COVID-19 and Social Distancing: Disparities in Mobility Adaptation by Income

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In response to the coronavirus disease 2019 (COVID-19) pandemic, governments have imposed orders upon or encouraged citizens to decrease physical contact to slow down the spread of the virus. Current literature from the United States infers that only workers from limited socioeconomic groups have the ability to practice remote work. However, there has been little research on mobility disparity across income groups in US cities during the pandemic. The authors tried to fill this gap by quantifying the impacts of the pandemic on human mobility by income group in Houston-The Woodlands-Sugar Land, Texas utilizing pseudonymized cell phone location data. A longitudinal study was performed on mobility as measured by the total travel distance, the radius of gyration, and the number of visited locations in April 2020 compared to the data in January and February 2020. An apparent disparity in mobility has been found across income groups. In particular, there was a strong negative correlation (ρ = -0.90) between the estimated income bracket of a traveler and the travel distance in April. Furthermore, larger percentage drops among higher-income brackets in the radius of gyration and number of visited locations implied different adaptability in mobility. The findings of this study suggest a need to understand the reasons behind the mobility inflexibility among low-income populations during the pandemic.

Keywords: COVID-19, Social Distancing, Mobility, Economic Disparity, Equity, Travel Behavior

HIGHLIGHTS

• We investigated Houstonians’ mobility by income during the COVID-19 pandemic.
• There was an apparent disparity in mobility by estimated income group.
• Higher income was associated with larger mobility reduction.

1. INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a respiratory disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (World Health Organization, 2020). The pandemic has had a significant worldwide impact in terms of health and economy (Acter et al., 2020; Nicola et al., 2020; Torales et al., 2020). As of November 9, 2020, the total number of confirmed cases has surpassed 50 million globally and 10 million in the United States alone. The death toll by this same date reached over 1.2 million globally and 238,000 in the United States (Centers for Disease Control and Prevention, 2020a; Johns Hopkins University & Medicine Coronavirus Research Center, 2020). Estimates from The World Bank (2020) show that the global gross domestic product (GDP) will experience a 5.2 percent contraction in 2020 as a result of factors which include the global COVID-19 pandemic. More recent data estimates the US real GDP dropped an annual rate of 31.7 percent in its second quarter, making it the largest quarterly drop since the Great Depression (Bureau of Economic Analysis of the United States Department of Commerce, 2020).

The United States experienced its first confirmed case of COVID-19 on January 21, 2020, followed by an accelerated growth. The United States federal government implemented travel restrictions and travel warnings for heavily-infected regions beginning in late January and early February, and state and local governments issued "stay-at-home" and social distancing orders by mid-March (Peirlinck et al., 2020). Due in part to the stay-at-home orders, the US unemployment rate reported in mid-April went up to 14.7 percent (Bureau of Labor Statistics, 2020), with a significantly larger proportion of jobs lost among jobs which require person-to-person contact without the ability for remote work (Montenovo et al., 2020).

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As a result of the widespread unemployment, more than 1.5 million Americans are expected to have lost health insurance (Woolhandler and Himmelstein, 2020). American travel behaviors dramatically changed in terms of origins, destinations, modes, and travel frequency as a result of COVID-19 and the associated health and government mobility orders (Barbieri et al., 2020; De Vos, 2020).

Models and empirical data suggest that infectious diseases spread at a slower pace when social networks are impeded (Badr et al., 2020; Chinazzi et al., 2020; Chiu et al., 2020; Courtemanche et al., 2020; Kraemer et al., 2020). Lacking effective pharmaceutical treatments, one of the practices believed to be most effective at limiting the spread of COVID-19 was limiting the degree of physical contact with others and minimizing exposure at public places such as shopping malls. Governments have aimed to "flatten the curve" of infections by introducing measures to decrease physical contact between individuals, including implementing travel restrictions, enforcing border closures, and encouraging social distancing (Block et al., 2020; Centers for Disease Control and Prevention, 2020b; Chinazzi et al., 2020; de Haas et al., 2020; Phan and Narayan, 2020; Ruktanonchai et al., 2020). While these temporary limitations on human mobility have negatively affected short-term economic and employment growth (Nicola et al., 2020), they showed some positive disease-containment effects in May and June; during these two months, newly confirmed COVID-19 cases and fatalities dropped in many regions (Block et al., 2020; Courtemanche et al., 2020; Thu et al., 2020). Improvements were assumed to be at least partially due to the public's observance of the executive orders. However, different groups of the population may have engaged in different degrees of change in behaviors such as travel distance, frequency, modal shift, work schedules, and remote working. The different changes in behavior within different groups are worthy of a special study in order for policy makers to make effective policies and maintain social equity in future decision making. Our research focused on mobility changes across income groups during the pandemic period when people engaged in shelter-at-home policies and social distancing. This study focuses on the travel behaviors throughout the month of April 2020, during which an executive order to restrict "non-essential" travels was in effect throughout Texas.

