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Does Our Collective Stringency Control the Virus? Investigating Lockdown Effectiveness on Community Mobility Data

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Abstract—Facing the global crisis brought by COVID-19, many countries have adopted social distancing or stay-at-home measures to restrict individual mobility to control the virus. Meanwhile, the availability of anonymized and aggregated mobility data provides an opportunity to obtain a deeper understanding of the impact of these measures. In this paper, we utilize an open mobility dataset called Community Mobility Report published by Google on the Internet and other external data sources (e.g., statistics on daily confirmed cases, demographics, etc.) to quantitatively characterize people’s collective responses and model it with a proposed metric called Lockdown Stringency Score (LSS) after the lockdown measures have been taken. Then, by investigating the correlations between LSS and the increase of new confirmed cases across different regions and countries in the world, we explore how people’s collective response in terms of mobility pattern changes affects the control of the virus. The analysis results show that lockdown and social distancing measures do have a positive impact on virus control, and the restriction on different types of Point-of-Interests (PoIs) has different weights (significance) in terms of virus control effectiveness. These results reveal important insights and implication on public health policy making, such as the phased start of the lockdown or reopen of the economy.

Index Terms—COVID-19, lockdown, effectiveness, mobility data

I. INTRODUCTION

The whole world is facing the crisis brought by COVID-19. To contain and mitigate the COVID-19 epidemic, social distancing or stay-at-home measures have been adopted by many countries to restrict individual mobility. Meanwhile, the availability of anonymized and aggregated mobility data on the Web has been recognized as an opportunity to obtain a deeper understanding of the impact of these measures. For instance, human mobility behaviors and system usage collected from mobile phones and transportation systems will play a key role to understand COVID-19 transmission patterns, the impacts of disruptions to our social and economic activities, and recovery from those disruptions.

With these opportunities in mind, this paper specifically focuses on how to quantitatively measure people’s reaction to the pandemic, and how people’s collective responses eventually affect the spread of the virus. Specifically, we focus on the following two research questions (RQ).

(1) **RQ1:** *How to understand and quantify people’s responses based on crowd-sensed mobility data?* Geo-location data from different platforms and regions during the COVID-19 outbreak can be used to understand people’s compliance behavior. However, we are not clear how to build reasonable metrics and to qualify people’s mobility pattern changes.

(2) **RQ2:** *How people’s collective response in terms of mobility pattern changes affect the spread of the virus?* Here, the challenge is that we need to eliminate the effect of other relevant factors, such as the number of infectious people before lockdown and population density.

In this work, we aim to address the above two research questions based on the datasets from Google Community Mobility Reports, which are open to the public on the Web to combat COVID-19. Each Community Mobility Report is broken down by location and displays the change in visits to places like grocery stores and parks. In addition to the Google mobility datasets, we also utilize other open geographical and demographic data sources to assist the data analysis in this study.

To answer RQ1, we characterize mobility pattern to reflect the activity level in different PoIs, such as retailer, hotel, park, entertainment, etc, and then proposed an index named LSS to represent the degree to which citizens obey the mobility restriction policies regulated by governments. To answer RQ2, we adopt a Propensity Score Matching (PSM) based method to study the correlations between LSS and the virus control effectiveness across different regions or countries, while eliminating the co-funding factors such as population, population density, and infected population on the lockdown date.

The analysis results show that: (1) Overall, lockdown and social distancing measures do have a positive impact on virus control. The more significantly people reduce their mobility, the more effective it would be for the virus control. (2) The restriction on different types of PoIs has different weights (significance) in terms of virus control effectiveness. These results reveal important insights and implications on public health policy making, such as the phased start of the lockdown or reopen of the economy.

The contributions of this paper are summarized as follows:

1) We characterize mobility pattern change in different types of PoIs, and then integrate them into an index named LSS to represent the degree to which citizens obey the mobility

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restriction policies regulated by governments. To enable this integration, the weight of each type of PoI is learned by the Criteria Importance Through Intercriteria Correlation (CRITIC) method and validated by the Analytic Hierarchy Process (AHP) method. (Section III)

2) In order to study the correlations between people’s collective response in mobility restriction and the virus control effectiveness, we adopt the PSM based method to quantitatively study the difference among various regions or countries, while eliminating the co-funding factors such as population, population density, and infected population on lockdown date. (Section IV.A)

3) The results reveal important findings on the effect of people’s mobility reducing the control of the virus, not only in terms of the overall picture but also from the perspective types of PoI. We also discuss the possible implications of these findings for public health policy shaping. (Section IV.B, IV.C)

The rest of the paper is structured as follows. Section II gives a brief description of the datasets we used in this work. Section III presents the modeling of people’s mobility pattern changes with developed metrics. Section IV gives the correlation analysis to investigate how people’s responses affect the virus control, and summarize the findings and discuss the implications. Section V presents the related works. The paper then discusses its limitation in Section VI and concludes with Section VII.

II. DATASETS AND PRE-PROCESSING

In this paper, we have explored various types of datasets to achieve our data analytic goal, including population mobility data, data about the time of lockdown, number of confirmed cases, and population density in different regions.

