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The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the U.S. from March to September of 2020

Junghwan Kim [a], Mei-Po Kwan [b,*]

[a] Department of Geography and Geographic Information Science, University of Illinois at Urbana-Champaign, Natural History Building, 1301 W Green Street, Urbana, IL 61801, USA

[b] Department of Geography and Resource Management and Institute of Space and Earth Information Science, Fok Ying Tung Remote Sensing Science Building, The Chinese University of Hong Kong, Shatin, Hong Kong, China

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ABSTRACT

This paper examines changes in people's mobility over a 7-month period (from March 1st to September 30th, 2020) during the COVID-19 pandemic in the U.S. using longitudinal models and county-level mobility data obtained from people's anonymized mobile phone signals. It differentiates two distinct waves of the study period: Wave 1 (March–June) and Wave 2 (June–September). It also analyzes the relationships of these mobility changes with various social, spatial, policy, and political factors. The results indicate that mobility changes in Wave 1 have a V-shaped trend: people's mobility first declined at the early stage of the COVID-19 pandemic (March–April) but quickly recovered to the pre-pandemic mobility levels from April to June. The rates of mobility changes during this period are significantly associated with most of our key variables, including political partisanship, poverty level, and the strictness of mobility restriction policies. For Wave 2, there was very little mobility decline despite the existence of mobility restriction policies and the COVID-19 pandemic becoming more severe. Our findings suggest that restricting people's mobility to control the pandemic may be effective only for a short period, especially in liberal democratic societies. Further, since poor people (who are mostly essential workers) kept traveling during the pandemic, health authorities should pay special attention to these people by implementing policies to mitigate their high COVID-19 exposure risk.

1. Introduction

Since December 2019, the COVID-19 pandemic has become one of the most critical global public health crises (World Health Organization, 2020). In the U.S., since the first case was reported on January 20, 2020, there have been about 28.9 million confirmed cases and about 52.5 thousand deaths at the time of writing (mid-March 2021) (USA Facts, 2020). The COVID-19 pandemic has significantly affected various facets of our daily life. Among them, one important aspect that captures the attention of geographers and policymakers is people's mobility. Specifically, a growing number of researchers have examined how the COVID-19 pandemic has affected people's mobility patterns and travel behaviors (e.g., Cartenì et al., 2020; Chakraborty and Maity, 2020; De Vos, 2020; Gao et al., 2020a, 2020b; Huang et al., 2020b; Irawan et al., 2021; Lee et al., 2020a, 2020b; Liu et al., 2020; Willberg et al., 2021; Shamshiripour et al., 2020). Considering that mobility reduction can be an effective nonpharmacologic COVID-19 measure for controlling the spread of the virus, understanding how people's travel behaviors are affected by the COVID-19 pandemic and how they have changed over time can provide useful insights into effectively designing and implementing COVID-19 mitigation policies.

For example, Gao et al. (2020a) developed an interactive web-based geo-visualization platform where citizens and policymakers can easily learn about how the mobility levels of U.S. counties have changed over time and how these changes vary geographically. Focusing on the early stage of the COVID-19 pandemic in the U.S., Lee et al. (2020b) concluded that various human mobility metrics (e.g., miles traveled per person) had decreased after the declaration of a National Emergency on March 13, 2020, which is in line with the conclusions from Huang et al. (2020b). They also observed that states with higher income levels have higher percentages of people who stay at their homes. Liu et al. (2020) investigated the effect of the COVID-19 pandemic on the public transit ridership of 113 transit systems in the U.S. and concluded that regions with higher percentages of essential workers are more likely to maintain

* Corresponding author.
E-mail addresses: jk11@illinois.edu (J. Kim), mpkwan@cuhk.edu.hk (M.-P. Kwan).

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their usual transit ridership levels.

Although previous studies provided a useful ground for future research, they have two main limitations. First, previous studies largely focused on the early stage of the COVID-19 pandemic (e.g., March to April 2020). Considering that the COVID-19 pandemic in the U.S. is still an on-going public health crisis at the time of writing, investigating the mobility changes in a more comprehensive timeline would provide meaningful insights into the impacts of the COVID-19 pandemic on people's mobility patterns and travel behaviors. Second, although there are some exceptions (e.g., Campbell et al., 2021; Matson et al., 2021), most previous studies largely used cross-sectional data and analytical methods. Given the fact that the COVID-19 situation in the U.S. has been evolving drastically since March 2020, it is plausible that people's mobility behaviors have also been affected and changed substantially over time. However, using cross-sectional data and methods may have limitations for providing an in-depth understanding of people's mobility changes during the COVID-19 pandemic.

Thus, this research seeks to fill this important gap by employing longitudinal data analysis (LDA) methods. There are two research goals. First, we aim at investigating changes in people's mobility levels in the U.S. for a 7-month period (March 1st to September 30th, 2020). Second, we seek to examine how the changes in people's mobility levels over time are associated with social, spatial, policy, and political factors, such as poverty level, population density, COVID-19 severity, COVID-19 mobility restriction policies, and political partisanship.

2. Data and methods

2.1. Data

2.1.1. County-level mobility data

The key dataset of this research is the U.S. county-level daily mobility dataset, which is open to the general public and provided by Descartes Labs (Warren and Skillman, 2020). The original data contain each county's daily mobility level measured by the median value of the maximum distances (in kilometers) of the selected individuals' trips from home (i.e., the initial point of a certain day) to any daily activities that they undertook. The selected individuals of each county are those whose anonymized mobile phone location records are collected by the commercial data providers and provided to Descartes Labs (Warren and Skillman, 2020). The home and activity locations of the sampled persons are estimated from anonymized location records of their mobile phones. Daily mobility level is calculated for each county and each day. A high mobility level for a county indicates that the sampled individuals living in the county traveled long distances for undertaking their daily activities. Fig. 1 illustrates how county-level daily mobility level is measured. Readers are encouraged to refer to Warren and Skillman (2020) for technical details about how Descartes Labs processed the data and calculated county-level mobility level. Although county-level mobility is estimated daily in the original dataset, we calculate the monthly average for each month from March 1st to September 30th, 2020 (i.e., study timeline).

