Exploring the Relationship Between COVID-19 Transmission and Population Mobility over Time

Tanmoy Bhowmik*
Assistant Professor
Department of Civil and Environmental Engineering
Portland State University
Email: tbhowmik@pdx.edu
Tel: 1-407-927-6574, Fax: 1-407-823-3315
ORCiD number: 0000-0002-0258-1692

Naveen Eluru
Professor
Department of Civil, Environmental & Construction Engineering
University of Central Florida
Tel: 407-823-4815, Fax: 407-823-3315
Email: naveen.eluru@ucf.edu
ORCiD number: 0000-0003-1221-4113

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*Corresponding author

ABSTRACT

This study explores the dynamic relationship between COVID-19 transmission and transportation mobility, with an emphasis on understanding the time varying bi-directional interplay across the different phases of the pandemic. To gain insight into this relationship, we analyzed county-level data on transmission and mobility patterns from the US over a 74-week period using a comprehensive list of factors including (a) temporal factors, (b) socio-demographics, (c) health indicators, (d) health care infrastructure attributes, and (e) spatial factors. For our analysis, we proposed a simultaneous econometric model system that explicitly accounts for the bi-directional relationship between COVID-19 transmission and mobility patterns while also accounting for the influence of common unobserved factors on the two variables. The model results strongly support our hypothesis that COVID-19 transmission and mobility patterns are interconnected. Further, our findings show distinct phases of the bi-directional relationship influenced by behavior changes, vaccine availability and the emergence of new variants. Additionally, we conducted a validation exercise on a hold-out sample to assess the robustness of our model. The results confirm the superiority of the simultaneous model system with enhanced interpretability and prediction capability. By analyzing data from several weeks for COVID-19 pandemic, our study provides valuable insights into the evolving dynamics and potential strategies for future pandemics.

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INTRODUCTION

Coronavirus disease 2019 (COVID-19) pandemic has affected the mental and physical health of people across the world significantly taxing the social, health and economic systems (*1*). The multiple surges of COVID-19 cases in US, Europe and various countries around the world have burdened social, health and economic systems. While the number of COVID cases have substantially reduced post-Omicron, it appears that COVID will continue to burden health systems as we enter the endemic stage. The focus of the current research effort is on understanding the evolving time-varying bi-directional relationship between COVID-19 transmission and transportation mobility.

In March 2020, when COVID-19 was declared a pandemic, it was a major shock to the world population affecting work schedules, transportation mobility and nearly every facet of life. In the initial months of the pandemic, following social distancing guidelines and stay-at-home orders transportation mobility significantly reduced. A large section of the population voluntarily followed public health guidance to alter their social interaction and mobility patterns. However, as the pandemic continued to persist, there have been changes in behavior influencing mobility patterns. The changes in behavior can be described along two directions. First, the share of the population that reduced their mobility started to go down. Second, even among the population altering their behavior, the difference (or reduction) in mobility relative to early-pandemic levels were reducing. These changes have ebbed and flowed with local and global COVID-19 case numbers in the region over time. In this research, we hypothesize that as the pandemic continued, there were multiple phases in how the relationship between COVID and transportation mobility evolved.

The initial phase of the pandemic is characterized by large abrupt shifts in mobility patterns. Several research efforts analyzing US data found the effectiveness of social distancing measures in mitigating COVID-19 transmission (*2–10*). For example, Glaeser et al. 2022 (*7*) conducted an analysis across five cities in the United States and found that a 10% decrease in mobility tended to decrease the COVID -19 transmission rate by 19%. Similarly, Harris, 2022 (*10*) analyzed data from 111 counties in the US and found that every 1% decline in mobility during Week 1 could reduce COVID-19 transmission by 0.63% by the end of Week 3. In a related vein, some research efforts have utilized stay-at-home orders as a proxy for reduced mobility. For instance, Friedson et al., 2020 (*3*) found that the imposition of stay at home orders in California resulted in a reduction of about 200 COVID-19 cases per 100K population and about 1,600 fewer deaths. Inoue and Okimoto, 2023 (*9*) further supported these findings by demonstrating that the declaration of a State of Emergency (SOE) and stay-at-home orders significantly curtailed the COVID-19 transmission rate, underscoring the effectiveness of mobility restrictions in controlling the spread of the virus. On the other hand, several studies have focused on understanding the impact of COVID-19 on people's mobility or travel behavior(*2*, *11*, *12*). For instance, Engle et al., 2020 (*2*) found that people are altering their travel patterns in response to COVID-19 transmission. Specifically, the study found that a 0.003% increase in the COVID-19 transmission rate leads to a 2.3% reduction in mobility. Hao et al.2022 (*12*) examined the impact of the pandemic on human mobility patterns in New York State by comparing visits to Points-Of-Interest (POIs) in 2019 and 2020. Their study observed an average reduction rate of 40% in overall mobility, with variations ranging from a 34% decrease in visits to service shops such as travel agencies, furniture stores, and sporting goods stores, to a more pronounced reduction of 60% in other types of travel, including air travel, freight, and other transportation sectors. Similarly, Panik et al. 2023 (*11*) explored the impact of COVID-19 on travel behavior across 404 counties in the United States from April to September 2020 and found a significant decrease in overall mobility, particularly in urban areas. While research studies have focused on examining the uni-directional impact of mobility on COVD-19 transmission and vice-versa[1], it is plausible to consider the potential for a two-way relationship between COVID-19 transmission and transportation mobility. In regions with higher transmission rates, local agencies were likely to impose (or re-impose) stricter guidelines prompting individuals to reduce their travel during the high incidence period and cause a potential lowering of transmission rates.

As the pandemic persisted through 2021, transportation mobility recovered at varying rates during differ time periods. The behavioral response to emerging COVID waves has also varied across population groups. For example, months into the pandemic, younger adults were less likely to adhere to public health guidelines compared to their older counterparts. These changes in behavior were further accentuated with wide availability of vaccines. As vaccination rates increased, there was more openness among the vaccinated population to increase their social interactions and return to early-pandemic mobility patterns. Further, while large parts of the population are attempting to return to some sort of normalcy, a small but significant share of the population that is either unvaccinated due to vaccine unavailability for children, immuno-compromised or worried about COVID impacts continue to alter their mobility patterns. In summary, the post-pandemic mobility trends are a result of the interaction across these various population segments.

