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Spatial association of mobility and COVID-19 infection rate in the USA: A county-level study using mobile phone location data

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Author statement

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Spatial Association of Mobility and COVID-19 Infection Rate in the USA: A County-level Study Using Mobile Phone Location Data

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Spatial Association of Mobility and COVID-19 Infection Rate in the USA: A County-level Study Using Mobile Phone Location Data

Abstract

Introduction: Human mobility has been a central issue in the discussion from the beginning of COVID-19. While the body of literature on the relationship of COVID transmission and mobility is large, studies mostly captured a relatively short timeframe. Moreover, spatial non-stationarity has garnered less attention in these explorative models. Therefore, the major concern of this study is to see the relationship of mobility and COVID on a broader temporal scale and after mitigating this methodological gap.

Objective: In response to this concern, this study first explores the spatiotemporal pattern of mobility indicators. Secondly, it attempts to understand how mobility is related to COVID infection rate and how this relationship has been changed over time and space after controlling several sociodemographic characteristics, spatial heterogeneity, and policy-related changes during different phases of Coronavirus.

Data and Method: This study uses GPS-based mobility data for a wider time frame of six months (March 20-August’20) divided into four tiers and carries analysis for all the US counties (N=3142). Space-time cube is used to generate the spatiotemporal pattern. For the second objective, Ordinary Least Square (OLS), Spatial Error Model (SEM), and Geographically Weighted Regression (GWR) were used.

Result: The spatial-temporal pattern suggests that the trip rate, out-of-county trip rate, and miles/person traveled were mostly plummeted till the first wave reached its peak, and subsequently, all of these mobility matrices started to rise. From spatial models, infection rates were found negatively correlated with miles traveled and out-of-county trips. Highly COVID infected areas mostly had more people working from home, low percentages of aged people and educated people, and high percentages of poor people.

Conclusion: This study, with necessary policy implications, provides a comprehensive understanding of the shifting pattern of mobility and COVID. Spatial models outperform OLS with better fits and non-clustered residuals.

Keywords: mobility, COVID-19, social distancing, spatial autoregressive model, geographically weighted regression, space-time cube
1. Introduction

The novel Coronavirus has impacted our lives in many ways. In blocking its transmission, one of the non-pharmaceutical recommendations from administrations was asking city-dwellers strongly to stay at home, which essentially reduced human mobility. The relation of virus transmission with mobility is vital and bidirectional. For the increased number of COVID cases, people reduced mobility, which, in turn, slowed community transmission (Jamshidi et al., 2020). Both directions of relationship—impacts on and of mobility—have received massive attention of scholars globally. Studies that investigated the impact of COVID on mobility have strongly depicted multifaceted effects, including changes in travel demand (Arellana et al., 2020), modal share (Bucskey, 2020), transit ridership (Huang et al., 2020; Jenelius and Cebecauer, 2020), bicycle usage (Tokey, 2020), destination choice (Aloi et al., 2020), etc. On the other hand, many studies found mobility an essential driver to the transmission of COVID (Zhou et al., 2020; Hadjidemetriou et al., 2020; Carteni et al., 2020; Chinazzi et al., 2020; Jiang and Luo., 2020). The latter group of studies mostly quantified the delay in transmission and reduced death caused by mobility reduction.

In the USA, after the first identification of the COVID case on January 21, 2020, the total case on March 1 was 75, and within 30 days, it reached 197,727. Governors started to announce stay-at-home order in their states from the last half of March. Consequentially, mobility started to fall sharply after these announcements, and this shortfall continued in April (Warren and Skillman, 2020). From early May, states started to reopen with different phases, which, in turn, let the mobility bounce back (Jamshidi et al., 2020; Tokey 2020).

While the body of literature on infection and mobility is burgeoning and researchers worldwide have been shedding light from different angles on this geographically and temporally heterogeneous issue, some issues should receive more attention in further studies. Firstly, in modeling practice, accounting for spatial autocorrelation is less commonly seen in contemporary works. Xiong et al. (2020a) also recommended addressing this issue in future studies. The second issue is about the data. Researchers mostly leveraged different open-source data in tracking mobility from aggregated view, including mobile GPS data, mobility reports from Apple, Google, Twitter, etc. A major concern raised against the mobility data from Google and Apple is the expression of change in mobility which is in percentage compared with their defined baselines. These percentages overshadowed the actual observation of mobility units (e.g., trip rate, mileage). In addition, the baselines—which are January 3- February 5 for Google and February 13 for Apple—represent only times in winter and do not capture the seasonal variation. Thirdly, broader temporal coverage with countrywide spatial coverage of data is not much common in US-based studies.
The few studies, who used wide timeframes, have underscored the extreme temporal heterogeneity to be taken into consideration (Gatalo et al., 2020; Li et al., 2020).

To this end, our study wants to extend the current understanding by incorporating spatial autocorrelation where a relatively broader timeframe (6 months long) is considered. Although the practice of focusing shorter timeframe performed by many studies is beneficial as it offers the ability to pay attention to detail, seeing a picture from a broader timeframe with several phases might help us understand the trends. Therefore, this is particularly important to understand the mobility patterns and their relationship with COVID severity in different phases. The primary aggregated data in this study comes from GPS-based, anonymous, and disaggregated locational information having actual mobility calculation, free from comparison against any assumed baseline. Dividing the first two waves of COVID infection into four tiers (detail in the methodology), this study aims to

1. explore the spatial-temporal pattern of mobility
2. identify the associations of mobility with COVID cases in different phases of Coronavirus

The remainder of the paper is arranged into four more sections. In the next section, the focuses and findings from concurrent studies have been reviewed. Section 3 discusses the details of data sources, processing, and methodological approaches. Section 4 reports the results of regression models, the elasticities over time, and the spatial distribution of local spatial models. The last section concludes with a summary of this study and discusses the result, policy implication, limitation of this study, and future research direction.

2. Literature Review

2.1 Overview from US studies

Availability of the mobility data and virus infection statistics from different sources has enabled researchers to gauge the association of mobility and COVID-19 from different temporal and spatial scales in the United States. Engle et al. (2020) captured a short and early period (February 24 to March 25) of COVID onset in their study. They used mobile phone data of all the USA counties, amalgamated with socio-demographic and epidemiological data. After defining mobility by distance traveled, they found an increase in infection rate by .003% is associated with a reduction of mobility by 2.31%. Counties with more senior citizens (above 65-year-old), fewer Republican Party voters in the 2016 presidential election, and higher population density were found more responsive to disease prevalence and stay-at-home orders. Lasry et al. (2020) analyzed the community mobility and major political decisions regarding COVID-19 in the metropolitan areas of Seattle, San Francisco, New York City, and New Orleans. From February 26
to April 1, the community mobility decreased as virus infection increased and community mitigation policies were issued. Li et al. (2021) presented the correlation coefficients of mobility and COVID case rate in maps using the mobility data from the Google community report from February to April. The positive relationship between transmission rate and mobility to workplaces, transit stations, groceries, etc., is more robust in urban areas and not apparent in rural areas. Xiong et al. (2020b), using the same data source like ours, modeled no. of trips per person and average daily person-miles traveled with the help of policy status (stay at home order) and the daily number of newly confirmed coronavirus cases from COVID onset to April 11. They found that policies only led to about a 5% reduction in average daily human mobility. Interestingly, person-miles traveled is more significantly reduced than the number of trips per person, indicating that more short-distance trips were made. This data is also used by Lou et al. (2020), where they assessed the difficulties of following stay-at-home orders for low-income groups. Their data from January 1 to April 14 showed that the effect of the stay-at-home order on the lower-income group’s mobility is smaller than that for the high-income group. Using different mobile phone data provided by a Switzerland-based company, Badr et al. (2020) tried to understand the mobility and virus transmission in 25 US counties. Combining no. of trips to, from, and within each county into a single ratio, this study considered the ratio as a basis to compare with the case growth. Pearson’s correlation for each of the counties in their study suggests that mobility pattern is strongly correlated with the case growth rate and social distancing is an effective way to mitigate COVID transmission. These studies were mostly up until April 20, which generally covers the time of pre-stay-at-home order and during the stay-at-home order period in the USA.