Among about 3000 counties in the U.S., we select 2639 counties for this study. First, we focus on counties that are within the conterminous U.S. Second, some rural counties with small populations do not provide mobility data to protect the geoprivacy of their residents (Buckee et al., 2020; Kim and Kwan, 2021; Kim et al., 2021; Warren and Skillman, 2020). Third, some counties that reported excessively high mobility levels (e.g., $\geq 50km$) are also excluded because they may reflect non-routine daily mobility patterns (e.g., recreational trips from/to national parks or long-distance trips to special annual events). Lastly, counties that do not have complete sociodemographic information are excluded.

2.1.2. Other data

We utilize data of the percentage of below-poverty population, population density, political partisanship, COVID-19 severity, and the mobility restriction policy of each county. First, we use the data on the percentage of each county's below-poverty population from the 2018 American Community Survey (ACS) 5-year estimates. Second, we use the 2020 Presidential Election results from McGovern (2020), which are the most up-to-date data that attempt to capture the overall political partisanship of U.S. counties. A county is considered as a "Democrats" county when the percentage of people who voted for the presidential

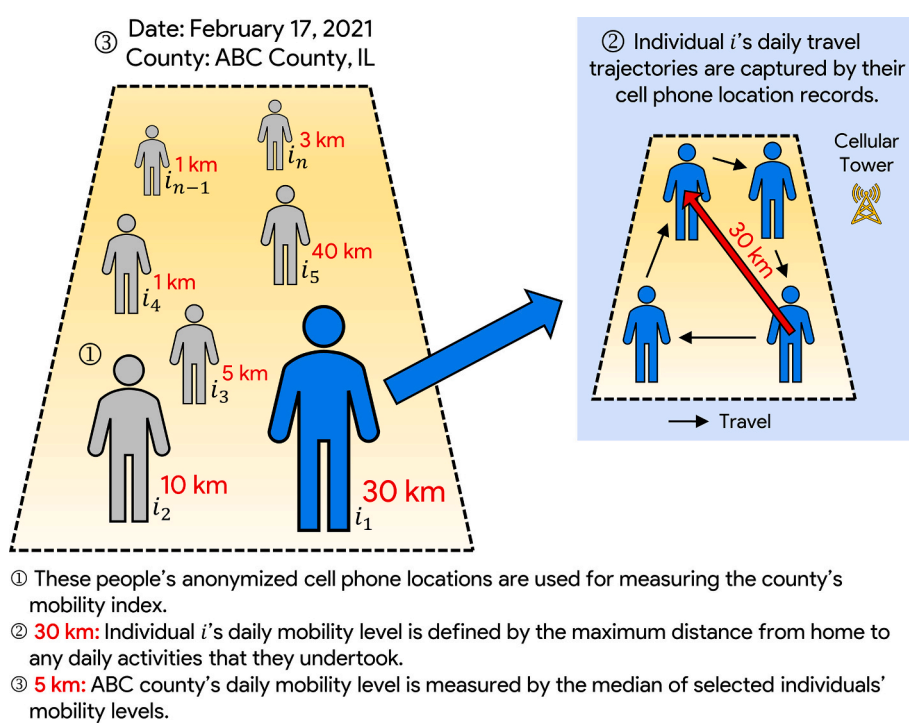

Fig. 1. An illustration of how county-level daily mobility level is measured by Descartes Labs (Image Source: Authors).

candidate of the Democratic Party (Joseph R. Biden) is higher than that of people who voted for the presidential candidate of the Republican Party (Donald J. Trump). Third, COVID-19 severity is assessed by the total new confirmed COVID-19 cases per capita for each county (USA Facts, 2020).

Lastly, we utilize state-wide mobility restriction policy data ("Stringency Index") from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). The data consist of a composite score for each U.S. state reflecting the extent to which each state-level government implemented several mobility restriction policies (e.g., reduction of public transit operations, workplace and school closures, restrictions on private gatherings, and so on). A higher score indicates that the state in question implemented stricter mobility restriction policies. Although it would be ideal to consider more spatially detailed COVID-19 policy data, to our best knowledge, there is no such publicly available county-level data for the U.S. However, given that state-wide policies play the most critical influences on county-level policies and people's behaviors, using state-level data (instead of county-level data) is justifiable for investigating the policy's effects on people's mobility.

2.2. Methods

2.2.1. Longitudinal data analysis (LDA)

We employ longitudinal data analysis (LDA) methods (also known as growth modeling) to investigate changes in people's mobility levels over time and how the changes are associated with various social, spatial, policy, and political factors (Grimm et al., 2016). We adopt a multilevel modeling framework for estimating longitudinal changes (Grimm et al., 2016). Specifically, Level-1 equations estimate within-county differences, while Level-2 equations estimate between-county differences. We use the *nlme* R-software package to conduct the multilevel modeling (Pinheiro et al., 2020).

