Mobility and the effective reproduction rate of COVID-19

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A B S T R A C T

Objectives: Due to the infectiousness of COVID-19, the mobility of individuals has sharply decreased, both in response to government policy and self-protection. This analysis seeks to understand how mobility reductions reduce the spread of the coronavirus (SAR-CoV-2), using readily available data sources.

Methods: Mobility data from Google is correlated with estimates of the effective reproduction rate, R_t, which is a measure of viral infectiousness (Google, 2020). The Google mobility data provides estimates of reductions in mobility, for six types of trips and activities. R_t for US states are downloaded from an on-line platform that derives daily estimates based on data from the Covid Tracking Project (Wissel et al., 2020; Systrom et al., 2020). Fixed effects models are estimated relating mean R_t and 80% upper level credible interval estimates to changes in mobility and a time-trend value and with both 7-day and 14-day lags.

Results: All mobility variables are correlated with median R_t and the upper level credible interval of R_t. Staying at home is effective at reducing R_t. Time spent at parks has a small positive effect, while other activities all have larger positive effects. The time trend is negative suggesting increases in self-protective behavior. Predictions suggest that returning to baseline levels of activity for retail, transit, and workplaces, will increase R_t above 1.0, but not for other activities. Mobility reductions of about 20–40% are needed to achieve an R_t below 1.0 (for the upper level 80% credible interval) and even larger reductions to achieve an R_t below 0.7.

Conclusions: Policy makers need to be cautious with encouraging return to normal mobility behavior, especially returns to workplaces, transit, and retail locations. Activity at parks appears to not increase R_t as much. This research also demonstrates the value of using on-line data sources to conduct rapid policy-relevant analysis of emerging issues.

Policy measures to reduce the spread of COVID-19 have included "shelter-in-place" orders, shutdowns of sectors of the economy, and requirements for social distancing. These policies, as well as individual protective strategies, have effectively reduced the mobility of people in every country where they have been enacted. In this paper, I examine how mobility reductions are associated with the effective reproduction rate, R_t, of COVID-19, and forecast the potential increase in R_t should mobility return to its level in January 2020, as well as what level of further mobility reductions are needed to reduce R_t to levels that curb spread of the SARS-CoV-2 virus responsible for COVID-19. A key innovation of this work is the use of readily available on-line data sources to address a rapidly emerging crisis.

The effective reproduction rate is an indicator of how many people are infected by one individual. For example, if $R_t = 2$, this implies that each infected person transmits the virus to two others, resulting in an uncontrolled epidemic. The effective reproduction

rate is distinct from the basic reproduction number (R_0) which represents the biological transmissibility of the virus, which is a fixed constant. R_t, on the other hand, can be affected by policy as well as the level of viral immunity in the population (Delamater et al., 2019). Achieving a value of $R_t < 1$ is a necessary condition to stop the spread of any virus. Thus, I examine changes in R_t associated with changes in mobility and do this for all US states plus the District of Columbia.

Policy measures to prevent the spread of COVID-19 were first implemented in Wuhan, China on Jan 23, 2020 (Pan et al., 2020). These included a shutdown of public transit, traffic restrictions, home quarantine, and closure of all public places except essential shops (grocery stores and pharmacies). Face masks were required in all public spaces. These measures, in combination, were shown to reduce the effective reproduction rate from 3.8 to almost 1.0, with further measures reducing it well below 1.0 (Pan et al., 2020).

Various studies (most published as pre-prints) have examined the effectiveness of specific policies for curbing the spread of COVID-19. An analysis of policies implemented in US states determined that social distancing measures were effective at reducing case-loads, with a lag of up to 15 days (Courtemanche et al., 2020). The same study found no statistically significant reductions associated with school closures and bans on large events; however, "shelter-in-place orders" and bans on restaurant and entertainment centers were effective. Another study evaluated how various policies affected mobility, using Google mobility data for US states (Abouk and Heydari, 2020). Their results suggest that stay-at-home orders were the most effective at reducing mobility while closure of non-essential businesses and restaurants was moderately effective. They found school closures and bans on large events as not affecting mobility; another study found that these two policies also did not affect case-loads (Courtemanche et al., 2020). It is likely that banning large events is not noticeable in the aggregated Google Mobility data, and school mobility is not one of the mobility factors in the data. Another study found that state shelter-in-place orders were effective at reducing total case-loads after about a three-week lag (Dave et al., 2020). An analysis of Google data for US states linked to case reports determined there was a growing incidence over time and that time spent at parks increased the incidence of COVID-19 (Paez, 2020).

These studies suggest that policies aimed at reducing mobility have curbed the number of cases, but they do not estimate mobility effects directly. Reductions in mobility have typically occurred before lockdown orders were issued. For example, many universities moved to remote learning and limitations on working in the office before lockdowns were issued. Likewise, many firms began limiting employee travel, for example to business meetings prior to lockdowns. One recent study examined mobility changes in 25 US counties and found evidence that reductions in mobility reduced growth in cases (Badr et al., 2020). Other research has demonstrated the effectiveness of lockdowns in reducing R_t, but here I focus on the underlying mobility behavior for all 50 states and the District of Columbia, rather than the explicit policies (Arroyo-Marioli et al., 2020).