A. Original Datasets Description

1) *Population Mobility Data*: Since March 2020, countries around the world have begun to implement lockdown policies. To assess the implementation of lockdown measures in each country, we adopt the mobility data, which is sourced from COVID-19 Community Mobility Reports published by Google¹. It records the proportion of people moving in public places including parks, supermarkets, schools and some other places relative to the baseline, after the outbreak of COVID-19. We suppose the degree to which lockdown measures are implemented can be reflected by the mobility of the population in public places.

2) *Lockdown Dates*: In the study, lockdown dates are set as a boundary in the comparison of population movement rates and confirmed case growth rates. The COVID-19 lockdown dates for each country were acquired by going through each country that had at least 1 confirmed case and organized by Kaggle website².

3) *Daily Confirmed Cases of COVID-19*: The total number of confirmed COVID-19 cases for each country and some specific regions within countries were sourced from the COVID-19 situation reports made publicly available by the WHO³. The current data includes confirmed cases in the sample regions between 10 days before and 30 days after lockdown dates.

4) *Population and Population Density*: Some confounding factors affecting the rate of case growth need to be excluded in order to study lockdown policy’s effect. Here we take some important confounding factors into consideration, including the case base (number of confirmed cases on lockdown date), the population and the population density of the region. The case base is obtained from the datasets mentioned above. The population and its density (population per square kilometer) by country in 2020 are sourced from the world population review website⁴.

B. Data Pre-Processing and Linkage

137 regions worldwide are selected as samples, including 93 countries in the world and 44 states in the United States, based on the following selection principles to study people’s response to lockdown policy and the correlation between lockdown stringency and epidemic control. First, the sample region requires to contain all the indicators described above, like lockdown dates and population density, etc. Moreover, the sample sets can cover various continents, cultures, and include developing and developed countries as well, therefore, we could study the impact of lockdown policy under different social and cultural backgrounds. The sample regions are marked in Fig. 1.

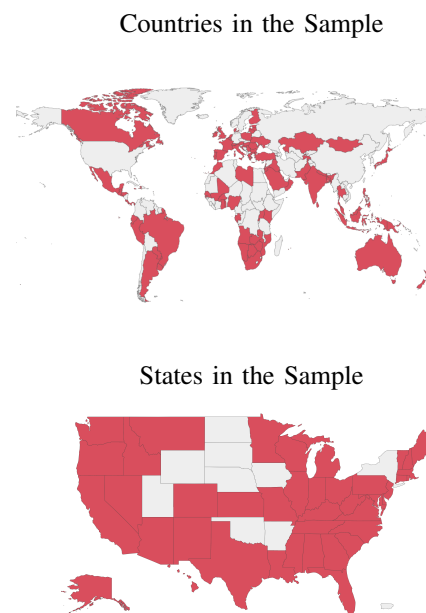


Fig. 1. Sampled Regions in This Study (44 states in the USA and 93 countries in the world)

¹Data source: <https://www.google.com/covid19/mobility/>

²Data source: <https://www.kaggle.com/jcyzag/covid19-lockdown-dates-by-country>

³Data source: <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports>

⁴Data source: <https://worldpopulationreview.com/countries>

III. MODELING LOCKDOWN STRINGENCY

Based on the datasets described above, we will first present a descriptive analysis to show some findings on how people’s mobility pattern changes after the lockdown and social distancing measures have been taken. Then, we formally define the LSS to characterize people’s collective responses based on their reduction of mobility.

A. Descriptive Analysis and Findings

According to the Google Mobility Report, we use mobility indicators to represent the people’s mobility, which shows the trend of people flows in different places based on the average level of last year. The six sub-indicators are retail and recreation, grocery and pharmacy, workplace, transportation stations, park and residence respectively. Based on our dataset, we confirm the specific lockdown date for each sample. For each sample, we calculate the average value of the mobility of six indicators 30 days before and 30 days after lockdown to represent the general situation of people’s mobility before and after lockdown. The difference between the two averages represents the change in the flow of people in the sample area after lockdown. In the process of data visualization, we found that most of the samples showed similar trends (the examples are shown in Fig. 2). The vertical axis represents the percentage change in mobility based on the baseline, and the dividing line in the middle of the chart indicates the date for lockdown in the region. We summarize it into the following four patterns with speculations.

- After the lockdown was implemented, the number of people at home gradually exceeded the baseline, and the flow of people in public places was significantly lower than the baseline. Speculation: Most people have a high degree of compliance with lockdown. Choose to isolate yourself at home.
- People in pharmacies and supermarkets show a brief increase before lockdown until reaches a small peak, and then gradually decreases. Speculation: Panic over the epidemic has led to a rush to buy medical and daily supplies.
- People in the park fluctuates in a jagged pattern before and after lockdown. Most areas are lower than the normal level after lockdown. Speculation: The jagged peaks almost always occur on weekends, and people’s tolerance for lockdown declines.
- People in recreation facilities, traffic stations, and workplaces have shown a marked decline before lockdown. Speculation: Some people have increased awareness of COVID-19 prevention, and intentionally reduced going out to public places.

