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Metrics of Mobility: Assessing the Impact of COVID-19 on Travel Behavior.

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# Abstract

The COVID-19 pandemic disrupted typical travel behavior worldwide. In the United States (U.S.), government entities took action to limit its spread through public health messaging to encourage reduced mobility and thus reduce the spread of the virus. Within statewide responses to COVID-19, however, there were different responses locally. Likely some of these variations were a result of individual attitudes toward the government and health messaging, but there is also likely a portion of the effects that were because of the character of the communities. In this research, we summarize county-level characteristics that are known to affect travel behavior for 404 counties in the U.S., and we investigate correlates of mobility between April and September (2020). We do this through application of three metrics that are derived via changepoint analysis-initial post-disruption mobility index, changepoint on restoration of a "new normal," and recovered mobility index. We find that variables for employment sectors are significantly correlated and had large effects on mobility during the pandemic. The state dummy variables are significant, suggesting that counties within the same state behaved more similarly to one another than to counties in different states. Our findings indicate that few travel characteristics that typically correlate with travel behavior are related to pandemic mobility, and that the number of COVID-19 cases may not be correlated with mobility outcomes.

## **Keywords**

planning and analysis, traveler behavior and values

- The COVID-19 pandemic disrupted typical travel patterns in the United State (U.S.)
- Mobility metrics derived from cell phone GPS traces provide insight into changing travel behavior.
- Employment statistics are significantly correlated with mobility during the pandemic.
- Stay-at-home orders and case numbers are largely not related to mobility outcomes.

The COVID-19 pandemic disrupted typical travel across all of the U.S. As the first cases of the virus were reported in the U.S., government entities began acting to limit its spread. Governmental responses to the pandemic varied from state to state, ranging from stay-at-home orders to non-essential business closures to-in some cases-nearly no response (1). In addition, authorities at all levels distributed public health messaging to help people make educated choices about their behaviors. The "flatten the curve" campaign, for example, was a widespread public health education effort; the message encouraged people to take immediate action to quell the spread of the disease so that the number of cases did not exceed local hospitals' capacities to care for COVID-19 patients (2, 3). Likely both emergency governmental action and public health campaigns changed trip-making behavior.

Thanks to technological advancements, we can now track and analyze the changes in travel which resulted from the pandemic in new ways. Location intelligence companies now track travel patterns via aggregated and anonymized cell phone data, a practice that has expanded since the beginning of the pandemic. Google, for example, released data that captured changes in visits to common destinations (grocery stores, parks, work, etc.) (4). Similarly, Descartes Labs, a geospatial

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thinktank, released mobility index metrics measuring the furthest distance traveled from a starting point (via device triangulation) to create a mobility score (5, 6).

These data showed that the responses to the COVID-19 pandemic were heterogeneous both across states and within states. Descartes data showed that Georgia's Fulton County (which contains much of Atlanta proper) traveled less than 4% of "typical" mobility in early April, 2020. Other Georgia counties, such as Lowndes and Bibb Counties, maintained 34% and 28% of their typical mobility, respectively (6). Different mobility scores may be because of inconsistent health messaging about the risks of the pandemic, or concentrations of jobs that are amenable to teleworking. Alternatively, some counties may have more people who were especially vulnerable to the pandemic and thus chose to travel less. Assessing the community characteristics that are associated with changes in trip-making during the pandemic can help us understand which characteristics may be the most powerful in shaping mobility in future crisis situations.

In this research, we create a dataset of county-level characteristics that are known to affect travel behavior for a cross-section of counties in the U.S., and we investigate which characteristics are significantly correlated with mobility between April 2020 and November 2020. Results include analyses of counties in five states: California, Georgia, Minnesota, New York, and Ohio.

## Literature Review

Given the recency of the COVID-19 pandemic, the literature on travel behavior changes because of the pandemic is limited. The first confirmed cases of COVID-19 presented in the U.S. in mid-January 2020 (7). In May 2020, DeVos predicted that typical travel patterns would change, and that mobility would decrease as a response to social distancing requirements, stay-at-home orders, and other policies intended to slow the virus's spread (8). Even though voluntary changes in travel behavior are difficult to measure and even more challenging to predict, the pandemic's effect was extreme. Virtual schooling, teleworking, and policies limiting out-of-home activities forced dramatic shifts from typical trip-making behavior (9, 10).

Early investigations of travel changes resulting from COVID-19 centered on mode shifts, attitudinal changes, and teleworking preferences—but few of these studies have been based in the U.S. Bucksy found that the pandemic induced more driving trips and walking/biking trips and fewer transit trips in Budapest (11). Transit trips require people to share space with others, so it may be perceived as a "riskier" form of transportation (8). An online survey of people in Germany, Austria, and

Switzerland (n = 1,158) across two time periods showed that increasing age correlated with decreased perception of travel risk, but that the perceived risk of traveling increased for all respondents over time (12).

In the U.S., research on travel change in response to the pandemic focused on perceptions and trip-taking on local scales. The findings parallel those from international studies. Shamshiripour et al. measured changing opinions of teleworking, shopping, and mode of travel in the Chicago area via stated and revealed preferences (9). Results (n = 915) showed that participants perceived shared transportation options (transit, ride hailing, etc.) as riskier than solo forms of traveling, such as driving, walking, and biking. Concerning modal shifts, Brough et al. found that King County, Washington, experienced decreases in transit trips and that people with lower incomes had lower travel intensity (measured via cell phone data) than those with higher incomes, indicating economic disparities often seen in travel behavior research (13).

