Understanding Health Impacts of

COVID-19 Lockdown Policies in Los Angeles Using Traffic Data

<Authors and affiliations go here, we can fill in later>

Keywords:

# **Abstract** (275 words)

Background:

Methods:

Results:

Conclusion:

Research Question:

Contributions:

1. what demographics contributed to the lockdown effect (or should we call it rebound effect?)

Results

A graph of a number of years

Description automatically generated

**OLS Regression Results (racial)**

==============================================================================

Dep. Variable: diffindiff R-squared: 0.039

Model: OLS Adj. R-squared: 0.037

Method: Least Squares F-statistic: 20.37

Date: Tue, 03 Oct 2023 Prob (F-statistic): 5.44e-27

Time: 10:35:59 Log-Likelihood: -21734.

No. Observations: 3484 AIC: 4.348e+04

Df Residuals: 3476 BIC: 4.353e+04

Df Model: 7

Covariance Type: nonrobust

======================================================================================

coef std err t P>|t| [0.025 0.975]

--------------------------------------------------------------------------------------

const 122.7464 22.573 5.438 0.000 78.488 167.005

total -0.0006 0.000 -4.436 0.000 -0.001 -0.000

population density 0.0003 0.000 1.129 0.259 -0.000 0.001

other\_ratio 700.4977 254.213 2.756 0.006 202.076 1198.920

black\_ratio 59.3946 24.709 2.404 0.016 10.950 107.839

asian\_ratio -142.9254 34.100 -4.191 0.000 -209.784 -76.067

hispanic\_ratio -34.3089 20.966 -1.636 0.102 -75.416 6.799

diverse index -13.7445 24.923 -0.551 0.581 -62.610 35.122

==============================================================================

Omnibus: 2409.828 Durbin-Watson: 1.737

Prob(Omnibus): 0.000 Jarque-Bera (JB): 147965.655

Skew: 2.630 Prob(JB): 0.00

Kurtosis: 34.490 Cond. No. 6.74e+06

==============================================================================

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 6.74e+06. This might indicate that there are

strong multicollinearity or other numerical problems.

**OLS Regression Results (employment)**

==============================================================================

Dep. Variable: diffindiff R-squared: 0.064

Model: OLS Adj. R-squared: 0.059

Method: Least Squares F-statistic: 12.45

Date: Tue, 03 Oct 2023 Prob (F-statistic): 4.65e-38

Time: 10:33:37 Log-Likelihood: -21689.

No. Observations: 3484 AIC: 4.342e+04

Df Residuals: 3464 BIC: 4.354e+04

Df Model: 19

Covariance Type: nonrobust

===========================================================================================

coef std err t P>|t| [0.025 0.975]

-------------------------------------------------------------------------------------------

const 3663.3181 1826.077 2.006 0.045 83.022 7243.614

total -0.0005 0.000 -3.998 0.000 -0.001 -0.000

population density -0.0009 0.001 -1.361 0.174 -0.002 0.000

median income (dollars) 0.0005 0.000 2.043 0.041 2.01e-05 0.001

employed\_ratio 365.2724 201.894 1.809 0.071 -30.572 761.116

class\_private\_wage -3095.0745 1786.654 -1.732 0.083 -6598.076 407.926

class\_government -3445.4112 1795.127 -1.919 0.055 -6965.025 74.202

class\_self -3399.7040 1736.683 -1.958 0.050 -6804.730 5.322

industry\_1 -24.9661 957.783 -0.026 0.979 -1902.842 1852.909

industry\_2 -310.5169 281.450 -1.103 0.270 -862.342 241.308

industry\_3 -1469.3149 208.275 -7.055 0.000 -1877.670 -1060.960

industry\_4 -732.8283 383.055 -1.913 0.056 -1483.865 18.209

industry\_5 -1125.3794 244.590 -4.601 0.000 -1604.935 -645.824

industry\_7 -810.0076 200.752 -4.035 0.000 -1203.611 -416.404

industry\_8 -628.5202 268.737 -2.339 0.019 -1155.419 -101.621

industry\_9 -528.1654 223.247 -2.366 0.018 -965.875 -90.456

industry\_10 -989.9575 173.856 -5.694 0.000 -1330.829 -649.086

industry\_11 -730.7084 183.377 -3.985 0.000 -1090.246 -371.171

industry\_12 -78.3412 313.451 -0.250 0.803 -692.909 536.227

industry\_13 -1207.3722 606.550 -1.991 0.047 -2396.604 -18.140

==============================================================================

Omnibus: 2384.439 Durbin-Watson: 1.776

Prob(Omnibus): 0.000 Jarque-Bera (JB): 145997.755

Skew: 2.587 Prob(JB): 0.00

Kurtosis: 34.288 Cond. No. 1.39e+08

==============================================================================

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.39e+08. This might indicate that there are

strong multicollinearity or other numerical problems.

**OLS Regression Results (commuting)**

==============================================================================

Dep. Variable: diffindiff R-squared: 0.047

Model: OLS Adj. R-squared: 0.044

Method: Least Squares F-statistic: 19.00

Date: Tue, 03 Oct 2023 Prob (F-statistic): 2.48e-31

Time: 10:30:57 Log-Likelihood: -21721.

No. Observations: 3484 AIC: 4.346e+04

Df Residuals: 3474 BIC: 4.352e+04

Df Model: 9

Covariance Type: nonrobust

======================================================================================

coef std err t P>|t| [0.025 0.975]

--------------------------------------------------------------------------------------

const 213.8475 38.192 5.599 0.000 138.966 288.730

total -0.0010 0.000 -5.428 0.000 -0.001 -0.001

population density 0.0023 0.001 2.725 0.006 0.001 0.004

commuting\_carpool -570.3224 120.131 -4.747 0.000 -805.857 -334.788

commuting\_public -167.2304 121.253 -1.379 0.168 -404.964 70.503

commuting\_walked -531.2047 120.835 -4.396 0.000 -768.120 -294.289

commuting\_other 439.9463 251.932 1.746 0.081 -54.004 933.897

commuting\_at\_home -127.0368 90.732 -1.400 0.162 -304.930 50.856

commuting\_time -1.1739 1.018 -1.153 0.249 -3.170 0.822

num\_cars 0.0005 0.000 3.232 0.001 0.000 0.001

==============================================================================

Omnibus: 2436.936 Durbin-Watson: 1.753

Prob(Omnibus): 0.000 Jarque-Bera (JB): 158718.608

Skew: 2.658 Prob(JB): 0.00

Kurtosis: 35.636 Cond. No. 8.71e+06

==============================================================================

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 8.71e+06. This might indicate that there are

strong multicollinearity or other numerical problems.