Results show a strong correlation between mobility and R_t. Specifically, retail/recreational activity, such as eating in restaurants, office work activities, and public transit usage all are associated with increases in transmission of the virus. Shopping at grocery stores and pharmacies has a smaller association, while affects associated with parks are minor; staying at home reduces transmission. Implications for reducing the spread of the coronavirus are that the reductions in mobility have been effective, but also need to be maintained for longer periods.

1. Data and methods

Mobility data was made publicly available by Google (2020) and is based upon cell phone tracking data that measures clustering of individuals at six place categories. The places are grocery/pharmacy stores, retail stores/recreation (including restaurants), parks, transit stations, workplaces, and residential locations. The data are anonymized and aggregated by Google and are used to estimate visits and lengths of stays at specific places in Google Maps. The data for each place location and for each US state is relative to a median value between Jan 3 – Feb 6, 2020 and changes are relative to the same day of the week and reported as percent changes; data was downloaded on June 26th, 2020 and was current up to June 23rd, 2020.[1] An example of the change in mobility is shown in Fig. 1 and Fig. 2 for the states of Arizona and New Jersey. New Jersey was one of the most hard hit states early in the pandemic (with nearly 15,000 deaths as of late June 2020); Arizona experienced large case loads in late June 2020. New Jersey implemented an early lockdown on March 18, 2020, while Arizona had a later lockdown on March 30, 2020, that was removed on May 15, 2020 (Lee et al., 2020; Popovich, 2020). As can be seen, time spent at retail, work, and transit locations declined noticeably and even before the lockdowns implemented in each state. Time spent at grocery/pharmacy locations also was lower, suggesting both fewer trips to these locations and less time spent there. There is variability in time spent at parks, primarily due to variation in weather. Time spent at residential locations increased. While these lockdowns clearly affected mobility, it largely coincided with self-protective measures that businesses and individuals were already taking. Badr et al. (2020) also documented reductions in mobility before lockdowns were implemented. Mobility began to gradually increase even before the lockdowns expired.

Data for R_t for each state in the United States (including the District of Columbia) was downloaded from https://rt.live/ and is explained in associated blog posts (Systrom et al., 2020). Estimates are based on methods outlined in Bettencourt and Ribeiro (2008). Case data for https://rt.live/ are from the Covid tracking project at https://covidtracking.com/ (Wissel et al., 2020). Estimates of R_t are Bayesian and dependent on prior information and thus change as more data becomes available. An 80% credible interval is provided with the estimates. Given that replicability by doing an updated download is not possible, the full dataset used is available at https://github.com/rbnoland/COVID-data.

To evaluate the impact of mobility on R_t, fixed effects models that control for state-level effects are estimated. That is, these models

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[1] Additional data was downloaded on Nov 29th, 2020, in order to update the Fig. I did not update the analysis as COVID-19 testing started to suffer major delays starting in the Summer of 2020 and thus data on cases was not as reliable.
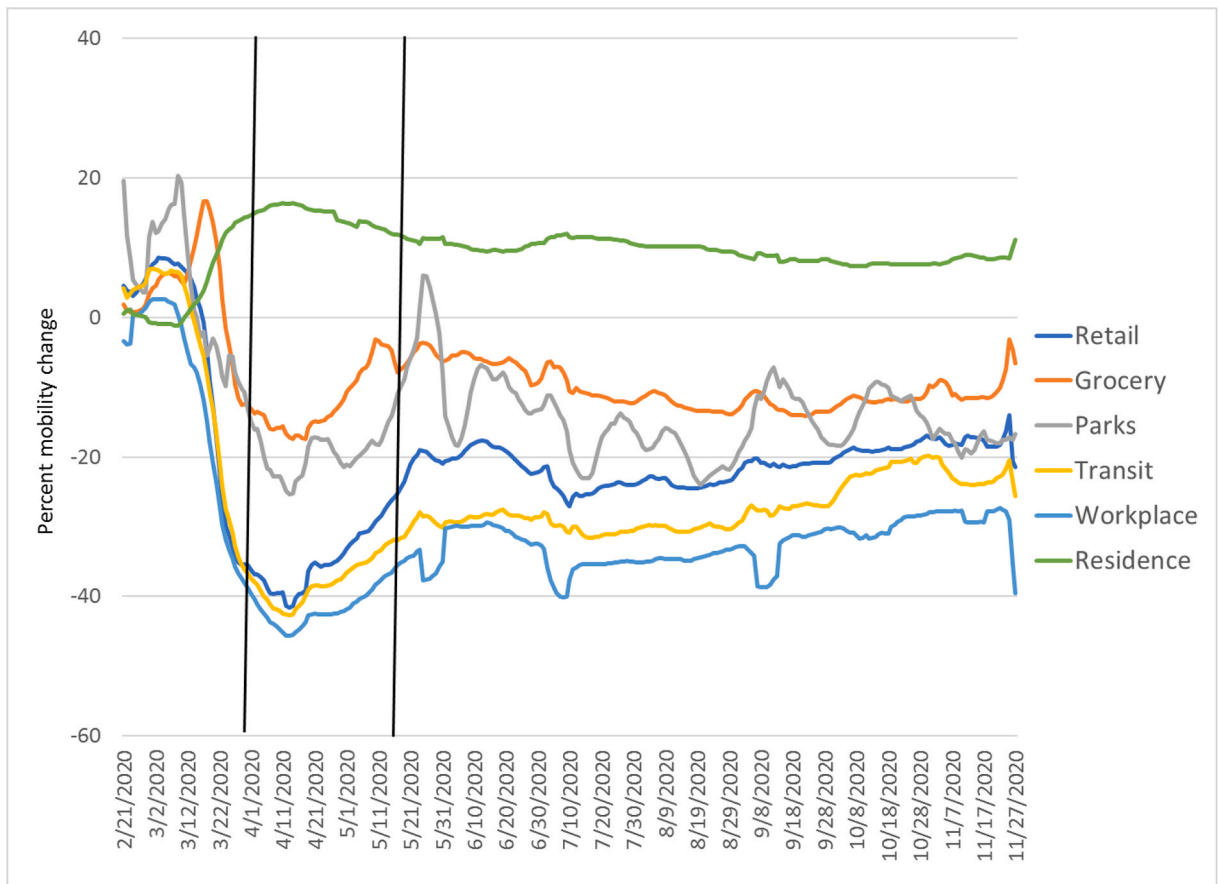
Fig. 1. Mobility data for Arizona, from Feb 15, 2020 to Nov 27, 2020. Represents percent change from baseline between Jan 3, 2020 to Feb 6, 2020, measured relative to each day of the week. Seven-day moving average is shown. A statewide lockdown was initiated on March 30, 2020 and ended on May 15, 2020. Both are shown by the vertical lines(Lee et al., 2020; Popovich, 2020).