For our longitudinal models, we divide the study timeline (March–September) into two sub-timelines, consisting of Wave 1 (March–June) and Wave 2 (June–September), because of the following two reasons. First, the trend of mobility changes over time (i.e., the dependent variable of the longitudinal models) is substantially different between Waves 1 and 2. Fig. 2 presents a longitudinal plot of mobility level against time, and Fig. 3 geo-visualizes Fig. 2. These figures show that mobility changes over time have different patterns in Wave 1 (i.e., V-shaped lines) and Wave 2 (i.e., weak growth lines). Second, COVID-19 severity and the level of state-wide mobility restriction policies are substantially different between Waves 1 and 2. For example, Fig. 4 shows new confirmed daily COVID-19 cases in the U.S. and indicates two peaks (April and July). Also, the levels of state-wide mobility restriction policies are different between Waves 1 and 2: more state-wide "reopening" policies (i.e., fewer restrictions) were implemented in Wave 2 than Wave 1. Thus, adopting different longitudinal models for each wave would be desirable. Table 1 presents the descriptive statistics of the variables used in the models.

2.2.2. Modeling mobility changes over time in Wave 1 (March–June)

Recall that Fig. 1 shows that overall mobility levels in the U.S. decreased between March and April but then increased between April and June (i.e., V-shaped lines). This suggests that a *nonlinear spline growth model with one knot point and time-invariant covariates* would be suitable to model people's mobility levels over time for this period (Grimm et al., 2016). In other words, the purpose of estimating this model is to examine (1) whether people's mobility levels have changed in a nonlinear (spline type) relationship over time and (2) whether the changes are associated with other covariates (Table 1) that are assumed not to be changed over time. A knot point indicates where the trend substantially changed (e.g., from a decreasing trend to an increasing trend). In our study, April is selected as the knot point based on the trends in the data. The time-invariant covariates include the independent variables that are assumed to remain unchanged over time.

To choose the best-fit model, we need to compare the explanatory power (i.e., model-fit indices) of the proposed model with other simpler models (Grimm et al., 2016). Thus, in addition to the proposed model, we also estimated two simpler models for the purpose: *a no-growth model* (Model 1) and *a nonlinear spline growth model with one knot point without time-invariant covariates* (Model 2). In other words, Model 1 investigates whether mobility levels do not significantly change over time. Model 2 is similar to Model 3 except that we do not estimate the association between mobility levels and other covariates. We then compare the model-fit indices of our proposed model (Model 3) with these two simpler models. Specifically, we compare the Akaike information criterion (AIC), Bayesian information criterion (BIC), and the log-likelihood to choose the best-fit model. Low AIC and BIC scores and a high log-likelihood value indicate a good-fit model.

In mathematical form, Model 1 (*no-growth model*) is represented as follows (Grimm et al., 2016, p. 47):

$$\begin{cases} m_{ti} = b_{1i} + u_{ti} \ldots (1) \\ b_{1i} = \beta_1 + d_{1i} \ldots (2) \end{cases}$$

where m_{ti} is the monthly mobility level for county i ($i = 1, 2, 3, \ldots, 2639$) at time t ($t = 1 : March, 2 : April, 3 : May, 4 : June$), b_{1i} is the random intercept for county i, and u_{ti} denotes the time-specific residual that is

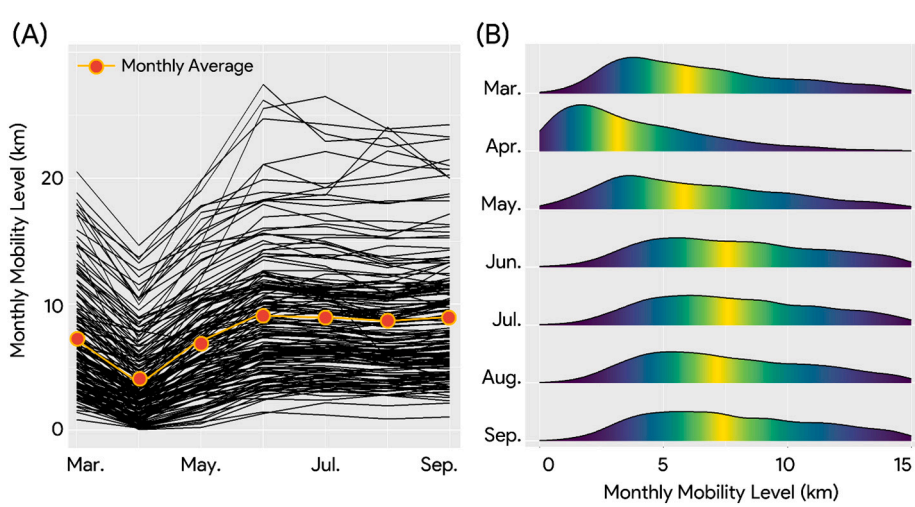

Fig. 2. (A) A longitudinal plot of mobility levels against time. (B) Probability density functions of mobility levels against time (*Notes:* These figures represent counties that are randomly selected for visualization purposes.)