A number of studies also analyzed the link of interest during stay-at-home order to reopening phases. An evaluation was carried out on five US cities by Glaeser et al. (in press) from April 4 to June 7. They found that with a 10% decrease in mobility, total cases per capita is also decreased by 19%. The control of mobility worked greatly in New York, Boston, and Philadelphia, and a smaller effect of mobility on infection rate was found in Atlanta and Chicago. Gatalo et al. (2020) used the daily distance difference metric as an expression of reduced mobility. Like many other studies mentioned above, they found that decreased mobility and reduced COVID-19 case growth are highly correlated between March 27 and April 20, 2020. However, in the subsequent phase (e.g., April 21 to July 22, 2020), the power of this correlation diminished, partially for the stronger effect of personalized behavioral control (e.g., wearing a mask, maintaining six feet distance) on case growth. While this finding documents temporal variation of the mobility effect, Yamamoto and Wang (2020) indicated spatial variation. Analyzing mobility data for Arizona between April 24 to June 19, they found that, in rural areas, controlling mobility related to retail and recreation can prevent 32% population from getting affected, while for cities/metro areas, this
strategy may not be sufficient. Unlike general mobility, bike mobility showed more resiliency towards COVID-19 and quickly regained its regular ridership. Tokey (2020) found that the central parts were more affected and more resilient in five US cities when the bike-share ridership was dropped and recovered, respectively. This resiliency of bicycles can be linked with the heterogeneous perception over the social classes regarding reopening services. Rahman et al. (2021) analyzed the factors associated with positive and negative sentiments of the people about reopening the economy. They found that people with lower educational and income levels, higher house rent, and people in the labor force are more interested in reopening the economy than high-income people. Kuo and Fu (2021) built a machine learning model and found that instead of reopening, a 1-week and a 2-week lockdown could reduce 4-29% and 15-55% infections in the future weeks.

With the availability of recent data, there is an emerging number of studies with more extended periods. Xiong et al. (2020a) analyzed the inflow mobility in US counties from March 1 to June 9. He found a positive relationship between the COVID cases and inflow in counties. Using a GPS-based location mapping platform, GeoDS, Gao et al. (2020) provided insights from their data regarding mobility reduction, breaking the study period into three phases: pre-stay-at-home, during the stay-at-home, and reopening period. According to them, a high level of adherence to social distancing at the beginning of the stay-at-home orders effectively reduced the median travel distance, while since early May, increased mobility was observed with the relaxation of stay-at-home orders. Li et al. (2021) also have similar findings after analyzing mobility from March 1 to July 13. Policies like stay-at-home orders, workplace closure, and public awareness programs effectively decreased the confirmed case growth rate. While the former two policies significantly decrease mobility, their impacts on mobility diminished over time, echoing Gatalo et al. (2020). Jamshidi et al. (2020) investigated the impact of mobility, density, weather, and mask usage on COVID transmission in the USA. Using GPS data from Safeguard, they showed that mobility reduction was more remarkable in the eastern part than the western part. The temporal range of this study is relatively broad, from March to July. From May to June, mobility was found to be significantly correlated with the weekly COVID case rate. While this study shows the spatial distribution of mobility changes, it does not tell anything about the spatial distribution of the effect. Noland (2021) analyzed Google mobility data from January 3 to June 23. He found that mobility is correlated with the effective reproduction rate of the virus. He recommended mobility reductions of about 20%-40% to drag the effective rate down below one.

2.2. Overview from global research
Research conducted in countries other than the USA has also measured COVID-19 and mobility change from different spatial and temporal scales. The effect of mobility on virus transmission there is fairly documented. In China, a reduction in mobility by 20–60% flattened the peak number of cases by 33% (Zhou et al. 2020). Travel quarantine delayed epidemic progression there by 3-5 days (Chinazzi et al. 2020). Gondauri and Batashvili (2020), analyzing the mobility in nine countries, found that trips performed one day are directly related to COVID-19 cases after 15-20 days. According to Cot et al. (2021), this lag period is two to five weeks. Italy was one of the most hard-stricken countries in the world. Consistent with other studies, Carteni et al. (2020) found that the performed mobility effectively increases infection rate after 21 days. The restriction about mobility and human-to-human interaction has reduced transmission by 45% in the early days (February 21- March 25) of COVID-19 in Italy (Gatto et al., 2020). Analyzing Facebook activity, Beria and Lunkar (2021) found a sharp and dramatic fall of movement from few days before the lockdown. The population of large cities fell, and they moved into other cities in the urban belt, although not in remote areas. Similarly, in Japan, the shrink in daily travels has also reduced the population density in crowded central areas up to 90% (Arimura et al., 2020). People’s reduction in non-essential travels is influenced by the perception of the degree of self-restriction of others (Parady et al., 2020). In Poland, Borkowski et al. (2020) found that working from home, being in an obligatory quarantine, and being afraid of infection worked towards a decrease in travel time after-COVID compared to the before-COVID situation. However, working from home is not an option for every societal class. Rahman et al. (2021) found that countries with a higher number of elderly people, employment in the service sector, and higher globalization trends are the worst victims of the coronavirus pandemic. Nouvellet et al. (2021), analyzing 52 countries, found that virus transmission decreased with mobility in 73% of countries. Analysis of 41 cities worldwide, conducted by Soucy et al. (2020), similarly tells that a 10% decrease in mobility is associated with a 14.6% decrease in the daily growth rate of infection. Cot et al. (2020) found that maintaining social distancing effectively reduced infection rates by 20%-40%. In a nutshell, mobility reduction helped to block COVID infection over the world. However, the relation between mobility and infection is not constant and can change over time. Nouvellet et al. (2021) reported that mobility was associated with low transmission in some countries with control relaxation. Therefore, this is the particular interest of our study to evaluate the changes of the effect of mobility on COVID infection rate over time.

3. Data and methods

3.1 Data source and processing

This study considered a six-month timeframe as the study time ranging from March 1, 2020, to August 27, 2020. This timeframe consists of the first two waves of Coronavirus in the USA regarding daily new
cases. We further divided this timeframe into four tiers; rise of the first wave (38 days), fall of the first
wave (70 days), rise of the second wave (30 days), and fall of the second wave (42 days) (Figure 1). This
partitioning allows us to interpret the temporal dynamics more logically. Every county has one
observation per day and thus, the four tiers had total of 119396, 219940, 94260, and 131964 daily
observations respectively for all the counties. These records were then aggregated into averages for each
county so that every county has single observation per tier and each tier has 3142 observations for 3142
counties.

