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Timing and Support Safeguards for Reopening an Economy During COVID-19

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Abstract: Before the COVID-19 vaccines from Pfizer and Moderna were authorized, governments around the world have adopted strict lockdown measures in response to the threat from the unprecedented COVID-19 pandemic. Because of the negative impact on freedom of movement, the economy, and society at large, the question of when and how to safely reopen an economy is urgent. Based on the data of daily confirmed COVID-19 cases from all 31 provincial capitals on the Chinese mainland, this paper is the first to apply the synthetic control method to empirically analyze the causal effect of reopening the economy in three provincial capitals on their increase in new cases. Data showed that the number of new infection cases in all three cities remained at zero for several consecutive days before reopening. Reopening the economy did not have a significant adverse effect on the increase in the number of new infections in these three cities for at least a week after reopening. This study contains lessons for other countries of the world by providing timely and reliable causal evidence on the timing and support safeguards for reopening an economy during COVID-19.

Keywords: COVID-19, Reopening Economies, Increase of Newly Confirmed Cases, Synthetic Control Method

1. Introduction

COVID-19 first appeared in the city of Wuhan in the Hubei Province of China in early December of 2019 [1, 2]. It spread mainly through human-to-human contact [3]. It is unclear how well the COVID-19 vaccines from Pfizer and Moderna will contain the spread of the virus. The emergence of a new variant of coronavirus in the UK further makes the future of the COVID-19 pandemic even more uncertain. The 2002–2004 SARS outbreak revealed that non-pharmaceutical interventions (NPIs) or public health measures can be effective in preventing the spread of the virus even without vaccines [2]. Therefore, many countries have considered and implemented measures to restrict the movement of people as part of their response plan [4-7].

There is now fierce policy debate on whether these economies can be reopened too quickly. The stay-at-home orders have, on the one hand, increased the proportion of people who are safely isolated at home [8], reduced the number of COIVD-19 infections and saved lives [9-11]. But on the other hand, stay-at-home orders result in high economic cost and significantly increase unemployment [12, 13]. A key

question was raised by Stock [14]: "How can one most effectively reopen the economy while achieving some public health objective, whether flattening the curve or sharply reducing infections and deaths?"

So far, the answer to this question has been very elusive. By using the SIR epidemiology model, Alvarez et al. [15] find that the optimal policy suggests a strict lockdown two weeks after the outbreak, covers 60% of the population after a month, and is gradually withdrawn covering 20% of the population after three months. By calibrating an SIR model with a heterogeneous population, Rampini [16] proposes a sequential approach to reopen the economy. That is, we should first lift interventions for the less vulnerable fraction of the population and then later for the more vulnerable fraction of the population. The goal being to control mortality while increasing economic activity by allowing a fraction of the population to return to work. Based on state-level daily cases, deaths and test data, and using the synthetic control method, Zhou [13] finds that reopening the economy resulted in an additional 2,000 deaths in six U.S. states (including Alabama, Colorado, Georgia, Mississippi, Tennessee, and Texas) in the three weeks following the reopening. After the first, second,

and third weeks of reopening, the number of daily confirmed cases increased by 40%, 52%, and 53%, respectively.

After the Chinese authorities officially confirmed human-to-human transmission on January 20, China has adopted a variety of NPIs to curb the COVID-19 outbreak. At the national level, COVID-19 was classified as a statutory class B infectious disease on January 20, and prevention and control measures for class A infectious diseases (including only plague and cholera) have been taken. At the provincial level, Zhejiang, Hunan, and Guangdong were the first to activate a Level I public health emergency response on January 23. With the final activation in Tibet, all 31 provinces and equivalent administrative units on the Chinese mainland (hereafter provinces) had declared a Level I response by January 29 [2]. As the growth and scale of the COVID-19 epidemic in China has been effectively contained [17], several provinces began to achieve multiple consecutive days of zero growth in confirmed cases. At 2: 00 p.m. on February 21, 2020, Gansu province was the first to decide to lower the response level from the top level to the third level. Liaoning and Guizhou provinces made the same decision on February 22 and 23 respectively and additional provinces have successively lowered their emergency response levels to the COVID-19 threat. The downgrading of the emergency response level means that the focus of each province begins to shift to restoring economic and social order, which provides us with an opportunity to critically examine the relationship between reopening the economy and the spread of the virus.

The purpose of this study is to quantify the causal impact of reopening the economy on the increase of new daily confirmed cases and lay a foundation for answering the question posed by Stock [14]. This paper is the first to separately quantify the causal impact of reactivating the economy on the spread of COVID-19 in three provincial capitals (including Lanzhou, Shenyang, and Guiyang) by applying the synthetic control method based on daily confirmed COVID-19 cases in all 31 provincial capitals from the Chinese mainland. The results show that all three cities had achieved zero growth in new cases for several consecutive days before the reactivation and reopening the economy did not make a significant contribution to the increase in new COVID-19 cases at least for the first week after reopening.