**OLS Regression Results (all)**

==============================================================================

Dep. Variable: diffindiff R-squared: 0.082

Model: OLS Adj. R-squared: 0.073

Method: Least Squares F-statistic: 9.895

Date: Tue, 03 Oct 2023 Prob (F-statistic): 7.80e-45

Time: 10:41:20 Log-Likelihood: -21656.

No. Observations: 3484 AIC: 4.338e+04

Df Residuals: 3452 BIC: 4.357e+04

Df Model: 31

Covariance Type: nonrobust

===========================================================================================

coef std err t P>|t| [0.025 0.975]

-------------------------------------------------------------------------------------------

const 2625.9286 2629.124 0.999 0.318 -2528.867 7780.724

total -0.0003 0.000 -1.221 0.222 -0.001 0.000

median income (dollars) -0.0001 0.000 -0.340 0.734 -0.001 0.001

other\_ratio 368.4428 437.203 0.843 0.399 -488.760 1225.646

black\_ratio 35.6323 77.585 0.459 0.646 -116.485 187.749

asian\_ratio -137.1311 72.567 -1.890 0.059 -279.409 5.147

hispanic\_ratio -272.6420 62.210 -4.383 0.000 -394.614 -150.670

employed\_ratio 1161.7294 281.660 4.125 0.000 609.492 1713.966

population density -0.0010 0.001 -0.811 0.417 -0.003 0.001

commuting\_carpool -707.3058 289.239 -2.445 0.015 -1274.402 -140.210

commuting\_public -729.8335 220.539 -3.309 0.001 -1162.233 -297.434

commuting\_walked 668.0818 229.700 2.908 0.004 217.720 1118.443

commuting\_other 78.9756 411.857 0.192 0.848 -728.532 886.483

commuting\_at\_home -450.2408 288.823 -1.559 0.119 -1016.522 116.041

commuting\_time 3.9710 1.930 2.057 0.040 0.186 7.756

class\_private\_wage -3357.9953 2556.032 -1.314 0.189 -8369.483 1653.493

class\_government -3102.3053 2570.683 -1.207 0.228 -8142.518 1937.907

class\_self -3418.3214 2548.687 -1.341 0.180 -8415.408 1578.765

industry\_1 -702.9704 1055.696 -0.666 0.506 -2772.822 1366.881

industry\_2 649.6064 487.019 1.334 0.182 -305.267 1604.480

industry\_3 326.3278 433.112 0.753 0.451 -522.854 1175.509

industry\_4 -514.3719 509.975 -1.009 0.313 -1514.256 485.512

industry\_5 -543.1379 346.022 -1.570 0.117 -1221.567 135.291

industry\_7 -454.4325 513.963 -0.884 0.377 -1462.136 553.271

industry\_8 -447.2043 464.677 -0.962 0.336 -1358.275 463.866

industry\_9 -161.9984 308.932 -0.524 0.600 -767.705 443.709

industry\_10 -519.1964 355.793 -1.459 0.145 -1216.781 178.389

industry\_11 917.9281 394.185 2.329 0.020 145.069 1690.787

industry\_12 1095.4422 637.227 1.719 0.086 -153.938 2344.822

industry\_13 -1071.3636 777.912 -1.377 0.169 -2596.579 453.851

num\_cars 0.0002 0.000 0.620 0.535 -0.000 0.001

diverse index -152.8498 58.441 -2.615 0.009 -267.433 -38.267

==============================================================================

Omnibus: 2433.254 Durbin-Watson: 1.808

Prob(Omnibus): 0.000 Jarque-Bera (JB): 163295.423

Skew: 2.642 Prob(JB): 0.00

Kurtosis: 36.120 Cond. No. 2.23e+08

==============================================================================

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.23e+08. This might indicate that there are

strong multicollinearity or other numerical problems.

**Highlights** (After the abstract, please include a highlights section that lists **2-4 short bullet-point sentences** summarizing the article’s main takeaway points.)

**Introduction**

During the first year of the outbreak of COVID-19 (March 2020 - January 2021), Los Angeles County (LAC) reported over 800,000 confirmed cases and 12,000 COVID-19-related deaths. LAC issued several policies (6 feet distance, face mask mandates, and the stay-at-home order) to impede the transmission of COVID-19. However, it is unclear how these policies

Different restrictions, orders, and social events took place in LAC during 2020, possibly impacting the transmission of COVID-19. On March XX, the Governor issued the first lockdown order, which remaind effective until XX. Afterward, restaurants and shops gradually reopened during XX. During this time, the likelihood of large gatherings were also influenced by social and political events. For instance, Black Lives Matter supportive movements took place in several regions of LAC, which brought large group gatherings during XX. When the holidays of 2020 approached while businesses were re-opened for a few months, the Governor issued the second stay-at-home order in realizing the increasing number of infections.

<insert sentences here about what is unknown – while the lockdowns anecdotally reduce traffic, population surges were reported in beaches and parks. And even if the lockdown decrease gatherings in some areas and increased gatherings in others, it remains unclear what effect it had on COVID prevalence and incidence. >

In this study, we are particularly interested in how these events and mandates influenced people’s activities and disease transmission. This paper integrates three main components of COVID-19 in LAC: policies and social events, social inter- actions, and disease transmission. Specifically, we want to answer the following questions:

* Were lockdowns effective at reducing population flow in LAC overall?
* Was the lockdown effective at reducing infections and deaths?