B. LSS Architecture

LSS is defined to quantitatively measure how people reduce their mobility after the lockdown measure has been taken. It is defined as the weighted sum of absolute value change across different types of PoIs. However, the challenge here is

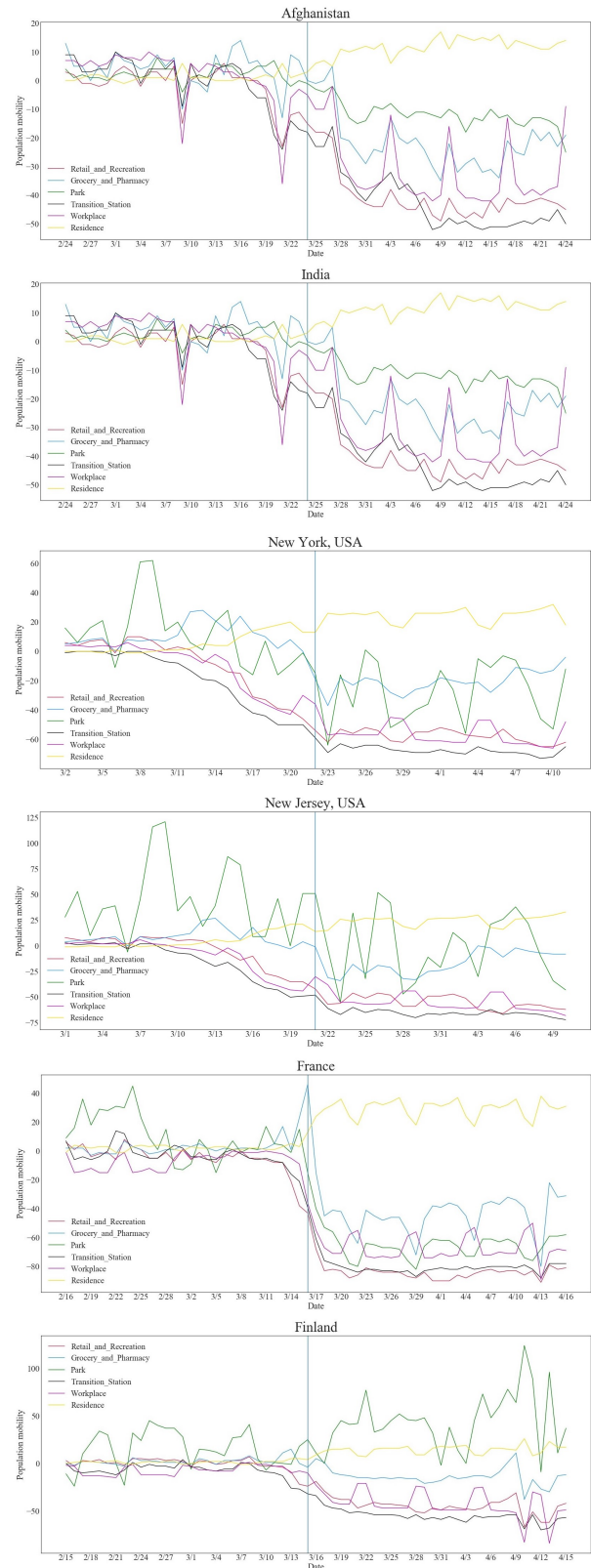


Fig. 2. Samples from Asia, USA and Europe

how to determine the weights. In this subsection, we will first

leverage CRITIC Based Learning to generate the weight we are supposed to use and then validate the results using AHP Based Evaluation.

1) *CRITIC Based Weight Learning*: As mentioned before, we leveraged six sub-indicators, such as workplace and transportation stations, to represent people's travel conditions. We then assigned the weight to each indicator so that we can produce the LSS to estimate the overall situations for people in different areas.

CRITIC method is an objective weighting method proposed by Diakoulaki et al. in 1995. It is used to overcome the doubt that subjective weighting may lead to unreliable results (6). In the weighting process, the method includes both the standard deviation of the criterion and the correlation between other criteria and uses the product of the contrast intensity within the evaluation indicator and the conflict between the indicators to determine the weight of each indicator (21). The objective weight can be determined by the CRITIC method as (10)

$$C_j = \sigma_j \sum_{k=1}^n (1 - r_{jk}), j = 1, 2, \dots, n \quad (1)$$

where σ_j denotes the standard deviation of the j 'th criterion and r_{jk} as the correlation coefficient between the j 'th and k 'th criteria.

Then, each objective weight can be normalized as

$$W_j = C_j / \sum_{k=1}^m C_k \quad (2)$$

Consequently, take the weighted sum of each data, then we get the final LSS samples.

After obtaining the weights and values, the weighted sum of each indicator is calculated, then the absolute value of this variable is denoted as LSS.

$$LSS = |W_1 * x_1 + W_2 * x_2 + \dots + W_n * x_n| \quad (3)$$

where x denotes the sub-indicators. The larger the LSS is for a certain region, the more disciplined and strictly people restrict their mobility.

2) *AHP Based Weight Evaluation*: To ensure the weight is appropriate to decision-makers' experience, we leverage a popular subjective weighting method to test the validity of the CRITIC method.