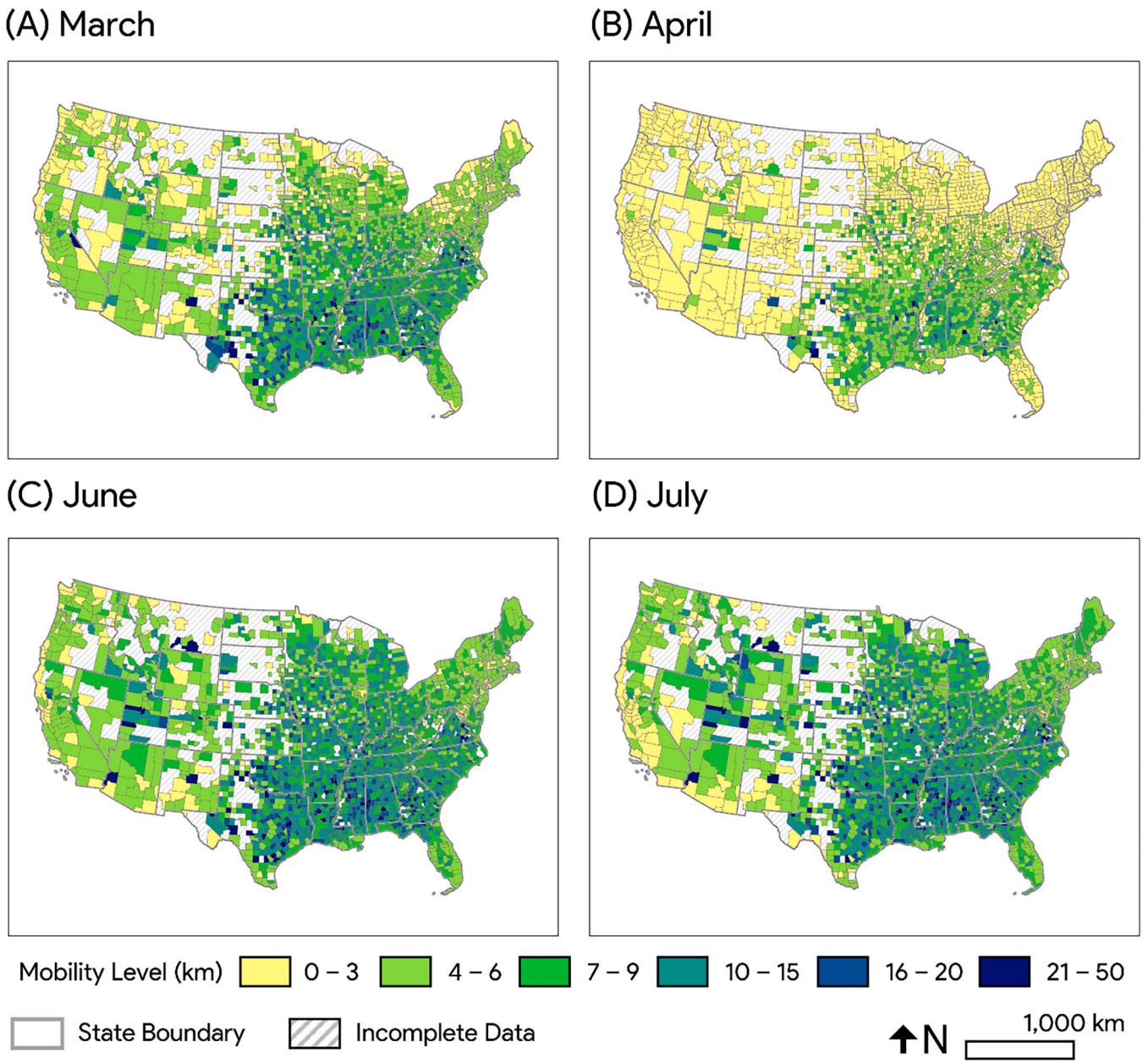

Fig. 3. Monthly average mobility level of 2639 counties (selected months).

assumed to follow a normal distribution of $N(0, \sigma_{\mu}^2)$. β_1 denotes the sample mean for the intercept, and d_{1i} is county i's deviation from the sample mean that is assumed to follow a normal distribution of $N(0, \sigma_1^2)$. Namely, Eq. (1) indicates a Level-1 equation (within counties), and Eq. (2) indicates a level-2 equation (between counties).

Model 2 (*nonlinear spline growth model with one knot point and without time-invariant covariates*) is represented as follows (Grimm et al., 2016, p. 210):

$$\begin{cases} m_{ti} = b_{1i} + b_{2i} \cdot min(t-2, 0) + b_{3i} \cdot max(t-2, 0) + u_{ti} \ldots (3) \\ b_{1i} = \beta_1 + d_{1i} \ldots (4) \\ b_{2i} = \beta_2 + d_{2i} \ldots (5) \\ b_{3i} = \beta_3 + d_{3i} \ldots (6) \end{cases}$$

where b_{1i} is a random-effects intercept at a knot point ($t = 2$), b_{2i} denotes a pre-knot random-effects linear slope for county i, and b_{3i} denotes a post-knot random-effects linear slope for county i. β_1 is a fixed-effects parameter for the intercept, β_2 is a fixed-effects parameter for the pre-knot linear slope, and β_3 is a fixed-effects parameter for the post-knot linear slope. d_{1i}, d_{2i}, and d_{3i} are individual county i's deviations from the fixed effects and are assumed to follow a multivariate normal distribution (Grimm et al., 2016, p. 211):

$$d_{1i}, d_{2i}, d_{3i} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{11}^2 & & \\ \sigma_{21} & \sigma_{22}^2 & \\ \sigma_{31} & \sigma_{32} & \sigma_{33}^2 \end{bmatrix} \right) \ldots (7)$$

Lastly, the overall structure of Model 3 (*nonlinear spline growth model with one knot point and time-invariant covariates*) is similar to that of Model 2 except that five time-invariant covariates are included in the Level-2 equations. These time-invariant covariates, which may be significantly associated with changes in mobility levels, were described in Table 1.

