of COVID-19.

2. Methodologies

2.1. Data Collection

We considered the epidemic data of numbers of the positive individuals in Wenzhou, Shanghai, the United States counties, and the corresponding covariate information related to COVID-19. The data sources and their descriptions are listed as follows.

The epidemic data were from the date when the positive individuals were firstly reported to one month later for Wenzhou and Shanghai from the health commission of local municipal cities. The total of 504 positive individuals from January 21, 2020, to February 21, 2020 for Wenzhou, and the total of 333 positive individuals from January 20, 2020, to February 20, 2020 for Shanghai were collected. Meanwhile, the daily positive individuals of COVID-19 for each infected county of the United States from March 1, 2020, to March 31, 2020, were compiled from Johns Hopkins University (The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University 2020).

We compiled the covariate data including demographics information (residential population, population density (residents per square kilometer), the percentage of the population aged over 65), and the latitude of Wenzhou and Shanghai from the 2019 statistical yearbook of the Zhejiang Provincial and Shanghai Municipal Bureau of Statistics (Statistics Bureau of Zhejiang Province 2019; Shanghai Bureau of Statistics 2019). For the geographical characteristic, the average daily temperature for a month starting with January 21, 2020 for Wenzhou, and January 20, 2020 for Shanghai were collected from the website of Weather Underground, which was supported by International Business Machines Corporation (IBM) (The Weather Company An IBM Business 2020). Respect to the economic condition, GDP per capita statistics nationwide in China were obtained from the latest statistical yearbooks.

Correspondingly, the populations, population density (residents per square kilometer), the percentage of the population aged over 65, latitudes, and GDP per capita of the counties of the United States were collected from the United States Census Bureau (USCB) (The United States Census Bureau 2020), and the average daily temperature of the United States' counties were available from the National Centers for Environmental Information offered by National Oceanic and Atmospheric Administration (NOAA) (National Centers for Environmental Information 2020). Our essential data, including residential population, population density, age stratification, latitude, temperature, GDP per capita, and the observed trajectories of COVID-19, were used in the analysis to provide efficacy evaluation of the COVID-19 outbreak. The codes and data are available on the GitHub: *https://github.com/tingT0929/The-Effects-of-Stringent-and-Mild-Interventions*.

2.2. Modified Synthetic Control Method

To evaluate the treatment effects of interventions implemented in both Wenzhou and Shanghai, the number of individuals diagnosed positive for COVID-19 per 100,000 people was recorded at the time t with the assignment of interventions denoted as D_t, defined as:

$$P_t(D_t) = \frac{\text{Number of total positive individuals}}{\text{Resident population of an infected area}} \times 100,000,$$

where D_t is the assignment indicator, and "$D_t = 1$" represents the interventions issued as opposed to the "$D_t = 0$". $P_t(1)$, $P_t(0)$ are both the potential outcomes of interventions at the time t. As a result, the corresponding treatment effect of interventions is $(P_t(1) - P_t(0))$, but one of the potential outcomes $(P_t(0))$ at the post-intervention period was missing and counterfactual (Rubin 1978) due to the implementation of interventions in Wenzhou or Shanghai.

To estimate the missing values of $P_t(0)$, we modified the synthetic control method (SCM) (Abadie, Diamond, and Hainmueller 2010; Abadie 2020) to construct a "synthetic" target city by combining a series of control areas, which were the absence of interventions. Here, we selected the United States counties, where there were no official interventions at the early stage of epidemic. A majority of the United States' infected counties had reported positive individuals since March 1, 2020 (The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University 2020) and the "call to action" for coronavirus guidelines was released on March 16, 2020 (The White House 2020). Thus, there were 16 days before the nationwide public response mounted in the United States. We used 16-day epidemic data in the United States compared with the 16-day epidemic data in Wenzhou from January 21 to February 5, 2020, and in Shanghai from January 20 to February 4, 2020 (Tian, Luo, et al. 2021).

In doing so, let "$t = 1$" correspond to January 21 for Wenzhou (or January 20 for Shanghai) and March 1 for the United States counties. The estimates of treatment effects are assumed as follows:

$$P_t(1) - \hat{P}_t(0) := P_t(1) - \sum_{i=1}^{I} w_i P_{t,i}(0), \text{for } t > T_0, \quad (1)$$

where $P_{t,i}(0)$ is the number of positive individuals of COVID-19 per 100,000 people at time t in the i^{th} county of the United States. The stage when $t > T_0$ is the post-intervention period and w_i is the positive weight parameter s.t. $\sum_{i=1}^{I} w_i = 1$. We took T_0 as 11 for Wenzhou and 4 for Shanghai, respectively, according to the considerations in the supplementary materials, Section B.1.

The weighted linear combination of I control counties was built using similar features between Wenzhou (or Shanghai) and the United States counties. To explore the critical components related to the number of the positive individuals, we considered important covariants associated with the spread of COVID-19, for example, demographics information, geographical characteristic, and economic condition (Carozzi, Provenzano, and Roth 2020; Kang et al. 2020; Sajadi et al. 2020; Sarmadi, Marufi, and Kazemi Moghaddam 2020; Zhang et al. 2020). The population density size ($\mathcal{P}$), the percentage of people aged over 65 ($\mathcal{O}$), latitude ($\mathcal{L}$), temperature ($\mathcal{T}$), and GDP per capita ($\mathcal{G}$, whose distribution is shown in Figure A.1 of the supplementary materials, Section A) of the target cities were used in constructing the control region.