The contribution of this study is four-fold. First, this paper employs the synthetic control method developed by Abadie and Gardeazabal [18] and Abadie et al. [19], which allows for a more objective assessment of reopening the economy. By reproducing the counterfactual outcome trajectory that the treated group would have experienced in the absence of the intervention using a weighted average of available control units, the synthetic control method overcomes the sample selection bias and policy endogeneity problems that can occur in the selection of control groups in previous empirical approaches. Second, although China has implemented a large number of intensive policy adjustments as the rapid spread of the virus has been contained, this study uniquely disentangles and quantifies the causal impact of reactivation on COVID-19

transmission by selecting an appropriate sample time window. Third, as the first provincial capital city to reopen the economy, local government officials in Lanzhou may face strong incentives to underreport the number of COVID-19 cases. In contrast, confirmed cases in other capital cities are likely to be accurate, as they have less incentive to underreport. Therefore, this paper further analyzes Shenyang and Guiyang separately to minimize the impact of possible downward bias of the officially reported cases after reopening. Finally, as the virus continues to spread globally, this paper enriches the economic and epidemiological literature on the timing and support safeguards for reopening an economy. We contribute to the evaluation of different approaches to lift interventions and switch from suppression to mitigation strategy and provide timely policy guidance for all countries.

The remainder of the paper proceeds as follows: Section 2 briefly summarizes the classification and control measures for the public health emergency response to COVID-19. Section 3 introduces the empirical strategies used in this study. Section 4 describes the data and empirical results. Section 5 performs robustness checks to assess the credibility of synthetic control counterfactuals and measures the significance of the reactivation effect. Conclusions and policy implications are included in Section 6.

2. Public Health Emergency Response to COVID-19

The Law in the People's Republic of China on Prevention and Treatment of Infectious Diseases and the "Master State Plan for Rapid Response to Public Emergencies" requires government at all levels to classify public health emergencies as part of the process of formulating an emergency response plan. According to the nature, hazard level, and scope of the public health emergency, the emergency response is categorized into four levels: extremely severe (Level I), severe (Level II), large (Level III), and general (Level IV). Each level has corresponding emergency prevention and control measures as well as the responsibilities from different levels of government.

The activation of a Level I response means that the central government is responsible for the unified management and dispatch of medical and health resources. The main measures taken include isolation of suspected and confirmed cases, suspension of public transportation, closure of schools and entertainment venues, ban of public gatherings, health checks on migrants ("floating population"), prohibition of entry and exit from the city, and widespread dissemination of information [17]. When the response is lowered to Level II, instead of a unified command from the central government, provincial governments begin to adopt differentiated prevention and control strategies. Strategies adopted include preventing the residents in low-risk areas to fully resume work and normal life, stemming the spread of the virus within medium-risk areas and beyond to quickly restore normal work and life, and strictly controlling the epidemic situation in

high-risk areas on the basis of forestalling inbound and intra-city transmission to ensure an orderly return to work and normal life. The level III response corresponds to more precise prevention and control measures, which are differentiated, region-specific, and tiered. Municipal governments have the power to make more decisions for their own administrative regions, such as lifting restrictions on entry to Beijing for people from high-risk areas (e.g., Wuhan), opening entertainment venues and domestic tourism in due course, and organizing the orderly reopening of schools. The Level IV response is coordinated and managed by the county-level government and its goal is to control the progression of the epidemic through adjustment in medium-and high-risk areas. Narrowing the scope of control provides a more accurate and targeted ability to control the virus. It is also more conducive to producing a better result when resuming work and reopening schools.

3. Empirical Strategy

For causal inference and policy evaluation, propensity score matching (PSM) and the difference in differences (DID) approach were commonly used in prior literature. However, the PSM method only controls the influence of observable variables. If the selection is based on unobservable variables, hidden biases will occur. The DID approach is subjective and arbitrary for the selection of the reference group. Also, policy endogeneity arises because systematic differences between the treated city and the control city may be responsible for the implementation of the policy in the target city. Besides, the parallel trend hypothesis may not be feasible because unobserved confounders may have time-varying effects on the results. Further, the PSM-DID design cannot control for unobservable factors that change over time.

In contrast, the synthetic control method (SCM) [18, 19] addresses those problems. Its advantages are also reflected in: (1) the contribution of each control unit to the entire synthetic unit is explicitly reflected so the transparency of the counterfactual allows the weights to be validated [20]. (2) No extrapolation is required, and the synthetic weights are calculated and selected without using the post-intervention data, ruling out the risk of specification cherry-picking or p-hacking [21]. Athey and Imbens [22] believe that the SCM method is "arguably the most important innovation in the policy evaluation literature in the last 15 years".

By employing a SCM technique we adopt a data-driven procedure that uses a weighted average of a set of control cities to construct a "synthetic" target city. The goal of the synthetic target city is to reproduce the trajectory of the real target city in terms of epidemic spread before reopening. Then, the difference in the trajectories between the synthetic and the real target city after the reactivation can be summarized as the causal effect of reopening.

The outcome variable of interest in this study is the increase of newly confirmed COVID-19 cases (*NewGrowth*). Considering the effectiveness of policy implementation, we choose provincial capitals instead of provinces as the research

objects for this study. Following the conventional setting used by Abadie et al. [19], suppose we observe the outcome of $K + 1$ cities during the period $t(= 1, \dots, T)$. Let Y_{it}^N be the outcome for city $i(= 1, \dots, K + 1)$ at time t if reopening is not implemented. Let Y_{it}^I be the outcome for city i at time t if city i is restarted in periods $T_0 + 1$ to T, where T_0 is the time to perform the restart. In the lockdown period (for $t \in \{1, \dots, T_0\}$) we have $Y_{it}^I = Y_{it}^N$ for all $i \in \{1, \dots, K + 1\}$. Let $\alpha_{it} = Y_{it}^I - Y_{it}^N$ be the effect of reopening the economy on city i at time t. We can observe Y_{it}^I of the city that has been reopened, but we cannot observe Y_{it}^N of this treated city. Therefore, this study uses the following factor model proposed by Abadie et al. [19] to estimate Y_{it}^N.