While pandemics and world-wide disruptions are not unprecedented, what *is* unprecedented are the vast amounts of data available to quantify this pandemic's impact. Several entities provided regularly updated, publicly available mobility data during 2020 (4, 14–16). The datasets used in this research are those created from aggregated cell phone GPS traces. Cell phone data is useful for tracking changes in population-level mobility trends, which is of particular interest for measuring population-level behavior changes in response to the pandemic (17).

Despite such accessible data, there is a gap in the literature on mobility during the pandemic and its relationship to community characteristics. Gao et al. used Descartes' data to map changes in mobility in early April 2020, showing drastic decreases in mobility in most counties in the U.S. (18). Much of the pandemic-related research that uses mobility data does so to predict the spread of COVID-19 (19–25). The basis of this approach is that the virus spreads through airborne droplets (and thus is easily transmitted through proximity to others in enclosed spaces) (7). Mobility data was operationalized as a proxy for exposure and used to model potential spread of the virus. In these studies, mobility measurements provided the basis for modeling potential infection or for measuring social distancing (19). In general, the studies (arguably) measure the potential for disease exposure, but they do not consider mobility itself to be the object of interest.

While the literature shows that mobility data has been used to estimate exposure to COVID-19 and to assess changes in travel on local scales, with the exceptions listed previously, there are no peer-reviewed studies (to the authors' knowledge) that systematically relate mobility to changes in community characteristics across different areas of the U.S.

There is even less research on using mobility metrics as a measurement of response to public health messaging, with two exceptions. A paper from the University of Madison at Wisconsin modeled 3.142 counties' mobility while controlling for perceived risk and restriction orders, where the measurement of perceived risk is based on age, political bias, and population density (26). Engle et al. find that mobility is significantly correlated with stay-at-home orders and a rise in COVID-19 case numbers; stay at home orders correspond to a decrease in 8% of mobility. They also find that increases in the number of COVID-19 cases correlates to a smaller but significant decrease in mobility. These effects differ depending on the population's political affiliations (as measured by voting in the 2016 election). While they do not frame their findings in the form of response to health communications and interventions, they are essentially capturing the effect in their models. A notable limitation is that they do not include other variables in their model that may more fully account for variations in mobility, such as income, car ownership, or employment status at the time of measurement.

A second exception is a study of the response to nonvoluntary governmental actions in Tokyo, which showed that mobility decreased by nearly half of typical rates (which correlated with a decrease in infection) (7). It would be worthwhile to explore if there are similar responses to government interventions in the U.S., a population with markedly different cultural structure and respect for authority/institutions (27).

Our research fills two gaps in the literature. First, we investigate general mobility as the variable of interest, while controlling for community characteristics that may affect the way people move. We design and assess mobility metrics at the county level across five states representing a diverse cross-section of regions of the country. Second, we attempt to measure the impact of stay-athome orders on mobility, in which we consider these governmental interventions as health communications, and mobility metrics as the populations' response to those communications.

# **Materials and Methods**

In this work, we investigate correlates of generalized mobility using novel metrics. For the control variables, we created a dataset through amalgamation of existing county-level data from various sources, including American Community Survey (ACS) demographic data from 2018, employment data from the Bureau of Labor Statistics, COVID-19 risk levels, and governmental responses consolidated to the county level, and political leanings (28–34). We considered variables for this analysis based on conceptual models; each variable we tested is known to correlate to travel behavior generally. Note that, while individual-specific variables such as attitudes are also known correlates of travel behavior, we cannot include individually measured variables at the countylevel unit of analysis.

The variable of interest—mobility—is also reported at the county level from Descartes Labs (14). Mobility is measured through a sample of cell phone GPS trace data, where the mobility score for each county is the median of the sample's distribution of maximum (Euclidean) distance from a device's starting point (29). The starting points are determined temporally as the location of the mobile device at midnight local time. The GPS traces have a median accuracy of 15 to 20 m, and those traces that have a position accuracy of greater than 50 m were removed from the data before its publication by Descartes.

Mobility scores are indexed back to more "typical" mobility values for each county before the pandemic, where a county's "typical" values are the median values from a sample of cell phone data collected between February 17, 2020, and March 7, 2020 (29). Each of the community characteristics, mobility metrics, and other control variable that we tested in our models is shown in Table 1 below.

These statistics were gathered for all counties in five states: California, Georgia, Minnesota, New York, and Ohio. These states were selected purposefully to represent a diverse cross section of the U.S. in relation to geographical region, political tendencies, and governmental interventions. These states were also chosen initially because of their varying degrees of infection spread but, by the time this research concluded, cases of COVID-19 had grown quickly in each of these states (33). The first iteration of the dataset consisted of n = 454, with each case representing a county within one of the five states. Cases with null values, too few cases, and cases with clearly error-ridden mobility data were removed, reducing the number of cases in the final dataset to n = 404.

All of the variables are continuous, with two exceptions: the COVID-19 case variable, which was originally reported in average number of cases normalized by county population per 100,000 people but were ultimately binned into three categories for simplicity, and the political affiliation variable, which is a binary variable. Additionally, we augmented the variable for government response to COVID-19 variable. The dataset contains various stay-at-home order dates in relation to proleptic Gregorian ordinal of the date. To make the scale more interpretable, we convert the variable to a discrete value representing the number days between March 1 and the date that county/state governments implemented stay-at-home orders.