Notice that the per-intervention period for Shanghai ($T_0 = 4$ for Shanghai) was not long enough considering the reported studies about the incubation period of COVID-19 (Lauer et al. 2020). We used the first 11 days for Wenzhou and 5 days of Shanghai to propose the clustering and SCM procedure below, where the assumed period (which length denoted by K) of Shanghai was 1 day of the post-intervention period combined with its pre-intervention period (Abadie 2020), and Wenzhou was the exact days before the broad interventions implemented.

As there were over 3000 counties in the United States, we desired to scale down the candidate counties to reduce the computational burden in SCM procedure. We employed the clustering with spatial constraints to obtain the candidate counties (Chavent et al. 2018), where the details are presented in the supplementary materials, Section B.2. Once the selection of I counties was determined, the estimation of weight parameters in Equation (1) are given as (Abadie 2020; Abadie, Diamond, and Hainmueller 2010)

$$\hat{\boldsymbol{w}}(\mathcal{M}) = \operatorname{argmin}_{w_i \geq 0, \sum_{i=1}^{I} w_i = 1} ||\boldsymbol{\mathcal{Y}} - \mathcal{X}\boldsymbol{w}||^2_{\mathcal{M}} \quad (2)$$

$$:= \operatorname{argmin}_{w_i \geq 0, \sum_{i=1}^{I} w_i = 1} \mathrm{MSE}_{\mathcal{M}}(\boldsymbol{w}),$$

where $\boldsymbol{w} = (w_1, ..., w_I)^T$, $||\boldsymbol{u}||^2_{\mathcal{M}} = \boldsymbol{u}^T \mathcal{M} \boldsymbol{u}$ and $\mathrm{MSE}_{\mathcal{M}}(\cdot)$ denotes the mean square errors given a positive semidefinite matrix $\mathcal{M}$. $\boldsymbol{\mathcal{Y}} := \begin{pmatrix} \boldsymbol{\mathcal{Z}_1} \\ \mathcal{P} \\ \mathcal{O} \\ \mathcal{T} \\ \mathcal{G} \end{pmatrix}$, $\mathcal{X} := \begin{pmatrix} \mathcal{Z}_2 \\ \mathcal{P}_1 \cdots \mathcal{P}_I \\ \mathcal{O}_1 \cdots \mathcal{O}_I \\ \mathcal{T}_1 \cdots \mathcal{T}_I \\ \mathcal{G}_1 \cdots \mathcal{G}_I \end{pmatrix}$. $\mathcal{Z} := (\boldsymbol{\mathcal{Z}_1}, \mathcal{Z}_2)$ is the covariate matrix achieved by the transformation of the observed COVID-19 trajectories. The principal component analysis (PCA) was used to construct $\mathcal{Z}$ by the informative principal component of the first $(K-1)$ days trajectories of all regions and the positive individuals of COVID-19 per 100,000 of all regions on Kth day (denoted as $\boldsymbol{P}_K$). We referred the supplementary materials, Section B.3 for more details. $\mathcal{P}_i$, $\mathcal{O}_i$, $\mathcal{T}_i$, and $\mathcal{G}_i$ are the population density size, the percentage of the population aged over 65, the temperature, and the GDP per capita of the ith county of the United States, respectively. The estimation of $\boldsymbol{w}$ and $\mathcal{M}$ for Wenzhou and Shanghai were calculated using R package `Synth` (Abadie, Diamond, and Hainmueller 2011), which optimization procedure is given in the supplementary materials, Section B.4.

We also employed a placebo test (Abadie, Diamond, and Hainmueller 2010) to inference the treatment effects of interventions. A "placebo effect" was obtained by repeated allocating a sample of I counties in the United States as a "treated region". Wenzhou (or Shanghai) and the remaining $(I-1)$ counties followed the proposed procedure to form a combined control region, the difference of the positive individuals of COVID-19 per 100,000 between any of the "treated region" and corresponding combined control region during the post-intervention period yields a permutation distribution. If such a difference from Wenzhou or Shanghai was extreme compared to the remaining differences in the permutation distribution, the treatment effect of interventions issued in Wenzhou or Shanghai was considered statistically significant (Abadie, Diamond, and Hainmueller 2010).

2.3. Regression Discontinuity

To vertically examine whether the implementation of strict intervention policies of Wenzhou on February 1, 2020, and of mild intervention policies of Shanghai on January 24, 2020, had a significant effect on their COVID-19 epidemic, we propose the regression discontinuity (RD) (Hahn, Todd, and Van der Klaauw 2001; Imbens and Lemieux 2008) formulated as one of the following versions:

$$\begin{aligned}
\log P_t &= \alpha_0 + \alpha_1 h_t + \alpha_2 (t - c) + \zeta_t, \\
\log P_t &= \alpha_0 + \alpha_1 h_t + \alpha_2 (t - c) + \alpha_3 h_t (t - c) + \zeta_t, \\
\log P_t &= \alpha_0 + \alpha_1 h_t + \alpha_2 (t - c) + \alpha_3 (t - c)^2 + \zeta_t, \\
\log P_t &= \alpha_0 + \alpha_1 h_t + \alpha_2 (t - c) + \alpha_3 h_t (t - c) \\
&\quad + \alpha_4 h_t (t - c)^2 + \zeta_t, \qquad (3)
\end{aligned}$$