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}. \tag{1}$$

In equation (1), δ_t is the time fixed effects, Z_i is a vector of control variables for city i that can be observed, θ_t represents a corresponding vector of unknown parameters, μ_i is a vector of unobserved local fixed effects, λ_t denotes a vector of unknown common factors, and the error terms ε_{it} are unobserved transitory shocks with zero mean at the city level.

Suppose that the first city ($i = 1$) is reopened, and the remaining K cities ($i = 2, \dots, K + 1$) are not. Consider a ($K \times 1$) vector of weights $W = (w_2, \dots, w_{K+1})'$ such that $w_k \geq 0$ for $k = 2, \dots, K + 1$ and $w_2, \dots, w_{K+1} = 1$. Each particular value of W represents a potential synthetic control, which is a weighted average of all cities in the control group. The outcome variable for each synthetic control indexed by W is

$$\sum_{k=2}^{K+1} w_k Y_{kt} = \delta_t + \theta_t \sum_{k=2}^{K+1} w_k Z_k + \lambda_t \sum_{k=2}^{K+1} w_k \mu_k + \sum_{k=2}^{K+1} w_k \varepsilon_{kt}. \tag{2}$$

Suppose that there are $(w_2^*, \dots, w_{K+1}^*)$ such that

$$\sum_{k=2}^{K+1} w_k^* Y_{k1} = Y_{11}, \sum_{k=2}^{K+1} w_k^* Y_{k2} = Y_{12}, \sum_{k=2}^{K+1} w_k^* Y_{kT_0} = Y_{1T_0}, \text{and} \sum_{k=2}^{K+1} w_k^* Z_k = Z_1. \tag{3}$$

If $\sum_{t=1}^{T_0} \lambda_t' \lambda_t$ is nonsingular, then,

$$Y_{1t}^N - \sum_{k=2}^{K+1} w_k^* Y_{kt} = \sum_{k=2}^{K+1} w_k^* \sum_{s=1}^{T_0} \lambda_t \left(\sum_{n=1}^{T_0} \lambda_n' \lambda_n\right)' \lambda_s' (\varepsilon_{ks} - \varepsilon_{1s}) - \sum_{k=2}^{K+1} w_k^* (\varepsilon_{kt} - \varepsilon_{1t}). \tag{4}$$

Abadie et al. [19] have proved that the right-hand side of equation (4) converges to zero under several parsimonious requirements. Therefore, after reopening ($t \geq T_0$), $\sum_{k=2}^{K+1} w_k^* Y_{kt}$ can be used as an unbiased estimate of Y_{1t}^N to evaluate the effect of the reactivation.

The weight vector $W^* = (w_2^*, \dots, w_{K+1}^*)'$ is chosen by minimizing the distance function $\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$. In this function, X denotes the feature vector of cities, which corresponds to the observable control variable Z and the outcome Y before reopening. The importance of different feature vector X in constructing weights depends on the selection of the symmetric and positive semidefinite matrix V. We include in X the values of predictors of the increase of new COVID-19 cases for the target city and the remaining 14 potential controls. Our

predictors of COVID-19 transmission are population density (*Dens*) and medical resources (*MedIndex*). These variables are averaged over the period from January 30 to the day before reopening and extended by adding the daily increase of new diagnoses (*NewGrowth*) during this period.

4. Empirical Analysis

4.1. Data Source and Variable Selection

The data used in this study were collected from multiple open-access databases. Data on COVID-19 daily confirmed cases were obtained from the Johns Hopkins University's Center for Systems Science and Engineering (JHU CSSE), which provides daily updates on COVID-19 confirmed, death, and recovered cases in each Chinese city. Moreover, demographic and socio-economic development data of each city come from the China City Statistical Yearbook 2019 and the most recent Sixth National Population Census of China.

Our sample data, which covers 31 cities in China between January and April 2020, is generated by matching the above datasets according to city names and dates and retaining only all provincial capitals on the Chinese mainland. With the effective control of the COVID-19 pandemic, Gansu province lowered the public health emergency response from Level I to Level III at 2: 00 p.m. on February 21, 2020. Liaoning and Guizhou provinces made the same decision on February 22 and 23, respectively. Most of the other provinces in our sample have also successively downgraded their emergency response levels since February 28, making them unsuitable to remain as potential control units. Therefore, in order not to attenuate the reactivation effect estimate that we obtain for the target city, we restrict our data period to February 27 and exclude other restarted cities other than the target city before then. This means that our analysis is limited to approximately one week after reopening. We set the restart dates for Lanzhou, Shenyang, and Guiyang as February 21, 22, and 23, 2020, respectively, to match the official government announcement that the provinces where these three cities are located will restart on that day. Abadie [20] recommends that if there is an anticipation effect, the researchers should backdate the intervention date in order to fully estimate the entire scope of the policy intervention. Therefore, we tested different starting dates and are assured that our results are not sensitive to the choice of date.