In our proposed research effort, the emphasis is on understanding this multi-phased relationship between COVID-19 transmission rate and mobility patterns. The development of model frameworks that examine the influence of factors affecting the uni-directional impact (the impact of transmission on mobility or the impact of mobility on transmission) while useful might lead to inaccurate or misleading conclusions on the influence of various independent variables. For instance, a traditional modeling approach may suggest that increased mobility leads to higher transmission, but it fails to capture the influence of the feedback where higher transmission subsequently reduces mobility. To be sure, addressing the bi-directional relationship between COVID-19 transmission and mobility presents a complex scenario for modeling and analysis. Specifically, to address this endogeneity and capture the bi-directional relationship, simulation based simultaneous modeling techniques can be employed. In this approach, transmission and mobility are simultaneously modeled allowing us to account for interconnectedness across these dependent variables. The approach allows us to obtain more accurate estimates of the impact of various factors affecting these dependent variables. Further, the simultaneous framework allows us to incorporate the influence of common unobserved factors that affect these variables. The consideration of these interactions between the dependent variables allows us to represent the dynamics of the pandemic comprehensively. The approach by quantifying the bi-directional interplay between transmission and mobility will allow us to develop useful policy tools that target both variables, leading to more informed and efficient decision-making.

In our research, the simultaneous framework is built upon data compiled at the county level in the US. Specifically, we address these questions:

1. What is the relationship between county level COVID-19 transmission rate and mobility patterns?
2. How has the relationship evolved from March 2020 to August 2021?

[1] It is beyond the scope of our paper to extensively review the vast literature concerning uni-directional models that separately analyze the impacts of COVID-19 on mobility and mobility's effects on COVID-19 transmission. (Please see (*31, 32*) for detailed literature review).

3. What will the long-term influence of COVID-19 on mobility patterns be as it becomes endemic (like Flu)?

The proposed spatio-temporal analysis of county level dependent variables is undertaken using an exhaustive database of transmission rates, mobility patterns and a comprehensive list of county level variables including socio-demographics, health indicators, health care infrastructure attributes and spatial and temporal factors. The research employs data from March 25th, 2020, to August 24th 2021 for the dependent variables (COVID-19 transmission rate and population mobility) on a weekly basis. The proposed research develops a simultaneous econometric model system that allows for the bi-directional impact across the two dependent variables while controlling for the influence of common unobserved factors affecting the two variables. The framework will also specifically allow for variation of the impact over time by considering various phases of the pandemic in the US such as (a) initial part of the pandemic, (b) first wave, (c) second wave, and (d) vaccination phase.

The insights gained from this paper remain highly relevant and critical for future public health preparedness, even though the immediate crisis of the COVID-19 pandemic has largely passed. During the pandemic, we observed an interconnected bi-directional relationship between COVID-19 transmission and people's mobility. Increased mobility led to higher transmission rates in subsequent weeks. The increased transmission rates prompted a reduction in mobility in the following periods, possibly due to public responding to the increase and the implementation of various health measures by local agencies. The resulting reduction in mobility contributed to a lower transmission rates. The cycle continues with a relaxation in restrictions and a subsequent increase in mobility as people felt safer and less restricted. The overall relationship is underscoring the connected impacts of mobility and transmission, highlighting a complex feedback loop that earlier research typically overlooked by focusing only on unidirectional effects. Such insights are crucial for developing more effective public health strategies that can dynamically respond to changes in pandemic conditions. Recognizing this, we developed a simultaneous econometric model system in our study that offers a robust framework for understanding the bidirectional impacts of mobility and COVID-19 transmission. By capturing this interplay, the model provides more accurate forecasts and insights. As we anticipate future pandemics potentially related to COVID-19 variants or other novel pathogens (*13*), the demonstrated need for models that account for such bidirectional influences becomes increasingly pertinent. This paper serves as a reference for future research and policy development, aiming to enhance our preparedness and response strategies for upcoming public health challenges.

The remainder of the paper is organized as follows. The next section (Data) provides details about data source, preparation of the dependent and independent variables, and descriptive analysis results. The details of econometric framework used in the study are discussed in the Methodological Framework section. The model estimation results, validation outcomes and elasticity effects are presented in the Empirical Analysis section. The final section concludes the paper with a summary of findings and some future research directions.

DATA

In our analysis, we study two per capita dependent variables: (a) COVID-19 weekly transmission rate and (b) weekly mobility trends (sourced from exposure data). The COVID-19 transmission data is sourced from Center for Systems Science and Engineering (CSSE) Coronavirus Resource Center at Johns Hopkins University (*14*). The mobility data is sourced from PlaceIQ which is based on smartphone movement data within and across the counties in US (*15*). From the movement data, for each smartphone device visiting a location, the total number of distinct devices visiting that location at that particular time is calculated (*15*). These distinct devices will serve as exposure for the particular device. Similarly, one can compute the exposure for all the devices residing in a county per week and finally compute the weekly average exposure at the county level. In our analysis, exposure is employed as a surrogate for mobility.