where α_i are the regression coefficients of each version of the RD model. ζ_t are the iid noise variables. P_t is the number of the positive individuals of COVID-19 at time t. In RD, t is regarded as the rating variable, where "$t = 1$" represents January 21, 2020, for Wenzhou and January 20, 2020, for Shanghai, respectively. $h_t := \mathbb{I}_{[c,\infty)}(t)$ is an indicator variable for implementing policies in Wenzhou or Shanghai, where c is the number of days corresponding to the cutoff-point, whose value is taken as $(T_0 + 1)$ for Wenzhou or Shanghai. We proceed with the model selection procedure by Bayesian information criterion (BIC) (Schwarz 1978) among different versions of RD models (3).

2.4. State-space Compartmental Model

To reflect the pre-symptomatic and asymptomatic transmission of COVID-19 (Gao and Li 2020; Furukawa, Brooks, and Sobel 2020), we divided the total population into four compartments: susceptible class (S), infectious class (I), self-healing class (H), and COVID-19-positive class (P). The susceptible class (S) contains individuals who are susceptible to infectious disease and the infectious individuals (I) are contagious and not isolated (or quarantined), removed after self-healing or the onset of symptoms. The self-healing class (H) includes the individuals who caught the virus but self-heal without being identified positive. The COVID-19-positive individuals (P) are identified by testing and assumed to be in well-isolation (or self-quarantine). We supposed that the individuals of H and P are no longer transmissible and immune to re-infection.

Let $\boldsymbol{W}_t := (S_t, I_t, H_t, P_t)$ be the numbers of compartments S, I, H, P at time t s.t. $S_t + I_t + H_t + P_t = N$, where N is the total number of population. We proposed a state-space model for the dynamic of four compartments

$$\boldsymbol{W}_{t+1} = \mathcal{T}_t(\boldsymbol{W}_t) + \boldsymbol{\varphi}_{t+1}, \tag{4}$$

$$P^{ob}_{t+1} = P_{t+1} + \epsilon_{t+1}, \tag{5}$$

where T is the length of time and $\mathcal{T}_t$ is the dynamic operator indexed by time t. P_t^{ob} is the observation of P_t and P_1 is assumed to be P_1^{ob}. $\boldsymbol{\varphi}_t$, ϵ_t are some independent noise variables, where $\epsilon_t \sim \mathrm{DisN}(0, \sigma)$ are the iid discrete Gaussian noises with the mean 0 and standard deviation σ (Wolodzko 2017).

To define a suitable dynamic operator $\mathcal{T}_t$ for the latent process, we firstly proposed a deterministic dynamic equation of compartments S, I, H, P (Tian, Tan, et al. 2021)

$$\begin{aligned}
\frac{\mathrm{d}S}{\mathrm{d}t} &= -\theta(t)\frac{S(t)}{N}I(t),\\
\frac{\mathrm{d}I}{\mathrm{d}t} &= \theta(t)\frac{S(t)}{N}I(t) - \frac{1}{\mathcal{H}}I(t) - \frac{1}{\mathcal{I}}I(t),\\
\frac{\mathrm{d}H}{\mathrm{d}t} &= \frac{1}{\mathcal{H}}I(t),\\
\frac{\mathrm{d}P}{\mathrm{d}t} &= \frac{1}{\mathcal{I}}I(t),
\end{aligned} \tag{6}$$

where $(S(t), I(t), H(t), P(t))$ are the dynamic numbers of corresponding compartments at time t. $\theta(t)$ is the product of the time-varying contact number and transmissibility of infectious disease. $\mathcal{H}$ is the average length of the duration between catching the virus and self-healing for the individuals of I, which is chosen as 9.5 according to the clinical study of the communicable period of COVID-19 (Hu et al. 2020). Similarly, $\mathcal{I}$ is the mean length of the duration between catching the virus and confirmed by testing, which is assumed to be shorter than $\mathcal{H}$ but longer than the reported median (5.1) of the incubation period of COVID-19 (Lauer et al. 2020). By the setting above, the effective reproduction number R_t (Becker 1989) of the deterministic SIHP model was calculated as (assuming $S(t) = N$ for all t):

$$R_t = \frac{\mathcal{H}\mathcal{I}}{\mathcal{H}+\mathcal{I}}\theta(t). \tag{7}$$

To reflect the stagewise effect of the interventions, we assume $\theta(t)$ following the piecewise constant structure

$$\theta(t) = \theta_1 \mathbb{I}_{[0,T_1)}(t) + \theta_2 \mathbb{I}_{[T_1,T_2)}(t) + \theta_3 \mathbb{I}_{[T_2,\infty)}(t), \tag{8}$$

where $\theta_1 \ge \theta_2 \ge \theta_3 \ge 0$. We consider two important timings of the implementation of interventions: the first-level public health emergency response and the physical/social distancing policy. We chose T_1 as 3 and T_2 as 12 for Wenzhou (or 5 and 15 for Shanghai) based on the reported timeline of major implementation of policies in Figure 1. We abuse of notation $\boldsymbol{\theta}$ to denote $(\theta_1, \theta_2, \theta_3)$ simultaneously. Let $\mathcal{T}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)$ be the dynamic number at time $(t+1)$ in Equation (6), determined by the initial condition $\boldsymbol{W}_t$ and the parameters $(\boldsymbol{\theta}, \mathcal{H}, \mathcal{I})$, which could be efficiently calculated by the `ode()` function implemented by R package `deSolve` (Soetaert, Petzoldt, and Setzer 2010).