control for unmeasured attributes that might affect the dependent variable. A time-trend variable, which starts on the first day that R_t is estimated for each state is also included; these start dates vary based on the cases in each state, thus our time trend normalizes for the start of infectious spread in each state. The time trend controls for changes over time and could represent practices such as increased mask-wearing, increased home shopping deliveries, and additional protective measures taken by firms and individuals. Increasing herd immunity may also be represented by the time trend. Estimates suggest this could be much larger than actual reported cases (Hortaçsu et al., 2020)

Standard errors were estimated using a bootstrap with 100 repetitions. This was done as qq-plots suggested some minor deviations from normality in the residuals. However, this made little difference in the standard errors given the high levels of statistical significance in the models and correspondingly low standard errors on the coefficients of interest.

The mobility measures provided are all highly correlated, making individual inferences on each impossible if all are included within the same model. Others who have used this data have aggregated it into an index (Arroyo-Marioli et al., 2020). Paez (2020) estimated models with park and workplace mobility only, as these are the least correlated with each other. The models that I estimate include each separately. This allows a comparison of the relative impact of each independently. Models with a 7-day and 14-day lag of each mobility variable are estimated, given that that the onset of symptoms can take almost up to seven days and actual case reports (usually when symptoms are more severe) can take longer. An average incubation period of 11.5 days has been estimated (Lauer et al., 2020). Estimated models are log-linear, using the log of R_t to avoid predictions less than zero.

The goal of policy makers is to keep R_t below one. A value below one implies that infections are decreasing and aiming for this will result in reductions in total cases and can be effective at stopping an epidemic.[2] The estimates of R_t include an 80% credible interval, that is, the actual value has an 80% likelihood of being somewhere within the reported range. Focusing policy on the median value may not be effective, thus additional models using the upper limit of the credible interval are estimated. If one wants greater certainty in the

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[2] In the UK, government officials have stated a goal of getting and keeping R_t below one (BBC News, 2020), although this policy has been criticized as other metrics also need to be considered (Adam, 2020).
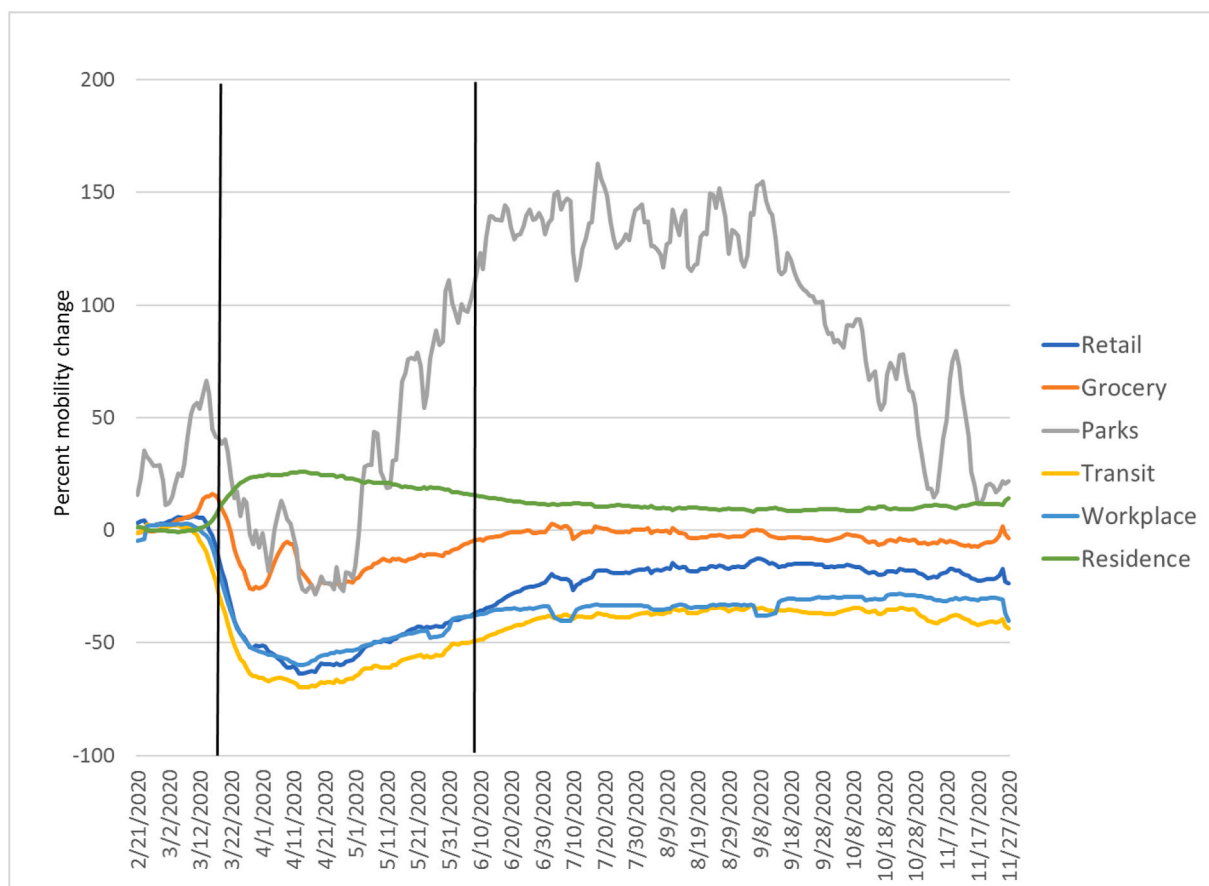
Fig. 2. Mobility data for New Jersey, from Feb 15, 2020 to Nov 27, 2020. Represents percent change from baseline between Jan 3, 2020 to Feb 6, 2020, measured relative to each day of the week. Seven-day moving average is shown. A statewide lockdown was initiated on March 18, 2020 and expired on June 9, 2020, with a slow reopening of various businesses. Both are shown by the vertical lines(Lee et al., 2020).