AHP method is a practical multi-objective decision-making method proposed by T. L. Saaty in the 1970s. It is a decision analysis method with quantitative analysis.

According to the result of the CRITIC method, we first come out with the rank of each indicator. We then construct the judgment matrix on the basis of the fundamental scale, which denotes the relative importance of two indicators (16). The fundamental scale is shown in TABLE I.

The judgment matrix can be represented as

$$\begin{matrix} & A_1 & A_2 & \dots & A_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \dots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} \end{matrix}$$

where A_n denotes the n 'th indicator and w_1/w_2 denotes the value according to the fundamental scale. Then calculate the eigenvector $W = (W_1, W_2, \dots, W_n)^T$, which is also the vector of weights.

To test the weights' validity, we do the consistency check. Firstly, we come out the eigenvalue λ , then the Consistency Index (CI) can be denoted as

$$CI = (\lambda - n)/(n - 1) \quad (4)$$

where n denotes the number of indicators. In order to measure the size of CI, the Random Consistency Index (RI) is introduced in TABLE II.

TABLE II
THE DISTRIBUTION OF RI

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Then the Consistency Ratio (CR) can be represented as:

$$CR = CI/RI \quad (5)$$

Generally speaking, when the consistency ratio $CR < 0.1$, it is considered that the degree of inconsistency of A is within the permissible range and passes the consistency check. By doing this, we figured out that the LSS weighting made by the CRITIC method is reasonable, since the $CR = 0.09$.

IV. LOCKDOWN EFFECT ANALYSIS

After the LSS is defined in Section III to represent how people obey the lockdown policies, we will then investigate how this index affects the virus control in different regions or countries worldwide in this section. We will first introduce the approach for this analytic and then show the results, findings, and implications.

TABLE I
THE FUNDAMENTAL SCALE

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement strongly favor one activity over another
5	Essential or strong importance	Experience and judgement strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgements	When compromise is needed

A. Analysis Approach

A correlation test has to be conducted to examine the correlation between LSS and the effectiveness of epidemic control. Here, the technical challenge is that there are many other confounding factors, such as, active cases(active cases on the exact date of lockdown), population density, gross population, which also affect the control effect. Therefore, we need to adopt an appropriate approach to eliminate their disturbance in this process. To tackle this challenge, the PSM based process is first employed to exclude confounding factors, and then the Independent-sample T test is executed to test the correlation between LSS and the epidemic control effectiveness.

1) *PSM Based Approach*: In the statistical analysis of observational data, PSM is a statistical matching technique that attempts to estimate the effect of a treatment, policy, or other intervention by accounting for the covariates that predict receiving the treatment. PSM attempts to reduce the bias due to confounding variables. In this paper, this method is used to exclude other factors that may also have an impact on the spread of the virus (i.e., confounding variables). In our work, three attributes are set as confounding variables, namely the cardinal number of active cases, population density, gross population.

First, samples are divided into high and low LSS score groups respectively, representing the experimental group and the control group by the score from Section III. The independent variable is the LSS score and the dependent variable is the control effect, which is defined as the increase in the number of confirmed cases on the 20th to 30th days after the lockdown. Then the high groups are matched with the low groups. The point of matching is to find two regions with similar confounding factors from the regions with high and low grouping respectively to become a new set of data. Since it is difficult to select two groups of samples that are consistent in many covariates, it is necessary to convert many covariates into one score, which is called the Propensity Score (PS). The Logistic regression model is usually used to estimate the probability of the sample being in the experimental group and the predictive probability calculated by its PS (15).

When the Logistic regression model is used, the value range of data is a set of real numbers. However, in the problem we studied, the values of dependent variables are probabilities, which range from 0 to 1. Therefore, the values of the dependent variables need to be Logit transformed first, denoted as $\text{logit}(P)$. Suppose that the probability of the event is P , and the probability of non-occurrence is $1 - P$, then the Logit transformation is:

$$\text{logit}(P) = \ln\left(\frac{P}{1-P}\right) \quad (6)$$

If dependent variable has j influencing factors: x_1, x_2, \dots, x_j , the Logistic regression model constructed by the conditional probability P is:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_j x_j \quad (7)$$

where j represents the change amount of $\text{logit}(P)$ when the independent variable x_j changes a unit, which can be understood as the weight coefficient of each influencing factor (23).

We can get the probability by transforming formula (6):

$$P = \frac{1}{1 + e^{-(\beta_0 + \sum_{k=1}^j \beta_k x_k)}} \quad (8)$$

Then the PS of each sample can be obtained, and two groups are ranked according to the size of the propensity score. One object is selected from the experimental group in turn, and one object whose propensity score is most similar to the experimental group is found from the control group as the matching individuals. If there are two or more individuals in the control group with the same difference of propensity score, the selection will be carried out by random. The matched objects are removed from the source data, and then the matching process of the next processed object is carried out until all the matched objects in the experimental group are matched (9). In the matching, the matching accuracy, that is the difference value of propensity score is set less than 0.02. Note that not all samples will be remained since it could be impossible to match for some standalone sample points.