To motivate the stochastic dynamics in Equation (4), we assume that

$$\boldsymbol{W}_{t+1}|\boldsymbol{W}_t \sim \mathrm{Mult}(\boldsymbol{W}_{t+1}|N, \mathcal{T}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)/N)$$

$$= \frac{\begin{array}{c}\mathrm{Po}(S_{t+1}|\mathcal{T}^{(1)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)) \cdot \mathrm{Po}(I_{t+1}|\mathcal{T}^{(2)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t))\\ \cdot \mathrm{Po}(H_{t+1}|\mathcal{T}^{(3)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)) \cdot \mathrm{Po}(P_{t+1}|\mathcal{T}^{(4)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t))\end{array}}{\mathrm{Po}(N|N)},$$

where $\mathrm{Mult}(\cdot; n, \boldsymbol{p})$ and $\mathrm{Po}(\cdot|\lambda)$ is the density of multinomial distribution with the total number n and the incident rate vector $\boldsymbol{p}$ and the Poisson mass with mean λ, respectively. $\mathcal{T}^{(k)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)$ be the kth component of vector $\mathcal{T}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)$. Make use of the fact that: $N, S_t \gg I_t, H_t, P_t$, which implies the parallel Poisson approximation could be used to efficiently represent the joint conditional distribution of $\boldsymbol{W}_{t+1}$, that is,

$$\begin{aligned}
p(\boldsymbol{W}_{t+1}|\boldsymbol{W}_t, \boldsymbol{\theta}, \mathcal{I}) \approx\ & \mathrm{Po}(I_{t+1}|\mathcal{T}^{(2)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t))\\
& \cdot \mathrm{Po}(H_{t+1}|\mathcal{T}^{(3)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t))\\
& \cdot \mathrm{Po}(P_{t+1}|\mathcal{T}^{(4)}_{t+1,\boldsymbol{\theta},\mathcal{I}}(\boldsymbol{W}_t)).
\end{aligned}$$

We employed the Bayesian procedure for the statistical inference of the state-space SIHP model, where the details were given in the posterior distributions of parameters C. Once the posterior distributions of parameters and latent process were extracted, the simulated numbers could be achieved by Equation (6).

To assess the effect of policy intervention, we defined some operators on the estimated $\theta(t)$ and used the posterior distribution of the simulated numbers of the positive individuals to visualize different hypothetical situations. Briefly, we mainly focused on two scenarios: all the implementations of policy intervention delayed three days or five days, that is, $\theta(t) \leftarrow \theta(t-a)$, $\forall t \ge T_1$, $a = 3, 5$ and all interventions or the latter policy intervention was not implemented, that is, $\theta(t) \leftarrow \theta_1$, $\forall t \ge T_1$ or $\theta(t) \leftarrow \theta_2$, $\forall t \ge T_2$. The first one was used to visualize the delay effect of the intervention, and the second one was aimed to quantify the effect of different policies.

3. Case Study

3.1. Synthetic Control Method Analysis for the Treatment Effect

After spatial clustering employed, there are 44 and 27 candidates infected counties of the United States synthesized to Wenzhou and Shanghai, respectively. Tables D.1 and D.2 summarize the corresponding weights of each candidate county of the United States in the posterior distributions of parameters D.1, and the synthetic values of $\mathcal{P}$, $\mathcal{O}$, $\mathcal{T}$, $\mathcal{G}$, the components, and $\boldsymbol{P}_K$ were shown in Table 1 for Wenzhou and Shanghai, respectively.

During the pre-intervention period, $\mathcal{P}$ and $\mathcal{G}$ were substantially lower in the average of candidate counties than in Wenzhou and Shanghai, while $\mathcal{O}$ was higher on average in the 44 counties than in Wenzhou. Moreover, the values of the selected components were negative on the average of the 44 counties for Wenzhou but positive on the average of the 27 counties for Shanghai. In contrast, the "synthetic Wenzhou" reproduced

Table 1. The synthetic and average values of $\mathcal{P}$, $\mathcal{O}$, $\mathcal{T}$, $\mathcal{G}$, the selected components (explaining the percentage of variance) and P_K over candidate counties for Wenzhou ($K = 11$) and Shanghai ($K = 5$).