impact of mobility reductions, keeping the upper limit of the credible interval below one is a more risk-averse policy. Predictions are also presented based on the models with a 7-day lag and how this affects the upper level of the credible interval. Finally, I use the models to predict how much mobility needs to be reduced to achieve an upper level credible value of $R_t = 1$ and $R_t = 0.7$, as the latter would be most effective at stopping further spread of the coronavirus.

2. Results

Fixed effects modeling results are presented in Tables 1–4 for US state-level models. In all cases the coefficients are positive, except for residential locations. That is, increased mobility at locations other than one's residence is associated with increases in R_t. This demonstrates the effectiveness of reductions in mobility to reduce the spread of COVID-19. Coefficient values for models with the upper level of the credible interval of R_t are slightly larger (Table 2 and Table 4). The models have slightly lower coefficient values when the mobility variables are lagged 14 days, but the patterns are similar.

Comparing the values of mobility coefficients within each set of models shows that activity spent at parks has the smallest coefficient value, suggesting less viral spread associated with time spent at parks. Other mobility coefficients are generally similar, though grocery/pharmacy coefficients are larger in the models with 7-day lags. Mobility coefficients for residences, while negative, have a larger absolute value, suggesting time spent at home is protective of viral spread.

The time trend variable for days since the start of the epidemic in each area is uniformly negative. This variable represents unmeasured effects that change over time. It may be accounting for individual protective actions being taken by people and firms, such as requirements to wear masks or the installation of protective barriers in stores, among other actions.

Predictions of potential increases in R_t without mobility reductions are also estimated. Setting the mobility values to zero assumes mobility returns to the average of activity from Jan 3 – Feb 6, 2020. The time trend is set to its value on June 23rd, 2020, thus incorporating individual protective actions taken to date. The RMSE for each model is shown, which is a measure of predictive accuracy; there is little variation between models. Using the models in Table 2, based on the upper level of the credible interval and a 7-day lag, predicted results for each US state are shown in Table 5. Every state has a predicted R_t above one, for retail, transit, workplaces,

Table 1

US State level models with fixed effect estimation of median value of ln(R_t) versus mobility variables lagged by 7 days. Fixed effects for each state are not shown. All estimates have *P=0.000*. 50 states plus the District of Columbia are included in the regressions.

Dependent variable: median value of R_t	coef.: Mobility, 7-day lag	95% conf interval		coef.: Days	95% conf interval		N	Adj-R2	RMSE
retail/recreational	0.0113	0.0110	0.0116	−0.0036	−0.0037	−0.0035	5986	0.701	0.179
grocery/pharmacy	0.0133	0.0126	0.0139	−0.0046	−0.0048	−0.0044	5986	0.500	0.232
parks	0.0021	0.0020	0.0023	−0.0066	−0.0069	−0.0063	5967	0.381	0.258
transit station	0.0111	0.0107	0.0114	−0.0029	−0.0030	−0.0027	5986	0.675	0.187
workplace	0.0117	0.0113	0.0121	−0.0020	−0.0021	−0.0018	5986	0.635	0.198
residential	−0.0272	−0.0281	−0.0263	−0.0030	−0.0032	−0.0029	5986	0.635	0.198

Table 2

US State level models with fixed effect estimation of upper level 80% credible interval of ln(R_t) versus mobility variables lagged by 7 days. Fixed effects for each state are not shown. All estimates have *P=0.000*. 50 states plus the District of Columbia are included in the regressions.