For the current research effort, we confined our attention to the counties of United States with at least 100 COVID-19 cases. With this requirement, a total of 1,986 counties across 51 States are included in the analysis. The counties considered for analysis represent approximately 97% of the total population and 98% of the total confirmed COVID-19 cases in the US. Figure 1 represents the weekly pattern as well as the 3-week moving average for COVID-19 transmission rate and Mobility of the selected counties. The reader would note that in the figure, week 1 starts from January 31st , 2020 and week 82 ends on August 24th , 2021. The figure clearly highlights the effect of COVID-19 on population mobility and vice-versa as well as demonstrating how the relationship evolved over the different phases of the pandemic. For instance, as the COVID-19 cases started to be detected in the US in beginning of March (7^{th} and 8^{th} week), we can see a sudden drop in weekly mobility in the mid of March (10^{th} and 11^{th} week). Similarly, reduced social interactions in the mid of March lead to a steady decline in COVID-19 transmission rate by the end of March (week 15^{th} and 16^{h}). However, with increasing familiarity with COVID around Fall 2020, we observe a weakened relationship between the COVID-19 transmission and mobility patterns. Interestingly, the mobility characteristics in Fall 2020 actually exceed the initial baseline (pre covid mobility in January 2020). The trends after wide vaccine availability are quite intuitive illustrating a steady decline in the virus transmission rate while mobility gradually increased over time. However, from July 2021, the COVID-19 cases again started to rise as a new strain of COVID-19 were discovered (Delta). Despite the new wave of the COVID-19 transmission, weekly mobility was on the rise for some time before presenting a steady decline at the end of August. The overall trend in the figure clearly supports our hypothesis of a multi-phase relationship between COVID-19 transmission and population weekly mobility patterns over the different phases of the pandemic. The trend will be evaluated across the following multiple phases: (a) early part of the pandemic (March 2020 through June 2020), (b) first wave (July 2020 through October 2020), (c) second wave (November 2020 through February 2021), and (d) vaccination availability (March 2021 through August 2021).

In terms of independent variables, we consider a comprehensive set of factors affecting COVID-19 and the mobility trends including (a) temporal factors: indicator variables representing different phases of the pandemic; (b) socio-demographics: distribution by age, gender, race, income, education status, income inequality and employment; (c) health indicators: percentage of population suffering from cancer, cardiovascular disease, hepatitis, Chronic Obstructive Pulmonary Disease (COPD); diabetes, obesity, Human Immunodeficiency Virus (HIV), heart disease, kidney disease, asthma; drinking and smoking habits, (d) health care infrastructure attributes: hospitals per capita, ICU beds per capita, COVID-19 testing measures and covid vaccination measures (like when the vaccination starts and what is the rate); and (e) spatial factors: regional location, tourism status and airport density. Further, both the COVID-19 transmission and mobility trends will be used as an independent variable in the other equation. An exhaustive list of these variables are presented in Table 1. The reader would note that out of 1,986 counties, we randomly selected 1,755 counties as our estimation sample and the remaining 231 counties were set aside for the validation exercise.

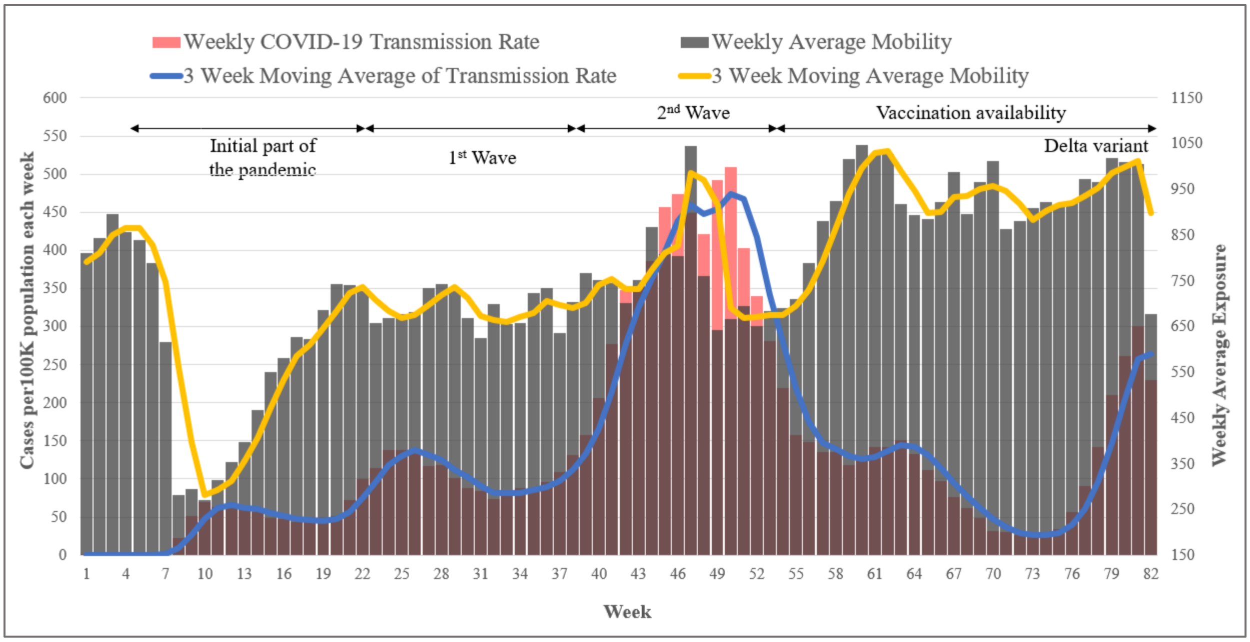

Figure 1: Weekly COVID-19 Transmission Rate and Mobility Trends in US (1,986 counties)

Table 1 Descriptive Statistics of the Dependent and Independent Variables

Variables	Source	Mean	Min/Max	Sample Size
Dependent Variables				
Ln (COVID case per 100 people)	CSSE [a]	4.235	0.000/9.297	129,870
Ln (Daily Average Exposure)	CEI[b]	4.544	1.574/6.824	129,870
Independent Variables				
Demographic Characteristics				
Young people percentage	ACS[c]	22.403	7.155/35.987	1755
Senior people percentages	ACS	17.558	6.724 /56.944	1755
Hispanic percentage	ACS	10.015	0.653/96.322	1755
African American percentage	ACS	9.720	0.113/76.331	1755
Female percentage	ACS	50.348	37.041/56.145	1755
Employment Rate per 100K population	ACS	10.689	9.878/11.061	1755
Income inequality ratio (80th /20th percentile)	CHRR[d]	4.540	2.987/9.148	1755
Health Indicators				
Asthma % for >= 18 years	CDC	9.417	7.400/12.300	1755
Ln (number of cardiovascular patients per 1000 Medicare beneficiaries)	CHRR	4.119	3.157/4.891	1755
Hepatitis C Cases per 100K population	CDC[e]	1.064	0.000/5.600	1755
Ln (HIV rate per 100K population)	CDC	4.780	0.723/7.859	1755
Ln (cancer rate per 100K population)	CDC	6.119	5.489/6.436	1755
Health Infrastructure Attribute				
Testing rate, 5 days lag	CTP[f]	8.431	0.000/12.015	3,700
Spatial factors				
West region	USA map	0.120	0.000/1.000	1755
Mid-West region	USA map	0.108	0.000/1.000	1755
North-East region	USA map	0.308	0.000/1.000	1755

Top 10 tourist state	CHRR	0.252	0.000/1.000	1755
Number of airports per 100k population	CHRR	1.269	0.000/24.927	1755

[a] = Center for Systems Science and Engineering Coronavirus Resource Center at Johns Hopkins University (*16*); [b]= COVID Exposure Indices (*15*); [c] =American Community Survey; [d] = County Health Rankings & Roadmaps; [e]= Central for Disease Control System; [f]= Center for Systems Science and Engineering Coronavirus Resource Center at Johns Hopkins University (*17*).