Variable	Source	Operationalization
Population density	American Community Survey (ACS) Table B01003 (2018 5- year estimates); TIGER line shapefiles used to determine	Total population per county, normalized by county area
Transit users	county area ACS Table S0801 (2018 5-year estimates)	Percent of workers 16 years or older by mode who use transit for their commute per county
Work from home	ACS Table S0801 (2018 5-year estimates)	Percent of workers 16 years or older who telecommute per county
Household income	ACS Table B19001 (2018 5-year estimates)	Median household income per county
Poverty	ACS Table B08122 (2018 5-year estimates)	Percent of people living below 100% of the poverty level per county
Vehicles available	ACS Table S0801 (2018 5-year estimates)	Percent of county with 0, 1, 2, 3+ vehicles available per county
Age	ACS Table B01002 (2018 5-year estimates)	Median age per county
Work in county of residence	ACS Table B01002 (2018 5-year estimates)	Percent of employed people who work in the county in which they live
Employment	Bureau of Labor Statistics quarterly census of employment and wages (2020, Quarter 1)	Location quotient (LQ) per four-digit North American Industry Classification System (NAICS) code for each county (35, 36): - 1011: Natural resources and mining - 1012: Construction - 1013: Manufacturing - 1021: Trade, transportation, and utilities - 1022: Information - 1023: Financial activities - 1024: Professional and business services - 1025: Education and health services - 1026: Leisure and hospitality - 1027: Other services
Government response to COVID-19	"A county-level dataset for informing the United States' response to COVID-19." (29)	Number of days taken to institute a stay-at-home order, referenced from March I, 2020
COVID-19 cases	Brown School of Public Health COVID19 Risk Dashboard (January 1 through November 24, 2020)	<ul> <li>Average of daily number of cases, normalized by county population per 100 k people, categorized into three bins following Center for Disease Control categorization of risk:</li> <li>Low: &lt;10 per 100,000</li> <li>Medium: 10-20 per 100,000</li> <li>High: &gt;20 per 100,000</li> </ul>
Mobility index	Descartes Lab mobility data (March 15 through November 24, 2020)	Daily mobility scores for each county indexed for comparison with more typical travel behavior
State	NA	Dummy variable for each of the five states: California, Georgia, Minnesota, New York, and Ohio, where Minnesota is the reference variable
Political trend	MIT election labs (34)	Binary variable, where I = the largest percentage of voters for the Democratic candidate in the 2020 election, and 0 = the largest percentage of voters for the Republican candidate in the 2020 election (there were no counties in the sample where the largest percentage of voters voted for another political party)

Table 1. Data Sources Considered in Models and Variable Operationalization

NA = not available.



Figure 1. Changepoint analysis applied to two counties, Bibb (*left*) and Huron (*right*), showing different changepoints and pre- and post-changepoint means.

For the variable of interest, we create mobility metrics that together characterize mobility responses to COVID-19. We calculated these metrics based on mobility scores from Descartes data between March 15 and November 24, 2020. Creating singular metrics to represent a time series presents a challenge; meaningful nuance can be lost by reducing an entire trend to a single value.

We address the challenge by conducting a (single) changepoint analysis (37, 38). The "changepoint" in a time series is defined as the time at which the "properties of a sequence of observations change," such that the observations before and after the change point are different in some measurable way (37). Simply put, changepoints are points in time series when there is a statistically significant difference in the "before" and "after" of that point. In this analysis, the changepoints represent the time at which a county's mobility began to "recover," or return to more typical mobility, during the early onset of the pandemic in 2020. Detecting a single change point utilizes a hypothesis testing approach, where  $H_0 =$  no change point (m = 0), and  $H_A =$  a single change point (m = 1). The hypothesis is tested by comparing the maximum log-likelihood of two parameters (mean and variance) under both H<sub>0</sub> and H<sub>A</sub>. The location of a changepoint in a time series is considered among all possible change points, which for this data is 255 possible points.

We illustrate the method by applying it to two counties (Bibb County, GA, and Huron County, OH) in Figure 1. Note that the two counties used in this illustrative example appear to have different mobilities, as shown by the fluctuating mobility index. The changepoint analysis captures the differences between the trends with metrics: the changepoint (day 59 for Bibb County and day 79 for Huron County) and the pre- and postchangepoint means.

We calculated a single changepoint for each county in the sample. The histograms in Figure 2 show the distribution of each state's county-level changepoints, where the changepoints represent the time at which each county's mobility began to return to pre-pandemic levels. The xaxis indicates the day at which the changepoint occurred, and the *y*-axis shows the percent of counties in each state. The distributions of changepoints are different between states, showing a heterogenous mobility response to COVID-19. For example, in Georgia many of the counties' mobility began to return to pre-pandemic levels around the same time, as shown by the clustering of changepoints around 40 to 50 days after March 1, 2020. The changepoints in Ohio, however, are more spread out, which shows heterogeneity among the counties' mobility patterns over time. Table 2 provides descriptive statistics for each of the variables used in our models.