1.1 COVID-19 and human mobility

As mobile communication devices have integrated into society over the past two decades, data from location-enabled devices have been used to analyze human mobility patterns and to assist decision making processes of the public and policy makers (Bwambale et al., 2020; Demisie et al., 2020; Huang et al., 2020; Lai et al., 2020). Researchers have found that mobile phone data is an appropriate source of information to analyze aggregated and individual mobility (Bonnel et al., 2015; Calabrese, 2011; Csáji, 2013).

Mobility change is often characterized by the change in travel distance, approximate spatial range of travel, and the frequency of uniquely visited locations. Some research indicates that this human mobility data could be used to model the spread of infectious diseases (Wesolowski et al., 2012). In fact, there are ongoing efforts to understand the spread of COVID-19 by using location data during the COVID-19 pandemic (Buckee et al., 2020; Smith and Mennis, 2020; Oliver et al., 2020). Other research efforts have used cell phone location data to report overall reductions in human mobility measures during the pandemic (Dasgupta et al., 2020; Gollwitzer et al., 2020; Fraiberger et al., 2020; Galeazzi et al., 2020; Kavanagh et al., 2020; Painter and Qiu, 2020; Pepe et al., 2020; Ruktanonchai et al., 2020; Weill et al., 2020). For example, Pepe et al. (2020) found in Italy a reduction greater than 30 percent in total trips and in radius of gyration during a lockdown compared to baselines before the COVID-19 outbreak. In Houston, Texas, Apple Inc. (2020) and Google, LLC (2020) reported an approximate 60 percent reduction in the number of routing requests within map services in April 2020 from their assumed baselines. A valuable application of the analysis of human mobility data is to assist medical professionals and policy makers with informed decision making during future public health epidemics.

Records suggest that individuals within urban areas face different hospitalization rates and fatality rates per capita based on their economic status (Raifman and Raifman, 2020), but few studies in the United States have investigated this topic from an individual transportation mobility perspective. Weill et al. (2020) compared mobility metrics in census tracts and counties across the United States and concluded high-income areas had larger reductions in mobility than low-income areas. Additionally, Dasgupta et al. (2020) examined aggregated anonymized cell phone location data in 2,633 US counties to reveal "a social distance privilege." Social distance privilege in this context means the level of ability a system provides an individual to engage in social distancing and stay-at-home orders if the individual chooses to do so. It is hard, however, to conclude on a nationwide basis that the observed differences were due to inequity rather than to voluntary actions based on
certain political decisions or personal beliefs. In fact, observed mobility patterns varied during lockdowns among countries (Fraiberger et al., 2020; Galeazzi et al., 2020). Even within the United States, the degree of travel restriction varied by jurisdictions. In addition, there are inferences that local policies and political beliefs played a role in people's travel decisions during the pandemic (Gollwitzer et al., 2020; Kavanagh et al., 2020; Painter and Qiu, 2020), so it is worth investigating the mobility disparity within a smaller, more politically uniform region.

The links between human mobility patterns and economic status are especially worth studying during the COVID-19 pandemic since social distancing and its resultant reduced mobility have been shown to be effective means to control the spread of the COVID-19. If records correctly suggest that the disproportionality in COVID-19 fatalities is correlated with disparity among income groups of the population and their different levels of mobility, it would naturally allude to a possible correlation between economic status and change in mobility during the pandemic. A longitudinal survey in the United States indicates a smaller proportion of lower-income respondents shifted to remote work by July than did higher-income responders (Circella, 2020). In Tokyo, Yabe et al. (2020) reported a negative correlation between assumed taxable income per household and the reduction in mobility during COVID-19 pandemic. It also mentions the scarcity of available research on how human mobility, stratified by different economic statuses, has been affected by the pandemic. Few longitudinal studies have been conducted on COVID-19-related mobility using pseudonymized cell phone location data, as opposed to anonymized data, as most existing human mobility research uses nationwide aggregated zonal statistics at either state or county levels without considering the differences in local policies.