4.2. Empirical Results

Figure 1 plots the daily trends of the increase of newly confirmed cases in target cities (red line) and other provincial capitals (dashed grey line). As this figure suggests, the time series of each target city before reopening the economy is significantly different from that of other cities in China. Therefore, other cities in China may not provide a suitable comparison group for each target city to study the impact of reopening the economy on the spread of the virus. Specifically, the increase in newly diagnosed cases in other cities in China

has gradually declined after the activation of the Level I public health emergency response, while the increase in new cases in Lanzhou, Shenyang, and Guiyang all peaked on January 31 and then made an uneven decline. The fluctuation of the decline gradually decreased over time and remained at zero 3 days before the restart. This suggests that the initiation of the Level I response has reduced the number of new cases in the target cities and has delayed the COVID-19 outbreak. After reopening the economy, the number of new cases in each of the target cities, along with those in other cities, remained zero for the following week.
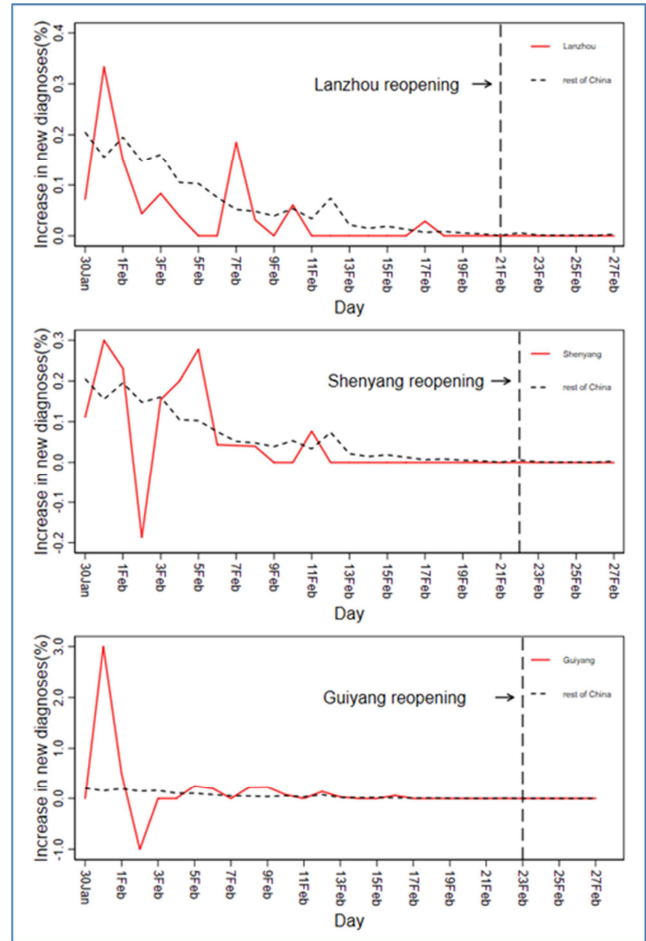

Figure 1. *Trends in NewGrowth: target cities vs. the rest of China.*

To assess the impact of reopening the economy on the spread of COVID-19, the central question is how these trends would have evolved in Lanzhou, Shenyang, and Guiyang after February 21, 22, and 23 in the absence of reopening. The synthetic control method provides a systematic way to estimate this counterfactual. As explained above, we construct the synthetic target city as the convex combination of cities in the control group, which most closely resembled the target city in terms of the pre-reopening value of each predictor. The results are shown in Table 1, which compares the pre-reopening characteristics of the actual target cities with those of the synthetic target cities, as well as with the population-weighted average of the 14 cities in the control group.

Table 1. *Predictor means for NewGrowth.*

Variables	Lanzhou		Shenyang		Guiyang		Average of 14 control cities
	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	
Den (people per km^2)	248.64	343.39	580.09	713.64	519.71	201.19	636.51
MedIndex	13,655.00	17,095.78	31,745.00	30,490.25	16,897.67	18,020.02	35,219.14
NewGrowth (30Jan)	0.07	0.14	0.11	0.20	0.00	0.27	0.21
NewGrowth (31Jan)	0.33	0.21	0.30	0.22	3.00	0.35	0.16
NewGrowth (01Feb)	0.15	0.15	0.23	0.22	0.50	0.17	0.20
NewGrowth (02Feb)	0.04	0.10	-0.19	0.09	-1.00	0.23	0.15
NewGrowth (03Feb)	0.08	0.10	0.15	0.13	0.00	0.18	0.16
NewGrowth (04Feb)	0.04	0.05	0.20	0.10	0.00	0.06	0.10
NewGrowth (05Feb)	0.00	0.10	0.28	0.10	0.25	0.20	0.10
NewGrowth (06Feb)	0.00	0.05	0.04	0.07	0.20	0.10	0.08
NewGrowth (07Feb)	0.19	0.03	0.04	0.05	0.00	0.07	0.05
NewGrowth (08Feb)	0.03	0.01	0.04	0.05	0.22	0.03	0.05
NewGrowth (09Feb)	0.00	0.02	0.00	0.03	0.23	0.05	0.04
NewGrowth (10Feb)	0.06	0.03	0.00	0.03	0.07	0.10	0.05
NewGrowth (11Feb)	0.00	0.02	0.08	0.03	0.00	0.03	0.03
NewGrowth (12Feb)	0.00	0.02	0.00	0.03	0.14	0.04	0.07
NewGrowth (13Feb)	0.00	0.02	0.00	0.02	0.03	0.01	0.02
NewGrowth (14Feb)	0.00	0.01	0.00	0.01	0.00	0.03	0.01
NewGrowth (15Feb)	0.00	0.00	0.00	0.01	0.00	0.03	0.02
NewGrowth (16Feb)	0.00	0.00	0.00	0.01	0.06	0.01	0.01
NewGrowth (17Feb)	0.03	0.00	0.00	0.00	0.00	0.00	0.01
NewGrowth (18Feb)	0.00	0.00	0.00	0.00	0.00	0.00	0.01
NewGrowth (19Feb)	0.00	0.00	0.00	0.00	0.00	0.00	0.01
NewGrowth (20Feb)	0.00	0.00	0.00	0.00	0.00	0.01	0.00
NewGrowth (21Feb)			0.00	0.00	0.00	0.00	0.00
NewGrowth (22Feb)					0.00	0.00	0.01