Using these data, we generate linear regression models for the following dependent variables obtained from the changepoint analysis:

1) *Mobility Changepoint* (MCP), which is the number of days after March 15, 2020, a change point

Table 2. Summary Statistics for Variables of Interest, II – 40	Table 2.	Summary	Statistics for	Variables of	Interest, $n = 40$
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Statistic	Mean	SD	Min.	Max.
Descriptive statistics				
Median Age*	40.26	4.33	27.70	55.10
% commuters using a car*	89.77	7.97	7.90	98.40
% commuters driving alone*	80.36	7.96	6.00	91.60
% commuters carpooling*	9.41	2.55	1.90	21.90
% commuters using transit*	1.73	5.75	0.00	61.00
% commuters walking*	2.56	2.11	0.00	20.30
% commuters biking*	0.39	0.76	0.00	8.00
% commuters walking*	1.17	0.87	0.00	8.70
% commuters working from home*	4.39	2.07	0.20	14.00
% commuters working in their county of residence*	60.84	18.07	11.50	98.20
% commuters with a travel time $<10$ min*	17.73	8.18	2.80	53.10
% commuters with a travel time $>60 \text{ min}^*$	8.30	5.19	2.00	35.70
Mean travel time*	25.07	5.12	11.80	44.50
% population with 0 car ownership*	3.18	4.90	0.40	72.30
% population below poverty level*	7.22	3.03	2.00	21.00
Average mobility index	70.78	22.25	18.14	215.08
Maximum mobility index	151.01	79.94	101.00	893.00
Minimum mobility index	1.24	3.10	0.00	23.00
Mobility index recovery rate	135.09	45.07	24.00	233.00
Location quotient (LO #)				
Natural resources and mining (1011)	2.30	3.58	0.00	35.20
Construction (1012)	0.89	0.54	0.00	4.42
Manufacturing (1013)	1.60	1.12	0.00	5.98
Trade, transportation, utilities (1021)	1.02	0.29	0.28	2.74
Information (1022)	0.45	0.58	0.00	5.98
Financial services (1023)	0.60	0.31	0.00	2.76
Professional, business services (1024)	0.51	0.34	0.00	1.84
Education, health services (1025)	0.92	0.40	0.00	3.02
Leisure and hospitality services (1026)	0.90	0.36	0.00	3 20
Other services (1027)	0.86	0.35	0.00	3.11
Quarter 2 cases**	4 16	2 49	1.00	9.00
Quarter 3 cases**	6 70	2.61	1.00	9.00
Quarter 4 cases**	8.18	1.53	3.00	9.00
Stav-at-home order date***	11.03	5.62	3.00	19.00
No gatherings greater than 50 people***	19.62	4	11.00	23.00
First school closure date***	20.10	0.56	19.00	21.00
Restaurant closure date***	20.10	2 14	18.00	23.00
Dependent variables	20.75	2.11	10.00	25.00
Mohility mean L (MML)	34 75	17 22	0 79	78 22
Mobility mean 2 (MM2)	79 18	25.11	20.22	248 15
Mobility changepoint (MCP)	55 70	1641	13.00	249.00
	55.70	10.11	15.00	277.00

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

\*Based on American Community Survey (ACS) data, 2018 5-year estimates.

\*\*\*Case rates of COVID-19 are reported in a nine-bin categorical variable, based on Brown School of Public Health COVID-19 Risk Dashboard.

\*\*\*\*Number of days from March 1 to the date at which local/county governments implemented the public health measure, based on Killeen et al. (28).

occurred and captures the initial travel response to the pandemic.

- 2) *Mobility Mean 1* (MM1), which is the average mobility index before the changepoint and captures the time taken to begin to increase mobility.
- Mobility Mean 2 (MM2), which is the average mobility index after the changepoint and represents the value at which mobility reached a "new normal" in 2020.

Before modeling, we reviewed correlation tables for all variables considered for the model, removing highly correlated variables to avoid multicollinearity. Variable selection for the final models followed a multistep process. First, we created conceptual models for each of the regressions, choosing variables we suspected correlated significantly with each metric. We then created multiple iterations of each model, considering the interactions among variables and their significance levels in each

#### Table 3. Linear Regression Models of the Mobility Mean I (MMI) Metric

	Dependent variable MMI				
	States model		Political affiliation model		
Intercept	52.730***	P = 0.000	56.653***	p=0.000	
Mean travel time	- <b>0.784</b> ***	p = 0.000	-0.563***	p = 0.0001	
Natural resources and mining location quotient (LQ)	0.212	p = 0.252	0.208	p = 0.357	
Construction LQ	0.415	p = 0.697	0.527	p = 0.693	
Manufacturing LQ	0.570	p = 0.372	0.308	p = 0.684	
Trade, transportation, utilities LQ	0.629	p = 0.748	4.169*	p = 0.082	
Information LQ	- <b>3.126</b> ***	p = 0.004	-4.613***	p = 0.001	
Financial services LQ	<b>-7.054</b> ***	p = 0.0005	-4.319*	р = 0.084	
Professional, business services LQ	-2.83 I	p = 0.133	2.788	p = 0.238	
Education, health services LQ	-0.573	p = 0.726	-7.027***	p = 0.0004	
Leisure and hospitality services LQ	3.141*	р = 0.073	7.540***	p = 0.0004	
Other services LQ	-3.821**	p = 0.030	14.378***	p = 0.000	
Ref. COVID-19 cases: Low		•		•	
COVID-19 cases: Medium	-3.651**	p = 0.019	0.846	p=0.657	
COVID-19 cases: High	0.263	, p = 0.848	8.362***	$\dot{P} = 0.00000$	
Ref. Minnesota		•		•	
California	-0.242	p=0.915	NA	NA	
Georgia	22.195***	p = 0.000	NA	NA	
New York	- <b>9.280</b> ***	p = 0.00001	NA	NA	
Ohio	6.737***	p = 0.0002	NA	NA	
Largest share voted democrat (%)	NA	NA	-10.707***	p = 0.00000	
Observations	404		404		
R <sup>2</sup>	0.673		0.470		
Adjusted R <sup>2</sup>	0.6	59	0.451		
, Residual standard error	10.079 (	df = 386)	12.782 (0	df = 389)	
F statistic	46.712*** (df = 17; 386)		24.624*** (df = 14; 389)		