Features	Wenzhou		Average of counties	Shanghai		Average of counties
	Real	Synthetic		Real	Synthetic	
Population density size ($\mathcal{P}$)	768	749	378	3823	4535	1214
The percentage of population aged over 65 ($\mathcal{O}$)	13.0%	13.7%	16.9%	15.0%	15.0%	15.1%
Temperature ($\mathcal{T}$)	10.46	9.31	11.56	7.88	7.88	5.22
GDP per capita ($\mathcal{G}$)	64931.5	65340.2	48011.3	135305.3	135268.6	87252.0
The first component (Wenzhou: 45.09%; Shanghai: 90.46%)	1.435	1.579	−0.033	−0.957	−0.949	0.035
The second component (Wenzhou: 29.38%)	4.566	1.102	−0.104	–	–	–
The third component (Wenzhou: 10.10%)	0.152	−0.200	−0.003	–	–	–
P_K	2.591	2.562	0.776	0.136	0.136	0.669

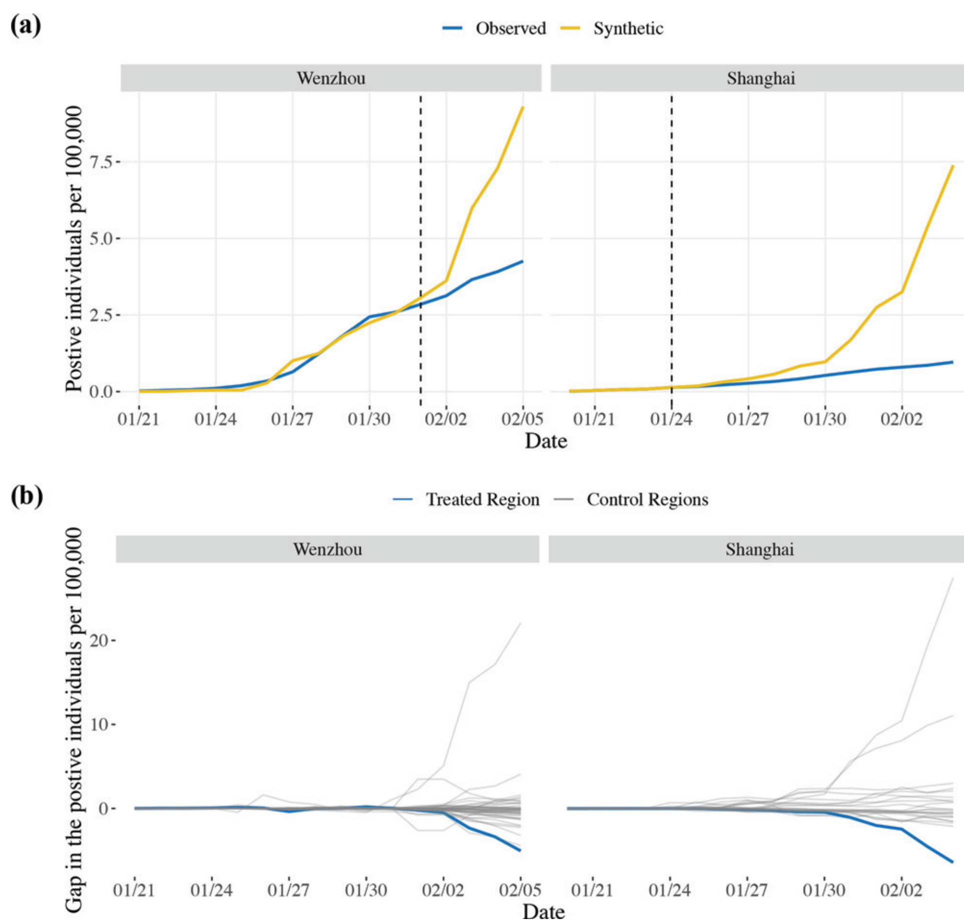

Figure 2. (a) The epidemic trends between treated regions and their "synthetic" regions. The black dashed lines indicated the corresponding time with the interventions implemented. (b) The permutation test of the treatment effect of implementing the policies in treated regions and their corresponding control regions. Discard the counties with the extreme pre-intervention MSE values. The blue curves and gray curves represent the difference between treated regions and their "synthetic" regions and the difference between a county from the control regions and its "synthetic" region.

the similar values of matched covariants. $\mathcal{T}$ and $\mathcal{G}$ between Shanghai and "synthetic Shanghai" were similar, and the "synthetic Shanghai" exactly produced the values of observed positive individuals of COVID-19 per 100,000 people on the fifth day.

The observed COVID-19 trajectories for the real and synthetic region of Wenzhou or Shanghai were highly similar before the broad strict or the mild interventions were issued. The number of the positive individuals of COVID-19 per 100,000 people in "synthetic Wenzhou" on February 5, 2020, was 9.30, which is 2.18 times the actual Wenzhou (4.26) (Figure 2 (a)), and in "synthetic Shanghai" on February 4, 2020, was 7.38, which is 7.69 times the actual Shanghai (0.96) (Figure 2 (a)).

A placebo test was performed to determine the significance level of the difference in the trends of the number of positive individuals of COVID-19 per 100,000 people (Figure 2 (b)). To this end, we plotted the gap curves between Wenzhou and "synthetic Wenzhou" by in turn exchanging Wenzhou and one of each 44 counties in the homogeneous group of Wenzhou. A similar procedure of Shanghai and its "synthetic Shanghai" was produced. Here, the counties with substantially higher MSE than Wenzhou's (or Shanghai's) were discarded, because the proposed SCM procedures for them were not matched for the pre-intervention period (Abadie, Diamond, and Hainmueller 2010) (1 county and 2 counties were discarded for Wenzhou and Shanghai, respectively).