Literature Review (Add a paragraph about how mobility is connected to COVID cases)

Since the outbreak of COVID-19, many studies have used different mathematical models to analyze the transmission pattern of COVID-19 (Liu et al., 2020; COVID et al., 2020; Viguerie et al., 2020; Godio et al., 2020; Yang et al., 2020). Liu et al. (2020) suggested a linear integral-differential equation system to express the infections of covid-19 in China considering the lag effect and human mobility. COVID et al. (2020) built a statistical model for forecasting hospital demands and deaths in the US. Viguerie et al. (2020) used a partial differential equations system to formulate a compartment model which might describe spatial dynamics more naturally. Godio et al. (2020) constructed a compartmental model to describe the dynamics of COVID-19 in Italy. Yang et al. (2020) incorporated AI techniques (trained sing 2003 SARS data) into traditional compartmental modeling for predicting new infections.

Among these different models, a compartmental model is commonly used to describe the complex dynamics of disease transmission (Beckley et al., 2013). Modeling COVID-19 using compartmental models usually consists of susceptible (S), exposed (E), infected (I), death (D), and recovered (R). Different studies have made extensions based on this basic setting to make the model more realistic. Godio et al. (2020) considered quarantined population; Li et al. (2020) considered undocumented cases in their study. Nda¨ırou et al. (2020) considered asymptotic and hospitalized population in Wuhan.

Mobility data are widely used in the modeling of COVID-19 as evidence suggests geographic variation in the prevalence level of COVID-19 (Gaskin et al., 2021). Citron et al. (2021); Iyer et al. (2022) used an activity map to estimate probabilities that two people from different counties spend time nearby one another and the time spent over geographical space that help model the geographical interactions during COVID-19. Chang et al. (2021) integrated a mobility network into a simple SEIR model to more accurately fit the real case trajectory.

For a more thorough overview of different mathematical modeling choices for COVID-19, please see Clement et al. (2021); Cao and Liu (2022); Adiga et al. (2020); Rahimi et al. (2021).

**Methods**

Data Sources

To model the COVID-19 dynamics across LAC, we use publicly available COVID-19 data, census data, and traffic data that help incorporate social activities into the model.

### LAC COVID-19 Data

LAC COVID-19 data consists of zipcode-level data: identified cases, deaths, and hospitalizations. This data is publicly available through the website [CITE]. The COVID-19 data contains the cumulative number of cases over the past 14 days, from which we can compute the daily number of cases. Note that COVID-19 data in Pasadena and Long Beach are retrieved from different sources [CITE] as they are not provided by the LAC Department of Public Health because….

### Census Data

We use demographic data from several surveys by US Census Bureau [CITE]. Variables we considered include race, ethnicity, income, employment, population, population density, diversity, commuting ways and time, job industry, job class, and number of vehicles from each region. We were able to match demographics to the 167 associated zip codes. The baseline characteristics of the study population are shown in Table 1.

### Traffic Data

To analyze the impact of COVID-19 on the traffic pattern of Los Angeles County (LAC) during the year 2020, we used highway sensor data from 2019 to 2020 to create a zip code-level traffic flow. The original datasets are downloaded from the California department of transportation performance measure system (CalTrans PeMS) [CITE]. The traffic flow data records the number of vehicles passing by in a 5-minute duration by sensors on the highway. We used the metadata provided by the PeMS website to aggregate the traffic flow to the zip code level. Using this information, we computed the daily average 5-minute traffic flow for each zip code. We found that the PeMS data recorded traffic flow information for 219 zip codes over the XXX period.

To account for social interactivities across different regions within LAC, we develop an origin-destination (OD) model [CITE] that helps us estimate the number of vehicles going from one region to the other daily. This processed data will be used in the compartmental model as a proxy for true social interactivities in LAC.

## Time Intervals

We define four intervals to quantify the health impacts of COVID-19 and policies: pre-lockdown (January 1st - March 17th), lockdown (March 18th - May 16th), re-opening (May 17th - November 19th), and holidays (November 20th - December 31st). LAC had two lockdowns during the year 2020 (lockdown and holidays).

## Health Districts

We study the impact of COVID-19 in LAC on the health district (HD) level, which are defined by the LACDPH. LAC has 26 HDs (primarily for supporting geographic prioritization of the health resources) that can be used to help analyze health impacts on a geographic level. Each HD contains several zip codes without overlapping with other HDs. All data collected in section 2.1 can be aggregated into HD level with zip code as the key.

## Traffic Data Analysis

We statistically compare the traffic pattern between time intervals defined in section 2.2, 2019 and 2020, and different demographic groups. Specifically, we compute the average 5-min traffic flow over different HDs over each interval from 2019 to 2020. Then we perform hypothesis testing (t-test) on these data points between years (same interval, the year 2019 and the year 2020) and between intervals (same year, one interval and consecutive interval after this interval). These quantify the COVID-19 and policy impacts on population flow, considering the seasonal and policy changes.

Moreover, as different demographic groups might have various responding patterns, we perform unpaired t-tests among different demographic groups stratified by the variables from table 1. We create two groups based on each demographic variable’s values (group 1 *<*median of values, and group 2 *≥*median of values) except for income (we instead use $50,000 as the threshold for the division as it is the United States Department of Housing and Urban Development (HUD) low-income level for the single-family in Los Angeles.) We use the percentage decrease of the traffic flow from 2019 to 2020 during the pre-lockdown, lockdown, re-opening, and holidays to indicate the change in traffic patterns.

## Compartmental Model

To capture COVID-19 disease dynamics, we propose using a compartment model of disease where pop- ulations may flow between different groups (Susceptible (S), Exposed (E), Unidentified Infected, Identified Infected (I), Hospitalized (H), Recovered (R), and Dead (D), see figure 1).

### Model Structure

Below is the model schematic of our compartmental model, in which each HD *k* has the following dynamics:

Here each compartment is stratified by HD *k*, we assume all parameters except for are invariant over different HDs. is the rate at which an exposed patient becomes identified infected (unidentified if the subscript is *U*). is the rate at identified infected (unidentified if the subscript is *U*, hospitalized if the subscript is *H*) moves to the recovered group. is the rate at identified infected (unidentified if the subscript is *U)* individuals in the region *j* transmits the disease to a susceptible individual in the region *k*. is the death rate for identified infected individuals (unidentified if the subscript is *U* , hospitalized if the subscript is *H*). is the rate for identified infected becomes hospitalized. is the rate for unidentified infected becomes hospitalized. We assume all parameters are time-varying. We assume *β*(*t*) depends on the traffic flow data. Specifically, , , where , are calibration parameters.