Note: p < 0.1; p < 0.05; p < 0.01.

**Bold** variables are significant at p < 0.01 in the states model.

Italicized variables are significant at p < 0.01 in the political party model.

NA = not available.

iteration. We selected final versions of the models based on conceptual validity and variance explained. We ultimately pruned these final models, removing most of the variables that were insignificant.

# Results

Figure 3 shows the trend of mobility indexes averaged for each of the five states in our study from March 1 to November 24, 2020. Mobility indexes for the state were aggregated at the state level. For clarity in this figure, the indexes reported in Figure 3 have been averaged over 7 days, allowing trends to present more clearly. We also show the daily new cases per 100,000 people averaged over 7 days in Figure 4. Comparing these graphics shows that the trends of mobility did not necessarily follow the trends of new cases. Note that we only use state-level averages *in these graphics*; the rest of the analysis uses county-level mobility metrics.

In calculating MCP, MM1, and MM2, the first 15 days (March 1–March 15, 2020) are not included. We

excluded these dates as we wanted the MM1 value be more representative of the "trough"—the lower average before the change point, not including the peaks in mobility before the "trough." When we included dates before March 15, 2020, our changepoint analysis captured local maximums in mobility that captured sudden increases in mobility that were likely the result of people preparing for the first lockdowns, which we did not want to capture in our models.

As shown in the figures, mobility dramatically decreases in all five states starting in early March 2020, corresponding to the first cases of COVID-19 discovered in the U.S. Each state's minimum mobility scores, or the "troughs," appear at different times temporally. New York experienced a lower minimum score than the other states, and it lasted much longer than the other states' minimum scores. After the states' mobility indices reached their lowest points, all mobility scores increased at varying rates. Each state appears to reach an "equilibrium" after the trough in which they maintain a

California S<sup>4</sup> counties California S<sup>4</sup> counties Corgia Contio Corgia Contio Contio Corgia 

**Figure 2.** The distribution of county-level mobility changepoints (MCPs) reported as the percentage of counties in each state.



Figure 3. Mobility index 7-day average by state.

relatively constant mobility index (generally between July and October, 2020). Each state's "equilibrium" occurred at a different time and at different average values. Both the recovery trends and the equilibrium trends were not uniform among states; the data seem to indicate that there is no singular trend to return to more typical mobility scores. In the following section, we investigate correlates of these trends using the three metrics described previously—MM1, MCP, and MM2.

# Model of Mobility Mean 1 (MM1)

We modeled correlates of the MM1 for each of the 404 counties in our sample, shown in Table 3. We created

two separate models for this metric: one that included the dummy variable for states, and one that included the dummy variable for political trend. We could not include both variables in the same model, as they were too highly correlated. We only report significant variables here, but we ran iterations of both models with many other variables, including median age, income metrics, travel mode variables, and population density, none of which were significant or created better model fits.

The model including the state variables has an adjusted  $R^2$  value of 0.659, and the model including political trend has an adjusted  $R^2$  value of 0.451. The states model also has a larger F-statistic and a standard error that is closer to zero than the political affiliation model, indicating a better fit overall.

Six of the variables in the states model have p-values that indicate a very likely significant relationship (plus a significant intercept). Mean travel time is negatively associated with the MM1 metric, meaning that higher mean travel times (in 2018, our closest estimate) are associated with lower MM1 values but with small effect. Two employment variables—Information and Financial Services location quotients (LQs)—are also negative, indicating that higher shares of these sectors are associated with lower MM1 values. Also, the dummy variable for states indicates significant (or at least likely significant) differences in several states compared with Minnesota, including Georgia, New York, and Ohio.

# Model of Mobility Changepoints (MCPs)

Results of a model in which the changepoint, MCP, is the variable of interest are shown in Table 4. For this metric, we present only one model, as the political trend variable was not significant in any of the iterations of modeling this metric.

The  $R^2$  value for the MCP model is 0.373 and the adjusted  $R^2$  value is 0.344—lower than the other models in our study. It is also of interest that more community-specific variables are significant in this model than the previous model. Median age is again significant and negative; higher median ages in counties are associated with lower changepoint values (i.e., an earlier changepoint in time). The percent of people living in poverty per county is also negatively associated with the county's changepoint, meaning that a higher number of people who are poor is associated with lower changepoint values. The employment variable Natural Resources and Mining LQ is also positive and significant. Again, all the states are significantly different from Minnesota at least at the p < 0.05 level.