We assume that COVID-19 severity and state-wide policies are static within each wave to estimate parsimonious models. In reality, COVID-19 severity, restriction policy strictness level, and people's mobility level may simultaneously affect each other. Although it would be ideal

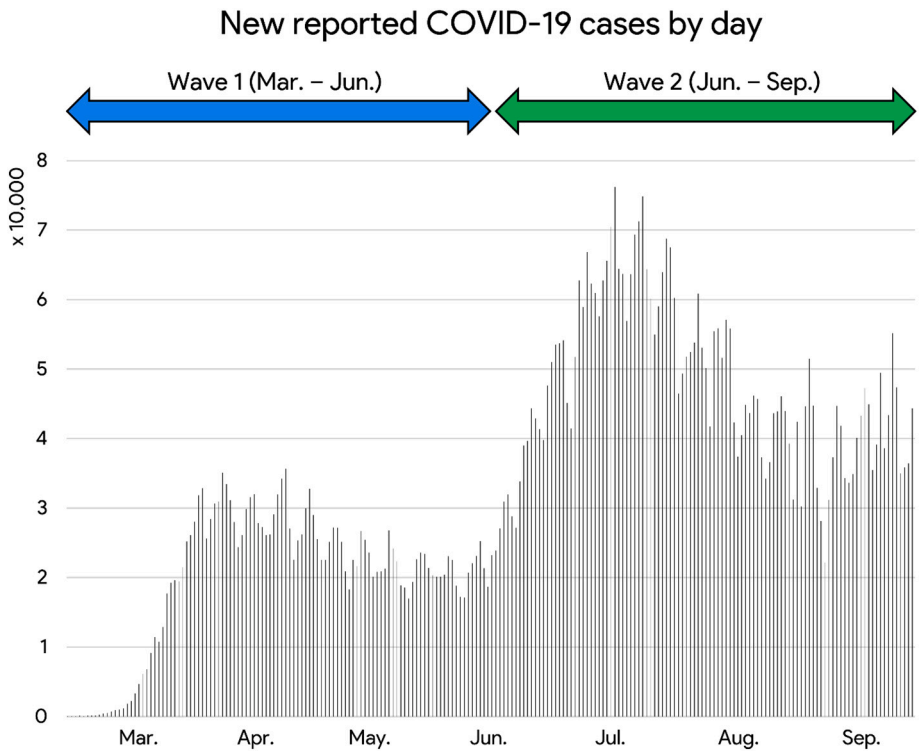

Fig. 4. New confirmed COVID-19 cases by day during the study timeline. (Source: The COVID-19 Tracking Project, 2020).

Table 1
Descriptive statistics of the county-level variables used in this research.

	Mean	Standard Deviation	Min	Max
Monthly mobility level (km)				
March	7.281	4.420	0.353	33.940
April	3.955	3.236	0.017	28.939
May	6.794	4.124	0.025	30.328
June	8.920	4.713	0.157	42.625
July	8.889	4.565	0.300	43.226
August	8.487	4.526	0.525	40.376
September	8.741	4.567	0.622	41.501
Covariates				
Democrats (2020 Presidential Election)	0.182[a]	0.386	0.000	1.000
% Below-Poverty	15.750	6.142	2.300	48.600
Population Density (people/km^2)	119.350	743.497	0.098	27,750.761
COVID-19 severity (Wave 1)	0.006	0.008	0.000	0.132
COVID-19 severity (Wave 2)	0.017	0.012	0.000	0.146
State Restriction (Wave 1)[b]	53.730	7.161	33.662	69.845
State Restriction (Wave 2)[b]	48.008	9.794	19.058	78.535

Notes: $n = 2639$; Wave 1: March to June; Wave 2: June to September.
[a] Note that although the Democratic candidate won the 2020 Presidential Election, this number is lower than one's expectation because the number of counties (e.g., low-dense rural counties) that voted for the Republican candidate is higher than the number of counties (e.g., high-dense urban counties) that voted for the Democratic candidate.
[b] A higher score indicates that the state in questions implemented stricter mobility restriction policies.

to consider the relationships among these variables, it may involve more complex models and thus require more detailed data and computing resources. Note that this is one of the methodological limitations of this study that should be addressed by future studies with more complex models when more detailed data are available.

Moreover, COVID-19 severity and population density variables are log-transformed because the distribution of these variables is highly skewed. For a small number of counties that have 0 confirmed COVID-19 cases, a very small number (ε) is added to the COVID-19 severity variable so that the log-transformation can be applied.

2.2.3. *Modeling mobility changes over time in Wave 2 (June–September)*

For modeling mobility changes over time in Wave 2, we adopt a similar approach as that of Wave 1. However, a longitudinal plot in Fig. 1 suggests a weak *linear growth model* instead of a *nonlinear spline growth model*. Thus, we estimate a *linear growth model with time-invariant covariates* (Model 6). In other words, Model 6 examines whether people's mobility levels have changed based on a linear relationship over time, and the changes are associated with other covariates (Table 1) that are assumed not to change over time. Next, we compare Model 6 with two simpler models: a *no-growth model* (Model 4) and a *linear growth model without time-invariant covariates* (Model 5).

3. Results

3.1. *Model estimation results of Wave 1 (March–June)*

Table 2 presents the estimation results of Models 1–3 focusing on Wave 1. We first compare the model-fit indices of Models 1–3. The values of the AIC, BIC, and the negative log-likelihood (−2LL) of Model 2 are smaller than those of Model 1, which indicates that there is an overall V-shaped line trend in mobility levels during Wave 1. Further, the model-fit indices of Model 3 are better than those of Model 2, and the chi-square difference test reveals that Model 3 is significantly better than Model 2 ($p < 0.001$). This indicates that the time-invariant covariates in the model help explain changes in people's mobility levels over time. Thus, we adopt Model 3, which is a *nonlinear spline growth model with one knot point and time-invariant covariates*, to explain the longitudinal changes in people's mobility levels during Wave 1.

In Model 3, with other things being equal, the pre-knot slope (−5.229, $p < 0.001$) is significant and negative, and the post-knot slope

Table 2
Estimation results of the models on mobility changes over time and the association between the changes and time-invariant covariates (Wave 1: March–June).

