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Evaluation of Various Health Interventions to Curb the Spread of COVID-19 in the United States of America

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Abstract

As of July 9, 2020, the cumulative cases of Covid-19 in the US passed 3,055,491, including 132,310 deaths, causing a serious public health crisis. There is an urgent need to curb the spread of Covid-19. In the absence of vaccines and effective medication, non-pharmaceutical interventions are the only option to mitigate the spread of Covid-19. To accurately estimate the potential impact of different non-pharmaceutical measures on containing Covid-19 is crucial for planning the most effective interventions to curb the spread of Covid-19. We applied time series regression models to the surveillance data of lab-confirmed Covid-19 cases in the 10 states of the US up to June 22, 2020 in order to evaluate the contributions of the Google mobility indexes, the rate of the virus test and protest to the number of the new cases of Covid-19. We found that the reason for the well-controlled spread of Covid-19 in NY and CT was more likely due to strong health interventions and reason for the less well-controlled spread of Covid-19 in CA, TX, FL and GA was due to weak health interventions. VT, NH and WV were less affected states.

Keywords: COVID-19; Public Health Interventions; Time Series; Transmission Dynamics; Control of the Spread

Introduction

As of July 9, 2020, the number of laboratory confirmed cases of Covid-19 in the US passed 3,055,491, including 132,310 deaths, causing a serious public health crisis. There is an urgent need to curb the spread of Covid-19 [1]. In the absence of vaccines and effective medication, non-pharmaceutical interventions are the only option to mitigate the spread of Covid-19 [2]. Some studies have shown that moderate interventions could reduce the size of the epidemic, but more intensive intervention measures would be required to curb the spread of Covid-19 [3,4]. To accurately estimate the potential impact of different non-pharmaceutical measures on containing Covid-19 has been crucial for planning the most effective interventions to curb the spread of Covid-19. We applied the time series regression models [5] to the surveillance data of laboratory confirmed Covid-19 cases in 10 states in the US up to June 22, 2020, to evaluate the contributions of the Google mobility indexes, the rate of the virus testing and the number of attendee in protesting to the number of the new cases of Covid-19.

Methods

Consider a time series regression model[2] where

$$y_t = \beta_0 + \beta_1 x_t + e_t$$

and

$$y_t = \beta_0 + \sum_{j=1}^{k} \beta_j x_t^j + e_t$$

where y_t is the number of new cases of Covid-19, x_t and are predictors including six Google mobility indexes, the rate of the virus testing and the number of attendees in the protest, and k=8.

The coefficient of determination, or R^2 between the number of new cases of Covid-19 and the Google mobility indexes, the rate of the virus testing and the number of attendees in the protest is used to measure the proportion of variation in the number of new cases of Covid-19 that is explained by the Google mobility indexes, the rate of the virus testing and the number of attendees in the protest. The simple R^2 is also equal to the square of the correlation between the number of new cases of Covid-19 and the individual intervention factor. The Bartlett's test is used to test for correlation between two time series [6].

Data Collections

Data on the number of confirmed and new cases of Covid-19 in 10 states in the US from March 5, 2020 to June 22, 2020 were obtained from the John Hopkins Coronavirus Resource Center (https://coronavirus.jhu.edu/MAP.HTML).

Results

Five less controlled states (CA, AZ, FL, TX and GA) and five well controlled states (NY, CT, NH, VT and WV) were selected for the analysis. Table 1 summarized individual R^2 of six Google mobility indexes, the rate of testing and the number of attendees in the protest and their total R^2 in 10 states. The P-values for testing their association with the number of new cases were summarized in Table 2. The total R^2 in the 10 states varied from 0.2610 (VT) to 0.9416 (WV). Eight factors explained equal or more than 50% of the variation in the number of new cases in six states: AZ, CA, NY, NH, TX and WV. The top 5 states with the highest R^2 for the rate of virus testing were AZ (0.6579), CA (0.6120), WV(0.5464), TX (0.4254) and NH (0.3788), which was also implied by the association tests (AZ (P-value < 1.04E-08), CA (P-value < 2.0E-16), WV(P-value <0.006), TX (P-value < 1.2E-07), and NH (P-value < 0.003)). The contributions of the Google mobility indexes to the number of new cases substantially varied across the state. The contributions of the Google indexes were the highest in NY, ranging from 0.3787 (transit? what is "transit"?) to 0.5965 (grocery). P-values in Table 2 also showed that the Google mobility index were significantly associated with the number of new cases in NY. All Google mobility indexes in CT were associated with the number of new cases, their R^2 varied from 0.2242 (park) to 0.3356 (transit) and P-values ranged from 0.0027 (park) to 0.0001 (transit). Only one index (park) was associated with CA (P-value < 0.000039), FL (0.0066) and (TX (0.0357), and two indexes (park and transit) were associated with GA with P-values < 0.0123 and P-value < 0.0065, respectively.