# Model of Mobility Mean 2 (MM2)

Finally, we model correlates of the MM2, which is the mean for the remaining data after the selected

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Table 4.	Linear	Regression	Model	of Mobility	Change	points (	(MCPs)	)
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	Dependent variable			
	MCP	P		
Intercept	79.328***	p=0.000		
Median age	- <b>0.807</b> ***	p = 0.00002		
Below poverty level (%)	- <b>1.215</b> ***	p = 0.00004		
Natural resources and mining location quotient (LQ)	0.530**	P = 0.030		
Construction LQ	-1.137	p = 0.405		
Manufacturing LQ	0.680	, p = 0.425		
Trade, transportation, and utilities LQ	3.342	p = 0.199		
Information LQ	1.366	p = 0.332		
Financial services LO	-0.789	p = 0.762		
Professional and business services LQ	2.704	p = 0.309		
Education, health services LO	3.636*	p = 0.100		
Leisure and hospitality services LO	2.390	, D = 0.301		
Other services LQ	-I.992	p = 0.394		
Ref. COVID-19 cases: Low		•		
COVID-19 cases: Medium	5.012**	p = 0.015		
COVID-19 cases: High	6.684***	p = 0.0003		
Ref. Minnesota		•		
California	17.477***	p = 0.000		
Georgia	-5.544**	p = 0.033		
New York	12.972***	p = 0.00000		
Ohio	7.863***	p = 0.001		
Observations	404	F		
R <sup>2</sup>	0.373			
Adjusted R <sup>2</sup>	0.344			
Residual standard error	3.288 (df = 385)			
F Statistic	12.745*** (df = 18; 385)			

*Note:* \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01.

**Bold** variables are significant at p < 0.01 in the states model.

Italicized variables are significant at p < 0.01 in the political party model.

changepoint. The number of days included in that mean vary with the corresponding MCP. Like the MM1 metric, we present two different models: one with the states variable and one with the political trend variable. As with the previous models, we showed the pruned results in Table 5.

In these models (adjusted  $R^2 = 0.539$  and adjusted  $R^2 = 0.414$ , respectively), we again find that the model containing the states variable better describes the variation in the data than the model containing political trend. In the states model, more community-specific variables are significant than in any of prior models; for example, the percent of people commuting by walking per county is associated positively with MM2, indicating that counties with higher numbers of people commuting by walking in 2018 is associated with higher MM2 values. Ohio, New York, and California are significantly different from the reference state, Minnesota, with large effects. Interestingly, this is the only model in which the share of employment in the Health and Education sectors is significant; here, it is negatively associated with the MM2 values for each county (and with a notable effect size).

# Discussion

The analysis presented in this paper has two major contributions. First, we show that three mobility metrics— MM1, MCP, and MM2—effectively describe the



**Figure 4.** Daily new cases, 7-day moving average per 100,000 people.

		Dependent variable				
	MM2					
	States model		Political party model			
Intercept	113.518***	p = 0.000	123.070***	p=0.000		
Walk (%)	3.464***	P = 0.00000	2.811***	$_{\rm P}^{\rm -} = 0.00003$		
Work in county of residence (%)	0.234***	, p = 0.005	-0.106	p = 0.200		
Mean travel time (minutes)	- <b>0.778</b> ***	, p = 0.004	-1.724***	p = 0.000		
Below poverty line (%)	0.884**	, p = 0.029	1.608***	p = 0.00004		
Natural resources and mining location quotient (LQ)	-0.029	, p = 0.928	-0.484	p = 0.157		
Construction LQ	-0.55 I	p = 0.766	-0.688	p = 0.739		
Manufacturing LQ	<b>-2.926</b> ***	p = 0.010	-0.908	, p = 0.439		
Trade, transportation, utilities LQ	-I.757	, p = 0.606	5.142	p = 0.169		
Information LQ	-2.256	p = 0.234	-0.315	p = 0.882		
Financial services LQ	-7.219**	p = 0.041	1.769	p = 0.651		
Professional, business services LQ	-7.813**	p = 0.021	-5.493	p = 0.142		
Education, health services LQ	<b>-9.425</b> ***	p = 0.002	-4.369	p = 0.154		
Leisure and hospitality services LQ	0.003	p = 1.000	- I. <b>794</b>	p = 0.583		
Other services LQ	-2.797	p = 0.351	-4.463	p = 0.174		
Ref. COVID-19 cases: Low		1				
COVID-19 cases: Medium	-6.606**	p = 0.013	- I.85 I	p = 0.527		
COVID-19 cases: High	-3.914*	, p = 0.094	2.791	, p = 0.249		
Population density	-0.004***	p = 0.0002	-0.003***	p = 0.004		
Ref. Minnesota		1				
California	-45.605***	D = 0.000	NA	NA		
Georgia	-5.000	p = 0.176	NA	NA		
New York	-27.065***	p = 0.000	NA	NA		
Ohio	<b>-9.856</b> ***	p = 0.002	NA	NA		
Largest share voted democrat (%)	NA	NA	<i>—18.295***</i>	P = 0.000		
Observations	40	404		404		
R <sup>2</sup>	0.5	0.563		0.441		
Adjusted R <sup>2</sup>	0.5	39	0.4	14		
Residual standard error	17.075 (c	if = 382)	19.243 (0	f = 385)		
F Statistic	23.434*** (c	23.434*** (df = 21; 382)		6.846*** (df =  8; 385)		

Table 5. Linear Regression Models of the Mobility Mean 2 (MM2) Metric

Note: p < 0.1; p < 0.05; p < 0.01.