The objective of this research is to highlight changes in mobility levels in the context of economic status at an individual level. In the United States, one census tract represents a community that represents a somewhat-homogeneous cluster of residents. Typically, each census tract has an average of 4,000 residents. Having a population of seven million, the Houston-The Woodlands-Sugar Land metropolitan statistical area (also known as the Greater Houston area) consist of 1,650 tracts. In this paper, each pseudonymized individual was tracked over three months – January, February, and April 2020 – to reveal the characteristics of mobility before and during the pandemic. To the author’s knowledge, it appears that this analysis is the first longitudinal study using the pseudonymized COVID-19 travel data from the income perspective in the United States. Results regarding mobility changes across income groups would allow policy makers to make informed decisions to ensure economic viability and social equity.

1.2 COVID-19 timeline in Texas

A brief description of the Texas COVID-19 timeline, with a focus on the Greater Houston area, is included to provide context for the analysis presented in this study.

Excluding evacuees from the Diamond Princess cruise ship, the first confirmed-positive case of COVID-19 in Texas was reported in Fort Bend County on March 4, with about a dozen more cases quickly following (Texas Department of State Health Services, 2020a). The first confirmed death caused by COVID-19 in Texas was reported in Matagorda County on March 14, 2020 (Texas Department of State Health Services, 2020b). By the end of March, the state had more than 3,266 cases and 101 deaths spread across nearly half of the state’s counties (Texas Department of State Health Services, 2020c). The number of daily cases grew at an accelerated rate until major social distancing policies were implemented.

On March 13, the Governor of Texas declared a state of disaster for all counties in Texas and ordered all public employees to work from home (Office of the Texas Governor, 2020). During the same week, many public school districts and universities announced extended spring breaks and with online-only instruction upon return (Najmabadi and Andu, 2020). Over the next few days, metropolitan areas including Houston ordered the closure of restaurants and bars and imposed stricter guidelines on the size of social gatherings.

On March 19, the Department of State Health Services (DSHS) declared a public health disaster (Texas Department of Health Services, 2020d), and the governor enacted executive order GA-08 to limit gatherings to ten people, discourage the patronage of bars, restaurants, and gyms, and temporarily close all schools (Abbott, 2020a). Harris County was one of 51 Texas counties to enact “shelter-at-home” orders by the end of March (Wilson, 2020). The governor instituted three mobility-related executive orders at the end of March; GA-11 and GA-12 imposed mandatory 14-day quarantines for travelers from heavily-infected areas, and GA-14 overruled the previous GA-08 to minimize social gathering and encourage social distancing from April 2 through April 30, 2020 (Abbott, 2020b, 2020c, 2020d). Additionally, the Harris County judge implemented a “Stay Home, Stay Safe” order from March 24 through April 24 (Harris County, 2020).
On April 17, the governor announced executive order GA-16, an initial reopening strike force which included the reopening of state parks, the allowance of some non-essential surgeries, and curbside pickup for retail stores (Abbott, 2020e). On April 27, the governor announced through a series of three executive orders a three-phase reopening plan which would overrule that of local jurisdictions (Abbott, 2020f, 2020g, 2020h). As of April 30, Texas had over 28,000 confirmed cases and 780 confirmed fatalities (Centers for Disease Control and Prevention, 2020a; Johns Hopkins University & Medicine Coronavirus Research Center, 2020). The effects of the stay-at-home orders on human mobility were apparent in Harris County. According to the Bureau of Transportation Statistics (BTS), the percentage of people not traveling from home in Harris County, Texas was reported as approximately 16.9 percent, or approximately 794,800 people, in January (Bureau of Transportation Statistics, 2020); these people are assumed to stay home for reasons other than the global COVID-19 pandemic. In March and April, this percentage increased to 20% (945,300 people) and 23.6 percent (1,107,800 people), respectively; in May and June, it dropped back toward the baseline with 19.3 percent (906,600 people) and 19.7 percent (925,200 people) respectively. Within Harris County, BTS used anonymized mobile phone data to record the average number of daily trips as approximately 15,952,000 and 16,736,000 trips in January and February. As people began to work from home, the average number of daily trips dropped to about 14,593,000 and 12,028,000 trips in March and April, respectively.