METHODOLOGY

The focus of the current study is to jointly model COVID-19 transmission and mobility trends. The two dependent variables: (a) COVID-19 weekly transmission rate and (b) weekly average mobility are continuous in nature and lend themselves to a system of linear regression models. The reader would note that we have repeated measures across each county (T weeks for each county) and the traditional linear regression model is not appropriate to study data with such repeated observations (*18*, *19*). Hence, we employ a joint linear mixed modeling approach that builds on the linear regression model while incorporating the influence of repeated observations from the same county as well as captures the simultaneity between the two dependent variables. A brief description of the proposed simultaneous panel linear mixed model is provided below:

Let *q = 1, 2, …, Q (Q =1,755)* be an index to represent each county, and *t = 1, 2, …, T (T =74)* be an index to represent the weeks for which data (cases and mobility) was collected. The general form of the joint mixed linear regression model has the following structure:

$$y_{qt}^{*} = \alpha X + \rho c_{qt} + \delta_q + \eta_{qt} + \varepsilon_q + \xi_{qt} \tag{1}$$
$$z_{qt}^{*} = \beta X + n v_{qt} + \delta_q + \eta_{qt} + \tau_q + \varepsilon_{qt} \tag{2}$$

where y_{qt}^{*} is the first dependent variable representing the new COVID 19 cases per 100K population per week, and z_{qt}^{*} represents the weekly average mobility at a county level. X is the vector of independent variables. As consistent with earlier studies (*19*, *20*), we believe that mobility will have a lagged effect on COVID-19 transmission i.e. total exposure to virus in the current week is likely to manifest as cases in the subsequent weeks. Similarly, COVID-19 transmission will have a lagged effect on the weekly mobility into the future weeks (1 or 2 weeks). In our analysis, we will test for different lag variables for both COVID-19 transmission and mobility including 1-week, 2-week, 3-week, and 4-week lags. The lag variables (lag mobility indicated by the c_{qt} term; and lag COVID-19 transmission data indicated by the v_{qt} term) providing the best model fit will be retained in the final specification. $\alpha, \beta, \rho, and\ n$ represent corresponding model coefficients. $\delta_q\ and\ \eta_{qt}$ captures the common unobserved county and county-week factors respectively that simultaneously impact the weekly COVID-19 transmission rate and weekly average mobility at the county level. The correlation parameters are parametrized as a function of observed attributes as follows:

$$\delta_q = \boldsymbol{\gamma}_q \boldsymbol{s}_q \tag{3}$$
$$\eta_{qt} = \boldsymbol{\alpha_{qt}} \boldsymbol{z}_{qt} \tag{4}$$

where $\boldsymbol{s}_q$ and $\boldsymbol{z}_{qt}$ are vector of exogenous variables and γ_q and $\boldsymbol{\alpha}_{qt}$ are the corresponding vector of unknown parameters to be estimated. Here, we will explore different indicator variables for different phases to see how the correlation changes over the phases of the pandemic.

The $\varepsilon_q, and\ \tau_q$ term in equation 1 and 2 will be same across each county and thus captures the dependencies across the repetition for each county for the corresponding dependent variable.

To account for the repeated dependencies, we used the Autoregressive moving average (ARMA) structure. The exact functional form of the covariance structure assumed is shown below:

$$ſ_{y,z} = \sigma_{y,z}^2 \begin{pmatrix} 1 & \phi_{y,z}\rho_{y,z} & \cdots & \phi_{y,z}\rho_{y,z}^{t-1} \\ \phi_{y,z}\rho & 1 & \cdots & \phi_{y,z}\rho_{y,z}^{t-2} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{y,z}\rho_{y,z}^{t-1} & \phi_{y,z}\rho_{y,z}^{t-2} & \cdots & 1 \end{pmatrix} \tag{5}$$

where, $\sigma_{y,z}^2$ represents the error variance of ξ_{qt} and ε_{qt} respectively, $\phi_{y,z}$ represents the common correlation factor across time periods for y_{qt} and z_{qt}, and $\rho_{y,z}$ represents the dampening parameter that reduces the correlation over time(*18*). The correlation parameters $\varepsilon_q, and\ \tau_q$, if significant, highlight the impact of county effects on the dependent variables. ξ_{qt} , ε_{qt} are the random error term assumed to be normally distributed across the dataset. Then the probability equation of the joint model can be written as follow:

$$P(y_{qt}) = \Psi\left(y_{qt}^{\sim}\right)/\sigma_y \tag{6}$$

$$P(z_{qt}) = \Psi\left(z_{qt}^{\sim}\right)/\sigma_z \tag{7}$$

where, $y_{qt}^{\sim} = (y_{qt} - y_{qt}^{*})/\sigma_y$ and $z_{qt}^{\sim} = (z_{qt} - z_{qt}^{*})/\sigma_z$. p_{yqt} and p_{zqt} is the probability that county q in week t has y_{qt} COVID-19 tranmission and z_{qt} average mobility. Ψ computes the standard normal probability distribution function. In estimating the model, it is necessary to specify the structure for $\boldsymbol{\gamma}, \boldsymbol{\rho},\ \varepsilon\ and\ \tau$ represented by Ω. In this paper, it is assumed that these elements are drawn from independent normal distribution: $\Omega \sim N\left(0, \left(\boldsymbol{\pi'^2}, \boldsymbol{\Phi^2}, \boldsymbol{\sigma^2}, \boldsymbol{\nu}^2\right)\right)$. Thus, conditional on Ω, the likelihood function across county can be expressed as:

$$L_q = \prod_{k=1}^{K}\left[\left(P(y_{qt}) \times P(z_{qt})\right)\right] \tag{8}$$

where K is the number of repetitions. In our analysis, we estimate the correlation for two repetition resolutions including (a) correlation for all records at weekly level (N=74 weeks), and monthly level (M= 18). The flexibility offered by the mixed model for testing dependencies enhances the model development exercise over its simpler form. Of these two models, we will select the model that provides the best result in terms of statistical data fit and variable interpretation. The unconditional log-likelihood function for individual county q is:

$$L_q = \int_{\Omega} \prod_{k=1}^{K}\left[\left(P(y_{qt}) \times P(z_{qt})\right)\right] d\Omega \tag{9}$$

The full log-likelihood function is estimated as:

$$LL = \sum_q Ln(L_q) \tag{10}$$

EMPIRICAL ANALYSIS

Model Fit

The model estimation was conducted using independent variables outlined in the data section. The reader will note that the covid transmission model was estimated using mobility variables and the mobility model was estimated using covid transmission variables. The empirical analysis involves a series of model estimations. First, we developed uni-directional linear regression models (ULRs) for both COVID-19 weekly transmission rate and the weekly mobility patterns without considering the bi-directional relationship and the corresponding temporal correlations. Second, we improve the ULRs by considering the temporal correlations outlined in the methodology section and named it as uni-directional mixed linear regression model (UMLRs). As discussed earlier, in our data, we had two level of repetitions: weekly level and monthly level. In our analysis the model capturing the weekly level dependencies offers the best fit and hence we selected this model for the next step. In the final step, we develop joint econometric model that allows for the bi-directional impact across the two dependent variables while also controlling for the influence of common unobserved factors affecting the two variables. We called this model joint bi-directional mixed linear model (JBMLR).

To evaluate the performance of the models, we calculated Bayesian Information Criterion (BIC). The BIC value for a given empirical model can be calculated as: $[-\ 2\ (LL) +\ K\ln(Q)]$, where LL is the log-likelihood value at convergence, K is the number of parameters and Q is the number of observations. The model with the lowest BIC value is the preferred model. The BIC (LL) values for the final specifications of the three models are: 1) separate uni-directional linear regression model system (with 39 parameters): 549525.02 (-274532.91); 2) separate uni-directional mixed linear regression model system (with 41 parameters): 539963.81 (-269740.53); and 3) joint bi-directional mixed linear regression model system (with 42 parameters): 519432.74 (-259469.11). The comparison exercise highlights two important observations. *First*, models incorporating temporal dependencies provides improved performances relative to their simpler counterparts as evidenced by the lower BIC value. The results demonstrate the effectiveness of the mixed modeling approach in handling data with repeated measures. *Second*, the BIC value of the joint model is considerably lower than separate mixed linear regression model system offering support to our hypothesis that a bi-directional relationship between the weekly COVID-19 transmission rate and mobility pattern is likely to exist.

Model Results

The model fit measures presented in the previous section clearly highlight the superior performance of the joint bi-directional mixed linear regression model system over its counterparts. Therefore, in this section, we discuss the effects of variables by variable category obtained from the joint model only. The reader would note that we tested several variables and functional forms during the model estimation process. The variables that yielded the best data fit and offered intuitive parameter interpretations were included in the final specification. The final model was selected through a systematic process of eliminating all the insignificant variables at a 90% significance level. The estimation results are presented in Table 2.

Table 2: Joint Bi-Directional Linear Mixed Regression (BLMR) Model Estimation Results

Model/Variable	Covid Transmission Model		Mobility Model	
	Estimates	t-statistics	Estimates	t-statistics
Constant	1.337	12.029	2.864	77.125
Temporal Factors (Base: Vaccination Phase)				
Pre pandemic period	-1.911	-32.007	-0.800	-102.829
1st wave	0.480	53.178	-0.428	49.161
2nd wave	1.630	182.419	-0.180	21.493
Mobility-related Variables				
Mobility, 2 weeks lag, in initial phase of pandemic	0.204	14.958	--	--
Mobility, 2 weeks lag, in 1st and 2nd wave of pandemic	0.471	27.909	--	--
Covid-related Variables				
Covid cases, 2 weeks lag, in initial phase of pandemic	--	--	-0.631	-6.56
Covid case, 2 weeks lag, during 1st wave of pandemic	--	--	-0.453	-19.458
Covid case, 2 weeks lag, during 2nd wave of pandemic	--	--	-0.297	-18.106
Covid case, 2 weeks lag, during vaccination phase	--	--	-0.071	-6.762
Health Care Infrastructure Attributes				
Testing rate, 5 days lag	0.028	12.230	--	--
Demographics				
% Young people	0.022	14.388	0.026	53.622
% Senior people	-0.005	-4.951	-0.01	-29.526
% African American people	0.005	14.692	-0.004	-41.802
% Hispanic people	0.001	3.819	-0.002	-22.538
% Female	0.009	4.324	--	--
Employment rate per 100K population	--	--	0.103	115.674
Health Indicators				
No. HIV patients	0.064	12.077	--	--
No. Hepatitis C patients	0.012	6.237	--	--
Spatial Factors				
Bottom 10 tourist states	-0.183	-16.731	--	--
South	0.021	1.983	0.706	231.408
Mid-West	0.085	8.359	0.261	82.541
No. airport per 100K population	0.171	15.619	0.331	6.821
Correlation Parameters				

σ^2	1.912	49.925	1.231	23.841
ϕ	0.286	102.854	0.331	86.439
ρ	0.830	12.561	0.497	37.822
η	0.683	102.236	0.683	102.236

COVID Transmission Model

Constant: The constant does not have any substantive interpretation after adding other independent variables.