Dependent variable: median value of R_t	coef.: Mobility, 14-day lag	95% conf interval		coef. Number of days	95% conf interval		N	Adj-R2	RMSE
retail/recreational	0.0121	0.0118	0.0123	−0.0032	−0.0033	−0.0030	5986	0.693	0.185
grocery/pharmacy	0.0140	0.0134	0.0146	−0.0042	−0.0044	−0.0040	5986	0.467	0.243
parks	0.0023	0.0021	0.0025	−0.0064	−0.0066	−0.0061	5967	0.345	0.270
transit station	0.0118	0.0115	0.0122	−0.0024	−0.0025	−0.0022	5986	0.667	0.192
workplace	0.0125	0.0121	0.0129	−0.0014	−0.0016	−0.0012	5986	0.626	0.204
residential	−0.0291	−0.0298	−0.0284	−0.0025	−0.0027	−0.0024	5986	0.624	0.204

Table 3

US State level models with fixed effect estimation of median value of ln(R_t) versus mobility variables lagged by 14 days. Fixed effects for each state are not shown. All estimates have *P=0.000*. 50 states plus the District of Columbia are included in the regressions.

Dependent variable: upper bound of 95% credible interval of R_t	coef.: Mobility, 7-day lag	95% conf interval		coef. Number of days	95% conf interval		N	Adj-R2	RMSE
retail/recreational	0.0097	0.0094	0.0100	−0.0024	−0.0026	−0.0022	5879	0.589	0.200
grocery/pharmacy	0.0092	0.0086	0.0098	−0.0040	−0.0042	−0.0038	5879	0.377	0.246
parks	0.0018	0.0016	0.0019	−0.0056	−0.0059	−0.0053	5864	0.328	0.255
transit station	0.0094	0.0090	0.0097	−0.0018	−0.0020	−0.0017	5879	0.556	0.207
workplace	0.0099	0.0095	0.0102	−0.0012	−0.0014	−0.0010	5879	0.522	0.215
residential	−0.0236	−0.0244	−0.0229	−0.0020	−0.0022	−0.0018	5879	0.539	0.211

Table 4

US State level models with fixed effect estimation of upper level 80% credible interval of ln(R_t) versus mobility variables lagged by 14 days. Fixed effects for each state are not shown. All estimates have *P=0.000*. 50 states plus the District of Columbia are included in the regressions.

Dependent variable: upper bound of 95% credible interval of R_t	coef.: Mobility, 14-day lag	95% conf interval		coef. Number of days	95% conf interval		N	Adj-R2	RMSE
retail/recreational	0.0104	0.0101	0.0107	−0.0018	−0.0020	−0.0017	5879	0.577	0.205
grocery/pharmacy	0.0098	0.0092	0.0105	−0.0035	−0.0038	−0.0033	5879	0.341	0.256
parks	0.0019	0.0018	0.0021	−0.0053	−0.0055	−0.0050	5864	0.290	0.266
transit station	0.0101	0.0098	0.0104	−0.0012	−0.0014	−0.0010	5879	0.542	0.214
workplace	0.0106	0.0103	0.0110	−0.0005	−0.0008	−0.0003	5879	0.505	0.222
residential	−0.0253	−0.0260	−0.0247	−0.0014	−0.0016	−0.0012	5879	0.522	0.218

and residences if mobility activity for these destinations returned to normal. Grocery/pharmacy locations are below 1.0 in most states, while parks are uniformly below 1.0. Prediction spreadsheets are available for all models at https://github.com/rbnoland/COVID-data and different levels of mobility increases or decreases can be tested with these.

While a return to normal mobility activity will not reduce R_t, this leads to the question of how much mobility reduction is needed to achieve an $R_t = 1$. In addition, mobility reductions to achieve $R_t = 0.7$ are also estimated. Using the same model for the upper level credible interval estimates and assuming the time trend up to June 23rd, 2020, the average across all states and the largest possible mobility reductions needed are shown in Table 6. Table 7 and Table 8 present the mobility reductions needed by each state to achieve $R_t = 1$ and $R_t = 0.7$, respectively. Large mobility reductions are needed for retail, transit, and work activities for achieving both levels of Rt. Mobility reductions for grocery shopping are also needed to achieve $R_t = 0.7$ and even for parks. The positive values for parks, for R_t

Table 5

Predicted value of upper level credible interval of R_t assuming mobility at base level from Jan 3-Feb 6, 2020 and time trend at June 23rd, 2020.