2. METHODOLOGY

The authors used Microsoft Office 365 ProPlus, PostGIS 3.0, QGIS 3.14, and Julia 1.4.1 (Bezanson et al., 2017) to investigate spatiotemporal changes in human mobility through smartphone location data obtained in Texas. Baseline travel behavior observations were recorded using average data from January and February 2020, since economic and travel activities were considered normal during this time. Observations of COVID-19-impacted travel behaviors were recorded using data from April 2020. This month included the duration of GA-14 (0:00:01 a.m. on April 2 through 11:59:59 p.m. on April 30), the executive order which encouraged residents to stay home except for essential travels. The observed April travel behaviors were compared to the baseline to draw conclusions about changes in mobility patterns caused by the global COVID-19 pandemic. March 2020 data was not analyzed due to the non-uniform implementation dates of various agencies’ stay-at-home orders.

2.1 Mobility data and independent variables

Data used for this study was sourced from mobile devices in Houston-The Woodlands-Sugar Land, Texas. Pseudonymized iOS mobility data between January 1, 2020 and April 30, 2020 were provided by SAFE2SAVE, LLC, a company operating a smartphone application (app). To reward users for not engaging with their phones while driving, the application records user locations approximately every two minutes (mean, or  = 1.84, standard deviation, or  = 3.16) while users moved at 10 miles per hour (mph) or greater. According to the company, the majority of users use an “auto-on” feature that automatically starts the app when they move at 10 mph or faster.

The provided mobility data consist of 89,928,723 data points, and each data point contains a pseudonymized user identification number (random integers), geographical coordinates, and a timestamp. To establish baselines, analyses included only data of those who recorded (i) at least one data point in April and (ii) at least one data point per week over the eight consecutive weeks between January 5 and February 29. After this filtering, 46,047,382 data points from 26,059 users were left for analysis. These data points implied approximately 6.6 million person trips as we later identified. No personal information such as income, age, or education was contained in the travel data.

This study utilized the geographic information of the mobile data together with a national survey, the American Community Survey, to estimate each traveler’s economic status. The American Community Survey is conducted based on census tracts, small homogeneous groups within an urban area, and contains average demographic information about residents within each tract. Users’ trip information gathered from the mobile application was used to estimate their trip origins and destinations assuming the census tract is where each user resides within. The results of the American Community Survey for a mobile user’s home tract were used to estimate the user’s likely financial status.

As an economic variable, 2018 per-capita income based on the American Community Survey was overlaid at the resolution of United States census tracts using a circular area with 0.5-miles diameter around each user’s median latitude and longitude of the first and last records of each day between February 2020 and April 2020. When the circular cordon overlapped multiple census tracts, weighted averages of census metrics were considered as that user’s likely per-capita income. While each observation was collected on a roadway, it is
reasonable to assume each observation was geographically near users’ residential areas when the data were aggregated (Chen et al., 2014). This geographical assumption was a methodological limitation of our research, typical as well in other literature using mobile phone data, since the authors did not ultimately know the true identity or demographics of any user. However, additional literature suggests that overlaid socioeconomic attributes tend to have acceptable validity at an aggregated level (Frias-Martinez and Frias-Martinez, 2010; Prestby et al., 2019). To narrow down geographic confounding variables, we conducted a longitudinal mobility study on users who were likely to reside within Houston–The Woodlands–Sugar Land, Texas. Further analyses included only the data of 10,398 users who were presumed to reside in the selected metropolitan statistical area (Fig. 1).

![Map](image)

**Note:** White areas indicate the lack of income data.

**Fig. 1.** Per-capita income by census tract in Houston–The Woodlands–Sugar Land.

### 2.1.1 Dependent variables

The authors were interested in how long, how often, and how much area people traveled during the COVID-19 pandemic compared to the baseline. These questions were approached by measuring the monthly total travel distance, radius of gyration, number of visited locations, and per-trip distance.