### Origin Destination Estimation

An optimization model is formulated to estimate the number of cars from origin to destination (OD) [CITE]. We minimize the square error from estimated traffic flow compared with the true traffic flow with reasonable assumptions (symmerticity, non-negativity, etc.). We estimate the OD matrix over different time intervals and use it to help us calibrating , .

### Time Intervals for Compartmental Model

To more accurately model the dynamics of COVID-19 transmission through a compartmental model, we modified our selected time intervals defined in section 2.2 to following: lockdown (45 days), social events (45 days), re-opening (45 days), second wave (75 days), and holidays (90 days). We allow all parameters from above to change between each intervals.

### Calibration

Most parameters in our model vary in different literature. Also, not all values are directly observable (e.g., the rate of becoming infectious for unidentified infected individuals). We therefore calibrate the model by changing the following calibrated parameters: . We assume these parameters can change over different time intervals defined in section 2.5.3. We then calibrate these parameters via minimizing following calibration targets.

We have four calibration targets: cumulative death, cumulative identified infected, identified infected, and hospitalized, where hospitalized number is in aggregate (LAC) level and rests are in HD level. are weights for different calibration objectives. is the weight for each HD *k* and is defined as. are observed from our compartmental model, and (cumulative identified cases for HD *k* at time *t*), can be computed from data.

For each of the intervals listed in section 2.5.3, we run the ordinary least squares model with above cost function as the objective. We use the calibrated parameter set from the last interval as the initialization point for the current interval. The calibration process is done in Python 3.9.

**Results**

## Effect of Lockdown Policies on Traffic Volume

We first determined whether there were statistically significant differences between traffic flow in 2019 versus in 2020, which helped us confirm that the effect of the lockdown policy could be observed in our traffic data. As expected, we found that the pre-COVID interval had statistically indistinguishable traffic volumes from the prior year, while the lockdown interval showed statistically significant decreases in traffic volume in 2020 compared to 2019. These results held in an overall analysis (see Table X) as well as across all zip codes (see Appendix Table Y). Our results also show that there was decreased traffic volume during the re-opening interval (X in 2019 versus Y in 2020, p-value=Z), but this effect disappeared in the holiday period (X in 2019 versus Y in 2020, p-value=Z), showing that traffic fully rebounded to the prior year’s levels by Thanksgiving and was unaffected by the second lockdown.

run t-tests on average traffic flow (average 5-minute) between 2020 and 2019 in each interval. During the pre-COVID interval, there was an average of 180 cars passing by in 2019 and an average of 183 cars passing by in 2020 (p-value = 0.67), which yields no obvious distinction in traffic patterns between 2020 and 2019 during the pre-lockdown interval. During the lockdown interval, there was an average of 129 cars passing by in 2020 compared with 183 cars passing by in 2019 (p-value *<* 0.001), meaning there was a significant decrease in traffic during the lockdown period. The lockdown has an impact on the traffic pattern. During the re-opening interval, the average traffic flows for 2019 and 2020 are 188 and 172 (p-value= 0.035), respectively. During the holiday interval, the average traffic flows for 2019 and 2020 are 175 and 166 (p-value = 0.211), respectively. Even though there is a significant decrease in the traffic flow during the re-opening interval, the amount of traffic flow decreased during the re-opening interval is not as much as during the lockdown interval. This suggests a rebound in the traffic after the first lockdown ended. Also, there is a decrease in the average traffic flow during the holiday interval. However, the p-value suggests the decrease is insignificant, which suggests the second lockdown is ineffective at reducing LAC population flows.

<You might want to discuss differences across time here, e.g., comparing across intervals in 2020 (and 2019)>

<You can either discuss the zip code-level analysis in this section or a subsection>

Effect of Lockdown Policies by Demographic Group

We then performed hypothesis tests to study associations between each demographics and the decrease in traffic flow (in percentage) in each interval to find out demographic variables that are significantly connected to the change in traffic. During the pre-lockdown interval, there is no significant difference in terms of the traffic decrease, though the two groups may have different means of traffic flow. This is consistent with the assumption that the traffic pattern should not change between 2019 and 2020, as COVID-19 has not started yet.

During the lockdown interval, there is an average of 30% decrease in the traffic flow from 2019 among all zip codes (SD = 0.187). Regions with less than median non-Hispanic Asian population proportion have an average of 24.6% decrease while the other group has an average of 32.8% decrease (p-value = 0.006). Also, regions with less than the median Hispanic population proportion have an average of 31.8% decrease, while the other group has an average of 25.6% decrease (p-value = 0.03). Regions with a commuting time less than the median commuting time have an average of 31.2% decrease, while the other group has an average of 26.1% decrease (p-value = 0.08). For different job industries, finance and insurance, real estate and rental and leasing (25.4% vs. 32%, p-value = 0.02), educational services, and health care and social assistance (23.8% vs. 33.7%, p-value *<* 0.001), arts, entertainment, and recreation, and accommodation and food services (32.7% vs. 24.3%, p-value = 0.004), and public administration (26.2% vs. 31.3%, p-value

= 0.08) show a significant difference in traffic decrease between groups. Additionally, government workers (26.2% vs. 31.2%, p-value = 0.1) also yield a significant difference in traffic decrease.