	Retail	Grocery	Parks	Transit	Work	Residence
Alabama	1.24	0.94	0.81	1.23	1.56	1.39
Alaska	1.03	0.82	0.65	1.27	1.36	1.19
Arizona	1.45	1.14	0.95	1.59	1.80	1.56
Arkansas	1.18	0.91	0.77	1.23	1.53	1.33
California	1.55	1.08	0.88	1.69	1.73	1.60
Colorado	1.26	0.95	0.74	1.50	1.57	1.38
Connecticut	1.24	0.96	0.69	1.44	1.52	1.39
Delaware	1.25	1.01	0.75	1.46	1.56	1.41
District of Columbia	1.64	1.17	0.84	1.90	1.85	1.62
Florida	1.54	1.22	0.99	1.86	1.81	1.62
Georgia	1.34	1.04	0.85	1.65	1.71	1.51
Hawaii	1.43	1.12	0.85	1.77	1.55	1.45
Idaho	1.20	0.89	0.69	1.18	1.58	1.33
Illinois	1.33	0.95	0.76	1.52	1.61	1.44
Indiana	1.19	0.92	0.69	1.16	1.53	1.35
Iowa	1.28	0.83	0.68	1.19	1.53	1.37
Kansas	1.26	0.98	0.71	1.18	1.58	1.38
Kentucky	1.32	0.96	0.79	1.36	1.68	1.46
Louisiana	1.30	0.97	0.87	1.45	1.61	1.43
Maine	1.20	0.91	0.68	1.33	1.45	1.28
Maryland	1.34	1.06	0.75	1.60	1.69	1.56
Massachusetts	1.28	0.97	0.68	1.67	1.56	1.42
Michigan	1.24	0.92	0.63	1.30	1.53	1.34
Minnesota	1.26	0.92	0.67	1.54	1.54	1.39
Mississippi	1.21	0.96	0.86	1.25	1.62	1.41
Missouri	1.26	0.95	0.78	1.34	1.60	1.40
Montana	1.16	0.84	0.72	1.16	1.44	1.23
Nebraska	1.23	0.92	0.72	1.14	1.51	1.38
Nevada	1.43	1.06	0.92	1.71	1.84	1.56
New Hampshire	1.19	0.94	0.69	1.32	1.51	1.37
New Jersey	1.46	1.00	0.71	1.70	1.65	1.55
New Mexico	1.27	0.90	0.81	1.25	1.58	1.39
New York	1.42	0.96	0.73	1.66	1.60	1.46
North Carolina	1.32	1.01	0.82	1.53	1.64	1.44
North Dakota	1.18	0.91	0.70	1.19	1.38	1.29
Ohio	1.26	0.96	0.69	1.24	1.59	1.40
Oklahoma	1.26	0.97	0.84	1.23	1.67	1.45
Oregon	1.33	0.99	0.77	1.45	1.64	1.41
Pennsylvania	1.36	1.04	0.75	1.58	1.65	1.47
Rhode Island	1.27	1.03	0.69	1.66	1.61	1.46
South Carolina	1.31	1.02	0.89	1.31	1.67	1.47
South Dakota	1.23	0.85	0.69	1.15	1.52	1.39
Tennessee	1.27	0.98	0.83	1.38	1.64	1.42
Texas	1.44	1.13	0.95	1.63	1.81	1.64
Utah	1.25	0.91	0.72	1.47	1.64	1.41
Vermont	1.23	0.99	0.68	1.41	1.51	1.31
Virginia	1.33	1.01	0.78	1.56	1.66	1.49
Washington	1.19	0.89	0.67	1.42	1.52	1.31
West Virginia	1.13	0.89	0.74	1.10	1.45	1.25
Wisconsin	1.28	0.94	0.66	1.25	1.50	1.38
Wyoming	1.19	0.88	0.76	1.04	1.49	1.31

Table 6

Average and largest mobility reduction needed to achieve Rt = 1 and Rt = 0.7 (on June 23rd, 2020) for all 50 states and the District of Columbia.

	Retail	Grocery	Parks	Transit	Work	Residence
Average reduction to achieve $R_t = 1$	−20.88	2.31	120.56	−28.43	−37.14	11.89
Largest reduction to achieve $R_t = 1$	−41.01	−14.15	6.08	−54.30	−48.89	6.02
Average reduction to achieve $R_t = 0.7$	−50.45	−23.24	−34.69	−58.57	−65.61	24.15
Largest reduction to achieve $R_t = 0.7$	−70.58	−39.70	−149.16	−84.44	−77.36	18.27

= 1, means that additional mobility associated with parks is possible to stay at a value of $R_t = 1$, though to achieve a lower level of R_t, mobility would need to be lower than the baseline values (i.e., from Jan 3 to Feb 6, 2020). The positive values for residential activity indicate that increases in staying at home are needed to achieve desirable levels of R_t.

Table 7

Mobility reduction needed on June 23rd, 2020 for upper level credible interval of $R_t = 1$.