Temporal Factors: In the COVID transmission model, we introduced different temporal time period specific indicator variables to examine how the different phases affected virus transmission rate. The temporal attributes considered include: (a) early-pandemic period (March 2020 through June 2020), (b) 1st wave defined as the time period from July 2020 to October 2020, (c) 2nd wave defined as time period from November 2020 to February 2021and (d) Vaccination period defined as time period from March 2021 to August 2021). The model parameters for these indicator variables estimated with vaccination phase as the base variable offered expected results. The coefficient for the early-pandemic period highlights the lower COVID-19 transmission rate relative to the vaccination period. The result can be attributed to implementation of strict lockdown measures, travel restrictions, and public awareness campaigns promoting preventive measures. In the middle phases, the model results reveal a significant increase in the COVID-19 transmission rate as evidenced by the positive coefficient observed for both 1st and 2nd wave period of the pandemic. Interestingly, the impact is more pronounced during the 2nd wave period, underscoring a substantial rise of COVID cases during that particular period. Increased social interactions and emergence of new variants are some of the factors that facilitated such increased transmission of the virus.

Mobility-related variables: As discussed earlier, we recognize that mobility will have a lagged effect on COVID-19 transmission i.e., exposure to virus today is likely to manifest as a case in the next 5 to 14 days. Hence, in our analysis, we tested several lag combinations in the model development. Based on our model estimation, the best statistical and intuitive fit was obtained for the specification with 2-weeks lag mobility. As expected, the overall mobility effect shows a positive contribution in transmitting COVID-19 virus (*21*, *22*). The effect is a clear indication of the significant role of mobility on transmitting the virus within communities. However, the effect is substantially different across different phases of the pandemic lending support to our hypothesis that the relationship between mobility and COVID-19 transmission varies over time. Specifically, the impact of mobility is more pronounced in the later phase of the pandemic (1st and 2nd wave) in comparison to the beginning of the pandemic. The results clearly highlights that the impact of mobility on COVID-19 transmission is not constant but rather influenced by the specific phase of the pandemic, highlighting the importance of considering temporal dynamics in understanding the virus's spread.

Health Care Infrastructure Attributes: With respect to health care infrastructure related variables, we find that higher testing rate is generally linked to higher COVID-19 transmission (*19*, *23*). The finding is intuitively understandable as higher testing efforts lead to increased identification of COVID cases. In absence of adequate testing, individuals with mild symptoms are deterred from testing themselves due to long wait times.

Socio-demographics: Among socio-demographic variables, we find several attributes to have a significant impact on the COVID-19 transmission rate. Counties with higher share of young people are likely to report an increased incidence of COVID-19 cases while a larger percentage of senior people in the county is negatively associated with the transmission rate (*20*). The results follow expected trends as young people are likely to engage more in social gatherings while seniors are more cautious and follow preventive measures. Further, the results indicate that a higher share of African-American, Hispanic and female population in a county contributes positively to COVID-19 transmission. The findings are consistent with findings from previous research (*24–26*).

Health Indicators: Several health indicators were considered in the model (see Table 1). The parameters of health indicator variables underscore their importance on understanding the COVID-19 transmission. Our results indicate that counties with a greater number of HIV and Hepatitis C patients are likely to experience higher COVID-19 transmission rates. The results are intuitive because individuals with such conditions have a compromised immune system and are more susceptible to contracting and transmitting COVID.

Spatial Factors: The final variable group considered in our model correspond to spatial factors including variables related to tourism, regional location, and airport density. We considered the tourism status of the state in our analysis by identifying the top and bottom 10 desirable states with respect to tourism activity. The counties were allocated to Top and bottom 10 tourism status based on their respective state ranking. As expected, we find a negative effect of the bottom 10 tourist attraction states on COVID transmission rate. The result might be indicative of reduced travel activity in such regions. In terms of regional location, we find higher COVID-19 incidence in the South and mid-west regions. A possible explanation for these effects is probably related to the population density and variation of public health measures in such areas. Finally, the parameter regarding the number of airports suggests that areas with more airports are likely to experience higher incidence of COVID cases, perhaps indicative of the increased travel and higher exposure in those locations (*19*).

Mobility Model

Constant: The constant does not have any substantive interpretation after including other independent variables

Temporal Factors: As described in the COVID model results section, mobility patterns of people have undergone significant changes across different phases of the pandemic. For instance, during the early stage of the outbreak, we found a sharp decline in mobility as indicated by the negative parameter for the early-pandemic phase. This decrease could be attributed to the implementation of lockdowns and restrictive measures during the early stage of the pandemic. Interestingly, as the pandemic progressed, we find noticeable changes in the mobility pattern. Specifically, the effect on mobility was less severe during the 1st and 2nd wave of the pandemic compared to the initial stage of the pandemic. It appears that as time went on, mobility starts to recover to some extent compared to the early-pandemic period (see (*27*) for similar results). However, the reader will also note that the mobility levels during these periods were lower relative to the mobility levels in the vaccination phase. The varying temporal parameters can be attributed to familiarity with COVID, use of masking, ease of lockdown and fatigue associated with the pandemic.

COVID-19 related Variables: Similar to the COVID model, we hypothesize that COVID-19 incidence reported today will likely impact mobility behavior in the future. We tested several lagged transmission variables, and the two-week lag COVID-19 transmission variable offered the best fit. The presence of several COVID-transmission related variables in Table 2 demonstrates the impact of COVID-19 on mobility patterns. Consistent with earlier research (*28*, *29*), our analysis also found a negative association between COVID-19 transmission and mobility patterns. The result suggests that counties experiencing an elevated number of COVID-19 cases today will likely have lower travel related activities 2 weeks into the future. Interestingly, the model results show that as the pandemic progressed, the negative effect gradually diminished over the different phases of the pandemic indicating a partial recovery in mobility despite the presence of higher COVID-19 transmission rate. It appears that people may have responded to the ongoing pandemic situation by adopting safety measures, adjusting their behaviors, and finding ways to resume certain activities while managing the risks.