The principal data used in this study is secondary data which is collected from the COVID-19 Impact
Analysis Platform of Maryland Transportation Institute (2020), or MTI. This platform collects movement
data from the mobile devices of over 20 million anonymous individuals daily (150 million monthly) and
incorporates locational data from different sources including GPS, Wi-Fi, beacons, and networks of their
mobile devices (Hu et al 2021). Sources like these offer enormous usefulness for their efficacy to assess
the intervention impact (Grantz et al., 2020). We consider such sources appropriate for our study due to
their high volume, accuracy, and spatial coverage. The anonymized locational data are used to measure
the mobility indicators (i.e., no. of trips, trip distance, or, making no trip) with imputation algorithms and
multi-level weighting which was again validated with the independent data sources like National
Household Travel Survey (NHTS), American Community Survey (ACS) and other mobility data sources
like Google, Apple, and Safegraph. More information regarding data collection and validation
methodology is available at the University of Maryland COVID-19 Impact Analysis Platform (Maryland
Transportation Institute, 2020), Zhang et al. (2020), and Hu et al (2021). This dataset provides data for a
total of 39 variables grouped into four categories. There are nine variables from Mobility and Social
Distancing category (e.g., Social Distancing Index, trips/person, miles/person, percentage of residents
staying at home, etc.) and 15 variables from COVID and Health category (e.g., new case/1000 people,
imported COVID case, test done/1000 people, percentage of ICU utilization, etc.). This other two
categories are Economic Impact category (5 variables) where unemployment, consumption etc. are
captured, and Vulnerable population category (10 variables) where statistics about the groups vulnerable
by income, race, age are mostly provided. While data of the first two categories are collected by MTI and
other COVID monitoring dashboards (e.g., CDC, US hospital Beds Dashboards), the data of the last two
categories are mostly collected by US census and Department of Labor.
3.2. Variable description

From the MTI dataset, the variables were carefully chosen for this study. The description of the variables of this study is presented in Table 1. The dependent variable is the number of COVID cases per 1000 people of a county. The records of this variable come on a daily basis, and we aggregated all the daily records in a tier into the average for each county. This approach was followed for most of the independent variables that have temporal variations. The MTI data provides different mobility measures from which three indicators were selected in this study. Firstly, we used out-of-county trips, which might have a relationship with COVID transmission. We disregarded a similar variable, the percentage of out-of-state trips, since the unit of analysis of our study is counties. Secondly, miles traveled per person was considered since many studies used this as the primary mobility indicator (Engle et al., 2020; Xiong et al., 2020b; Gatalo et al., 2020). Lastly, daily trips/person was considered from some other similar variables available in the MTI dataset (i.e., work trip/person, non-work trip/person). This is another widely used mobility indicator in COVID-related studies (Pullano et al., 2020; Xiong et al., 2020b; Badr et al., 2020; Jamshidi et al., 2020). Three more variables from the MTI dataset were included in our study, which primarily played their role as control variables. Since working from home can impact traveling during this pandemic (Borkowski et al., 2020), in our study, we controlled the percentage of the workforce working from home. Also, since the number of COVID cases detected in an area can intuitively be contingent upon the number of tests done, we chose the variable express testing performance normalized by 1000 people. With a similar intuition, we controlled for the number of imported cases that can directly be linked with the response variable. Four sociodemographic variables that represent educational attainment (BACH25), age (AGE65), poverty (POV), and population density (DENS) of counties were used as other variables.
determinants of COVID infection rate. Relation of age, density, and education with COVID infection rate was previously considered in a US study by Hamidi et al. (2020). Lastly, we incorporated the heterogeneity in strictness of policies by different states, which was believed to have a connection with mobility, mortality, and social distancing by many previous studies (Jinjarak et al., 2020; Frey et al., 2020; Wielechowski et al., 2020). We have collected data of policy stringency index (PSI) of the US states from https://github.com/stccenter/COVID-19-Data/tree/master/Policy/US_Policy. The PSI is defined by Oxford COVID-19 Government Response Tracker (OxCGRT) Project (Hale et al., 2020) and can be calculated from Equation 1. This index uses the rescaled value of seven kinds of policies with their different stringency levels and expresses PSI in a 1-100 scale where 100 denotes the strictest policy response. While the formula is quite self-explanatory, a description of the policies and stringencies can be found at Li et al. (2021).

\[
\text{Policy Stringency Index} = \frac{1}{7} \left[ \text{rescaled (school closure + popularity)} + \text{rescaled (workplace closure + popularity)} + \text{rescaled (public events cancellation + popularity)} + \text{rescaled (public transport closure + popularity)} + \text{rescaled (public information campaign + presence)} + \text{rescaled (internal movement restriction + popularity)} + \text{rescaled (international/national travel control + popularity)} \right] \quad (1)
\]

Table 1 Description of the variables used in this study

| Label       | Variable description                               | unit                  | source |
|-------------|---------------------------------------------------|-----------------------|--------|
| Dependent variable (DV)                      |                      |                      |        |
| CASE        | Daily COVID cases/1000 people                      | Case/1000 people      | MTI    |
| Mobility indicators (Independent variables)  |                      |                      |        |
| OCT         | Percentage of total trips that cross county boarder| Percentage            | MTI    |
| MP          | Average daily person-miles travelled per person    | Miles/person          | MTI    |
| TP          | Average daily no. of trips taken per person        | Trips/person          | MTI    |
| Other independent variables                   |                      |                      |        |
| WFH         | Percentage of workforce working from home         | Percentage            | MTI    |
| TEST        | No. of COVID test completed per 1000 people        | Test/1000 people      | MTI    |
| IMPORT      | No. of imported case (external trips by infectious person) per 1000 people | Case/1000 people | MTI |
| BACH25¹     | Proportion of people (25+ years old) who have bachelor’s degree | Proportion            | ACS    |
| AGE65¹      | Percentage of total population who are 65+ years old | Percentage            | ACS    |
| POV¹        | Proportion of people below poverty                 | Proportion            | ACS    |
3.3. Methodology

3.3.1. Emerging hotspot analysis

The term "hotspot" in spatial science is generally used to indicate a spatial entity (i.e., polygon) with a particular value higher than its neighbors. Emerging hotspot extends this idea by incorporating time as the third dimension. Before finding emerging hotspot a variable of interest, we had to create a netCDF (Network Common Data Form) "space-time cube" structure that creates bins considering space in the x and y-axis and time in the z-axis. The shapes of the space-bins are the original boundaries of the counties. It then is used as input of the emerging hotspot tool of ArcGIS Pro. The process to obtain the final output goes through two stages. The first stage involves finding the significant clustering of high or low values in a place relative to its neighbors. The Getis-Ord Gi* statistic is used to find the significant hot/cold spots with a Z score below -1.96 or above 1.96 (Getis and Ord 1995). In the second stage, each bin's temporal trend and significance are investigated using Mann-Kendall statistics (Mann, 1945). This statistic is also associated with a Z score and p-value. A significant Z score above 1.96 or below -1.96 indicates a significant increase or decrease, respectively, of the value in a specific place compared to the previous temporal bin of that place. This study aggregated each temporal bin with a 3-day averaged time-step interval, which allowed us to have a maximum bin and a consistent interval over the four tiers. With the Z scores obtained in these two stages, the output map is expressed with 17 categories of trend; 8 for hotspots, 8 for cold spots, and one for no significant pattern. The eight categories are described in the Table A1. This method is close to another method for geo-visualization of space-time structures which is taxel or time volumes (Forer, 1998). Unlike the space-time cube, the taxel is a 3D raster viewed as a point cloud (Rush and Kwan, 2011).

3.3.2. Statistical modeling

We fitted several spatial and non-spatial models to assess the associations of COVID cases and mobility indicators. Firstly, Ordinary Least Square (OLS) is used as the non-spatial model with the following equation 2.

\[ y = \beta_0 + X\beta + \varepsilon \]

Here, y is an N × 1 vector outcome where (N = 3142 counties), X is the independent variables in the form of 3142 × k matrix (k = 11), \( \beta_0 \) is the intercept, \( \beta \) is an 11 × 1 vector of regression coefficients, and lastly, \( \varepsilon \) is the error of the model. In contrast to the non-spatial model, the spatial models are useful as they
account for the spatial autocorrelation of a spatial entity’s values with its neighbor. Therefore, we used
Spatial Error Model (SEM), where each county’s error term is not assumed to be completely independent
and is decomposed into random error and spatially correlated error (Anselin and Bera, 1998). The
standard basic form of this model is the same as Equation 2. The error term, \( \varepsilon \), is decomposed in Equation
3.

\[
\varepsilon = \lambda W \varepsilon + \xi \quad \text{…………………………………………………………………………………………………………………. (3)}
\]

There, \( \lambda \) is the spatial autoregressive coefficient for the error lag \( W \varepsilon \), a 3142 × 3142 weight matrix that
captures the neighbors of a given county, and \( \xi \) is an uncorrelated error term. The model uses Queen’s
contiguity approach to define the spatial weight matrix.