The t-tests for lockdown periods reveal regions are more or less influenced by the lockdown policies. For the rest of the intervals, t-tests will shed light on areas more or less likely to have a rebound effect after the lockdown. For most demographic variables, the results show a similarity between re-opening and holiday intervals. Regions with less than the median non-Hispanic Asian population proportion have an average of 3.7% decrease during re-opening and -0.5% decrease during the holiday season, while the other group has an average of 13.9% decrease (p-value *<* 0.001) during re-opening and 10.1% decrease (p-value = 0.002) during the holiday season. Also, regions with less than the median Hispanic population proportion have an average of 10.6% decrease during re-opening and 7.7% decrease during the holiday season, while the other group has an average of 7% decrease (p-value = 0.16) during re-opening and 1.7% decrease (p-value = 0.08) decrease during the holiday season. Regions with less than median employment-population proportion have an average of 4.4% decrease during re-opening and 1.6% decrease during the holiday season, while the other group has an average of 13.2% decrease (p-value *<* 0.001) during re-opening and 7.9% decrease (p-value = 0.06) decrease during the holiday season. Regions with less than median diverse index have an average of 7.4% decrease during re-opening and 3.0% decrease during the holiday season, while the other group has an average of 12.9% decrease (p-value = 0.07) during re-opening and 9.9% decrease (p-value = 0.08) decrease during the holiday season. Regions with less than median commuting by public transportation population proportion have an average of 11.1% decrease during re-opening and 7.9% decrease during the holiday season, while the other group has an average of 6.3% decrease (p-value = 0.07) during re-opening and 1.2% decrease (p-value = 0.05) decrease during the holiday season. Regions with a commuting time less than the median commuting time have an average of 12.4% decrease during re-opening and 11.3% decrease during the holiday season, while the other group has an average of 5% decrease (p-value = 0.004) during re-opening and -2% decrease (p-value *<* 0.001) during the holiday season. Regions with median income less than $ 50,000 has an average of 4.6% decrease during re-opening and -0.3% during the holiday season, while the other group has an average of 9.7% decrease (p-value = 0.13) during re-opening and 6.5% (p-value = 0.02) decrease during the holiday season. For different job industries, agriculture, forestry, fishing and hunting, and mining (11.1% vs. 6.2%, p-value = 0.06, 7% vs. 2.2%, p-value = 0.16), construction (9.9% vs. 7.6%, p-value = 0.39, 8.3% vs. 1%, p-value = 0.03), educational services, and health care and social assistance (4.9% vs12.8%, p-value

= 0.002, 1% vs. 8.7%, p-value = 0.02), and public administration (4.6% vs. 13.2%, p-value *<* 0.001, 2.4% vs. 7.2%, p-value = 0.15) show a significant difference in traffic decrease between groups during both re-opening and holiday season. Additionally, government workers (5.3% vs. 12.3%, p-value = 0.007, 2.1% vs. 7.4 %, p-value = 0.12) also yields a significant difference in traffic decrease during re-opening and holiday season.

Details of unpaired t-tests results during lockdown and re-opening can be found in appendix table 2 and appendix table 3. To sum up, the first lockdown was effective at reducing the population flow (traffic) with a rebound after the lockdown. However, no significant decrease was observed during the second lockdown (holiday season). Some demographic groups show differential traffic behavior in responding to COVID-19: Non-Hispanic Asians, Regions with different commuting time, etc.

## Disease Dynamics of COVID-19 in LAC

We calibrate the compartmental model against calibration targets on HD level sequentially over time intervals (section 2.5.3). Figure 2 shows the simulation results on the aggregate level. The compartmental model is able to match both calibration targets over the first 300 days of COVID-19. From the simulation results, there are XX identified infected and XX deaths, compared to XX identified infected and XX deaths from the LAC COVID-19 dashboard. From the simulation results, the peak hospitalization from 2020 is XX, compared to XX from the data.

Figure 3 describes the disease dynamics of COVID-19 across LAC over the first 300 days. There are X times (under-reporting multiplier) unidentified infected people than identified infected people at the be- ginning of the pandemic. this under-reporting multiplier is observed to decrease to X as more testing are available to the public. By the end of 2020, X% population remains susceptible if re-infections are not in consideration. Daily averages of individuals in infectious state (I+U) are X, Y, Z, M, and N for lockdown, social events, re-opening, second wave, and holidays intervals. Total deaths are X, Y, Z, M, and N for lock- down, social events, re-opening, second wave, and holidays intervals. During the holiday season, even the second lockdown remains effective, the number of infections is the highest among different intervals (daily average of individuals in identified infectious is X).

### HD Level Calibration

Our model also captures the HD level heterogeneity of COVID-19 transmissions as traffic information can help capture geographic trends in disease dynamics. Figure 4 shows calibrated case rate against actual case rate for Antelope Valley and South from mid-September to Late December 2020. The actual case rate at Antelope Valley is higher than South, which is also captured by the model.

Among different HDs, X has the lowest number of infections and deaths. X has the lowest case rate and death rate. HDs with higher traffic tend to have higher infections. For example, XXXXYYYYZZZZ.Also, we find that X has the highest under-reporting multiplier (X), and X has the lowest under-reporting multiplier (X) during the early pandemic (compared to Y on an aggregate level).

## **No-Lockdown Scenario in LAC (Add reduction in cases VS infections averted)**

With the calibrated model, we know the number of people infected and dead from COVID-19. But, to learn if the first lockdown was effective at reducing the number of COVID-19 infections and deaths, we need to build a counterfactual scenario where the traffic pattern is similar to the post-lockdown periods. We use the calibrated model as the lockdown scenario. For the no-lockdown scenario, we scale up the traffic flow matrix (OD matrix) during the first interval by X% to the same level in post-lockdown.

As shown in figure 5, the solid line shows the case where there was no lockdown from Y to Z, and the dashed line shows the case where there was lockdown (original calibrated model). Both deaths and infections (unidentified and identified) become higher without lockdown. Specifically, 7,190 deaths and 856,789 infections were averted by the lockdown Y to Z. Also, the entire sick months (when the number of people in the infected state is high) become longer in the no-lockdown scenario. We also run a sensitivity analysis on the traffic decrease due to the lockdown: even a 5% decrease in OD traffic due to lockdown will avert 0.1 million cases and 1,280 deaths. Therefore, while the LAC COVID-19 lockdowns were economically burdensome, they likely reduced the disease burden, saving thousands of lives and averting over a million cases.