#### 2.1.1.1 Total travel distance

Monthly total travel distances were calculated as the sum of Euclidean travel distances in a series of geographical coordinates recorded every 1.84 minutes on average. Because map matching was not used, the computed values are expected to be smaller than real travel distances of travelers. Nevertheless, this calculation (Equation 1) was considered a reasonable means to observe mobility changes within subjects.

\[
L^a(t) = \sum_{i=2}^{n^a} d_{r^a_i, r^a_{i-1}}
\]

where:
- \( t \) = time period
- \( L^a(t) \) = total travel distance of user \( a \) in time period \( t \)
- \( d_{r^a_i, r^a_{i-1}} \) = Euclidean travel distances between the \( j \)th position and \( k \)th position
- \( r^a_i \) = the \( i \)th position recorded for user \( a \)
- \( n^a_c \) = the number of positions recorded for user \( a \)

#### 2.1.1.2 Radius of gyration

Radius of gyration refers to the average distance to observed locations from the center of mass of all sets of observations for an individual traveler, indicating an approximate range of activity space. It has been known that the probability of trip distance can be modeled as a function of the radius of gyration (González et al., 2008). The radii of gyration for each user were calculated as follows (Equations 2 and 3):

\[
r^a_{cm} = \frac{1}{n^a_c} \sum_{i=1}^{n^a_c} r^a_i
\]

\[
r^a(t) = \sqrt{\frac{1}{n^a_c(t)} \sum_{i=1}^{n^a_c(t)} (r^a_i - r^a_{cm})^2}
\]

where:
- \( r^a_{cm} \) = the center of mass of the trajectory
- \( r^a(t) \) = radius of gyration as a function of time period \( t \)
- \( P^a(t) \) = per-trip distance of user \( a \) in time period \( t \)

#### 2.1.1.3 Number of visited locations

The number of visited locations (\( S \)) were identified as the first and last recorded locations in each trip aggregated within a regular hexagonal mesh with three-square kilometers. The temporally closest records of more than 400 seconds apart were considered as destinations and origins. This operation resulted in the averages of 3.39 trips per day per person in January and 3.54 trips per day per person in February, which were close to the statewide estimates by the Bureau of Transportation Statistics (2020). Overlapping visits were not counted even when one mesh had recorded multiple visits by one user.

#### 2.1.1.4 Per-trip distance
Per-trip distances were derived as the arithmetic mean of the travel distance of trips made by a user in unit time (Equation 4).

\[
P^a(t) = \frac{1}{m^a(t)} \sum_{i=1}^{m^a(t)} d_{a,i} \tag{4}
\]

where: \( P^a(t) \) = per-trip distance of user \( a \) in time period \( t \)
\( m^a(t) \) = the number of trips recorded for user \( a \)

All dependent variables were computed on a monthly basis (\( t = \) one month).

3. FINDINGS

Descriptive statistics of total travel distance, radius of gyration, and number of unique visited locations are summarized in Table 1. The observed values were grouped by projected per-capita income bracket with a 10,000-dollar interval. Income brackets that had fewer than 100 people were included with the nearest bracket. Baseline data for all three data types is the mean of January 2020 and February 2020 data. The data revealed April experienced 54.7 percent, 73.6 percent, 48.1 percent, and 4.3 percent reductions in mean total trip distances, mean radius of gyration, mean number of visited locations, and per-trip length, respectively, from the baselines. The overall percent reduction in the total travel distances (61.46 percent) was consistent with Apple Inc. (2020) and Google, LLC (2020), who each reported an approximately 60 percent reduction in the number of routing requests in April compared to January.

The distribution of trip distance, or the total distance traveled over the duration of a trip, typically has a long tail, meaning a small percentage of travelers disproportionately influence mean and standard deviations of aggregated mobility variables (González et al., 2008). Because analysis of interest was mobility trends by estimated income levels, each dataset’s median was used as average for further comparisons. Fig. 2 shows median total travel distance, radius of gyration, number of visited locations, and per-trip distance by projected per-capita income bracket.