	Model 1	Model 2	Model 3
Intercept			
Intercept	6.737*** (0.078)	4.074*** (0.064)	11.522*** (0.546)
Democrats	–	–	−2.076*** (0.158)
% Below-Poverty	–	–	0.115*** (0.009)
Ln COVID-19 Severity	–	–	0.470*** (0.055)
Restriction Policy Level	–	–	−0.085*** (0.008)
Ln Population Density	–	–	−0.487*** (0.046)
Pre-knot			
Pre-knot slope	–	−3.207*** (0.036)	−5.229*** (0.352)
Democrats	–	–	0.022 (0.102)
% Below-Poverty	–	–	0.037*** (0.006)
Ln COVID-19 Severity	–	–	−0.299*** (0.035)
Restriction Policy Level	–	–	−0.020*** (0.005)
Ln Population Density	–	–	0.230*** (0.029)
Post-knot			
Post-knot slope	–	2.482*** (0.024)	4.299*** (0.224)
Democrats	–	–	−0.147* (0.065)
% Below-Poverty	–	–	−0.024*** (0.004)
Ln COVID-19 Severity	–	–	0.054* (0.022)
Restriction Policy Level	–	–	−0.002 (0.003)
Ln Population Density	–	–	−0.309*** (0.019)
Model fit indices			
AIC	55,168.08	42,171.04	40,722.09
BIC	55,189.88	42,243.68	40,903.70
-2LL	55,162.08	42,151.04	40,672.08

Notes: * denotes $p < 0.05$; *** denotes $p < 0.001$. Standard errors in parenthesis. Model 1: *no-growth model*; Model 2: *nonlinear spline growth model*; Model 3: *nonlinear spline growth model with one-knot point and time-invariant covariates*.

(+4.299, $p < 0.001$) is significant and positive, which corroborates our earlier observations based on Fig. 1. These results indicate that people's mobility levels decreased at the early stage of the COVID-19 pandemic (March–April) but started to recover to the typical mobility levels from April to June. These results may reflect the "social distancing inertia" or "quarantine fatigue," which is the phenomenon that people felt tired of staying at their home for several months and tried to travel as usual like they did before the pandemic despite the ongoing crisis of the COVID-19 pandemic (Beck et al., 2020; Ghader et al., 2020; Gauvin et al., 2020; Hamidi and Zandiatashbar, 2021; Marques and Waldinger, 2020; Zhao et al., 2020). We further examine the results of Model 3 in terms of the key variables, including political partisanship, poverty level, and state-wide COVID-19 mobility restriction policy level. Fig. 4 illustrates the estimated mobility levels over time for different key variables while holding other covariates constant.

First, we focus on the role of political partisanship on the mobility changes over time (Fig. 5A). With other things being equal, the pre-knot slope is not significant ($p > 0.05$), but the post-knot slope is significant (−0.147, $p < 0.05$). This indicates that, after April (when overall mobility levels were recovering), the average rate of change in mobility levels of Democratic counties is significantly slower than that of Republican counties. This means that people who live in Democratic counties tend to minimize travel while people who live in Republican counties tend to travel as usual. The result not only corroborates the findings from similar studies but also reflects that how people in the U.S. respond to the COVID-19 pandemic has been highly politicized (e.g., Allcott et al., 2020; Fan et al., 2020; Grossman et al., 2020; Hart et al., 2020).

Second, we investigate the role of poverty level on the mobility changes over time (Fig. 5B). With other things being equal, both the pre-knot slope (0.037, $p < 0.001$) and the post-knot slope (−0.024, $p < 0.001$) are significant. This implies that, when all other things are the same, counties with a higher percentage of poor people are significantly associated with a slower decrease in mobility level during the pre-knot period and a slower increase in the mobility level during the post-knot period. This further means that poor people are more likely to travel as usual at the early stage of the COVID-19 pandemic. This result corroborates the findings from other studies as well as reflects the fact that poor people in the U.S. tend to keep traveling during the COVID-19 pandemic (Campbell et al., 2021; Fan et al., 2020; Jay et al., 2020; Lee et al., 2020b; Lou et al., 2020). One possible explanation is that poor people largely consist of essential workers, such as workers of grocery stores and food processing plants. During the pandemic, essential workers still need to travel as usual to go to their workplaces (McNicholas and Poydock, 2020; Roberts et al., 2020; Rogers et al., 2020; Van Dorn et al., 2020).

Lastly, we examine the role of state-wide COVID-19 mobility restriction policies on people's mobility changes over time (Fig. 5C). With other things being equal, the pre-knot slope is significant (−0.020, $p < 0.001$), but the post-knot slope is not significant ($p > 0.05$). This implies that counties implementing stricter mobility restriction policies are significantly associated with a faster decrease in their mobility levels during the pre-knot period, which is in line with the findings from similar studies and the general expectation (e.g., Gao et al., 2020b; Gauvin et al., 2020; Pullano et al., 2020). Interestingly, the level of mobility restriction policies is not associated with the post-knot slope. If these policies had worked effectively, a stricter policy would have been associated with a lower rate of increase in mobility levels during the post-knot period. However, our model result indicates that it is not the case. Thus, the result implies that mobility restriction policies might not be effective in decreasing U.S. people's mobility for a long period during the COVID-19 pandemic.

3.2. Model estimation results of Wave 2 (June–September)

Table 3 shows the model estimation results of Models 4–6 focusing on Wave 2. First, we compare the model-fit indices of Models 4–6. The values of AIC, BIC, and the negative log-likelihood (−2LL) of Model 6 are smaller than those of Models 4 and 5. Also, the chi-square difference tests reveal that Model 6 performs significantly better than Models 4 and 5 ($p < 0.001$). The results imply that a *linear growth model with time-invariant covariates* adequately estimates the longitudinal mobility changes during Wave 2. Therefore, we focus on Model 6 for analyzing the changes in people's mobility levels during Wave 2.