**Sensitivity Analyses**

**Discussion**

We examine the effectiveness of lockdown in reducing population flow at LAC using highway traffic information. We develop an optimization model to estimate the flow from one region to the other and incorporate it into a compartmental model that expresses geographic variations. We model a compartmental model to describe the complex dynamics of COVID-19 at LAC by considering both identified and unidentified people on the HD level. We calibrate the model to match calibration targets well and use the model to test if the lockdown was effective at reducing the number of infections and deaths. We find that the lockdown is necessary and effective at reducing the disease burden, though might be economically burdensome.

We must acknowledge several limitations of this work. Our model does not consider reinfections or new COVID variants. We assume traffic data capture true population flow patterns of LAC.

Despite these limitations, we believe that this work provides interesting insights for incorporating mobility data into compartmental modeling for policy evaluation. Our paper draws attention to evaluating the health impact of policy by considering geographic variations. We build an HD level compartmental model and run sensitivity analyses to test if the lockdown at LAC was effective. These results have implications for a wide variety of infectious disease problems and provide insight into future work on disease control problems.

**Tables and Figures**

|  |  |
| --- | --- |
| Characteristic | Mean (SD) |
| Population | 39374 (22064) |
| Population density | 8017 (5996) |
| Diverse index | 0.532 (0.154) |
| Hispanic population (%) | 44.5 (25.9) |
| Non-Hispanic White population (%) | 29.5 (24.2) |
| Non-Hispanic Black population (%) | 6.7 (9) |
| Non-Hispanic Asian population (%) | 15.7 (15.2) |
| Non-Hispanic Other population (%) | 3.6 (2) |
| Employment (%) | 93.6 (2.28) |
| Median income (dollars) | 74510 (26700) |
| Mean income (dollars) | 99247 (38197) |
| Number of Vehicles | 24790 (18479) |
| Commuting to work (%) |  |
| Drove alone | 72.9 (8.4) |
| Carpool | 9.4 (3.3) |
| Public transportation | 4.7 (4.6) |
| Walked | 2.4 (2.5) |
| Other | 2.2 (1.6) |
| At home | 8.4 (4.8) |
| Time (minutes) | 31.4 (3.45) |
| Job class (%) |  |
| Private wage | 78.9 (3.3) |
| Government worker | 12.3 (3.8) |
| Self-employed | 8.6 (2.7) |
| Unpaid | 0.2 (0.2) |
| Job industry (%) |  |
| Agriculture, forestry, fishing and hunting, and mining | 0.4 (0.4) |
| Construction | 5.7 (2.5) |
| Manufacturing | 8.8 (3.5) |
| Wholesale trade | 3.3 (1.4) |
| Retail trade | 9.9 (2.1) |
| Transportation and warehousing, and utilities | 6.0 (2.7) |
| Information | 4.6 (4.4) |
| Finance and insurance, and real estate and rental and leasing | 6.3 (2.7) |
| Professional, scientific, and management, and administrative and waste management services | 13.3 (4.6) |
| Educational services, and health care and social assistance | 21.5 (4.6) |
| Arts, entertainment, and recreation, and accommodation and food services | 10.9 (3.5) |
| Other services, except public administration | 5.6 (1.8) |
| Public administration | 3.6 (1.6) |

Table 1: Census data

|  |  |  |  |
| --- | --- | --- | --- |
| variable | group 1 | group 2 | p-valu |
| Population density  Diverse index Hispanic population  Non-Hispanic White population Non-Hispanic Black population Non-Hispanic Asian population Non-Hispanic Other population Employment  Median income (dollars)  Number of Vehicles | 30.6  27.8  31.8  28.1  28.1  24.6  26.9  27.4  25  31 | 28.5  31.5  25.6  29.3  29.2  32.8  30.5  30  29.5  29.6 | 0.46  0.28  0.03  0.69  0.70  0.00  0.22  0.39  0.23  0.57 |
| Commuting to work  Drove alone Carpool  Public transportation Walked  Other At home  Time (minutes) | 28  30.7  30.4  29.7  28  28.4  31.2 | 29.4  26.6  26.8  27.5  29.3  29  26.1 | 0.64  0.16  0.21  0.44  0.65  0.84  0.08 |
| Job class  Private wage Government worker Self-employed Unpaid | 30.5  26.2  29.8  29.5 | 26.8  31.2  27.4  27.7 | 0.20  0.09  0.41  0.55 |
| Job industry  Agriculture, forestry, fishing and hunting, and mining Construction  Manufacturing Wholesale trade Retail trade  Transportation and warehousing, and utilities Information  Finance and insurance, and real estate and rental and leasing  Professional, scientific, and management, and administrative and waste management services Educational services, and health care and social assistance  Arts, entertainment, and recreation, and accommodation and food services Other services, except public administration  Public administration | 30  30.3  20.6  27.5  29.1  30.6  28.8  25.4  26.9  23.8  32.7  30.6  26.2 | 27.2  26.9  26.7  30  28.3  26.6  28.6  32  30.5  33.7  24.3  26.5  31.3 | 0.33  0.24  0.19  0.38  0.77  0.17  0.94  0.02  0.23  *<*0.00  0.00  0.17  0.08 |

Table 2: Lockdown

|  |  |  |  |
| --- | --- | --- | --- |
| variable | group 1 | group 2 | p-valu |
| Population density  Diverse index Hispanic population  Non-Hispanic White population Non-Hispanic Black population Non-Hispanic Asian population Non-Hispanic Other population Employment  Median income (dollars)  Number of Vehicles | 7  7.4  10.6  9.7  8.9  3.7  8.8  4.4  4.6  7.5 | 10.5  12.9  7  7.8  8.7  13.9  8.7  13.2  9.7  10.9 | 0.22  0.06  0.16  0.47  0.92  *<*0.00  0.97  *<*0.00  0.13  0.18 |
| Commuting to work  Drove alone Carpool  Public transportation Walked  Other At home  Time (minutes) | 6.8  9.5  11.1  8.1  8.6  9.3  12.4 | 10.9  8.1  6.3  9.5  9  8.3  5 | 0.11  0.60  0.06  0.58  0.90  0.69  0.00 |
| Job class  Private wage Government worker Self-employed Unpaid | 9.4  5.3  11.1  9.6 | 8.1  12.3  6.3  7.8 | 0.61  0.00  0.06  0.49 |
| Job industry  Agriculture, forestry, fishing and hunting, and mining Construction  Manufacturing Wholesale trade Retail trade  Transportation and warehousing, and utilities Information  Finance and insurance, and real estate and rental and leasing  Professional, scientific, and management, and administrative and waste management services Educational services, and health care and social assistance  Arts, entertainment, and recreation, and accommodation and food services Other services, except public administration  Public administration | 11.1  9.9  9.2  7.3  9.3  8.4  9.2  7.6  8.5  4.9  10.9  9.3  26.2 | 6.2  7.6  8.3  10.5  8.3  9.2  8.3  10  9.1  12.8  6.5  8.2  31.3 | 0.06  0.39  0.71  0.22  0.71  0.74  0.73  0.34  0.83  0.00  0.09  0.64  0.08 |