Notes: (1) *NewGrowth (30Jan)* means that the variable *NewGrowth* takes the value of January 30, and the rest may be deduced by analogy. (2) *MedIndex* was measured by the average of the number of hospitals, beds, and licensed physicians at the city level.

We see that the average from cities that were not reactivated before February 21, 22, and 23 does not provide a suitable control group for Lanzhou, Shenyang, and Guiyang, respectively. Especially before February 13, the increase of newly confirmed cases was substantially different in the average of the 14 control cities from that in the target cities. Moreover, before reactivation other predictors on average in the 14 control cities were higher than those in the target cities. In contrast, the synthetic target cities accurately reproduce the values that the increase of new cases and its predictor variables had in the target cities prior to the reactivation of the economy.

Table 2. *City weights in the synthetic target cities.*

City	Weight	City	Weight
Panel A: synthetic Lanzhou			
Lhasa	0.283	Yinchuan	0.257
Changsha	0.459		
Panel B: synthetic Shenyang			
Lhasa	0.055	Xi'an	0.164
Yinchuan	0.073	Changsha	0.501
Zhengzhou	0.207		
Panel C: synthetic Guiyang			
Harbin	0.367	Yinchuan	0.633

Note: The remaining cities not listed in Panel A, Panel B, or Panel C are assigned 0 weights.

Table 2 displays the weights of each control city in the synthetic target cities. The weights reported by Panel A in Table 2 indicate that the pre-reopening trend in the increase of new cases in Lanzhou is best imitated by a combination of Lhasa, Yinchuan, and Changsha. Panel B shows that the trend in Shenyang before reopening is best reproduced through a combination of Lhasa, Xi'an, Yinchuan, Changsha, and Zhengzhou. According to Panel C, the pre-reopening trend in Guizhou is best captured by a combination of Harbin and Yinchuan.

Figure 2 plots the daily trends in the increase of newly confirmed COVID-19 cases in the target cities (red line) and the synthetic target cities (gray dashed line). Notice that, in contrast to the trends in other cities in China (as shown in Figure 1), the increase of new cases in the synthetic target cities very closely track the trajectory of this variable in each target city for the entire pre-reopening period, especially in the week before reopening. Combined with the high degree of balance on all predictors (Table 1), this indicates that each synthetic target city provides a reasonable approximation of each corresponding target city during the implementation of the Level I response in terms of the increase of new cases in the absence of reopening.

Our estimate of the impact of reopening the economy on virus transmission in each target city is the difference between the increase of newly confirmed COVID-19 cases in the target city and in its synthetic version after reopening. Figure 3 plots the daily estimates (blue line) of the impact of reactivation.
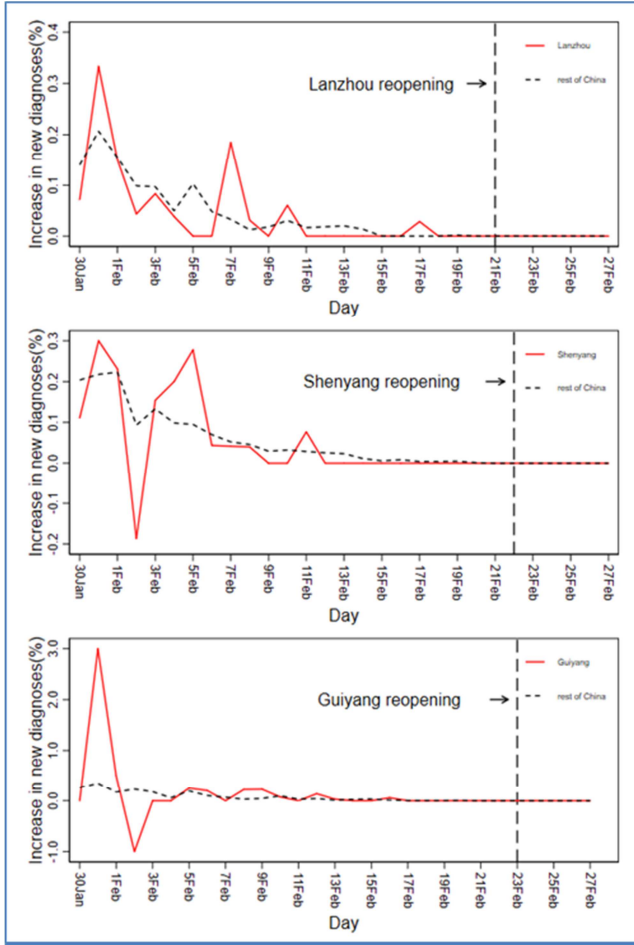
Figure 2. *Trends in NewGrowth: target cities vs. synthetic target cities.*