2) *Correlation Significance Testing*: After propensity score matching, we excluded the unmatched regions and used the Levene's Test and Independent-sample T test to determine the correlation (1; 4).

Levene's Test is employed to examine the homogeneity of the variances, which is regarded as a fundamental prerequisite of the T test. The variances will be assumed equal if the significance of Levene's Test is greater than 0.05, then the T test can be applied (4). According to the T test, the t score is calculated by

$$S^2 = ((n_1 - 1)S_1^2 + (n_2 - 1)S_2^2)/(n_1 + n_2 - 1) \quad (9)$$

$$t = (\bar{X}_1 - \bar{X}_2)/\sqrt{S^2(1/n_1 + 1/n_2)} \quad (10)$$

where n_1, n_2 denotes sample capacity of two groups, S_1^2, S_2^2 represents population variances, and \bar{X}_1, \bar{X}_2 the sample average.

Otherwise, equal variances are not assumed, and a corrected result will be adopted. We use the Satterthwaite approximate T test to correct the result, which was obtained by correcting the degrees of freedom. The degrees of freedom is the number of samples, and the number of samples v after correction is:

$$v = \frac{(S_1^2/n_1 + S_2^2/n_2)^2}{\frac{(S_1^2/n_1)^2}{n_1-1} + \frac{(S_2^2/n_2)^2}{n_2-1}} \quad (11)$$

If the significance probability of the two-tailed T test is greater than 0.05, then it proved that there is no significant difference between the two variables. Otherwise, they have significant differences (1).

Ultimately, several scatter charts are sketched with remained samples in order to observe the overall trend intuitively, where LSS are independent variables, and the variation of epidemic increment is regarded as an induced variable.

B. Analysis Results

This section analyzes the results of correlation through data visualization, following with T test to do the quantity analysis. The exclusion of confounding factors is explained as well.

1) *Descriptive Analysis:* According to the PSM-based approach in Section IV.A, we screened out 98 samples, with 49 in each group. To visualize the correlation, the figure of LSS and epidemic control effectiveness for all selected regions are sketched, shown in Fig. 3. The reason for the ratio is that firstly, other factors, such as the total number of people, population density, and base cases, will influence the difference between the 20th and 30th days and it will lead to false results when looking at the positive or negative correlation of the whole. Secondly, the number of confirmed patients on the 30th day increased based on the base cases, which was also affected by the total population and population density. Therefore, although the influence of confounding factors on the results could not be completely excluded by dividing the number of patients diagnosed on the 30th day, it is the most effective method to exclude confounding factors among the existing ways. It can be clearly seen that the ratio of the difference of confirmed cases between the 20th and 30th days gradually decreases with the increase of LSS after excluding a part of the influence of the confounding factors.

Furthermore, the samples of similar regions were divided into six classes according to the value of PS. The samples with adjacent PS value means their confounding factors are similar. Therefore, we could observe the correlation among similar regions without the influence of confounding factors. Then the plots of each group are sketched with y as the control effect, and x as the LSS score. In the results, the correlation tends to be negative according to Fig. 4.

2) *Results of Significance Testing:* Except for the correlation as seen from the figures, the variation of epidemic increment among these samples is examined based on the Independent-sample T test in terms of the two groups. The results are illustrated in TABLE III. The value of *sig.* in Levene's Test is 0.149, higher than 0.05, which indicates the variance of samples is homogeneous and the T test can be employed directly. And the two-tailed value in the T test is 0.030, less than 0.05, which suggests that there is a significant correlation between the LSS and epidemic control.

Similarly, the weights of each type of PoI are analyzed, illustrated in TABLE V to TABLE X, which represent the influence of posing restrictions on different sectors. For each LSS component, the specific two-tail value is highlighted in the table, according to Levene's Test and T Test, explained in Section IV.A. The factor of retailer and recreation facilities