Except for per-trip distance, the values were lower in April than in the baselines, indicating the overall reduction in mobility. Because this study does not necessarily assume a linear relationship between per-capita income and the mobility variables, the Spearman’s rank correlation coefficient, \( \rho \), was used to examine the rank correlations among the income group. The total travel distance had almost no correlation \( (\rho = -0.05) \) with the projected income bracket in the baseline, but it showed a strong negative correlation \( (\rho = -0.90) \) with the income bracket in April. The estimated income bracket had a strong positive correlation with the radius of gyration in the baseline condition \( (\rho = 0.93) \). However, the correlation turned out to be strongly negative in April \( (\rho = -0.83) \). The number of visited locations had strong negative correlations with the income level both in the baseline \( (\rho = -0.97) \) and in April \( (\rho = -0.98) \). Unlike the other variables, median mean per-trip distance was increased in April. While per-trip distance had a strong negative correlation with the income bracket in the baseline \( (\rho = -0.90) \) and in April \( (\rho = -0.76) \), the differences did not seem as evident as the other variables.

Fig. 3 through Fig. 6 present cumulative distribution functions of total travel distance, radius of gyration, number of visited locations, and per-trip distance by projected income bracket. It is evident that people with higher projected income brackets had larger mobility reductions in total travel distance, radius of gyration, and number of visited locations. For instance, median total travel distance was reduced by 81.0 percent for individuals with a projected income group of $80,000 or larger, but it was reduced by only 62.0 percent for individuals with a projected income bracket of $20,000 or less, compared to baseline travel distances. There was a strong negative correlation \( (\rho = -0.90) \) between income and total travel distance when comparing April values to baseline values. There was a strong negative correlation \( (\rho = -0.93) \) between income and radius of gyration when comparing April values to baseline values. Median radius of gyration was reduced by 72.4 percent for individuals with a projected income bracket of $80,000 or larger, but it was reduced by only 32.0 percent for individuals with a projected income bracket of $20,000 or less, compared to the baseline. Above the 70th percentile, all income groups showed somewhat similar radii of gyration during April, meaning their restricted activities happened within similar sizes of areas while they all observed the stay-at-home and social distancing orders. There was a strong negative correlation \( (\rho = -0.86) \) between income and number of visited locations when comparing April values to baseline values. The number of visited locations was reduced by 59.6 percent for individuals with a projected income bracket of $80,000 or larger, but it was reduced by only 47.5 percent for individuals with a projected income bracket of $20,000 or less, compared to baseline travel distances. The figure also suggests smaller changes in mobility among different economic brackets past $50,000 a year, as supported by all the three aforementioned measures. In median per-trip distance, there was a moderate rank correlation between per-capita income and the change in April from the baseline \( (\rho = -0.76) \).
The mobility drop in the radius of gyration for the higher-income groups can be partially explained in the context of larger baseline radii of gyrations in baselines (January and February).