**Bold** variables are significant at p < 0.01 in the states model.

Italicized variables are significant at p < 0.01 in the political party model.

NA = not available.

variation in mobility trends caused by COVID-19. Changepoint analysis could easily be applied to future events that disrupt travel. Together, our models create a simply derived yet meaningful picture of U.S. counties' reaction to COVID-19. We find the MCP metric via changepoint analysis to be particularly useful. It seems that mobility recovery, which is signaled by the changepoint, is a good indicator for some kinds of economic and travel recovery. Second, the explanatory variables that were significant (and the ones that were not) explain much about what influences people to travel even amid a pandemic.

It is interesting to review our results through a temporal lens, first considering the MM1 metric since it represents the average mobility measurement before the changepoint. We will first focus on the models which contained the state control variables instead of models with political trend variables, since they are better models generally. Average travel time (using 2018 estimates as a proxy), as well as the information on the financial services sectors, are powerful predictors of the MM1 regression model. Counties with more long commuters had lower MM1 metrics. This could mean a non-negligible number of people who typically commute long distances transitioned to working from home. It also makes sense that the significant employment sectors also had negative associations with the MM1 metric; these jobs also seem to be easily convertible to working from home, allowing people to reduce travel.

Next, in the MCP model, the significant variables are different from the MM1 model. It seems intuitive that the low-income variable is negative and highly significant, given that people with lower incomes may have returned to work earlier and may more often be essential

workers than higher income people. Also, California, New York, and Ohio have MCPs that are significantly later than Minnesota at baseline. In contrast, Georgia's MCP is significantly earlier than Minnesota at baseline. Together, this shows that what caused variations in travel is state-specific, but it is not related to the dates or political leanings of large shares of the population, since neither of those variables were meaningful in our analysis. We also found that counties with high numbers of COVID-19 cases had later changepoints (i.e., a slower mobility "recovery") compared with those with low case numbers. This makes sense, and it perhaps reflects that people, on average, altered their mobility in response to high volumes of COVID-19 cases in their communities. It should be noted, however, that the MCP model has a lower  $R^2$  value than our other models; clearly there is more affecting travel changes than what is captured here.

Additionally, we notice that median age is negatively correlated (albeit with small effects) with MCP in this model; counties with higher median ages had earlier changepoints. It struck us that counties with an older population would be more cautious in increasing mobility because older people are more vulnerable to the virus and thus may choose to reduce travel for longer. It is possible that this finding is simply an artifact of aggregation: just because we see this relationship with median age at the county level does not mean that this translates to the individual level. Alternatively, these results could actually indicate that communities with more older people increased travel more quickly than others. More delineated analysis is needed here. But since that is not possible in our work, we can only say that age seems to have some relationship with MCP, or, at the least, that some other variable combined with age does.

Finally, considering the MM2 model, the percent of the county that commutes by walking is important with a positive effect, and mean travel time is important with a negative effect. This implies that counties with more walking and shorter travel times had a higher average mobility after their changepoint than other counties. The percent of people who walk for their commute is not significant in the MM1 model; if we assume that people walk in places where it is convenient to do so, then we can say that these results imply that walkable communities had higher levels of activity during mobility recovery-a potentially interesting finding and policy implication. Also, Georgia is the only state that is not significantly different from Minnesota. A possible reason for this could be that the counties within Georgia differ from one another enough that the effect of the state is not significant, or it could be that the counties within Georgia behaved similarly to the counties within Minnesota. We think that either is possible. Since Georgia and Minnesota are notably politically different from one another, and since our models show that the political affiliation is relevant, we are inclined to believe the former—that the counties within Georgia are different enough from one another to mitigate the effect of the state variables.

In the MM2 model, all states except Georgia were significantly different from Minnesota with relatively large effects. Large effects because of state differences is a common theme across all three models. This makes sense; counties within a state *should* be, on average, more alike than counties in other states. Perhaps this does point to the effectiveness of state-level guidance as it affected traveling, even though our variable for stay-at-home order variable was not particularly meaningful in any of the models. There could be other public health communication efforts that are not captured here.

Because the states are powerful variables, we developed iterations of our models in which we varied the reference state. When using California as the reference, the intercepts of the MM1 and MM2 models (64.84 and 48.56, respectively) were unexpected. With all other variables at zero, we expected the mobility index to be higher in the MM2 model as travel returned to the new normal. In all other iterations, the intercepts were as expected, where the MM2 intercept was higher. However, the pandemic response was different in California, with most counties experiencing two major changepoints after March 15, 2020, the first of which reduced mobility even further and the second of which restored it. This is an interesting finding, suggesting that California is unique compared with other states. This indicates the need for multiple changepoints to be integrated in some cases.

Interestingly, the MM2 model is the only model using state control variables in which the Health and Education LQ is significant at the 0.01 significance level (negatively associated). A challenge of using LQs categorized by NAICS codes for this research is that health jobs and education jobs are grouped in the same occupational category. Trip-making during the pandemic has been different for people in the health compared with education workforces. For example, school districts around the country became partially or fully remote, but healthcare jobs may have required more trips as the pandemic worsened. Even though the health and education services LQ is significant in the MM2 model, we suspect the cumulative impact of these sectors would be larger if they were separately measured. These findings may indicate a need to recategorize the NAICS codes, since these industries seem to be characteristically different from each other in these circumstances.