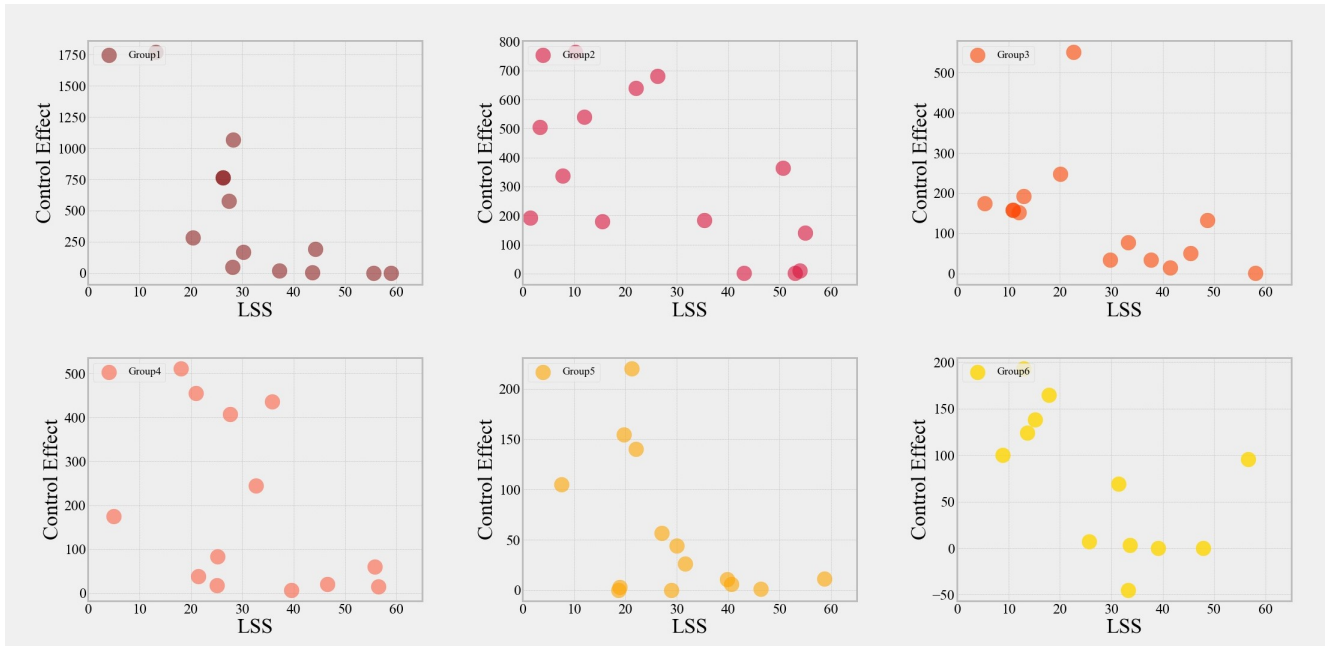


Fig. 3. Correlation between LSS and Variation of Epidemic Increment in Six Classes of Regions. Dependent variable is control effect which is defined as the increase in the number of confirmed cases on the 20th to 30th days after the lockdown and independent variable is LSS score.

TABLE III
THE INDEPENDENT SAMPLES T TEST RESULT OF THE VARIATION OF EPIDEMIC INCREMENT

		Levene's Test		T Test		
		F	sig.	df	t	two tail
Increase Rate	Equal variances assumed	15.747	0.149	96	-2.209	0.030
	Equal variances not assumed			49.839	-2.209	0.032

TABLE IV
THE INDEPENDENT SAMPLES T TEST RESULT OF CONFOUNDING FACTORS

		Levene's Test		T Test		
		F	sig.	df	t	two tail
Population	Equal variances assumed	0.404	0.527	94	-0.358	0.721
	Equal variances not assumed			89.587	-0.358	0.722
Population Density	Equal variances assumed	0.361	0.549	94	0.157	0.876
	Equal variances not assumed			92.972	0.157	0.876
InfectedPop on lockdown	Equal variances assumed	4.395	0.039	94	-1.078	0.284
	Equal variances not assumed			78.402	-1.078	0.284

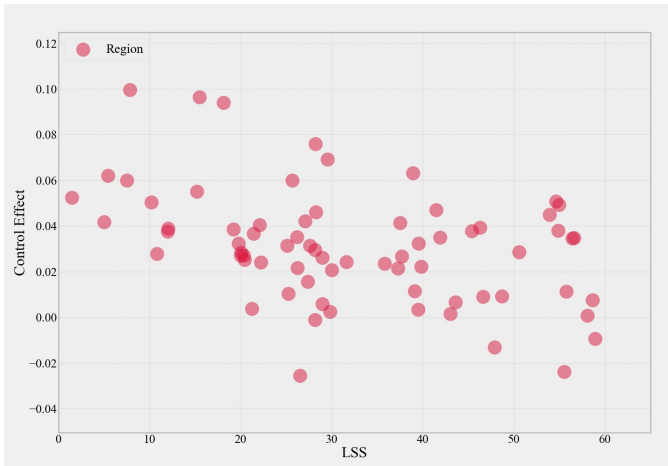


Fig. 4. Correlation between LSS and Rate of Epidemic Increment According to Regions Worldwide. Dependent variable is the ratio of control effect to the number of people diagnosed on the 30th day and independent variable is LSS score.

draw a weight of 0.107, which makes the factor the most influential, followed by station and workforce (0.117 and 0.118), respectively. These results are all greater than 0.05, showing no significant relationship. It is because the calculated results by only counting the influence of a single sector and ignoring the influence of other sectors will not obviously be correlated. However, these two-tail can reflect the degree of irrelevance. Therefore we analyze the effect in terms of the magnitude of the value of two-tail, the larger the value of two-tail, the smaller the correlation is. By contrast, parks with the two tail at 0.571 have a minimal impact among others on epidemic control. The results show that the lockdown of places where people tend to gather and the air mobility is poor has a significant impact on epidemic prevention and control, while that of outdoor place or sparsely populated place is less significant.