Table 1. Descriptive statistics of dependent variables

<table>
<thead>
<tr>
<th>Sample size</th>
<th>Total travel length (miles)</th>
<th>Radius of gyration (miles)</th>
<th>Number of visited locations</th>
<th>Per-trip length (miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>0 - $20,000</td>
<td>895</td>
<td>1,224.64</td>
<td>923.11</td>
<td>27.77</td>
</tr>
<tr>
<td>April</td>
<td>624.82</td>
<td>768.84</td>
<td>9.25</td>
<td>24.44</td>
</tr>
<tr>
<td>$20,000 - $30,000</td>
<td>2,525</td>
<td>1,199.49</td>
<td>879.80</td>
<td>28.31</td>
</tr>
<tr>
<td>April</td>
<td>553.89</td>
<td>645.34</td>
<td>10.57</td>
<td>32.47</td>
</tr>
<tr>
<td>$30,000 - $40,000</td>
<td>2,953</td>
<td>1,199.08</td>
<td>948.64</td>
<td>38.03</td>
</tr>
<tr>
<td>April</td>
<td>477.13</td>
<td>607.56</td>
<td>10.10</td>
<td>27.84</td>
</tr>
<tr>
<td>$40,000 - $50,000</td>
<td>2,290</td>
<td>1,200.23</td>
<td>1,054.40</td>
<td>39.33</td>
</tr>
<tr>
<td>April</td>
<td>441.56</td>
<td>623.12</td>
<td>11.24</td>
<td>33.46</td>
</tr>
<tr>
<td>$50,000 - $60,000</td>
<td>1,794</td>
<td>1,247.15</td>
<td>1,151.32</td>
<td>51.36</td>
</tr>
<tr>
<td>April</td>
<td>370.85</td>
<td>606.07</td>
<td>11.37</td>
<td>86.27</td>
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<tr>
<td>$60,000 - $70,000</td>
<td>477</td>
<td>1,330.57</td>
<td>1,405.74</td>
<td>65.39</td>
</tr>
<tr>
<td>April</td>
<td>345.54</td>
<td>454.35</td>
<td>10.94</td>
<td>30.24</td>
</tr>
<tr>
<td>$70,000 - $80,000</td>
<td>249</td>
<td>1,362.35</td>
<td>1,292.92</td>
<td>78.90</td>
</tr>
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<td>April</td>
<td>327.46</td>
<td>449.69</td>
<td>8.13</td>
<td>14.74</td>
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<tr>
<td>$80,000 - $150,000</td>
<td>215</td>
<td>1,379.97</td>
<td>1,742.41</td>
<td>84.50</td>
</tr>
<tr>
<td>April</td>
<td>356.94</td>
<td>551.27</td>
<td>15.85</td>
<td>65.83</td>
</tr>
<tr>
<td>All</td>
<td>11,398</td>
<td>1,221.46</td>
<td>1,039.68</td>
<td>40.35</td>
</tr>
</tbody>
</table>

Note. M = mean; SD = standard deviation.
Note. See Table 1 for the sample size in each income bracket. See Fig. 3 through Fig. 6 for the interquartile range.

Fig. 2. Median total travel distance (top left), radius of gyration (top right), number of visited locations (bottom left), and per-trip distance (bottom right) by projected per-capita income bracket.

Note. Parentheses indicate the sample size in each income bracket. Broken lines indicate the baseline (average of January 2020 and February 2020) whereas solid lines represent April 2020.

Fig. 3. Cumulative density functions of the total travel distance by projected per-capita income group.
Fig. 4. Cumulative density functions of the radius of gyration by projected per-capita income group.

Fig. 5. Cumulative density functions of the number of visited locations by projected per-capita income group.

Fig. 6. Cumulative density functions of per-trip distance by projected per-capita income group.
4. DISCUSSION AND CONCLUSIONS

Through this study, the authors used pseudonymized smartphone location data to investigate the effects of the COVID-19 pandemic on individual human mobility from Houston–The Woodlands–Sugar Land, Texas. This is part of an on-going effort to understand mobility change during the COVID-19 pandemic in a greater detail. Our attempt was unique in that it implemented a longitudinal study design with information from census tracts to capture mobility change in a single metropolitan statistical area with statewide executive orders to stay at home. This study investigated human mobility from four measurements: total trip distance, radius of gyration, number of visited locations, and per-trip distance.

4.1 Key findings

Overall, our analyses revealed mobility adaptation disparity by estimated income at a metropolitan level. The data indicated that human mobility in Houston–The Woodlands–Sugar Land dropped significantly in April 2020 compared to the baseline (January and February 2020). We found that individuals from census tracts with higher per-capita income had larger mobility reductions while the de facto stay-at-home orders were in effect.

In particular, the mobility disparity among income brackets was evident in total travel distances as higher-income individuals reduced travel distances both in relation to their baselines (January and February) as well as compared to other individuals from lower income brackets. In April, the median was 387.23 miles for those whose estimated per-capita income was under $20,000 and 185.82 miles for those with estimated income was $80,000 and over.

Users in higher-income tracts had larger average radii of gyration before the pandemic. However, users in higher-income tracts experienced slightly smaller levels of radius of gyration during the executive orders, revealing larger reductions among the population than in those in lower-income tracts. With the result of the travel distance alone, one might think the observed difference was largely due to the fact that tracts with higher income are located in the western center of Houston and thus enabled the residents to travel shorter distances during the executive orders. However, the smaller disparities in the radius of gyration and per-trip distance implies that people in higher-income tracts likely made fewer numbers of trips than those in lower-income tracts. The number of unique visited locations followed a pattern similar to the total travel distance.