The results of Model 6 indicate that, although the slope (change in mobility levels per month) is significant ($p < 0.001$), the magnitude of the slope is less meaningful in practice than Wave 1. In Wave 1 (Model 3), for Republican counties (i.e., *Democrats* = 0), the pre-knot slope is about −3.1 km per month and the post-knot slope is about +2.1 km per month when holding all covariates constant. In Wave 2 (Model 6), however, the slope is about −0.004 km per month. This means that the average mobility level of September is only 12 m ($0.012km = 0.004 \times 3$) lower than that of June, indicating that the decrease in mobility levels over time in Wave 2 is minimal in practice. Thus, although the results of Model 6 reveal that the rate of change in mobility levels is (statistically) significant, we conclude that there was very little change in mobility levels during Wave 2, which corroborates our earlier observations of the longitudinal plot (Fig. 1).

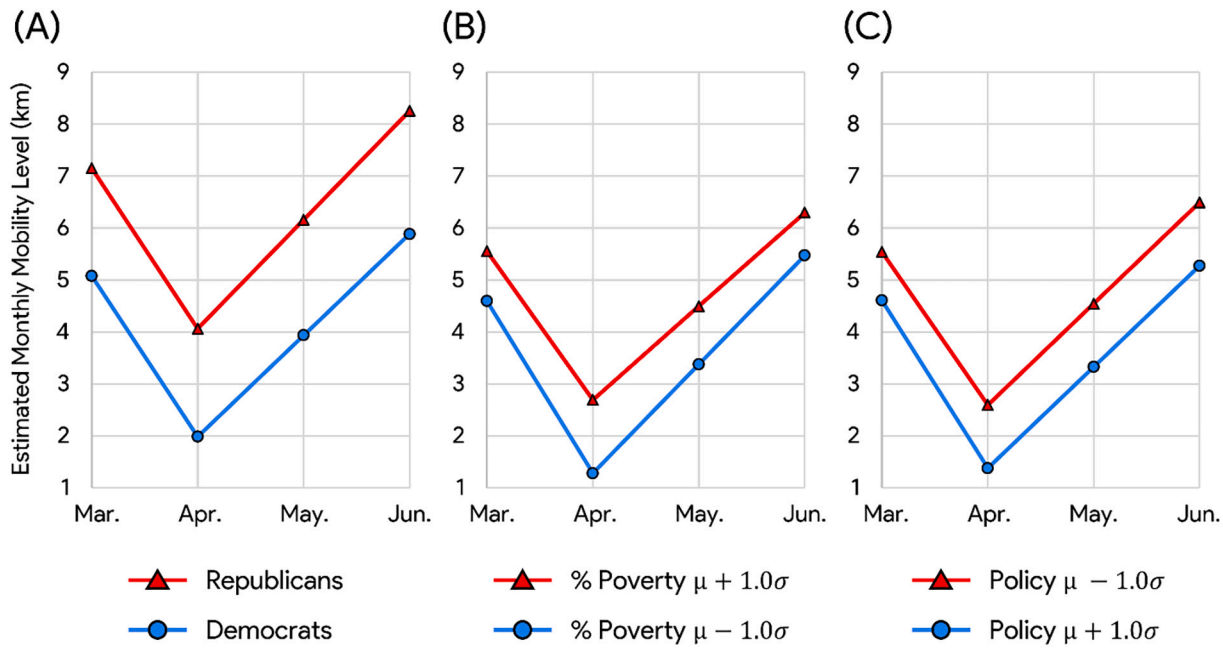

Fig. 5. Estimated mobility levels over time in different scenarios that focus on (A) political partisanship, (B) poverty level, and (C) COVID-19 mobility restriction policies. (*Notes:* Other covariates are held at their average levels. In Fig. 5 [B] and [C], the political partisanship is assumed to be Democratic.)

Table 3
Model estimation results of Wave 2 (June–September).

	Model 4	Model 5	Model 6
Intercept			
Intercept	8.759*** (0.089)	8.900*** (0.091)	17.883*** (0.648)
Democrats	–	–	−1.745*** (0.229)
% Below-Poverty	–	–	0.017 (0.015)
Ln COVID-19 Severity	–	–	0.986*** (0.114)
Restriction Policy Level	–	–	−0.023* (0.009)
Ln Population Density	–	–	−1.074*** (0.063)
Slope			
Slope	–	−0.094*** (0.007)	−0.345*** (0.054)
Democrats	–	–	0.069*** (0.019)
% Below-Poverty	–	–	−0.002 (0.001)
Ln COVID-19 Severity	–	–	−0.034*** (0.010)
Restriction Policy Level	–	–	0.001 (0.001)
Ln Population Density	–	–	0.028*** (0.005)
Model fit indices			
AIC	35,446.48	34,902.44	34,199.51
BIC	35,468.27	34,946.02	34,315.74
-2LL	35,440.48	34,890.44	34,167.52

Notes: * denotes $p < 0.05$; *** denotes $p < 0.001$. Standard errors in parenthesis. Model 4: *no-growth model*; Model 5: *linear growth model*; Model 6: *linear growth model with time-invariant covariates*.