While SEM has the ability to account for the spatial autocorrelation and drag out the influence of error
term of neighboring counties from the spatially correlated error term, it only provides global estimates of
parameters and can barely illustrate the spatial variability of the effects. The third model we used in this
study is Geographically Weighted Regression (GWR) (Griffith, 2008). This model uses the following
form (Equation 4):

\[
y_i = \beta_0(u_i) + \beta(u_i)X + \varepsilon \quad \text{…………………………………………………………………………………………………………………. (4)}
\]

Here, \( u_i \) is a function of coordinates of county \( i \) (\( u_{xi}, u_{yi} \)). \( \beta(u_i) \) is a function of \( u_i \). The basic idea of GWR
is that it assumes the effect of nearest features are stronger than the distant one, which was initially
offered by Tobler (1970). The influence is determined by a weighting function that uses a distance band,
where features only within the distance are considered neighbors. This spatial kernel function controls the
distance decay in the weighting function (Hadayeghi et al., 2010). As this study is on mobility, we used
Gaussian weighting schemes, which exponentially decrease the weights as the distance increases.
Bisquare scheme, in contrast, does not allow any neighbor beyond a specified distance to impact on a
target feature. The Gaussian kernel is calculated with the Equation 5:

\[
w_{ij} = \exp \left( -\frac{0.5 ||u_i - u_j||^2}{G_i} \right) \quad \text{…………………………………………………………………………………………………………………. (5)}
\]

The parameter \( G_i \) is also called the bandwidth. In this study, we employed GWR with around 30 iterations
for achieving the distance threshold, which yields the lowest AIC and the lowest/insignificant spatial
autocorrelation. Given the heterogeneity of the sizes of the states, we chose distance band instead of the
number of neighbors as neighborhood type. For finding statistically significant coefficients, the
expression of \( \left( \frac{\beta_i - 0}{SE_i} \right) \) is used as t-statistics where SE is the standard error of local regressions.
This study built four models for each tier and reported all three types of models (i.e., OLS, SEM, GWR). We assessed the multicollinearity effect of the OLS models, and the maximum Variance Inflation Factor (VIF) of a variable was found 1.84, whereas a VIF of more than 7 or 10 is generally considered as worrisome. To report the comparative effects of the variables over the tiers, we calculated elasticity with the following equation 6.

\[
\text{Elasticity}_i = \beta \times \frac{X_i}{Y} 
\]

Here, \( X_i \) and \( Y \) are the mean values of the independent and dependent variables. \( \beta \) is the estimated coefficient of the particular independent variable \( i \) (Yang et al., 2019). The elasticity denotes the percentage change in dependent variable due to 1 percentage change of the independent variable \( i \).

### 4. Findings

#### 4.1. Descriptive Statistics

The description of the variables and their descriptive statistics in each tier are provided in Table 2. Since the unit of analysis is the county, we have 3142 observations in each tier for 3142 counties. We considered the average daily cases per 1000 people as the dependent variable in our models. As an independent variable, we incorporated three measures of mobility (i.e., out-of-county trips, miles/person traveled, trip/person). The other covariates are described in Table 1 and section 3.2. From the central values, it’s clear that the mean daily COVID case and all the mobility indicators have increased gradually from tier one to tier four. The other time-variant covariates (i.e., WFH, test, import, PSI) were also increased but at a faster pace. On the one hand, counties became more stringent in policy, had more testing capacity, and had more people working from home. On the other hand, more people traveled out of county, and people made longer and more frequent moves.

Table 2 Summary statistics of variables

| Tier | Case | OCT | MP | TP | WFH | TEST | IMPORT | BACH25 | AGE65 | POV | PSI | DENS |
|------|------|-----|----|----|-----|------|--------|--------|-------|-----|-----|------|
| Min  | 0.00 | 0.39| 16.72 | 0.93| 13.63 | 0.29| 0.00 | 0.00 | 3.20 | 0.02| 0.00| 0.04 |
| Mean | 0.01 | 33.25| 38.69 | 3.19| 18.65 | 1.31| 0.09 | 0.22 | 18.79| 0.15| 22.18| 273.10|
| SD   | 0.03 | 10.99| 9.71 | 0.36| 2.73 | 0.94| 0.17 | 0.10 | 4.66| 0.06| 18.60| 1803.48|
| Median | 0.00 | 33.32| 37.59 | 3.18| 18.63 | 1.00| 0.05 | 0.20 | 18.40| 0.14| 14.00| 44.80 |
| Max  | 1.17 | 98.33| 136.2 | 5.01| 33.15 | 5.90| 5.02 | 0.78 | 56.80| 0.55| 66.00| 71886.2 |
Indeed, the space-time cube offers the ability to incorporate time in the most granular form—three days aggregation bin, in our case. Nonetheless, to be able to interpret the change of mobility with logical relevancy of COVID intensity, we created space-time cubes for each indicator for the four tiers mentioned above. From Figure 2 to Figure 5, we show all the maps for four indicators in four tiers. Also, to help grasp the broader picture, we attached the graph of weekly averages of the indicators across the six months with each figure. It should be noted that the graph provides highly aggregated information and restricts the ability to generalize this trend for every part of the USA. In contrast, the maps show high variability of the trends across the country and an adequate number of counties with statistically significant trends. In the following paragraphs, we will describe the trends of each mobility indicator.

**Figure 2 shows the emerging hotspots and trends of trips/person. While in the first tier, for trip/person, most parts of the USA showed oscillating coldspot and some eastern and northern parts had persistent and intensifying coldspot, most of them are replaced by oscillating hotspots and diminishing coldspots in the 2nd tier. This affirms the general aggregated graph where the trip rate is found to be reduced in March, as a combined effect of transmission risk and stay-at-home orders, and increased subsequently from April to June, for gradual reopening in different states. We found a mixed effect when the second wave started to rise from mid-June. The Midwest (i.e., Nebraska, Kansas, Iowa) and part of the West region (i.e.,
Colorado, Wyoming) had oscillating and persistent hotspots, while the South region and the border areas of the West region had consecutive and persistent coldspots. This indicates that the Midwest region people were somewhat indifferent to the rise of COVID cases in terms of trip-making compared to those of other regions. These findings align with Jamshidi et al. (2020), where they found more mobility reduction (no. of trips) in the eastern part than the western part in March. The increase of mobility from May to June, suggested by them, also supports our finding of the 3rd tier. In the 4th tier, most of the previous tier’s hotspots in the Midwest region were no longer significant, and the other parts (i.e., South and West region) inalterably had persistent and sporadic coldspots.
Figure 2 Emerging hotspots of trips/person
The trend and emerging hotspots of the percentage of out-of-county trips are shown in Figure 3. Like every other mobility activity, making out-of-county trips was also halted while the Coronavirus hit first, indicated by intensifying coldspots in most of the USA. As people started to make these trips gradually with the ease of lockdown, the coldspots started to diminish in those parts, and many hotspots were found in the Midwest and South regions. With the rise of the 2nd wave, the West coast (i.e., California, Arizona, Oregon) and Florida quickly retracted their out-of-county trips, which is evident from their persistent coldspots. For those areas, this trend continued in the 4th tier with some intensifying coldspots.
Figure 3 Emerging hotspots of out-of-county trips
Figure 4 shows the emerging hotspots and trend of miles traveled/person. Miles traveled by people is greatly influenced by the fluctuations of COVID cases. For reduced traveling due to travel restrictions, most of the USA had coldspots in the 1st tier. Moreover, as expected, these were turned into hotspots in the subsequent tier, indicating more extended traveling. The general trend on the graph also confirms these trends. Despite the rise of the 2nd wave, we observed the more prolonged traveling is significantly clustered in the counties in the Midwest region, and the number of significant counties in that region was increased when the wave started to fall. On the contrary, people from the South region states traveled shorter throughout the 2nd wave, pointed by some sporadic and persistent coldspots.
Figure 4 Emerging hotspots of miles traveled/person
Finally, the emerging hotspots and the trend of SDI are shown in Figure 5. Shortly after the beginning of the virus detection in March, people started to maintain social distance in outdoor activities for the strong recommendation of city authority. The SDI map of the 1st tier tells the same story with the oscillating hotspots in most of the USA. With the reopening, the relaxation of social distancing is also evident from the map of the 2nd tier, where most of the hotspots had turned into oscillating coldspots. The graph also confirms this rise and sudden fall of SDI. The 2nd wave comes with a mixed effect on SDI. A greater degree of adherence to social distance is observed in the southern and western border states (i.e., California, Arizona, New Mexico, Texas, Florida) during the rise of the second wave comparative to Midwestern states (i.e., Illinois, Iowa, Missouri, Wisconsin, Nebraska). The effect of the rise of this wave on SDI seemed to continue in the fall of the wave as more areas from the Midwest region fall into significant hotspots in the 4th tier.