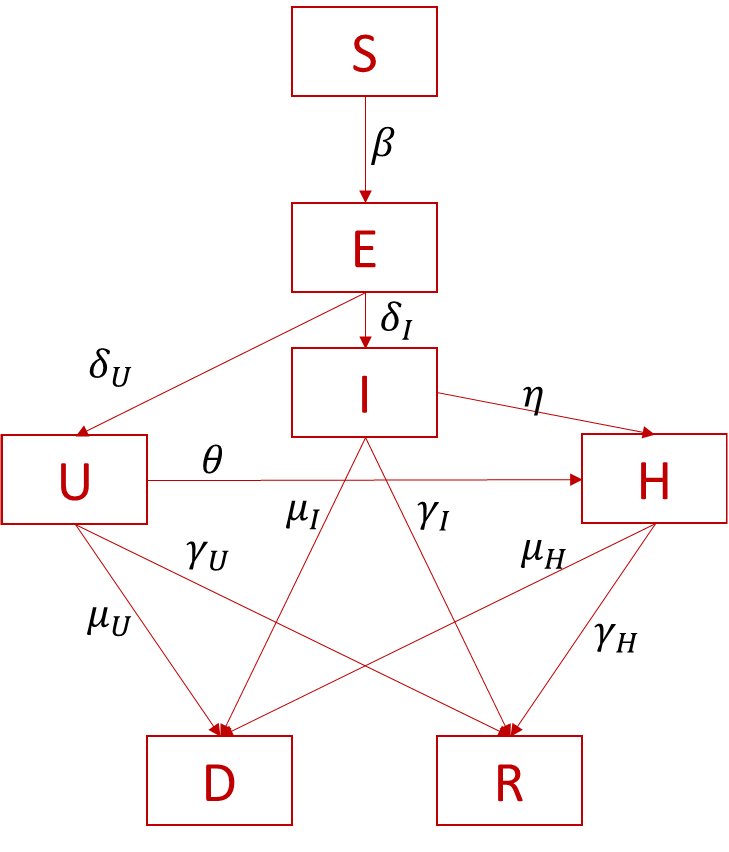
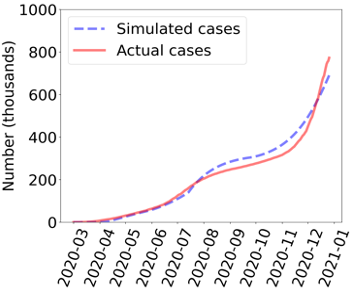
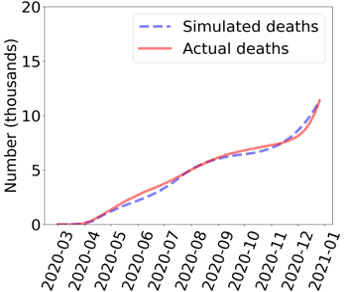
Table 3: Re-opening

Figure 1: Model structure

(a) (b)

Figure 2: (a) Simulation results – cumulative identified infected (b) Simulation results – cumulative deaths

Graphical user interface, text, application

Description automatically generated

Figure 3: Disease dynamicsupdate figure

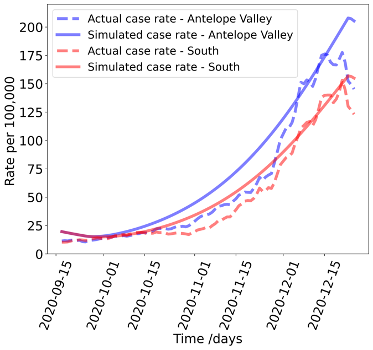
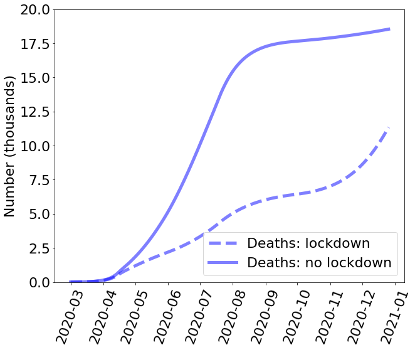
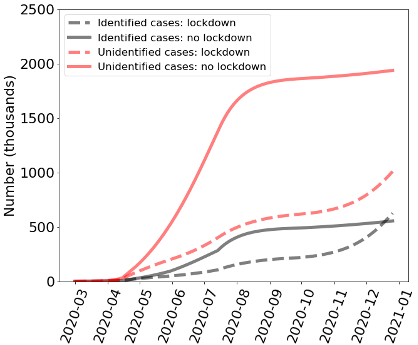


Figure 4: HD level calibration



(a) (b)

Figure 5: (a) Lockdown vs. no-lockdown: infections (b) Lockdown vs. no-lockdown: deaths

**Acknowledgments**. In the anonymized manuscript file, include an Acknowledgements header and the placeholder “(See Title Page for Acknowledgements)” at the end of the article, prior to the Declaration of Conflicting Interests, any notes, and your References.

**Permissions**. Authors are responsible for obtaining permission from copyright holders for reproducing or adapting any illustrations, tables, figures or lengthy quotations previously published elsewhere. For further information including guidance on fair dealing for criticism and review, please visit our [Frequently Asked Questions](http://www.uk.sagepub.com/journalgateway/authorFAQs.htm) on the [SAGE Journal Author Gateway](http://www.uk.sagepub.com/journalgateway/pubPolicies.htm).