Socio-demographics: Socio-demographic characteristics are found to play an important role in influencing mobility behavior. The population share by age in a county offered clear impact on mobility. Specifically, we find that an increase in the percentage of young people in a county contributes positively towards mobility. Usually, young individuals are more active and are less likely to curtail their mobility in the presence of COVID-19. Contrastingly, the opposite is true for senior people, that is in counties with higher share of senior population mobility is likely to be lower (*30*). The model estimation results show that counties with higher share of African-American and Hispanic people are likely to experience higher mobility. Finally, the positive coefficient associated with the employment rate indicates that an increase in the employment rate in a county resulted in increased mobility. A higher employment rate is associated with a higher need to travel (for work) and ability to engage in discretionary leisure activities.

Spatial Factors: Among spatial factors, our analysis indicates that several factors related to geographical location and airport accessibility have a positive effect on mobility demand. Specifically, people residing in the south and mid-west region exhibit higher mobility as indicated by the positive coefficient in Table 2. The higher mobility can be attributed to favorable weather conditions, extensive private transportation infrastructure and lower inclination for lockdown measures in these regions. Further, the parameter associated with airport density offers a positive contribution suggesting an increased mobility demand in the areas with better airport accessibility. In general, an increased number of airports in a county contribute to higher mobility.

Correlation Factors

As described in the methodology section, we developed a bi-directional simultaneous mixed linear model for estimating the daily COVID-19 transmission rate and the mobility pattern to incorporate two levels of dependencies: a. temporal correlations: dependencies across each county for weekly level repetitions (σ^2, ρ and ϕ,) and b. common unobserved factors affecting COVID-19 transmission and mobility pattern simultaneously (η). The last row panel of Table 2 present the estimated correlation parameters. All the parameters demonstrate high significance level highlighting the influential role of unobserved factors in shaping the relationship between COVID-19 transmission and population mobility level. In particular, the significant impact of the temporal correlations underscores the role of temporal dynamics and dependencies over time(74 weeks) in influencing COVID-19 transmission and mobility patterns. Additionally, the presence of significant common unobserved factors (η in Table 2) suggests interconnectedness between COVID-19 transmission and mobility patterns. The findings offer support to our hypothesis that it is necessary to develop a simultaneous model to capture the influence and feedback between COVID-19 transmission and mobility patterns.

Validation Analysis

In this section, we conducted a validation exercise, to evaluate the performance of the proposed joint model on observations set aside for validation and not used for model estimation (231 counties were set aside as the hold-out sample). In the validation exercise, the performance of the joint bi-directional mixed model is compared with the performance of the uni-directional mixed linear model and the uni-directional linear regression model. The comparison exercise across the three models is conducted based on the root mean square error value (RMSE). The results for the validation effort are presented in Table 3. The results clearly highlight the superior performance (as indicated by the lower RMSE values) of the joint model over its other counterparts across both estimation and validation samples. The validation exercise further confirms the suitability of the simultaneous bi-directional model for capturing the interconnectedness across COVID and mobility, as it offers enhanced interpretability as well as improved predictive capability. The reader would note the adoption of other metrics such as mean prediction bias (MPB), mean absolute deviation (MAD) offer similar results and are presented in the Appendix (Table A.1).

Table 3: Model Validation Results

Data	Model	COVID Model RMSE	Mobility Model RMSE
Estimation	Uni -directional linear regression model	201.151	61.561
	Uni-directional mixed linear model	189.49	53.871
	Joint bi-directional mixed model	89.167	42.990
Validation	Uni -directional linear regression model	239.981	76.340
	Uni-directional mixed linear model	222.891	66.910
	Joint bi-directional mixed model	100.674	56.110

Elasticity Effects

To further assess the effectiveness and robustness of our proposed simultaneous modeling framework, we conducted an elasticity analysis comparing the elasticity impact of variables from joint bi-directional model with the elasticity impact of variables from its uni-directional counterparts. This comparison exercise will uncover the pitfalls of uni-directional models and highlight the advantages offered by the bi-directional model. To that extent, we compute aggregate level elasticity effects for both BJMLR and UMLR models. In particular, we estimate the percentage change in the expected COVID -19 transmission and weekly mobility pattern in response to the increase of the explanatory variable by 10% (see (25, 26) for a discussion on the methodology for computing elasticities). For this purpose, we identify a subset of exogenous variables including COVID transmission rate, weekly mobility, percentage of young and senior people and no. airports in the county. The elasticity analysis results comparing the UMLR and JBMLR models are presented in Table 4.

Table 4: Elasticity Effects Across Two Models (UMLRs and JBMLR)

Variables/Model	UMLRs		JBMLR	
	Covid Model	Mobility Model	Covid Model	Mobility Model
Mobility, 2 weeks lag, in initial phase of pandemic	1.94%	--	2.04%	--
Mobility, 2 weeks lag, in 1st and 2nd wave of pandemic	5.31%	--	4.71%	--
Covid cases, 2 weeks lag, in initial phase of pandemic	--	-7.13%	--	-6.31%
Covid case, 2 weeks lag, during 1st wave of pandemic	--	-2.97%	--	-4.53%
Covid case, 2 weeks lag, during 2nd wave of pandemic	--	-1.91%	--	-2.97%
Covid case, 2 weeks lag, during vaccination phase	--	-1.13%	--	-0.71%
% Young people	4.70%	5.82%	4.93%	5.82%
% Senior people	-0.88%	-1.58%	-0.88%	-1.76%
No. airports per 100K population	2.17%	4.00%	2.16 %	4.20%

Two important observations can be made based on the elasticity effects presented in Table 4. First, we find significant differences in the estimated impact of variables between the UMLRs and JBMLR model. For example, while mobility with a 2-week lag during the early phase of the pandemic reveals a positive impact in both models, the effect is slightly higher in the JBMLR model compared to its uni-directional counterpart. However, the opposite is true in the later phases of the pandemic (1^{st} and 2^{nd} wave), i.e., mobility is found to have reduced positive effect in the JBMLR model. Similar results are also observed regarding COVID-19 related variables. The model incorporating the interplay between COVID-19 transmission and weekly mobility pattern (JBMLR) offers a higher negative impact of COVID-19 transmission on the mobility relative to the UMLR model. On the other hand, during the vaccination phase, the impact of COVID-19 transmission on mobility is less severe in the BJMLR model as indicated by the lower negative value in Table 4. These discrepancies clearly highlights the importance of considering the bi-directional relationship between COVID-19 transmission and mobility when interpreting the effects of independent variables. Second, we find smaller differences for demographics and airport effects across both models as indicated in Table 4. The results suggest that these effect remain relatively constant irrespective of the modeling framework.