3) *Effectiveness on Exclusion of Confounding factors:* Finally, in order to evaluate whether the confounding factors are eliminated, the Independent-sample T test is also employed on these three attributes (population, population density, and active cases on the lockdown date). The significant two-tail values of them are about 0.721, 0.876, and 0.284, respectively, shown in TABLE IV, which are greater than 0.05. This indicates that these confounding factors are unrelated to the

growth of confirmed cases after grouping and PSM method (11). Then the quantitative analysis on lockdown impact could be done effectively without the interference of the confounding factors.

C. Findings and Implications

After collecting the results of correlation tests stated in Section IV.B, several corresponding aspects are analyzed. Related statistics are based on different perspectives of social lives, such as social distancing and regional culture.

1) *The Overall Effectiveness of Social Distancing:* According to the results in our experiments, we have found that the development of the epidemic slows down significantly with more strict social distancing and lockdown measures by international comparison. This finding shows that social distancing and mobility restriction play a crucial role in epidemic control, and the government should pose these measures as early as possible to contain the virus and save more lives.

2) *Effectiveness of Restricting Different Sectors:* The weights of each type of PoI we obtained have important implications for public health policy shaping. First, entertainment facilities should be closed as early as possible during the epidemic period. And the administrative departments should strengthen supervision and inspection, and immediately order rectification if violating the lockdown measures. Retail stores are also prone to cause cluster infections, but given the need to provide necessities and food to the public during the epidemic, limiting the number of people entering the stores and wearing face masks are important to reduce the risk of the epidemic spreading. Second, the results suggest that the lockdown effect of the park is less significant, so the park and other ventilation areas can be the first to reopen. These places give citizens opportunities to do outdoor activities and relieve pressure, which is beneficial for people's physical and mental health, therefore, it is reasonable to open parks before the entertainment facilities like bars, movie theatres, etc.

V. RELATED WORK

A. Lockdown Analysis

Previous studies have shown a strong link between the spread of infectious diseases and human mobility, whether it is long air travel or a short commute (13). Lockdown policies effectively alleviate the spread of the epidemic and were also indicated in the literature related to the impact of lockdown on the development of the epidemic. Stringent

control measures in China have significantly reduced the local spread of COVID-19 (7). In Wuhan, after the lockdown, the doubling time of confirmed cases was significantly increased from 2 days to 4 days, and the rate of case growth was significantly reduced (8). The Malaysian Government has also moved swiftly to take public health action. They stipulate that all universities and non-essential departments have been closed, and Interstate travel is not allowed unless there is a valid reason. Only householders can buy groceries within a 10-kilometer radius. The secondary transmission and increase in cases have been prevented through these strict lockdown policies, tracing and quarantining contacts (17). Web scraping technology was used to abstract data from diverse websites to identify the possible spread rate of the epidemic from some Indian states. when predicted and evaluated the recent and prospective transmission of COVID-19, researchers compared diverse epidemiological models such as SIER. The relationship between “effective reproductive number”, R, and the lockdown was obtained. The R-value in thickly populated areas has a higher peak. Its curve may flatten due to lockdown and rose rapidly after the blockade was discursive (14). The lockdown policies in different cities around the world also brought a new tendency to reduce crime which can improve public safety. It can be seen from the daily crime reports of the crucial cities in the United States and Europe, by adopting different methods to assess the change of the crime, that Oakland and San Francisco for each cities’ community crime categories fell by about forty percent and traffic accidents, killing, and theft also fell keenly (18). As a result of the global implementation of social isolation measures, some people experienced serious psychological effects associated with life changes. Certain reports showed the extent to which people suffered loneliness, disappointment, and cognitive impairment during COVID-19 related environmental varies. The results revealed that introversion would forecast more serious anxiety. When probing demographic factors, the study found that living with others predicted more grievous psychological health symptoms than living alone (22). It urges us as well to find better lockdown measures to reduce the damage to people’s mental health caused by COVID-19.

Compared to the above studies on the lockdown effec-

tiveness analysis, this paper is different and novel in the following aspects. First, these related work only looked at a specific region or country, while our work is on a global scale and investigates the effectiveness of people’s collective responses after lockdown with an international comparison. Second, different from the above research works, this paper studies the effectiveness of lockdown from the perspective of people’s mobility patterns.

B. Other Factors Affecting the Virus Control

There are also other sets of research focusing on other factors affecting the control of COVID. Data of COVID-19 in the United States have revealed that social, poverty, and ethnicity are relevant to health. African-Americans and Hispanics account for a high proportion share of infections and deaths. Meanwhile, the likelihood that a woman will die of COVID-19 is less than men, because biological and social dynamics suggest that male traits, such as risk-taking, intemperance, and smoking, have different effects on men’s health and women’s. Besides, men had a higher probability of chronic sickness than women that deaths from COVID-19 were specifically related to pre-existing diseases (25). Research works related to our study from the perspective of development differences also show that if population density is the same between cities, there is a linear relationship between the number of latent and infected cases and the population size of the blockaded area (19). Also, until vaccines are widely available, the restricted available means of infection prevention are case-isolated, contact tracing, and physical distance isolation (3). One study used a Stochastic Dynamic Network-Based Compartmental SEIR Model and Individual ABM to predict the impact of widespread mask-wearing on the COVID-19 pandemic. The results showed that when masks were worn by at least 80 percent of people, they had a significant impact on slowing the spread of this disease. In contrast, the effect was minimal when only 50 percent or less wore masks. Besides, after the outbreak of the epidemic, the earlier the implementation of the mask policy, the more valid the impact on the epidemic control (5). Therefore, it is critical to provide decision-makers with information on COVID-19 health management by assessing the expected influence of the