These granular temporal bins of emerging hotspots and coldspots provide many useful insights about its spatial distribution, and some of them can be relatable to the country's COVID severity. Nonetheless, we cannot attribute the changes of virus severity of a particular area to the changes of its mobility pattern with much strength. The spatial modeling offers that ability, and the model results are presented in the following section.
Figure 5 Emerging hotspots of Social Distancing Index (SDI)
4.3. Association of mobility with COVID cases

We have fitted the models discussed in the methodology section for each of the four phases of Coronavirus. Each variable's daily records were aggregated into the average for each phase and were used as throughputs of the models. For gauging the relationship of mobility and COVID severity, OLS and SEM tell the global associations, while GWR helps to understand the spatially varying local impacts. In table 3 to table 6, we presented the model results with coefficients, standard error (for OLS and SEM), median local GWR estimate, and the percentages of counties with positive GWR estimates. Although all the models have VIF values less than 7, we did not include WFH in GWR for local multicollinearity. The fit of the models (i.e., adjusted $R^2$, or Adj. $R^2$) and the spatial autocorrelation test results are also reported in the tables. A significant Moran's I value more than the expected index ($I = -0.0003$) shows significant clustering of residual while a Moran's I significantly less than expected index denotes dispersed pattern. Insignificant Moran's I shows the randomness of residual. We have also analyzed the mediation effect with several auxiliary regressions, which we did not report in tables. In these regressions, the mediatory variables from the pool of independent variables were identified. One variable from independent variables can be called mediatory variables if the mobility variables can significantly explain it and are significant when dependent variables are regressed without it (Preacher and Kelley, 2011). In other words, in multivariate regression, a mobility variable, say OCT, can have a different relation to dependent variables depending on the presence of an independent variable, say PSI. If OCT can regress PSI significantly, PSI can be regarded as a mediatory variable that mediated the effect of OCT on the dependent variable.

4.3.1. Tier 1: Rise of the 1st wave

Table 3 presents the estimates of global models (i.e., OLS and SEM) and the median estimates of the local model, GWR. In OLS and SEM, the mobility variables do not show any significant effect. However, we found two mediatory variables that are DENS and BACH25. The TP and MP are inversely associated with COVID infection rates and significant in 95% and 99% confidence interval, respectively, only when the population density and percentage of bachelors in a county is not controlled. These effects are mediated when density and educational attainment is controlled in the model. The mediating variables do not seem to mediate OCT. In this tier, counties with high population density and a high percentage of bachelor's degree holders have significantly higher COVID infection rates. Among other covariates, testing performance and no. of imported cases per 1000 people were also positively affected COVID infection rate.
While comparing across the models, the coefficients of OLS, SEM, and the median coefficients of GWR are consistent for most of the variables. The spatial models showed a better fit—in terms of R2—over OLS. Moreover, the OLS residual shows significant clustering, which confirms the effectiveness of incorporating spatial models into deciphering the relation of interest. All these spatial models accounted for spatial clustering successfully, and the residual of SEM and GWR is dispersed and random, respectively. Furthermore, the significance of lambda in SEM proves that the residual of a target county in the model is significantly correlated with neighboring counties’ error terms, which remained unaddressed in OLS.

Table 3 Tier 1 model result

| Variables | OLS coefficient | Std. error | SEM coefficient | Std. error | GWR summary statistics |
|-----------|----------------|------------|----------------|------------|------------------------|
| Constant  | -0.00273       | 0.0084     | -0.0015736     | 0.00405    | 0.01049 74.07          |
| OCT       | -0.0000255     | 0.0001     | -0.0000464     | 0.00005    | -0.00011 14.94         |
| MP        | -0.0000595     | 0.0001     | 0.0000235      | 0.00006    | 3.79E-05 61.40         |
| TP        | 0.00242        | 0.0015     | 0.0013942      | 0.00148    | -0.00249 14.44         |
| WFH       | -0.000297      | 0.0003     | -0.0003856     | 0.00025    |                       |
| TEST      | 0.00354**      | 0.0011     | 0.00332574***  | 0.00082    | 0.000769 63.88         |
| IMPORT    | 0.0204*        | 0.0089     | 0.0124185***   | 0.00372    | 0.022712 98.82         |
| BACH25    | 0.0286*        | 0.0131     | 0.0315071***   | 0.00617    | 0.020642 80.87         |
| AGE65     | -0.000135      | 0.0001     | 0.0000361      | 0.00011    | -0.00024 15.37         |
| POV       | 0.0204         | 0.0105     | 0.0041641      | 0.00893    | 0.004332 59.25         |
| PSI       | -0.0000612***  | 0          | -0.0000483     | 0.00004    | -3.6E-05 28.98         |
| DENS      | 0.00000877**   | 0          | 0.0000980145***| 0.00000    | 5.96E-06 81.34         |
| lambda    | 0.02306        |            | 0.422286***    | 0.02306    |                       |

N 3142

Adj. R² 0.321 0.411 0.367
Moran’s I 0.231*** -0.031*** -0.001

* p < 0.10 ** p < 0.05 *** p < 0.001

4.3.2. Tier 2: Fall of the 1st wave
The relation of mobility indicators and daily average COVID cases during the fall of the 1st wave is reported in Table 4. Like tier 1, out-of-county trips have no significant relation with mean daily COVID cases as per the global spatial models. The travel lengths per person were significantly and negatively associated in this tier. This finding tells us that people traveled shorter in response to a high rate of disease infection in some parts of the USA. With that, people made significantly more trips where COVID cases are high. This is intuitive as in this tier, most of the states started to reopen different services with necessary precautions, mask requirements, and social distancing. The significant effect of TP is found in SEM, whereas we did not find its statistical significance in OLS after controlling for policy intervention. The effect of PSI is not significant in SEM, perhaps due to the significant autocorrelation in error terms. However, the GWR result points out that around 95% of counties had significantly lower COVID rates in response to more stringent policy intervention.

We did not find any mediation effect in this model. More people worked from home in areas affected with COVID more severely. More COVID cases were diagnosed with more testing. The effect of the imported case is not significant in this tier. Interestingly, unlike the 1st tier, areas with more educated people (bachelor’s degree or more) and more senior citizens (65 years or more) had significantly fewer COVID cases. High population density and high poverty rate were associated with a higher COVID infection rate.

Analogous to the 1st tier, OLS had the lowest fit and spatially autocorrelated error term. Among the three spatial models, SEM explains the highest variance. The Moran’s I result expresses the randomness of the residual of SEM and GWR.