The gap of the positive individuals of COVID-19 per 100,000 people between the real and synthetic Wenzhou or Shanghai was the largest negative compared to the rest, that is, the negative effect of the intervention policies on the number of positive individuals of COVID-19 per 100,000 people in Wenzhou or Shanghai was the lowest of all. The probability of having a magnitude gap for a target city under a random permutation of the control measures was 5%, which is conventionally regarded as statistical significance (Abadie, Diamond, and Hainmueller 2010). This suggested that the effect of the implementation of the policies in Wenzhou ($1/44 = 0.023$) was significantly different from the implementation of the policies in the remaining 43 counties, indicating that the strict interventions of Wenzhou might have significantly reduced the positive individuals of COVID-19 per 100,000 people. A similar conclusion can be drawn for Shanghai, which means that the effect of the implementation of the policies in Shanghai ($1/26 = 0.038$) was also significant.

3.2. Regression Discontinuity Analysis for the Treatment Effect

As indicated in Figure 1, no newly positive individuals reported in Wenzhou after February 18, 2020. It is nearly a month period from January 21 to February 18, 2020. We used the same length of the epidemic data for Shanghai. By examining BIC values in Table D.2 of the supplementary materials, Section D.2, we selected the optimal RD model in Equation (3) including the second-order interaction for Wenzhou and Shanghai. This is consistent with Figure D.1 in the supplementary materials, Section D.3, the points lied on the right side of Wenzhou and Shanghai are the quadric curve.

The coefficients of interventions and the interaction effect between interventions and time are -0.844 (p-value: <0.001) and -0.419 (p-value: <0.001), respectively, indicating that there was a significant treatment effect of highly stringent interventions implemented in Wenzhou on February 1, 2020. Similarly, there was also a significant treatment effect of mild interventions over time (p-value: 0.024) in Shanghai on January 24, 2020 (the coefficient: -0.490), and the coefficient of the interaction effect between interventions and time is -0.508 (p-value: <0.001) in Table 2. Conversely, if the policies were not implemented, the reported total number of positive individuals of COVID-19 would increase over time (corresponding coefficient of time: 0.511 for Wenzhou and 0.748 for Shanghai).

3.3. Compartmental Modeling Analysis for the Stagewise Effect

We utilized the reported 29-day number of the positive individuals of COVID-19 (from January 21 to February 18 for Wenzhou and from January 20 to February 17 for Shanghai, respectively) to proceed with the estimation procedure in the state-space compartmental model. We also proposed the assessment of the short-term prediction for the state-space SIHP model. Our results showed a good fit to the daily numbers of the positive individuals of COVID-19 (Figure D.2 in the supplementary materials, Section D.4). Also, the observed data in the prediction period were both covered by their credible bands, which indicated the reliability of the proposed compartmental model and simulation results below.

The posterior distributions of R_t in each period (defined by the chosen T_1, T_2 for different cities in Equation (8)) for Wenzhou and Shanghai are presented in Figure 3 and Table D.4 in the supplementary materials, Section D.5. We found that the $\hat{R}_t$ in period 1 of Wenzhou was higher than that of Shanghai, while the $\hat{R}_t$ in period 3 of Wenzhou was smaller than that of Shanghai. As the launch of the first-level public health emergency response and the physical/social distancing policy, $\hat{R}_t$ decreased 63.80%, 73.45% for Wenzhou and 52.90%, 55.79% for Shanghai at periods 2 and 3, respectively.

To explore the effect of intervention policies, we proposed simulation studies of two scenarios mentioned in methodologies in Figure 4. Our simulation projected that the expected total positive individuals of COVID-19 per 100,000 of Wenzhou would be 4.43 times and 20.83 times the observed ones for the 3- and 5-day delay on February 18, 2020, respectively (Figure 4 (a)). And for Shanghai, the simulated numbers would be 2.09 times and 4.19 times the observed ones on February 17, 2020, respectively. The simulation in Figure 4 (b) showed different effectiveness of intervention policies. The comparison between scenarios 1 and 2 in Figure 4 (b) indicated the expected positive individuals of COVID-19 would decrease more than 99% if the first-level public health emergency was launched for both cities. Under the first-level public health emergency, we observed that if the physical/social distancing policy was implemented, the expected positive individuals of COVID-19 would decrease 80.77% and 40.24% until February 17 and February 18 for Wenzhou and Shanghai, respectively.

Additional simulation considering two representative types of outbreak corresponding to Wenzhou (Type 1) and Shanghai (Type 2) with a relatively long period without effective control were also presented in the supplementary materials, Section D.6. Based on Figure D.3 in the supplementary materials, Section D.6, we also observed great decreases in the positive

Table 2. The variable coefficients with their corresponding p-values and adjusted R^2.

	Wenzhou		Shanghai	
Variables	Coefficients	p-values	Coefficients	p-values
Intercept	6.470	<0.001	4.035	<0.001
Policy (h_t)	-0.844	<0.001	-0.490	0.024
Time ($(t-c)$)	0.511	<0.001	0.748	<0.001
Policy $*$ Time ($h_t(t-c)$)	-0.419	<0.001	-0.508	<0.001
Policy $*$ Time^2 ($h_t(t-c)^2$)	-0.004	0.016	-0.006	<0.001
Adjusted R^2	0.993		0.987	