TABLE V
THE INDEPENDENT SAMPLES T TEST RESULT OF THE RETAILER COMPONENT

	Levene’s Test		T Test				
	F	significance	df	t	two tail	lower bound	upper bound
Equal variances assumed	9.303	0.003	112	-1.781	0.078	-1311.648	69.821
Equal variances not assumed			54.050	-1.640	0.107	-1380.060	138.233

TABLE VI
THE INDEPENDENT SAMPLES T TEST RESULT OF THE PARK COMPONENT

	Levene’s Test		T Test				
	F	significance	df	t	two tail	lower bound	upper bound
Equal variances assumed	0.979	0.325	112	-0.600	0.549	-928.526	496.672
Equal variances not assumed			77.001	-0.568	0.571	-972.454	540.600

TABLE VII
THE INDEPENDENT SAMPLES T TEST RESULT OF THE GROCERY COMPONENT

	Levene's Test		T Test				
	<i>F</i>	significance	df	<i>t</i>	two tail	lower bound	upper bound
Equal variances assumed	8.862	0.004	112	-1.466	0.146	-1217.645	182.221
Equal variances not assumed			49.618	-1.263	0.213	-1341.305	305.881

TABLE VIII
THE INDEPENDENT SAMPLES T TEST RESULT OF THE STATION COMPONENT

	Levene's Test		T Test				
	<i>F</i>	significance	df	<i>t</i>	two tail	lower bound	upper bound
Equal variances assumed	8.720	0.004	112	-1.674	0.097	348.310	-1273.354
Equal variances not assumed			56.526	-1.594	0.117	365.942	-1316.141

TABLE IX
THE INDEPENDENT SAMPLES T TEST RESULT OF THE WORKPLACE COMPONENT

	Levene's Test		T Test				
	<i>F</i>	significance	df	<i>t</i>	two tail	lower bound	upper bound
Equal variances assumed	8.875	0.004	112	-1.724	0.087	-1292.971	89.694
Equal variances not assumed			54.191	-1.588	0.118	-1361.190	157.913

TABLE X
THE INDEPENDENT SAMPLES T TEST RESULT OF THE RESIDENTIAL COMPONENT

	Levene's Test		T Test				
	<i>F</i>	significance	df	<i>t</i>	two tail	lower bound	upper bound
Equal variances assumed	7.048	0.009	112	-1.482	0.141	-1208.443	174.429
Equal variances not assumed			63.210	-1.531	0.131	-1191.989	157.975

lockdown and the feasible effectiveness of different policies (2).

The above research works reveal that poverty, the proportion of chronic diseases, population size, population density, mask policy, etc, can all affect disease transmission in one region and they provide directions for us to consider the influence factors on the development of the epidemic. Inspired by this work, we have considered excluding the impact of some co-funding factors such as population, population density, etc, which affect the control effect. Of course, as the open data is limited, we cannot include all the possible factors, but our approach still applies when new data is available.

VI. LIMITATION AND DISCUSSION

In this work, we have demonstrated that lockdown interventions in most countries/regions in the world are clearly successful in reducing the spread of COVID-19 and reducing local transmission, but there are still several limitations to our work. While constructing the LSS index, all possible perspectives of data cannot be included. In this work, three attributes are set as confounding variables, namely the cardinal number of active cases (active cases on the exact date of lockdown), population density, gross population. Except for these three factors, other confounding factors can probably affect the results. For example, culture, religions and races can also draw an impact. Due to data set limitations, we are unable to remove other co-funding factors, but our research

methods were generic. With the development of COVID-19, more samples of the epidemic can be collected. Once the data set is complete, it can be reanalyzed quickly. By using PSM modeling, we have demonstrated the correlation between LSS score and epidemic growth, and it is negatively correlated. Furthermore, we obtained the influence of different mobility indicators on the spread of the epidemic. However, there are still some deficiencies in the PSM-based Approach. During the propensity score matching for propensity matching, a small amount of sample data is incomplete and non-objective grouping, which will lead to certain errors in PSM grouping and fitting data. Consequently, more work needs to be done to determine the precise relationship between lockdown and people's mobility and the spread of COVID-19.

VII. CONCLUSION

In this paper, we utilized an open mobility dataset called Community Mobility Report published by Google and other external data sources (e.g., statistics on daily confirmed cases, demographics, etc.) to quantitatively model people's collective responses after the lockdown measures have been taken, and investigated how people's collective response in terms of mobility pattern changes affect the control of the virus. The analysis results have shown that: (1) Overall, lockdown and social distancing measures do have a positive impact on virus control. The more significantly people reduce their mobility, the more effective it would be for the virus control. (2) The

restriction on different types of PoIs has different weights (significance) in terms of virus control effectiveness. These results revealed important insights and implications for public health policy making.

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