	Retail	Grocery	Parks	Transit	Work	Residence
Alabama	−17.79	4.44	89.64	−17.32	−35.49	11.22
Alaska	−2.46	14.49	188.46	−20.32	−24.50	6.02
Arizona	−30.84	−9.17	22.15	−39.07	−46.87	15.35
Arkansas	−13.52	6.78	116.06	−17.64	−34.06	9.83
California	−36.34	−5.42	53.65	−44.41	−43.90	16.22
Colorado	−19.24	3.61	132.76	−34.30	−35.75	10.96
Connecticut	−17.55	2.89	163.71	−30.77	−33.35	11.36
Delaware	−18.63	−0.49	124.80	−31.71	−35.41	11.68
District of Columbia	−41.01	−11.04	74.85	−54.30	−48.89	16.59
Florida	−36.01	−14.15	6.08	−52.44	−47.19	16.66
Georgia	−24.07	−2.80	70.72	−42.14	−42.77	14.18
Hawaii	−29.57	−8.06	72.23	−48.39	−34.92	12.79
Idaho	−14.98	8.02	161.36	−13.95	−36.38	9.71
Illinois	−23.86	3.72	116.82	−35.37	−38.14	12.60
Indiana	−14.53	5.86	160.51	−12.37	−34.17	10.33
Iowa	−20.18	13.30	165.59	−14.74	−33.95	10.87
Kansas	−19.17	1.19	146.80	−13.80	−36.63	11.18
Kentucky	−22.95	3.00	103.57	−26.12	−41.55	13.01
Louisiana	−22.00	2.47	63.11	−31.36	−38.16	12.34
Maine	−15.46	6.94	168.44	−24.33	−29.57	8.52
Maryland	−24.38	−4.24	127.14	−39.67	−42.00	15.36
Massachusetts	−20.25	2.37	170.06	−43.27	−35.60	12.11
Michigan	−17.53	5.69	201.02	−22.41	−34.05	10.13
Minnesota	−19.28	6.23	171.94	−36.56	−34.44	11.32
Mississippi	−15.68	2.57	64.50	−19.10	−38.48	11.84
Missouri	−19.20	3.38	108.55	−24.90	−37.41	11.67
Montana	−12.61	12.24	145.67	−12.41	−29.28	7.10
Nebraska	−17.30	5.69	142.66	−10.76	−33.15	11.08
Nevada	−29.85	−3.92	38.18	−45.56	−48.55	15.25
New Hampshire	−14.43	4.24	163.52	−23.25	−32.91	10.85
New Jersey	−31.21	0.17	149.90	−44.70	−40.21	15.11
New Mexico	−19.55	7.33	93.39	−18.71	−36.58	11.43
New York	−29.23	3.24	136.75	−42.69	−37.37	12.99
North Carolina	−22.76	−0.40	88.42	−35.79	−39.61	12.61
North Dakota	−13.88	6.78	156.47	−14.98	−25.71	8.67
Ohio	−19.23	2.76	162.86	−18.44	−37.12	11.49
Oklahoma	−19.06	1.96	76.61	−17.72	−40.74	12.69
Oregon	−23.87	0.62	111.63	−31.54	−39.52	11.71
Pennsylvania	−25.62	−2.66	123.27	−38.44	−39.83	13.23
Rhode Island	−20.06	−2.14	161.83	−43.04	−38.21	12.93
South Carolina	−22.35	−1.31	52.11	−22.65	−40.85	13.13
South Dakota	−17.00	11.51	161.92	−11.61	−33.30	11.37
Tennessee	−19.94	1.46	82.86	−26.95	−39.59	12.14
Texas	−30.02	−8.67	23.93	−41.33	−47.39	16.94
Utah	−18.79	7.09	144.11	−32.31	−39.67	11.74
Vermont	−17.49	0.85	169.95	−28.92	−33.12	9.35
Virginia	−23.79	−0.83	107.83	−37.71	−40.53	13.78
Washington	−14.73	8.30	174.72	−29.80	−33.36	9.16
West Virginia	−10.41	8.55	132.28	−7.95	−29.76	7.64
Wisconsin	−20.28	4.26	181.34	−18.95	−32.45	11.05
Wyoming	−14.70	9.06	121.62	−2.91	−31.65	9.25

3. Discussion and conclusions

The effectiveness of mobility reductions at reducing the effective reproduction number of COVID-19 is clearly demonstrated by these results. This analysis does not include any policy variables enacted by individual US states or counties. Other researchers have or are evaluating the effectiveness of these policies on total case-loads, as opposed to infectiousness (Abouk and Heydari, 2020; Courtemanche et al., 2020; Dave et al., 2020; Hsiang et al., 2020; Pan et al., 2020). This work largely confirms the effectiveness of those policies that reduce mobility, which is the primary factor keeping people apart. Some of this is voluntary mobility reductions that are independent of actual government shelter-in-place orders as people took protective action prior to government mandated restrictions. However, the results suggest that further reductions in mobility might be needed to successfully reduce R_t values below 1 or even below 0.7, which would essentially end large scale community transmission.

While the each of the models presented only includes one mobility variable, due to collinearity, results still provide some differentiation of the effectiveness of specific mobility reductions. Activity at parks has the lowest impact on the effective reproduction rate, suggesting that with appropriate social distancing guidelines these should be left open for activities. Mobility associated with time spent at grocery stores and pharmacies also seems to not affect R_t as much, but additional reductions might be needed to reduce R_t

Table 8

Mobility reduction needed on June 23rd, 2020 for upper level credible interval of $R_t = 0.7$.