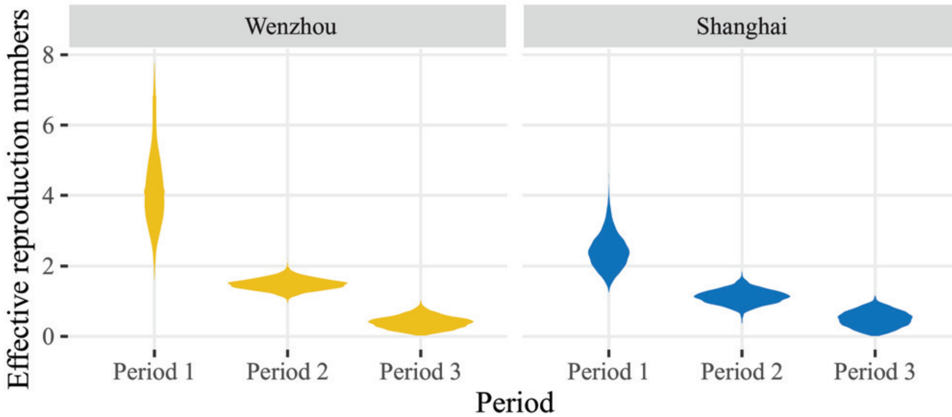

Figure 3. The posterior distributions of the effective reproduction numbers. Period 1: from January 21 to January 23 (Wenzhou) and from January 20 to January 24 (Shanghai); Period 2: from January 24 to February 1 (Wenzhou) and from January 25 to February 3 (Shanghai); Period 3: after February 1 (Wenzhou) and after February 3 (Shanghai).

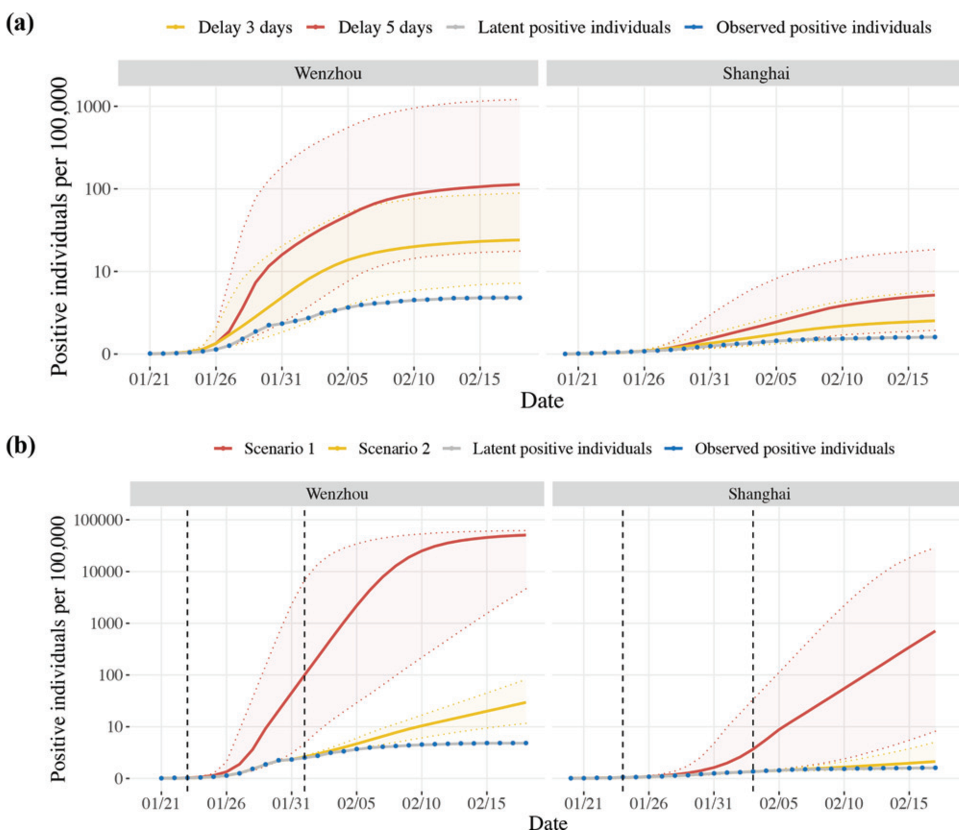

Figure 4. (a) The simulated numbers for the delay of all policies. (b) The simulated numbers for evaluating the effects of policies. Scenario 1: all intervention policies were not implemented. Scenario 2: the latter intervention was not implemented. The numbers of the latent positive individuals of COVID-19 per 100,000 were estimated by the P_t in the state-space SIHP model. The 95% credible intervals of the simulated numbers were given in both (a) and (b). The black dashed lines indicated the corresponding time with the interventions implemented.

individuals of COVID-19 for the region outside China if the interventions as used in Wenzhou or Shanghai were implemented in lieu of the absence of the interventions, respectively.

4. Discussion

We used the daily reported total number of positive individuals of COVID-19 per 100,000 people in Wenzhou and Shanghai, and the infected counties of the United States to evaluate the effects of intervention policies through the proposed SCM procedure. The horizontal comparisons were made to examine the treatment effects of the broad stringent intervention policies implemented in Wenzhou (the community's strictly closed management (Guangming Daily 2020; Wenzhou Municipal People's Government 2020b) and traffic blockade (Wenzhou Municipal People's Government 2020a)), and the relatively mild intervention policies implemented in Shanghai, which adopted closely following the close contact of the positive individuals of COVID-19 and isolating them (Shanghai Municipal Health Commission 2020).