State	Total R^2	Retail	Grocery	Parks	Transit	Workplaces	Residential	Test Rate	Attendee
TX	0.4987	0.0072	0.0176	0.0837	0.0007	0.0003	0.0068	0.4254	0.0027
CA	0.7396	0.0485	0.0006	0.1872	0.0122	0.0022	0.0036	0.612	0.0822
AZ	0.7375	0.0016	0.0092	0.014	0.0002	0.0007	0.00008	0.6579	0.0006
FL	0.3334	0.0941	0.0294	0.1386	0.0305	0.0721	0.1054	0.2176	0.0028
GA	0.4653	0.0817	0.0281	0.2341	0.2704	0.0401	0.0995	0.1379	0.0012
NY	0.7197	0.4445	0.5965	0.4083	0.3787	0.4031	0.4873	0.1213	0.0711
CT	0.431	0.2941	0.227	0.2242	0.3356	0.2401	0.3035	0.0015	0.0008
VT	0.261	0.0825	0.0552	0.0002	0.1525	0.1107	0.0793	0.0322	0.0006
NH	0.6015	0.0011	0.0025	0.0127	0.0018	0.00003	0.0006	0.3788	0.0597

Table 1: Total and individual R2 between the number of new cases and the Google mobility indexes, rate of the test and the number of attendees in the protest.

Retail: Retail & recreation, mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

Grocery: Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.

Parks: Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.

Transit: Transit indicates Transit stations, mobility trends for places like public transport hubs such as subway, bus, and train stations.

Workplaces: Mobility trends for places of work.

Residential: Mobility trends for places of residence.

Test Rate: Ratio of the number of individuals who have taken the virus test over the total population in the region.

Attendee: Number of attendees in the protest.

State	Retail	Grocery	Parks	Transit	Workplaces	Residential	Test Rate	Attendee
TX	0.546	0.344	0.0357	0.8549	0.8954	0.558	1.20E-07	0.711
CA	0.0442	0.825	3.94E-05	0.317	0.672	0.586	< 2e-16	0.0082
AZ	0.8232	0.5961	0.5122	0.941	0.8876	0.9595	1.04E-08	0.889
FL	0.027	0.224	0.0066	0.216	0.0543	0.0189	0.0005	0.707
GA	0.157	0.413	0.0123	0.0065	0.326	0.116	0.0617	0.864
NY	1.10E-08	1.30E-12	6.80E-08	2.70E-07	8.70E-08	1.10E-09	0.0074	0.043
CT	0.0004	0.0025	0.0027	0.0001	0.0018	0.0003	0.8198	0.866
VT	0.32	0.4187	0.9608	0.167	0.245	0.33	0.539	0.9344
NH	0.8889	0.828	0.6272	0.8564	0.9808	0.9182	0.003	0.2858
WV	0.478	0.9455	0.5349	0.7834	0.4694	0.6049	0.006	0.5686

Table 2: P-values for testing the significance of Google mobility indexes, test rate and the number of attendees.
Retail: Retail & recreation, mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
Grocery: Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.
Parks: Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
Transit: Transit indicates Transit stations, mobility trends for places like public transport hubs such as subway, bus, and train stations.
Workplaces: Mobility trends for places of work.
Residential: Mobility trends for places of residence.
Test Rate: Ratio of the number of individuals who have taken the virus test over the total population in the region.
Attendee: Number of attendees in the protest.

Discussion

We showed that the rate of testing was associated with most ten states. We found that the spread of Covid-19 in NY and CT being well controlled was due to strong health interventions and the spread of Covid-19 in CA, TX, FL and GA being less controlled was due to weak health interventions. VT, NH and WV were less affected states.

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