Figure 3 displays that the number of new cases in Lanzhou, Shenyang, and Guiyang remained at zero for at least one week after they reopened. This suggests that reopening the economy has not led to an increase in the spread of COVID-19 in these three target cities in the short term. Some of the answers to when and how we should safely reopen the economy can be found in China's prevention and control experience. From the perspective of the timing of reopening, effective control of the spread of infection such as zero growth for several consecutive days (as shown in Figure 1) should be a necessary condition for reopening the economy. From the perspective of supporting safeguards, reopening an economy does not mean that the alarm is lifted. Some safeguards such as temperature monitoring, wearing masks, and restricted access to entertainment venues should continue to be implemented. Only in this way can rebounds be prevented during the resumption of economic activity.

To assess the robustness of our results, we included additional predictors of the increase of new cases among the variables used to construct the synthetic control. Regardless of which and how many predictor variables we added, our results remained virtually unaffected. The predictor variables used for robustness checks included mortality rate, the proportion of the population aged 65 and over, and gross regional product per capita to capture the demographic, economic, and social
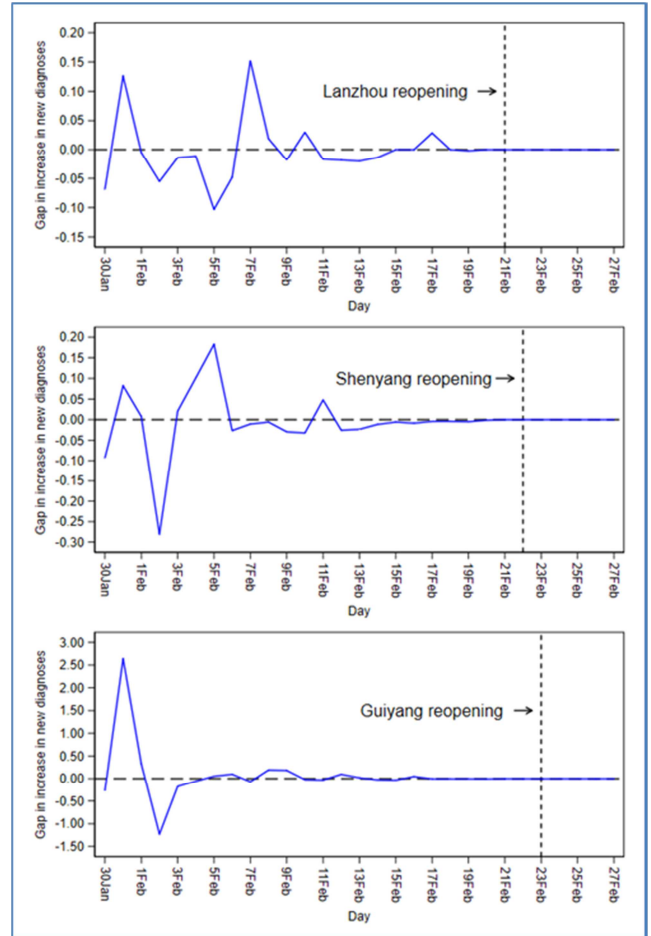
structure of each city.

Figure 3. *Gaps between target cities and synthetic target cities in NewGrowth.*

5. Placebo Tests

Following Abadie and Gardeazabal [18], Bertrand et al. [23], and Abadie et al. [19], we use placebo tests to verify the possibility that we would obtain results of this magnitude if we had randomly selected a city for the study instead of the three target cities. Specifically, we iteratively apply the synthetic control method used to estimate the effect of reopening the economy in the target city to every other city in the control group. In each iteration, we reassign the reopening intervention to one of the 14 control cities in our data and shift the target city to the control group. We then calculate the estimated effect associated with each placebo run. This iterative process provides us with a distribution of estimated gaps for the cities that have not been reopened. If the placebo studies show that the gap estimated for the target city is unusually large compared to the gaps for the cities that did not reopen, then our analysis provides significant evidence of the impact of reopening the economy on COVID-19 transmission in the target city. Conversely, if the placebo tests generate gaps of magnitude similar to the one estimated for each target city, then our analysis does not provide significant evidence of the impact of reactivation.
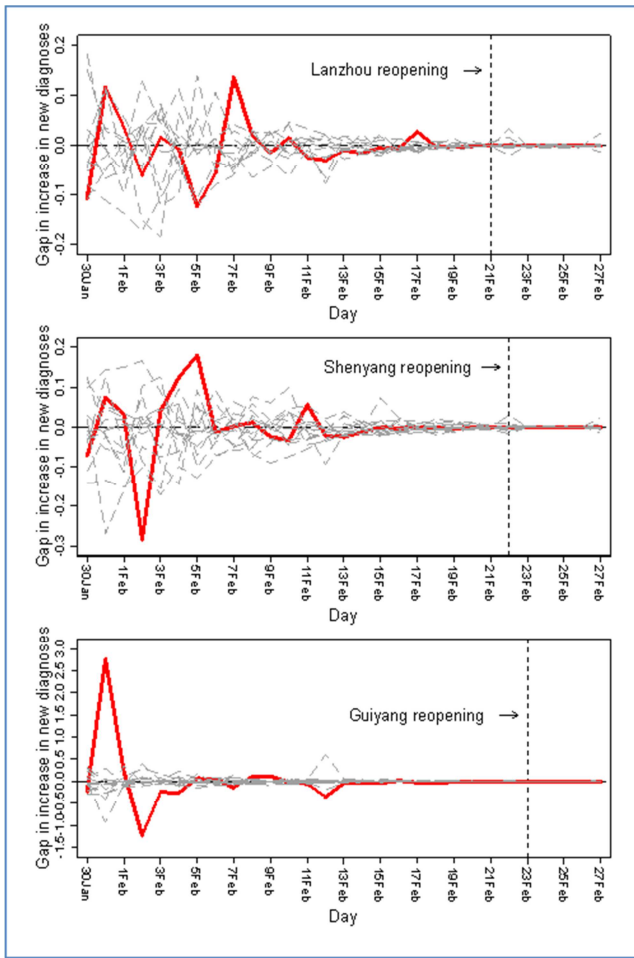
Figure 4. *NewGrowth gaps in target cities and placebo gaps in control cities.*