In summary, the differences in variable impacts further lends support to our hypothesis that allowing for the feedback between COVID-19 transmission and mobility will provide a more accurate representation of their relationship. Specifically, the JBMLR model incorporates the bi-directional relationship between COVID-19 transmission and mobility, thus providing a comprehensive understating of the reciprocal effects. In contrast, the UMLRs treat COVID and mobility as separate systems, potentially resulting in incorrect and/or biased interpretation of the effects of independent variables.

CONCLUSION

Earlier research studies typically focused on examining the uni-directional impact of mobility on COVID-19 transmission and vice-versa. However, it is possible that these variables are interconnected with each other. Addressing the presence of interplay between COVID-19 transmission and population mobility by recognizing the bi-directional relationship is essential for accurate analysis and policy formulation. The current research effort develops a simultaneous econometric model system that allows for the bi-directional impact across the two dependent variables (COVID-19 transmission and population mobility pattern) while also controlling for the influence of common unobserved factors affecting the two variables. With the bi-directional model, in our analysis, we explored the changing relationship between transmission and mobility by considering various phases of the pandemic in the US including (a) initial part of the pandemic, (b) first wave, (c) second wave, and (d) vaccination phase. We analyzed county-level data on transmission and mobility patterns from the US over a 78-week period using a comprehensive list of factors including (a) temporal factors, (b) socio-demographics, (c) health indicators, (d) health care infrastructure attributes, and (e) spatial factors.

The empirical analysis involves estimation of three different model system: a) uni-directional linear regression models (ULRs) where we develop separate linear regression models for both COVID-19 weekly transmission rate and the weekly mobility patterns; b) uni-directional mixed linear regression models (UMLRs) where we consider temporal dependencies within each ULR for COVID-19 weekly transmission rate and the weekly mobility patterns; and c) joint bi-directional mixed linear regression models (JBMLR) where we extend the UMLRs by allowing for the bi-directional impact across the two dependent variables while also controlling for the influence of common unobserved factors affecting the two variables. The three model systems were compared based on Bayesian Information Criterion (BIC). The findings highlighted the superiority of the proposed simultaneous framework (JBMLR) over its counterparts in analyzing COVID-19 transmission rates and mobility patterns.

Model estimation results highlight the presence of a complex and multi-phased relationship between COVID-19 transmission and mobility patterns. While the overall mobility effect shows a positive contribution in increasing COVID-19 transmission, the impact is different across different phases of the pandemic. Similarly, COVID-19 transmission is found to be negatively associated with mobility. However, the magnitude of the effect gradually went down as the pandemic progressed. Both these findings clearly highlight that the interplay between the two variables is not constant but rather influenced by the specific phase of the pandemic. Further, the significant impact of the common unobserved factors clearly provide credence to our hypothesis of the existence of the bi-directional relationship and the need to take into account such relationship while analyzing the COVID-19 transmission rates and the mobility patterns.

The analysis was further augmented by undertaking a validation exercise using the final model parameter estimates on both estimation and hold-out samples. The results further confirm the suitability of the simultaneous model for capturing the interconnectedness across COVID and mobility, as it offers enhanced interpretability as well as greater predictive capability. An elasticity analysis was also conducted to illustrate the importance of the bi-directional model vis-à-vis the uni-directional model. The uni-directional models are prone to over or under-estimate the influence of different variables considered.

The findings of the study can be used to develop strategies for managing future pandemics and reducing their impact on public health and transportation systems. To further illustrate the practical application of our findings, let's consider a scenario where we manage public spaces such as restaurants and parks during a pandemic with changing transmission rates, comparing the use of unidirectional versus bidirectional models. In a unidirectional approach, public spaces might experience rigid, uniform closures whenever COVID-19 cases rise, only considering how transmission affects mobility. This reactive approach could lead to delayed reopening even as case numbers decrease, extending economic and social losses well beyond what may be required. On the other hand, a bidirectional model will be able to capture the dynamic interplay between disease transmission and mobility. It not only responds to how rising cases might reduce mobility but also prepares for the increase in mobility as cases decline. Hence, this model might suggest tightening measures like outdoor dining or limited occupancy as cases rise and then implementing a phased, data-driven reopening as transmission decreases. This proactive approach aligns public health measures more closely with both epidemiological data and public behavior shifts, maintaining public trust and compliance. By integrating this bidirectional perspective, policymakers can devise strategies that effectively manage both the virus's spread and its socio-economic impacts, leading to more sustainable and successful pandemic management. Further, the proposed simultaneous approach can be applied across other fields where endogeneity plays a significant role, such as crash and citation analysis, crash severity and emergency medical service response time analysis.

To be sure, the study is not without limitations. Data availability issues prevent us from including the Omicron and post-Omicron phases in our analysis. Future research should incorporate data from these phases to obtain a more comprehensive understanding of the dynamics between COVID-19 transmission and population mobility patterns.

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The authors confirm contribution to the paper as follows: study conception and design: Naveen Eluru, Tanmoy Bhowmik; data collection: Tanmoy Bhowmik; analysis and interpretation of results: Tanmoy Bhowmik, Naveen Eluru; draft manuscript preparation: Tanmoy Bhowmik, Naveen Eluru. All authors reviewed the results and approved the final version of the manuscript.

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Appendix

Table A.1: Model Prediction Results (MPB and MAD)

Data	Model	COVID Model		Mobility Model	
		MPB	MAD	MPB	MAD
Estimation	Uni -directional linear regression model	10.21	36.47	5.43	19.29
	Uni-directional mixed linear model	8.96	33.61	5.11	18.77
	Joint bi-directional mixed model	7.32	26.83	5.02	15.53
Validation	Uni -directional linear regression model	13.73	46.32	9.58	29.72
	Uni-directional mixed linear model	13.11	44.17	8.13	28.98
	Joint bi-directional mixed model	12.51	40.98	7.97	26.53