### Table 4 Tier 2 model result

| Models | OLS | SEM | GWR summary statistics |
|--------|-----|-----|------------------------|
|        | coeff. | Std. error | coeff. | Std. error. | median coefficient | % of positive estimates |
| Constant | 0.0977** | 0.0313 | 0.0311653** | 0.01399 | 0.174875 | 99.97 |
| OCT | 0.000161 | 0.0003 | 0.0001496 | 0.00019 | -0.00069 | 15.31 |
| MP | -0.000661*** | 0.0002 | -0.000360454** | 0.00022 | 0.000328 | 57.89 |
| TP | 0.00696 | 0.0062 | 0.0120074** | 0.00500 | -0.01896 | 18.45 |
| WFH | 0.000553 | 0.0003 | 0.00105652** | 0.00040 | |
| TEST | 0.000519* | 0.0002 | 0.000796245*** | 0.00022 | 0.000162 | 61.86 |
| IMPORT | 0.00507 | 0.0042 | 0.0011114 | 0.00133 | 0.015404 | 98.76 |
4.3.3. Tier 3: Rise of the 2nd wave
As soon as the states started to reopen in different phases and pace, the 2nd wave hit the USA. Mobility also took different patterns in this tier (Table 5). We found a significant mediation effect (not reported in the table) of AGE65 on OCT. That is, areas with a high percentage of senior citizens had less COVID infection rate. Also, these areas had a significantly higher percentage of out-of-county trips. This outcome might be attributed to the fact that people most likely set out for vacations in summer (Zheng and Zhang, 2013). In the absence of AGE65, OCT demonstrated a significant ($p < 0.001$) negative effect on COVID cases mediated when AGE65 was included in the model. The negative association of miles traveled per person is persisting in this tier. However, the negative association of trip frequency is only significant in OLS. Its insignificance in SEM indicates the effect on TP of incorporating spatial autoregressive terms in the model. We did not find any full or partial mediation effect of any variable on MP and TP. Among the other covariates in SEM, areas with a high poverty rate have significantly more COVID infection. The signs of coefficients of SEM, disregarding the significance, are highly consistent with the signs found by GWR in the majority of counties (see % of positive estimates of GWR in Table 5). Like the other tiers above, SEM explained most of the variance of COVID cases and accounted for the spatially autocorrelated error term in this tier. The residuals of OLS and GWR are significantly clustered, while in SEM, we found a Moran’s I that shows a dispersed pattern of residual.

Table 5 Tier 3 model result

| Models | OLS | SEM | GWR summary statistics |
|--------|-----|-----|------------------------|
| Variables | coefficient | Std. error | coefficient | Std. error | median coefficient | % of positive |
| BACH25 | -0.0834** | 0.0273 | -0.0876164*** | 0.02180 | -0.14896 | 7.36 |
| AGE65 | -0.00377*** | 0.0005 | -0.00322331*** | 0.00039 | -0.00493 | 0.00 |
| POV | 0.162*** | 0.0391 | 0.187711*** | 0.03129 | 0.048164 | 57.48 |
| PSI | -0.000434*** | 0.0001 | -0.0002641 | 0.00017 | -0.00041 | 4.47 |
| DENS | 0.00000962* | 0 | 0.0000109894*** | 0.00000 | 1.05E-05 | 85.00 |
| lambda | | | 0.410364*** | | 0.02330 | |

N 3142
Adj. $R^2$ 0.100 0.20 0.15
Moran’s I 0.182*** -0.084 0.0005

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.001$
|                | Estimate       | Std. Error | t-value | p-value  |
|----------------|----------------|------------|---------|----------|
| Constant       | 0.405***       | 0.0329     | 0.115339*** | 0.02081  |
| OCT            | -0.000889      | 0.0005     | -0.00019219 | 0.00017  |
| MP             | -0.000619***   | 0.0001     | -0.00019184* | 0.00011  |
| TP             | -0.0501***     | 0.0057     | -0.00139442 | 0.00443  |
| WFH            | -0.000372      | 0.0004     | 0.00120673** | 0.00059  |
| TEST           | 0.0000602      | 0.0001     | 0.000161733 | 0.00012  |
| IMPORT         | 0.00448        | 0.0038     | 0.000146775 | 0.00044  |
| BACH25         | -0.0980**      | 0.0307     | -0.0167388 | 0.02218  |
| AGE65          | -0.00566***    | 0.0005     | -0.0046083*** | 0.00042  |
| POV            | 0.397***       | 0.0523     | 0.283659*** | 0.0392   |
| PSI            | -0.000201      | 0.0002     | 6.44E-05    | 0.00025  |
| DENS           | -0.00000190    | 0          | 8.83E-07    | 0.00000  |
| lambda         | 0.69317***     | 0.01617    |          |          |
| N              | 3142           |            |          |          |
| Adj. R²        | 0.218          | 0.47       | 0.42     |          |
| Moran’s I      | 0.382***       | -0.555***  | 0.003***  |          |

* p < 0.10 ** p < 0.05 *** p < 0.001

4.3.4. Tier 4: Fall of the 2nd wave

The association of the mobility indicators with COVID cases during the fall of the 2nd wave is presented in Table 6 with the model estimates. The mobility indicators are not significant in full SEM models, although MP and TP have a significant negative association with COVID infection in OLS. Among the mobility variables in SEM, the effects of MP and TP are not mediated by other variables. The only exception is OCT, which shows a significant inverse association in the absence of AGE65. Also, similar to 3rd tier, areas with a high percentage of senior citizen (65 years or over) has a significantly high percentage of out-of-county trips. Thus, the inclusion of AGE65 mediates the effect of OCT on COVID cases. Among the other covariates, areas where more testing was done, the percentage of bachelor’s degree holders is low, or the percentage of people living below the poverty level is high, significantly associated with high COVID infection rates. The signs of coefficients of SEM and signs of the majority of local GWR estimates are highly consistent. In effect, SEM outperformed OLS and GWR with the highest fit (R² = 0.54) and dispersed pattern of residual.
Table 6 Regression outputs for tier 4

| Variables | OLS | SEM | GWR summary statistics |
|-----------|-----|-----|------------------------|
|           | coefficient | Std. error | coefficient | Std. error | median coefficient | % of positive estimates |
| Constant  | 0.467*** | 3.1234 | 0.178945*** | 0.02963 | 0.377014 | 100.00 |
| OCT       | -0.000248 | 0.0365 | -3.27E-05 | 0.00021 | -0.00322 | 0.59 |
| MP        | -0.000343** | 0.0125 | -2.71E-05 | 0.00013 | -0.00018 | 36.71 |
| TP        | -0.0410*** | 0.5723 | -0.00027 | 0.00442 | -0.02555 | 2.73 |
| WFH       | -0.00388*** | 0.063 | 0.000903 | 0.00090 | 0.00090 |
| TEST      | 0.00506*** | 0.0316 | 0.000283848*** | 0.00009 | 0.000255 | 87.89 |
| IMPORT    | 0.000922 | 0.1199 | 0.000192 | 0.00027 | 0.022444 | 91.49 |
| BACH25    | -0.240*** | 3.4884 | -0.111034*** | 0.02761 | -0.14338 | 3.48 |
| AGE65     | -0.00631*** | 0.0599 | -0.005077*** | 0.00053 | -0.00579 | 0.00 |
| POV       | 0.362*** | 5.6903 | 0.245438*** | 0.04252 | 0.116567 | 97.02 |
| PSI       | -0.000885*** | 0.0157 | -0.00044 | 0.00032 | -0.00034 | 25.09 |
| DENS      | -0.0000043 | 0.0002 | 5.75E-07 | 0.00000 | 3.85E-06 | 83.57 |
| lambda    | 0.726529*** | 0.01510 | 0.01510 |
| N         | 3142 | | | | |
| Adj. R²   | 0.360 | 0.54 | 0.46 |
| Moran’s I | 0.435*** | -0.069 | -0.001 |

* p < 0.10 ** p < 0.05 *** p < 0.001

4.3.5. Discussion on temporal variation of the association

Since we have partitioned the study time into four tiers and made models for each of them, it is important to compare the associations of the variables across the tiers. Table 7 shows the elasticity of the independent variables. The effects of OCT are not significant in any tier. The percentage of senior citizens mediated their significant negative association in 3rd and 4th tiers. As discussed above, the effect of MP and TP was mediated in 1st tier by population density and percentage of bachelor’s degree holders. The effect of MP is significant in 2nd and 3rd tiers. 0.27% increase in COVID cases was associated with a 1% decrease in miles/person in the 2nd tier. The adverse relation of COVID cases with miles/person is also confirmed by Lou et al. (2020) and Engle et al. (2020). The effect was reduced in the 3rd tier, where a 1% decrease in miles/person was associated with a 0.09% increase in COVID cases. The effect went down
further in the 4th tier but without any statistical significance. The repulsion of the effect of miles traveled in later stages of COVID is also documented by Gatalo et al. (2020) and Li et al. (2021). After being mediated in the 1st tier, TP showed its large positive and significant impact in the 2nd tier. 1% increase in COVID cases was found associated with a 0.75% increase in trips/person. The positive association of trip frequency is in line with Badr et al. (2020). The finding regarding TP and MP suggests that people retracted their travel length while increasing the number of trips, echoing Xiong et al. (2020b). The effects of TP in the subsequent tiers were negative, weak, and statistically insignificant.