There was no clear disparity in per-trip distance. Interestingly, per-trip distance increased in April over the majority of percentiles regardless of the income brackets. In median, per-trip distances increased by less than a mile in all the estimated income groups. Conventionally, trip distance distribution shifts towards zero when the radius of gyration becomes smaller (González et al., 2008). While the data do not tell the reason behind the observed increase, it is possible that there was a fundamental change in people’s trip choice in the midst of the executive orders. In the meantime, it is recommended to interpret per-trip distance with other sources, because it is also possible that fewer stops due to traffic congestion might have reduced the 400-second no-record “windows” the authors used to operationally define trips. The data imply that financial status was a likely factor or mediator of the compliance or feasibility of stay-at-home orders. Considering that an individual’s “essential” fixed expenses to maintain the reasonable minimum standards of living (e.g., food, water, and electricity) do not differ vastly, it is intuitive that the disparity in mobility reduction seemed to be smaller among higher-income brackets than lower-income brackets (Fig. 2).

4.2 Indications of the findings

We conclude that it is likely that people in lower income brackets did not or could not reduce as much mobility as higher income groups did during the executive orders in the midst of the COVID-19 pandemic. In total travel distance, radii of gyration, and the number of unique visited locations, cumulative density functions revealed consistently lower mobility reductions for individuals in lower income brackets throughout most percentile ranges. While media and other articles have speculated that the disproportionality of COVID-19 impacts by different financial status, this is one of the first articles reporting the “mobility disparity” in the United States at census tract level. If combined with further studies, the findings can be valuable for macroscopic and mesoscopic COVID-19 epidemiological model development and calibration as well as policy evaluations hereafter.

Our study outcome matched the survey by Circella (2020), who reported difficulties in mobility adaptation among lower-income populations during the COVID-19 pandemic. Furthermore, the analyses supported what some nationwide studies have also claimed: higher income is associated with larger mobility reductions. Since preceding nationwide studies used aggregated location data to compare mobility across a nation (Dasgupta et al., 2020; Gollwitzer et al., 2020; Weill et al., 2020), it is noteworthy the disparity in mobility adaptation was
observed among different income groups within a metropolitan statistical area where uniform executive orders were enforced.

Our results would help local policy makers recognize the existence and approximate magnitude of mobility adaptation disparity among different income groups during the COVID-19 pandemic. Although further analyses would be required to understand the causation, the results were in line with media speculations, which might explain a reason behind disproportionate impacts of COVID-19: people with low income did not have a practical choice to stay at home. It is possible that individuals from communities with lower incomes had a higher probability of being an essential worker, such as bus drivers and cashiers at grocery stores who could not easily work remotely, resulting in larger exposure to infection. The authors do not endorse specific policies regarding mobility disparity. However, it should be noted that the results at least imply the need for special attention to financially vulnerable populations when the local government wants to promote social equity during the pandemic.

4.3 Limitations and future research directions

Our research had some limitations. One limitation of the present study, as well as existing literature, was that the mobile travel data may exhibit a systematic error. In other words, pseudonymized individuals may not represent each demographic group without bias. The authors still maintain reasonable confidence due to the fact that the sample sizes are all fairly large across the groups. However, this is a limitation that future research could address.

Another limitation was that the authors did not consider the possible effects of age or gender. In fact, the authors did not overlay any other socioeconomic variables (e.g., gender and household size) associated with each census tract. This was mainly because we preferred to avoid stacking ecological fallacies (Crampton, 1995). However, it has been known that age is a major covariate of income as income tends to show an inverted U-shape with age (Sturman, 2003). Although it is difficult to eliminate the effects of confounders completely, it would be ideal to control the variable if a research design allows. For example, essential businesses, such as grocery stores and gas stations, remained open during the executive orders, but there is little research that took such factors into account. Besides, disposable income, current assets, and net assets can be better variables than pre-tax income to indicate one’s financial leeway when such data are available in future research.

The authors also recommend conducting similar regional research at different states and countries to see comparative impacts and further generalizability of the associations between financial status and mobility disparity during travel restrictions. In the near future, it would be beneficial to conduct meta analyses to integrate insights about mobility changes related to the COVID-19 pandemic.

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