Figure 4 depicts the results of the placebo test for the three target cities. The gray dashed lines denote the difference in the increase of new COVID-19 cases between each city in the control group and its respective synthetic version. The superimposed red line represents the gap estimated for the target city. If the synthetic target city had failed to fit the increase in new cases for the real target city before reopening the economy, we would have argued that much of the post-reopening gap between the real and the synthetic target city was also artificially created by lack of matching, rather than by the effect of reopening. Thus, in Figure 4 (top) we focus only on those cities that could have fit almost as well as Lanzhou during the pre-reopening period, that is, those cities that had a pre-reopening mean squared prediction error (MSPE) of less than twice the MSPE of Lanzhou (the average of the squared differences between the increase of new cases in Lanzhou and in its synthetic counterpart between January 30 and February 20). To achieve this, we excluded 3 cities (including Harbin, Hangzhou, and Wuhan). The synthetic approach is clearly ill-advised for these cities. Similarly, Figure 4 (middle) excludes 1 city (i.e., Wuhan) with pre-reopening MSPE higher than twice the MSPE of Shenyang. Figure 4 (bottom) does not discard any cities because no city has a pre-reopening MSPE of more than twice the MSPE of Guizhou.

As shown in Figure 4 (top), almost all lines are tightly intertwined with the zero-gap line before reopening, especially in the first two weeks. Moreover, the pre-reopening MSPE in Lanzhou is 0.003, and the average MSPE of the other 11 cities before reopening is also 0.003, which is quite small. Together, the synthetic control method can well adapt to the increase of new cases in Lanzhou and 11 other cities prior to reopening. Figure 4 (top) shows that the effect in Lanzhou remained at zero for a week after reopening, while on average, four cities have trajectories above the zero-gap line during this period. Based on the 11 control cities included in the figure, the probability of estimating a gap of the magnitude of the gap for Lanzhou under a random permutation of the intervention in our data is 33.3%. Thus, reopening the economy did not significantly increase viral transmission in Lanzhou.

As Figure 4 (middle) indicates, the synthetic control method provides an excellent fit for the increase of new cases in Shenyang in the two weeks before reopening. The pre-reopening MSPE in Shenyang is about 0.006. The average MSPE of the other 13 cities before reopening is around 0.003, which suggests that the synthetic control method is well adapted to the increase of new COVID-19 cases in the other 13 cities before reopening. Figure 4 (middle) displays that the effect in Shenyang has been zero for the week after reopening the economy and that on average 2 cities have trajectories above the zero-gap line. Because this figure includes 13 control cities, the probability of estimating a gap of the same size as that of Lanzhou is 14.3%. Therefore, reactivation did not contribute significantly to the increase in new COVID-19 cases in Shenyang.

Figure 4 (bottom) shows the excellent fit of the synthetic control method to the pre-reopening COVID-19 transmission in Guiyang. The pre-reopening MSPE in Guiyang is approximately 0.4. The average MSPE of the other 14 cities before reopening is about 0.001, suggesting that the synthetic control method can provide a good fit for the spread of COVID-19 in the other 14 cities before reopening. Figure 4 (bottom) displays that on average 14 cities had trajectories above the zero-gap line during the week after reopening, while the effect in Guiyang was consistently zero. Based on the 14 control cities included in the figure, the estimated probability of having a gap of the same magnitude as that of Lanzhou is 93.3%, indicating that there was no significant increase in new cases in Guiyang after reopening the economy.

To avoid artificially choosing a cut-off point to exclude ill-fitting placebo runs, we further evaluated the target city gap relative to the gaps obtained from the placebo runs by looking at the distribution of the ratio of the post/pre-reopening MSPE. Figure 5 displays the distribution of the post/pre-reopening ratios of the MSPE for the target cities and all 14 control cities. The ratios for Lanzhou, Shenyang, and Guiyang are all zero and do not stand out significantly in the figure. This indicates that reopening the economy did not significantly affect the COVID-19 transmission in these three cities. Further, only one control city reaches the same ratio as Lanzhou and Shenyang, respectively, while three control cities achieve the same ratio as Guiyang, which reopened relatively late. This