The other covariates show intuitive association with COVID cases. Working from home is negative and insignificant in 1st tier. In the 2nd and 3rd tiers, the effects of working from home were positive and significant. 0.48% and 0.31% increase in COVID cases, respectively, were associated with a 1% increase in working from home. Although the effect in the 4th tier is insignificant, the overall trend of effects starting from the 2nd tier tells us that people, with the same increase in COVID cases, got more inclined to work from home over time. Throughout the four tiers, 1% increases in COVID testing were associated with 0.41%, 0.48%, 0.15%, and 0.18% increase in COVID positive cases; the effect of the 3rd tier is not significant, however. Imported cases demonstrated weak and statistically insignificant associations in most of the tiers. Areas with a high percentage of bachelor’s degree holders had more COVID cases in the 1st tier, while a reverse relationship was observed in the other tiers. Areas with 1% more bachelor’s degree holder had 0.65% more COVID cases initially in 1st tier, whereas areas with 0.36%, 0.03% (insignificant), and 0.15% fewer COVID cases were associated with 1% more educated people in the 2nd, 3rd, and 4th tier, respectively. This is intuitive since highly educated people find working from home more favorable (Bonacini and Scicchitano, 2021) and less inclined towards reopening (Rahman et al., 2021). Areas with 1% more senior citizens (65 years or above) had 1.16%, 0.86%, and 0.6% fewer COVID cases in the 2nd, 3rd, and 4th tier. This outcome is not surprising since the risk of 65-84 years older adults for COVID infection is half of that for 18-64 years older adults. Unlike getting infected, senior citizens are more vulnerable than the younger group (5-17-year-olds) at hospitalization (40 to 90 times more) and death (1300 to 8700 times more), which is not studied in this article (Center for Disease Control and Prevention, 2021). Our findings indicate that the effect of having a more senior population is, in general, convivial to block the virus, perhaps for their greater chance of confinement, although its effect is diminished over time. Effect of AGE65 was not significant in 1st tier, so as poverty rate (POV). From the 2nd tier to subsequent tiers, areas with 1% more people living below the poverty line had 0.54%, 0.43%, and 0.23% more COVID cases. Lack of scopes of staying at or working from home for poor people might be the reason behind this finding (Lou et al., 2020). This trend indicates that the poor people were affected by COVID, more in the initial phases (i.e., April, May, June) and less in later stages.
Policy stringency was not significant in any tiers. Effects of population density were significant only in 1st two tiers; that is, an 1% denser area has 0.25% and 0.05% more COVID cases, respectively.

Table 7 Elasticity of independent variables in different tiers

| Variables | Elasticity |
|-----------|------------|
|           | tier 1     | tier 2     | tier 3     | tier 4     |
| OCT       | -0.1452    | 0.0994     | -0.0727    | -0.0075    |
| MP        | 0.0855     | -0.2751    | -0.0962    | -0.0090    |
| TP        | 0.4186     | 0.7562     | -0.0480    | -0.0061    |
| WFH       | -0.6770    | 0.4831     | 0.3140     | 0.1830     |
| TEST      | 0.4116     | 0.4810     | 0.1528     | 0.2990     |
| IMPORT    | 0.1021     | 0.0303     | 0.0042     | 0.0070     |
| BACH25    | 0.6517     | -0.3695    | -0.0368    | -0.1532    |
| AGE65     | 0.0639     | -1.1622    | -0.8663    | -0.5990    |
| POV       | 0.0592     | 0.5443     | 0.4289     | 0.2329     |
| PSI       | -0.1008    | -0.2610    | 0.0291     | -0.1253    |
| DENS      | 0.2519     | 0.0576     | 0.0024     | 0.0010     |

**Bold**: 90% confidence interval

4.3.6. Spatial variation of the association

As imposing or lifting lockdown decisions are independently taken by local authorities of states at different times, identifying the dynamics of mobility pattern for the whole country is a complex and challenging task (Jamshidi et al., 2020; Badr et al., 2020). To understand spatially varying relationships, we represent the maps of the coefficients in Figure 3. We removed the statistically insignificant estimates from the map.

Figure 6 shows the local estimates of OCT from the GWR models of four tiers. Around 37% of counties showed significant estimates in 1st tier. Among them, in states at the east coast and the north border, counties with higher COVID infection rates had a lower rate of out-of-county trips. Some counties in Texas showed the reverse case; counties with more COVID cases also experienced more trips from other counties. The inverse relationship of COVID case and OCT sustained in all of the subsequent tiers, with more counties having statistically significant local estimates (49%, 93%, and 93%, respectively). In the 2nd tier, most of the eastern states had a relatively weaker negative association, while OCT in states at the north (mostly Midwest region) had a substantially stronger relationship with COVID. The spatial distribution of effects in 3rd and 4th tiers are very similar. States in the Southeast region (Florida,
Georgia, Virginia, etc.) had stronger association while the effect became weaker in other parts (mostly Southwest and West region). There is a clear shift in effect from the 2nd tier to the next two tiers. A close observation of the magnitudes of the effects tells us that the states that showed a relatively stronger effect in the 2nd tier did not have much difference in magnitude in the 3rd and 4th tier. Rather, the vital change was realized in states on the east coast (mostly in the Southeast region). While the reason for such variation demands another study, we did not find considerable variation or clustering of out-of-county trips in the last two tiers over the country.

The local estimates of MP in the GWR models for four tiers are shown in Figure 7. During the 1st tier, people in some states on the east coast (e.g., Virginia, North Carolina, Maryland, New Jersey) traveled longer in counties where more COVID cases were detected. Reverse phenomena were observed in southern states (e.g., Texas, Mississippi, Arkansas) in this tier, where people reduced their mobility in areas affected by COVID more severely. During the 2nd tier, more states on the east coast (e.g., Georgia, Alabama, Florida) experienced higher mobility in more severely affected areas. West region, which has a considerably low percentage of urban areas, the effect of MP was found negative. This inverse
relationship—areas with more COVID cases are associated with fewer miles traveled per person—was persistent and growing in the West and Southwest region in the subsequent tiers. And among these negative associations, relatively stronger associations (more negative) were found in areas where miles/person was low.

Figure 7 Spatial Distribution of local GWR estimates of MP

Figure 8 shows the local estimates for TP. Only a few counties (11%) showed significance in the 1st tier, and in the majority of them, trip frequency per person was reduced with higher COVID cases. In the 2nd tier, large parts of the Midwest and Southeast region (e.g., Minnesota, Iowa, Missouri, Mississippi, Alabama, Florida, Georgia) showed a similar inverse relationship as the 1st tier, with stronger magnitudes. In some states in the West region (e.g., California, Nevada, Utah), counties with higher COVID cases experienced more trips per person. The percentage of significant counties in this tier is 61%, while in the last two tiers, GWR performed with more significant counties (78% and 84%, respectively). The spatial distribution of effects in the 3rd and 4th tiers are quite similar, with the last tier having a higher magnitude. The magnitudes are strong in the southern part (mostly in Texas, New Mexico), while the effects became less strong as we move radially towards the northern states. In this tier, the southern part was critically stricken by COVID. All of the significant estimates are negative, which denotes that trips/person was reduced in areas with higher COVID infection rate.
5. Conclusion

This study sets its first aim to find the spatiotemporal pattern of several mobility indicators (i.e., percentage of out-of-county trips, miles traveled/person, no. of trips/person) and Social Distancing Index. The second focus of this study is to formalize the association of mobility indicators with COVID infection rate. Leveraging GPS-based, anonymous, and aggregated location data, we conducted our analysis for four sequential phases covering the first two waves of virus infection. The total study period is six months—from March 2020 to August 2020. Firstly, we created space-time cubes for finding emerging hotspots and deciphering the spatial-temporal pattern of mobility indicators. Secondly, to understand the association of those indicators with COVID infection rates, we used both non-spatial (OLS) and spatial models (SEM, GWR).