**Declaration of Conflicting Interests**. It is the policy of the MDM journals to require a declaration of conflicting interests from all authors that will appear in all published articles. When authors submit a manuscript, they must disclose all financial relationships (both personal and institutional) that could be viewed as presenting the appearance of a potential conflict of interest or that might otherwise bias their work. (If additional clearances are required by author institutions, these formal clearance statements must be provided by the authors in the manuscript as specified by their institutions.) To prevent ambiguity, authors must state explicitly whether potential conflicts do or do not exist.

When making a declaration the disclosure information must be specific and include any financial relationship that all authors of the article has with any sponsoring organization and the for-profit interests the organization represents, and with any for-profit product discussed or implied in the text of the article. Potential conflicts include, but are not limited to, any financial relationship that involves conditions or tests or treatments discussed in the manuscript and alternatives to the tests or treatments for those conditions. Financial relationships (e.g., employment, consultancies, honoraria, stock ownership or options, paid expert testimony, grants, patents received or pending, royalties) are the most easily identifiable potential conflicts of interest—and the most likely to undermine the credibility of the journal, the authors, and the science itself.

Disclosure of these relationships is essential not only for original research manuscripts but also for review articles, letters, and editorials. MDM publishes conflict of interest disclosures. When authors are uncertain whether a potential conflict of interest exists, they should err on the side of full disclosure. All such disclosures should be listed in a section headed “Conflict of Interests” immediately following the Acknowledgments section, at the end of the manuscript. If there are no conflicts to disclose, the section should explicitly say “The Author(s) declare(s) that there is no conflict of interest.”

**References**. MDM requires numbered, citation-sequence end references formatted in accord with National Library of Medicine standards. For more information, please refer to [*Scientific Style and Format: The CSE Manual for Authors, Editors, and Publishers*](https://www.scientificstyleandformat.org/Home.html). For those using software compliant with Citation Style Language (CSL) 1.0.1, we recommend the [SAGE-Vancouver CSL style available in the Zotero CSL library](https://www.zotero.org/styles?q=id%3Asage-vancouver). **However, we encourage inclusion of a Digital Object Identifier (DOI) formatted as “DOI: 10.XXX” at the end of the reference when available.**When possible and appropriate, data, program code, and other methods should be cited with a persistent identifier such as a DOI. Supplemental material should have a separate References list. References that appear in the text and an appendix should be placed in both documents.

Adiga, A., D. Dubhashi, B. Lewis, M. Marathe, S. Venkatramanan, and A. Vullikanti (2020). Mathematical models for covid-19 pandemic: a comparative analysis. *Journal of the Indian Institute of Science 100* (4), 793–807.

Beckley, R., C. Weatherspoon, M. Alexander, M. Chandler, A. Johnson, and G. S. Bhatt (2013). Modeling epidemics with differential equations. *Tennessee State University Internal Report* .

Cao, L. and Q. Liu (2022). Covid-19 modeling: A review. *medRxiv* .

Chang, S., E. Pierson, P. W. Koh, J. Gerardin, B. Redbird, D. Grusky, and J. Leskovec (2021). Mobility network models of covid-19 explain inequities and inform reopening. *Nature 589* (7840), 82–87.

Citron, D. T., S. Iyer, R. C. Reiner, and D. L. Smith (2021). Activity space maps: a novel human mobility data set for quantifying time spent at risk. *medRxiv* .

Clement, J. C., V. Ponnusamy, K. Sriharipriya, and R. Nandakumar (2021). A survey on mathematical, machine learning and deep learning models for covid-19 transmission and diagnosis. *IEEE reviews in biomedical engineering 15*, 325–340.

COVID, I., C. J. Murray, et al. (2020). Forecasting the impact of the first wave of the covid-19 pandemic on hospital demand and deaths for the usa and european economic area countries. *MedRxiv* .

Gaskin, D. J., H. Zare, and B. A. Delarmente (2021). Geographic disparities in covid-19 infections and deaths: The role of transportation. *Transport policy 102*, 35–46.

Godio, A., F. Pace, and A. Vergnano (2020). Seir modeling of the italian epidemic of sars-cov-2 using com- putational swarm intelligence. *International journal of environmental research and public health 17* (10), 3535.

Iyer, S., B. Karrer, D. Citron, F. Kooti, P. Maas, Z. Wang, E. Giraudy, A. Medhat, P. A. Dow, and A. Pompe (2022). Large-scale measurement of aggregate human colocation patterns for epidemiological modeling. *medRxiv* , 2020–12.

Li, R., S. Pei, B. Chen, Y. Song, T. Zhang, W. Yang, and J. Shaman (2020). Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (sars-cov-2). *Science 368* (6490), 489–493.

Liu, J., L. Wang, Q. Zhang, and S.-T. Yau (2020). The dynamical model for covid-19 with asymptotic analysis and numerical implementations. *Applied Mathematical Modelling*.

Nda¨ırou, F., I. Area, J. J. Nieto, and D. F. Torres (2020). Mathematical modeling of covid-19 transmission dynamics with a case study of wuhan. *Chaos, Solitons & Fractals 135*, 109846.

Rahimi, I., F. Chen, and A. H. Gandomi (2021). A review on covid-19 forecasting models. *Neural Computing and Applications*, 1–11.

Viguerie, A., A. Veneziani, G. Lorenzo, D. Baroli, N. Aretz-Nellesen, A. Patton, T. E. Yankeelov, A. Re- ali, T. J. Hughes, and F. Auricchio (2020). Diffusion–reaction compartmental models formulated in a continuum mechanics framework: application to covid-19, mathematical analysis, and numerical study. *Computational Mechanics 66* (5), 1131–1152.

Yang, Z., Z. Zeng, K. Wang, S.-S. Wong, W. Liang, M. Zanin, P. Liu, X. Cao, Z. Gao, Z. Mai, et al. (2020). Modified seir and ai prediction of the epidemics trend of covid-19 in china under public health interventions. *Journal of thoracic disease 12* (3), 165.