These results are interesting given the fact that the COVID-19 pandemic was still severe in the U.S. during Wave 2 (June–September). Recall that Fig. 3 shows that the number of new confirmed COVID-19 cases was much higher in Wave 2 than in Wave 1. In this light, one might expect that mobility levels would have decreased at the early stage of Wave 2 as similar to what we observed for Wave 1. However, our longitudinal model results indicate that people's mobility levels were much less affected during Wave 2 even though the COVID-19 pandemic situation has become more severe. One possible explanation is that many people may be tired of continuously staying at home for several months despite the COVID-19 pandemic still being rampant. This is in line with observations of "social distancing inertia" or "quarantine fatigue" from other studies and our model results of Wave 1 (Ghader et al., 2020; Gauvin et al., 2020; Hamidi and Zandiatashbar, 2021; Marques and Waldinger, 2020; Zhao et al., 2020).

Another possible explanation is that people's perceived risk of COVID-19 had decreased as they gained more knowledge about COVID-19 and thus became more familiar with it. For example, although some studies have concluded that U.S. people's COVID-19 risk perception had drastically increased at the early stage of the pandemic (e.g., Niepel et al., 2020; Wise et al., 2020), a later study has found that people's risk perception had decreased between April and July (Li et al., 2020). Further, the results may reflect that people thought traveling would be safe if they follow the safety measures, such as wearing a mask and washing hands often.

4. Conclusion and discussion

This research examined changes in people's mobility over a 7-month period (from March 1st to September 30th, 2020) during the COVID-19 pandemic in the U.S. using longitudinal models for two waves (Wave 1: March–June; Wave 2: June–September). It also analyzed how these mobility changes are associated with various social, policy, spatial, and political factors (e.g., political partisanship, poverty level, mobility restriction policies, and COVID-19 severity).

The results revealed that mobility changes in Wave 1 have a V-shaped trend: people's mobility first declined at the early stage of the COVID-19 pandemic (March–April) but started to recover to the typical mobility levels from April to June. The results further showed that the rates of change are significantly associated with most of the key variables, such as political partisanship, poverty level, and the strictness of mobility restriction policies. In Wave 2, there was very little mobility decline in practice despite the existence of mobility restriction policies and the COVID-19 pandemic becoming more severe.

Our research is important because it significantly contributes to the literature on the impact of the COVID-19 pandemic on people's mobility patterns and travel behaviors in the following aspects. First, it is among the first studies that examined mobility changes using longitudinal models, up-to-date data such as the 2020 Presidential Election results, and data on people's mobility levels spanning 7 months. Most previous studies largely focused only on the early stage of the COVID-19 pandemic (e.g., March–April) and used cross-sectional data and methods. These previous studies provide insights into people's mobility changes only over 2–3 months during the pandemic. However, our results based on 7-month data revealed that people's mobility levels first decreased but soon recovered to the pre-pandemic levels in Wave 1 and then tended to remain at similar levels during Wave 2 even though there was a more severe second surge of new confirmed COVID-19 cases.

Further, our study has important implications for COVID-19 control policies that aim at restricting people's mobility. Our results revealed that people's mobility levels quickly recovered after April despite the severe COVID-19 situation and state-wide mobility restriction policies in the U.S. Our findings thus suggest that restricting people's mobility to control the pandemic may be effective only for a short period, after which mobility restrictions may become ineffective in curtailing people's travel and mitigating the spread of the virus. Considering that people's mobility is one of the critical components of their daily life in modern liberal democratic societies, such as the U.S. (e.g., Cresswell, 2006; Kwan and Schwanen, 2016; Urry, 2007), policymakers should carefully design and implement pandemic control policies that constrain people's mobility.

Also, our results indicated that poor people kept traveling during the pandemic because they are mostly essential workers who are required to be physically present at their workplaces (e.g., Jay et al., 2020; McNicholas and Poydock, 2020; Roberts et al., 2020; Rogers et al., 2020; Van Dorn et al., 2020). Considering also that poor people are more likely to use public transit (e.g., Federal Highway Administration, 2019; Kim and Lee, 2019), certain built-environment features or venues where poor people frequently visit (e.g., public transit facilities and workplaces) may be risky for COVID-19 exposure (e.g., Kan et al., 2021; Hu et al., 2020; Huang et al., 2020a). Therefore, policymakers should pay special attention to these people by implementing policies to mitigate their high COVID-19 exposure risk. This would be critical because essential workers play an important role in maintaining our society's functioning even during the pandemic.

However, our study has several limitations that should be addressed in future studies. First, we assumed a simple one-directional causal relationship between COVID-19 severity, mobility restriction policies, and mobility levels. Moreover, we assumed that policy strictness levels and COVID-19 severity levels are static within each wave. In reality, these three factors may vary over time and simultaneously affect each other, which leads to highly complex interactions. Future studies may consider utilizing complex structural equation models or time-varying covariates (TVC) growth models to address this issue (Grimm et al., 2016). Also, we did not consider differences in policy strictness levels across counties by only considering state-wide policies. Since the counties in a certain state may have different levels of policy strictness, future studies would benefit from considering more fine-scale policy differences when these data are available. Next, we did not consider spatial dependency in our models, which should be addressed by future studies by utilizing non-linear growth models that address spatial dependency. Lastly, due to data limitations, we chose the county as the spatial unit and the month as the temporal unit of the analysis. This approach may involve several methodological problems (Helbich et al., 2020), such as the modifiable areal unit problem (MAUP; Fotheringham and Wong, 1991), the modifiable temporal unit problem (MTUP; Cheng and Adepeju, 2014), and the uncertain geographic context problem (UGCoP; Kwan, 2012, 2018). Future studies should thus try to use individual-level detailed mobility data (e.g., GPS trajectories) to mitigate these methodological issues to shed more light on people's mobility changes over time during the pandemic.

Author contributions

Junghwan Kim: Conceptualization, Data curation, Formal analysis, Writing - original draft, Writing - review & editing; Mei-Po Kwan: Conceptualization, Writing - original draft, Writing - review & editing.

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