We utilized the covariates related to the transmission of COVID-19 (the population density size, the percentage of people aged over 65, latitude, temperature, and GDP per capita) to assist the construction of the control group, which was the absence of intervention. The hierarchical clustering with spatial constraints and the PCA were used to reasonably reduce the candidate counties of the United States and compress the temporal information of the pre-intervention period within the SCM procedure.

On the comparisons of the "synthetic" trajectories with the treatment groups exposed to the interventions for Wenzhou and Shanghai, we observed that if the intervention policies were not implemented, the outbreak of COVID-19 was expected to expand to 2.18 times for Wenzhou on February 4, 2020, and 7.69 times for Shanghai on February 5, 2020. It indicated the implementation of strict or mild interventions could significantly suppress the transmission of COVID-19. A placebo test was also undertaken by combining a random sample of county drawn from the candidate counties of the "synthetic regions" with repeating the proposed SCM procedures. The numbers of positive individuals of COVID-19 per 100,000 people in Wenzhou and Shanghai were the lowest among their corresponding "synthetic regions," which were the absence of interventions. The outbreak of COVID-19 also supported our results, where the spread kept continued after March in the United States (The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University 2020), and the epidemics in Wenzhou and Shanghai were brought under control since February.

As an auxiliary, we also employed the vertical comparison before and after the interventions implemented in Wenzhou and Shanghai by RD to measure those "reduction effects." Similar to the placebo test, the effects of the intervention policies were statistically significant in RD. Hence, the horizontal and vertical comparisons suggested the significant treatment effects of both the stringent and mild interventions, providing the effectiveness of interventions could be elegantly identified. Besides the likely outcomes of the absence of interventions that there was a considerable increase in the positive individuals of COVID-19 for target cities, our results not only agreed with Lai et al. (2020) and Ruan et al. (2020), but also gave the statistical inference of the interventions' effects without assuming a specific dynamic mechanism.

Additionally, we proposed a state-space SIHP model by considering the transmission pattern of COVID-19 and the stage-varying effects of intervention policies to assess two main types of policies: the first-level public health emergency response and the physical/social distancing policy (the community's strictly closed management (Guangming Daily 2020; Wenzhou Municipal People's Government 2020b) and traffic blockade (Wenzhou Municipal People's Government 2020a) implemented in Wenzhou and the community management (Shanghai Observer 2020) implemented in Shanghai). Based on our simulation, we concluded that if these interventions were delayed by a few days, the outbreak would increase significantly for both cities. We also estimated higher decreasing proportions of the effective reproduction number between periods in Wenzhou, which is consistent with the stringent interventions of Wenzhou, compared with Shanghai.

Moreover, we found the crucial importance of the highest level alert to COVID-19 ahead of other interventions at the early outbreak, because it would substantially decrease the outbreak of the epidemic for Wenzhou and Shanghai (reduced more than 99% of the total positive individuals of COVID-19 one month later). To promote the joint prevention and the control of various departments, the public health emergency response requires all relevant departments and units to work together and share resources to effectively respond to the outbreak of the epidemic (Şirin, Ergüder, and Özkan 2020), hence the enthusiasm of the region joint defence would be greatly enhanced, which is conducive to the control of the epidemic.

However, the effective reproduction numbers were still higher than 1 after the public health emergency response was activated, indicating that the physical/social distancing policy was necessary for preventing the constant outbreak at the later stage of the epidemic. After implementing those policies, the decline percentages of the positive individuals of COVID-19 for Wenzhou were 80.77%, and for Shanghai were 40.24%, respectively. Not surprisingly, Wenzhou issued stricter physical/social distancing policies, which may be caused by the trade-off between the severity of the spread and the economic loss of different cities. The simulations (the supplementary materials, Section D.6) also reflected the effectiveness of the physical/social distancing policy of Wenzhou or Shanghai for the control of COVID-19 in an infected region outside China.

In summary, our contributions were to evaluate the effects of the intervention policies of Wenzhou and Shanghai by introducing causal inference (SCM and RD) and the epidemic compartmental model. We were aiming to present the varied frameworks to statistically estimate these treatment effects, therefore, it would be helpful for the policymakers to understand the potential impacts of the different intervention policies scientifically. We found that both the stringent and mild interventions had statistically significant treatment effects for the control of the epidemic, and the delay of them would substantially enhance the outbreak of COVID-19. Among those interventions, the first-level public health emergency response was practical and crucial at the early outbreak, and the physical/social distancing policy with suitable intensity would be necessary for the high-risk area where the outbreak was continued.

However, our analysis does not consider the price of economics for the control of the epidemic. Alternatively, we give the justification for the need to issue interventions in the control of the spread. The representative cities in our study issued the interventions to curb the spread of COVID-19 at the expense of economic loss during the first season of 2020 (Table A.1 in the supplementary materials, Section A), once the epidemic situation was under control, the economy was gradually recovered in Wenzhou and Shanghai. Our attempt could provide statistical inference for the timing and the intensity of interventions, which are practical experiments for the policymakers of other regions to evaluate specific interventions to subdue the outbreak of COVID-19. Specifically, a large industrial city could issue mild interventions with less economic damaging to control the epidemic effectively, but the more stringent physical/social distancing intervention of Wenzhou can be used for controlling the spread of COVID-19 in the high-risk areas.

Supplementary Materials

In the supplementary materials, we provide more details about the procedure of SCM and the state space compartmental model, along with additional supporting evidence with results summarized in tables and figures.

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