suggests that more cities are beginning to qualify for reopening their economies over time, which is consistent with the reality that more cities in China reopened after 23 February.
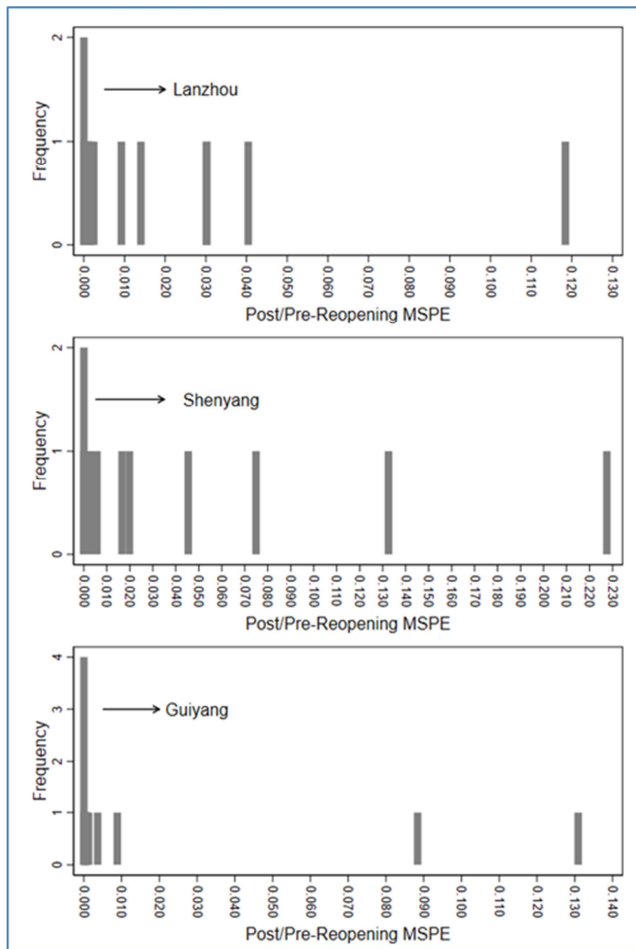

Figure 5. *Ratios of post/pre-reopening MSPE: target cities and 14 control cities.*

6. Conclusion and Policy Implications

In response to the rapidly spreading COVID-19 pandemic, governments around the world have adopted strict lockdown measures. However, it is crucial to clarify the causal impact of reopening the economy on the transmission of the virus due to the negative effects on the economy and society at large. Based on the data of daily confirmed COVID-19 cases in all 31 provincial capitals on the Chinese mainland, this study is the first to provide causal interpretations for the impact of reopening the economy of Lanzhou, Shenyang, and Guiyang on the increase in their COVID-19 infection cases, respectively, using the synthetic control method. The results show that all three capital cities have achieved zero growth in their newly confirmed cases for several consecutive days before reopening. None of the three cities showed a significant increase in new cases in the week after reopening.

Useful policy implications can be drawn from the empirical results of this paper. First, from a public health perspective, the continuous zero growth in the number of new cases in the

target cities of this study before reopening marks the effective control of the epidemic spread. Therefore, the overall stability of the epidemic situation should be a necessary condition for safely reopening the economy. It is useful to note that zero growth is based on sufficient testing for the virus rather than the result of underreporting or insufficient testing. Otherwise, people could choose to work remotely, self-quarantine, and remain cautious due to health concerns. This would have limited the ability to reopen the economy. Second, from an economic reactivation perspective, the successive downgrades of the emergency response level to COVID-19 in various provinces reflects the need to improve differentiated prevention and control strategies in reopening the economy in an orderly manner according to different regional conditions. To achieve this, local governments should, on the one hand, understand variations in local health sector readiness relative to the spread of the virus and on the other hand, understand economic specialization and local labor market dynamics in order to maximize the impact of reactivation on economic output and employment while minimizing the further spread of the virus. Finally, from a supporting safeguards perspective, the downgrade of the emergency response level only indicates a reduction in the intensity of prevention and control measures and changes in their implementation methods rather than the lifting of the alert. As the spread of COVID-19 still constitutes a public health emergency prescribed by law, some supporting safeguards such as body temperature checks in public areas, continued wearing masks in crowded places, holding meetings of up to 500 persons, and opening entertainment venues (including scenic spots, gyms, libraries, and museums) at up to 50 percent of their maximum visitation capacities will continue to be enforced. Only by reopening under supporting safeguards and establishing an economic and social order in the context of epidemic control can a rebound be prevented during the resumption of economic activities.

Notice that even though previous studies have confirmed that the official statistics on the number of confirmed cases were mostly accurate [7, 24], the robustness of the reopening effect to disproportionately systematic misreporting remains a useful subject for future research. Further, this paper shows that reopening the economy does not have a significant adverse effect on COVID-19 transmission in the short term (one-week period), provided that the downgrade criteria are met and the appropriate safeguards continue to be implemented after the downgrade. However, due to the limited time window of the sample data, it is not possible to definitively determine the long-term impact of reopening the economy on the spread of the virus. According to data from the Chinese Center for Disease Control and Prevention, as of March 25, 23 provinces have reported imported confirmed cases. As of June 14, 39 new domestic cases on the Chinese mainland had been reported, including 36 cases in Beijing and 3 cases in Hebei. Due to the hidden nature of the virus, the inevitable increase in human contacts and activities, as well as international trade as the economy restarts, coupled with the consequent decline in people's compliance with safeguards, more research is needed in the future to determine how to

prevent inbound cases and domestic resurgence while recovering the economy.

Conflicts of Competing Interests

The author declares no conflicts of interest regarding the publication of this paper.

Acknowledgements

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