	Retail	Grocery	Parks	Transit	Work	Residence
Alabama	−47.36	−21.11	−65.61	−47.46	−63.96	23.47
Alaska	−32.03	−11.06	33.21	−50.45	−52.97	18.27
Arizona	−60.42	−34.72	−133.09	−69.21	−75.34	27.60
Arkansas	−43.09	−18.77	−39.19	−47.78	−62.53	22.09
California	−65.92	−30.97	−101.59	−74.55	−72.37	28.48
Colorado	−48.81	−21.94	−22.48	−64.44	−64.22	23.21
Connecticut	−47.13	−22.66	8.46	−60.91	−61.82	23.62
Delaware	−48.20	−26.03	−30.45	−61.85	−63.88	23.94
District of Columbia	−70.58	−36.59	−80.40	−84.44	−77.36	28.84
Florida	−65.59	−39.70	−149.16	−82.58	−75.66	28.91
Georgia	−53.64	−28.35	−84.53	−72.28	−71.24	26.43
Hawaii	−59.15	−33.61	−83.02	−78.53	−63.39	25.05
Idaho	−44.56	−17.53	6.11	−44.09	−64.85	21.96
Illinois	−53.44	−21.83	−38.43	−65.50	−66.61	24.86
Indiana	−44.10	−19.69	5.26	−42.51	−62.64	22.58
Iowa	−49.75	−12.25	10.34	−44.88	−62.42	23.13
Kansas	−48.74	−24.35	−8.45	−43.94	−65.10	23.43
Kentucky	−52.52	−22.55	−51.68	−56.26	−70.02	25.26
Louisiana	−51.57	−23.08	−92.14	−61.50	−66.63	24.60
Maine	−45.03	−18.61	13.20	−54.47	−58.04	20.78
Maryland	−53.95	−29.79	−28.10	−69.81	−70.47	27.61
Massachusetts	−49.82	−23.17	14.81	−73.41	−64.07	24.36
Michigan	−47.11	−19.86	45.77	−52.54	−62.52	22.39
Minnesota	−48.86	−19.31	16.69	−66.70	−62.91	23.57
Mississippi	−45.26	−22.98	−90.75	−49.24	−66.95	24.09
Missouri	−48.77	−22.17	−46.70	−55.04	−65.88	23.92
Montana	−42.19	−13.31	−9.58	−42.55	−57.75	19.35
Nebraska	−46.87	−19.86	−12.59	−40.90	−61.62	23.33
Nevada	−59.42	−29.47	−117.06	−75.70	−77.02	27.50
New Hampshire	−44.00	−21.31	8.27	−53.39	−61.38	23.10
New Jersey	−60.78	−25.38	−5.28	−74.83	−68.68	27.36
New Mexico	−49.12	−18.22	−61.85	−48.85	−65.05	23.68
New York	−58.80	−22.31	−18.50	−72.82	−65.84	25.24
North Carolina	−52.33	−25.95	−66.83	−65.93	−68.08	24.87
North Dakota	−43.46	−18.77	1.22	−45.12	−54.18	20.92
Ohio	−48.80	−22.79	7.61	−48.58	−65.58	23.74
Oklahoma	−48.63	−23.59	−78.64	−47.86	−69.20	24.94
Oregon	−53.44	−24.92	−43.61	−61.67	−67.99	23.96
Pennsylvania	−55.20	−28.21	−31.97	−68.58	−68.30	25.48
Rhode Island	−49.64	−27.69	6.58	−73.17	−66.67	25.18
South Carolina	−51.92	−26.86	−103.14	−52.78	−69.32	25.38
South Dakota	−46.58	−14.04	6.68	−41.75	−61.77	23.62
Tennessee	−49.52	−24.09	−72.39	−57.09	−68.06	24.40
Texas	−59.60	−34.22	−131.32	−71.47	−75.86	29.19
Utah	−48.36	−18.46	−11.14	−62.45	−68.14	23.99
Vermont	−47.06	−24.70	14.71	−59.06	−61.59	21.60
Virginia	−53.37	−26.38	−47.42	−67.85	−69.00	26.03
Washington	−44.30	−17.25	19.47	−59.94	−61.83	21.41
West Virginia	−39.98	−16.99	−22.97	−38.09	−58.23	19.89
Wisconsin	−49.86	−21.29	26.09	−49.09	−60.92	23.31
Wyoming	-44.27	−16.49	−33.62	−33.05	−60.12	21.51

below 1. Time spent at home is very effective at reducing R_t. A limitation of this work is that we do not know the interactive effects of staying at home versus engaging in other activities; that is, more time spent at home, while protective, means less time spent elsewhere.

The time trend variable included in the estimates suggests other unmeasured factors are at play in reducing the effective reproduction rate. Increased use of face masks might be one of these, as research is showing that face masks are effective for mitigating spread of COVID-19 (Mitze et al., 2020). Further work is clearly needed to estimate the effect of these and other protective measures. Warmer and more humid seasonal weather may also account for some of the time trend effects (Wang et al., 2020; Paez et al., 2020). Protective measures taken by grocery stores and pharmacies, installing physical partitions and marking out distances to keep patrons separated may be another factor, as well as resulting in less infectiousness associated with these locations.

The predictions estimated suggest that there is still a need for caution in encouraging increased mobility, especially retail/recreational activity, such as eating in restaurants, office work activities, and public transit usage. The models estimated are associative and this means that predictions from these estimates must be considered with care; however, the underlying biology of viral transmission suggests that keeping people distant is effective and mobility reductions are one way to achieve this. Reductions in viral transmission, however, may be temporary, as infections can increase even after substantial reductions in R_t, as shown by simulations conducted by Kissler et al. (2020).

Mobility reductions and social distancing are useful policies for reducing peak case-loads, i.e. to "flatten the curve" and avoid overloading health care resources. As of this writing in early January 2021, health care systems are near or at capacity in many parts of the country and R_t exceeds 1 in a large majority of states. This is despite mobility levels not returning to baseline levels but also being higher than the reductions seen during the first wave of the pandemic in the Spring of 2020 (see Figs. 1 and 2). Ultimately, to achieve herd immunity, vaccinations must be administered, which began in December 2020.

While other studies have demonstrated the relationship between mobility and case-loads, one of the key innovations of this work is the use of readily available data. This allows analysts to quickly conduct analysis of critical issues, virtually in real time to provide guidance to policy makers, demonstrating the value of openly available "big data" to address rapidly emerging issues.

Author statement

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