Analyzing the spatial-temporal pattern, we found that most parts of the USA retracted their trip rate, out-of-county trip rate, work trip rate, and miles/person rate until the 1st wave reached its peak. With its fall, these mobility indicators expanded in most parts of the country, more prominently in the Midwest region. During the second wave, the Midwest region distinguishably had many more hotspots than the West,
South, and Northeast regions. The adherence to social distancing increased with the rise and dropped with the fall of the 1st wave ubiquitously. During the 2nd wave, however, we found a discernible pattern of SDI. The states from the South, West, and Northeast region, suggesting a high level of adherence to social distance, had a different kind of hotspots, while the Midwest region mostly had coldspots.

The modeling results of this study include three types of models for each of the four tiers. The regression models suggest the association of the mobility indicator and the variation in space and over time. Percentage of out-of-county trips were not significant in any final global models, although the significant negative association of it was found in 2nd and 3rd tier which was mediated by the negative association of percentage of senior citizens with COVID infection rate. Our local models, however, showed significant estimates in 37%-93% of counties, and almost all of them suggest that areas with more COVID cases were associated with less out-of-county traveling. The global estimates (from SEM) of miles traveled per person are significantly negative in 2nd and 3rd tier, while the local models do not unequivocally support that. While all of the significant counties, located in the Southeast and West region of the country, showed negative association in all of the tiers, several states along the east coast had a positive association in 1st and 2nd tier. These areas are mostly urban areas which can be the reason for the longer traveling to surprisingly be associated with more COVID cases. The global association of trips/person is significant and positive only in the 2nd tier—when the states had started to reopen different facilities. The local model of this tier specifies that the positive estimates are mostly in some states in the West region. In the 3rd and 4th tier, almost all of the states showed significant negative association in GWR while some counties at the north had a positive association, suggesting that people made more trips in more severely COVID-stricken areas. Consistent with many other studies, we have also found a diminishing effect of mobility on COVID infection.

There are several other covariates in our models which. Areas with more COVID cases generally were associated with more people working from home, more people tested for COVID, and more infected people came from outside. In addition, highly dense areas and more poverty-stricken areas had more COVID cases. Areas with more educated people had more COVID cases in the initial phase (1st tier), but they showed more resiliency in later phases where these areas significantly had fewer COVID cases than areas with a low percentage of bachelor’s degree holders. Similar to this, counties with more senior citizens had fewer disease infection. Finally, the effect of policy stringency worked towards reducing COVID cases, although this effect is significant only in OLS models.

The effectivity of incorporating spatial models is observed from different angles. First of all, the spatial models, mostly the global ones, successfully controlled for spatial autocorrelation of the error term and
thus left no significant cluster in residual. Secondly, the complexity associated with assigning single coefficients for the whole country by global models is overcome by GWR. Especially, the effect of out-of-county trips and trips/person was largely varying in space which might be the principal reason for their insignificance in global models. Thirdly, in terms of explaining the variance of COVID cases, spatial models outweighed the OLS.

The takeaways from this study have implications for future policies and research. Not all the models in all the tiers revealed a significant association of mobility indicators in our study. This underscores the role of control variables that should be carefully studied in formulating local policies regarding mobility and designing research in similar events. Mobility should be regarded as a spatially connected event, and therefore, ignoring spatial dependency might lead to incorrect estimation. Since with the increase of mobility, its effect on disease infection diminished over time, policymakers should focus on other preventive measures along with mobility in future events. Since people traveled in shorter length, shared-vehicle like e-scooter, e-bike, bike-share can be some resilient mode to promote.

There are several limitations in this study to acknowledge. First of all, the motivation of partitioning the study time into four tiers was the national trend of COVID cases while different states had varying trends of infection rate as well as varying timelines of stay-at-home order and reopening, which we could not accommodate separately. To compensate for this limitation, we incorporated the policy stringency index, which controlled the dynamics of different policies throughout the study time. Secondly, we cannot and do not say that a state in a tier had a homogeneous mobility pattern. As we took the averages of a tier, we could not account for the within-tier variation in our model. Nevertheless, as our study, unlike many others, covered a moderately long timespan, dividing it into four was a reasonable trade-off for granularity. Third, this study is based on GPS-enabled smartphone data, and therefore, this does not include people who have no smartphone. We cannot strongly suggest the findings for many rural and rustic places with a low share of smartphone usage for this weakness.

We strongly recommend our readers note this study’s inability to suggest the causal relationship between mobility and virus infection. Despite this and the other limitations stated above, this study offers a comprehensive understanding of the spatial and temporal variation of the association of interest and recommendation of several policies. Future research can focus on a smaller geographic scale, which will allow for incorporating many state-specific characteristics. If possible, with big data availability, investigating disaggregated mobility with personal attributes (i.e., age, preference, vehicle ownership) can be a future research direction. Also, using spatial panel models or Geographically and Temporally Weighted Regression models (GTWR) can help to capture the temporal variation in a more disaggregated
manner. Given the large spatiotemporal heterogeneity, later stages of COVID should also be studied and thus, can connect to and validate our study. What’s more, the distinct pattern and effects revealed in this study should be investigated in future works where some factors (e.g., urban area, agriculture-based industry, transport mode share, technology dominant service industry, etc.) may be identified affecting these variations.

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Appendix A

Table A Description of legends of emerging hotspots

| categories       | Definition                                                                                                                                 |
|------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| No Pattern       | Does not fall into any of the hot or cold spot patterns defined below                                                                     |
| New              | A location that is a statistically significant hot/cold spot for the final time step and has never been a statistically significant hot/cold spot before |
| Consecutive      | A location with a single uninterrupted run of statistically significant hot/cold spot bins in the final time-step intervals. The location has never been a statistically significant hot/cold spot prior to the final hot/cold spot run and less than ninety percent of all bins are statistically significant hot/cold spots |
| Intensifying     | A location that has been a statistically significant hot/cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high/low counts in each time step is increasing overall and that increase is statistically significant. |
| Persistent       | A location that has been a statistically significant hot/cold spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time. |
| Diminishing      | A location that has been a statistically significant hot/cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high/low values in each time step is decreasing overall and that decrease is statistically significant. |
| Sporadic         | A location that is an on-again then off-again hot/cold spot. Less than ninety percent of the time-step intervals have been statistically significant hot/cold spots and none of the time-step intervals have been statistically significant cold/hot spots. |
| Oscillating      | A statistically significant hot/cold spot for the final time-step interval that has a history of also being a statistically significant cold/hot spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant cold/hot spots. |
| Historical       | The most recent time period is not hot/cold, but at least ninety percent of the time-step intervals have been statistically significant hot/cold spots |
Highlights

- Relationship of three mobility measures with COVID cases were identified
- Miles traveled/person & Out-of-county trips were reduced where COVID cases are high
- Global association of trips/person is positive whereas locally it is widely negative
- Age (65 years+) & education (bachelor’s or more) have negative impact on COVID
- Poverty rate has positive association with COVID severity
We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

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Mobility During COVID-19 in the USA: Its Spatiotemporal Pattern and Associations with COVID Cases

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