Across all three metrics of mobility, we find that, when employment variables are correlated, they have large effects (although less so than states). We find that jobs that presumably can be done at home influence the MM1 metric, and jobs that more likely need to be done in person (natural resources, mining, healthcare, and some educational services) influence the MM2 metric which makes sense. Large shares of jobs that can be done at home likely drive the drop in mobility, and large shares of jobs that must be done in person likely drive the "recovered" mobility.

To our surprise, the variable we used for measuring health communication and governmental response to the pandemic does not seem to be significant in any of our models. Our results indicate that mobility was largely not affected by government health messaging, which could indicate failures of health messaging in general or in this instance. Alternatively, it could mean that, even if people wanted to stay at home because of health messages, they could not because of employment or other commitments.

All models in which we included a variable for political affiliation instead of the state dummy variable were poorer fits. The political party variable, however, was highly significant in both the MM1 and MM2 models, which indicates that it is not negligible. The counties where the largest share of people voted for the democratic candidate in the 2020 election had lower pre- and post- changepoint average mobilities than counties in which the largest share of voters voted for the republican candidate; said another way, counties that were more left leaning in the 2020 election traveled less as the pandemic began in the U.S. and as mobility began to increase after the changepoint. This indicates that travel during the pandemic was far from politically neutral. Future research should consider using alternative measurements of political affiliation, such as continuous variables along political spectrums instead of a binary variable.

#### Limitations

Our research has limitations that are relevant for interpretation of our models. First, it is important to compare our unit of analysis and the interactions that spread COVID-19. The virus is not spread at the county level but through individual interactions of infected people. The nuances of those interactions, the attitudes of individual people, work responsibilities, and even some of the messaging that people receive, cannot be described completely at the county level (9). We suspect that such variables are potent, and, if they could be included in these results, they might have altered our findings. Rather, this study attempts to model overarching trends of travel behavior in response to the pandemic. We eagerly await the results of ongoing survey efforts to better understand individual trip-making behavior in 2020.

An additional shortcoming of mobility data is that it is only representative of people who have cell phones and is not completely representative of even those populations. Given the completely anonymous nature of the data and the limitations of using data from a third party that did not disclose the market share covered or the demographic representativeness of the data, we cannot know the degree to which the data is unrepresentative. Grantz et al. noted this shortcoming well: "Using aggregate mobility flows to estimate population-level reductions in travel will fail to capture increased risk among essential workers that are unable to stay home." (17). We agree, and we would extend the notion to even more vulnerable populations, such as the very poor and the unhoused. Future work should seek to describe the representativeness of this data and to inform the interpretations of the findings using this kind of data.

### Conclusions, Policy Implications, and Future Research

In summary, our research shows that mobility data combined with changepoint analysis is a useful source to describe travel patterns during a major travel interruption. The three metrics we have delineated—initial postdisruption mobility index, changepoint on restoration of a "new normal," and recovered mobility index—are all useful to explain the phases of the travel disruption.

Some of the most significant variables relate to commute travel times and employment sectors. In particular, the longer the commute, the more willing people are to initially work from home or perhaps pressure their employer to allow them to do so. Information workers are most easily able to transition to work-from-home; however, our results indicate a need to recategorize NAICS codes to ensure that division of employment sectors by likelihood of ability to work-from-home is taken into account for disaster response purposes. Perhaps most critically, some workers are unable to transition to work-from-home no matter what public health guidelines suggest, and those workers must have transportation to their jobs, including the provision of public transportation, which often serves lower-income workers.

We have chosen five states to be representative of the U.S. experience more broadly. Although significant differences in mobility metrics are experienced between the states, travel behaviors appeared to have little to do with stay-at-home orders or the number of cases of COVID-19, indicating the need for better health messaging. Although the cultural and social context differs, government declarations were more closely correlated with behavioral changes in Japan (39). Japan's "3 C's" communications campaign—emphasizing avoiding closed environments, crowded conditions, and close contact settings—was evidence-based, clearly communicated, and easy to remember (40).

Given the limitations and our findings, we see ample space for more research on pandemic travel trends. An area to explore is additional methods and metrics to compare the trends among counties and states. While we stand by our analysis of MCP, it led us to think that there are more ways of comparing county responses. In future research we hope to apply other methods, such as advanced cluster analyses. We also see the need for models that can delineate by mode and trip purpose, as people may have walked, biked, or driven more than they would have normally. Changes in mobility may reflect different commute patterns, but they may also capture non-commute mobility changes. Given the increase of people staying at home more than they normally would, there may be a stronger urge to "just to get out and go somewhere (another form of variety-seeking)" (41). It would be interesting to see how a mode variable would interact with other variables related to travel behavior. We look forward to seeing these needs addressed in an increasing literature of COVID-19 impact assessment.

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### **Author Contributions**

The authors confirm contribution to the paper as follows: study conception and design: R. Panik, D. Ederer; data collection: R. Panik, D. Ederer; analysis and interpretation of results: R. Panik, K. Watkins; draft manuscript preparation: R Panik, D. Ederer, K. Watkins. All authors reviewed the results and approved the final version of the manuscript.

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