Cities 131 (2022) 104006

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

A tale of two Americas: Socio-economic mobility gaps within and across American cities before and during the pandemic

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ARTICLE INFO

Keywords:
Mobility equity
COVID-19
U.S. cities
Residential location
Smartphones
Big data

ABSTRACT

We examine differences in mobility outcomes between residents of highest and lowest socio-economic index (SEI) at the Census block group (CBG) level in nine major US cities prior to and during the COVID-19 pandemic. While low-SEI groups generally traveled shorter distances but visited more city-wide CBGs before the pandemic, high-SEI residents universally reduced their mobility to a greater extent during the pandemic. Although high-SEI residents were making more trips to parks and health-care providers, and fewer subsistence trips to retail stores already before the pandemic, COVID-19 significantly widened these differences thereby exacerbating "mobility gaps" between low-SEI and high-SEI groups. We further examine how such "mobility gaps" can be mitigated by spatial advantages of home locations, controlling for political inclination. We find that living in better transit-served or more walkable neighborhoods generally benefited high-SEI residents more than low-SEI residents, with some variation across cities. This suggests that built environments not only impact mobility outcomes during "normal" times, but also influence how different socio-economic groups are able to adapt during times of crisis.

1. Introduction

Mobility inequality and spatial segregation are linked to the social well-being (or the lack thereof) of urban residents (De Vos et al., 2013; Lucas, 2012; Martens, 2016). Studies in the U.S. have found that higher income households make about 30 % more trips, and their average trip length is >40 % larger than that of trips made by lower income households (Memmott & Bureau of Transportation Statistics, 2007). The mobility of low-income households is limited by relatively poor quality and coverage of public transit alternatives in most American cities, reduced access to private cars, and barriers to obtaining a driving license (Agrawal et al., 2011; King et al., 2019; Klein & Smart, 2017). Higher income groups enjoy convenient access to a diverse array of mobility options—multiple vehicles owned per household and lower financial barriers to using transit, ride-hailing services, or pay-per-use transport infrastructure—in addition to residing in locations from where more jobs, amenities, and social opportunities can be easily accessed. The ability to travel to diverse destinations results in greater access to urban resources and more expansive social networks, which contribute to social and financial benefits across urban populations (Pentland, 2014).

While the broad strokes of income-related mobility inequality in U.S. cities is widely acknowledged (Taylor & Ong, 1995; Wachs & Taylor, 1998), how people's mobility behavior at the opposite ends of the socio-economic spectrum varies within and across specific cities has not received adequate attention. How long, how widely, and to which kinds of destinations do the least and the most privileged residents travel in specific urban environments? How might such behaviors be mitigated by the characteristics of the neighborhoods where people live? And how has the COVID-19 pandemic affected changes in mobility outcomes across socioeconomic groups in the U.S.?

Mounting evidence suggests that COVID-19 has had significant adverse effects on marginalized racial and socioeconomic communities (Chang et al., 2021; Chen & Krieger, 2021; Gross et al., 2020). Similar trends had been observed during previous pandemics (Zhao et al., 2015), thus reinforcing the existence of longstanding inequities in the social determinants of health (Chowkwanyun & Reed, 2020; Van Dorn et al., 2020; Yancy, 2020). Examining mobility specifically, some evidence suggests that higher levels of mobility may have increased COVID-

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https://doi.org/10.1016/j.cities.2022.104006
Received 19 August 2021; Received in revised form 10 May 2022; Accepted 24 September 2022
Available online 4 October 2022

19 spread due to the possibility of increased inter-personal contact (Cartenì et al., 2020; Jia et al., 2020). In recognition of these risks, travel restrictions and stay-at-home orders were introduced as mobility reduction policies to curb the spread of COVID-19 with varying degrees of success (Block et al., 2020; Chinazzi et al., 2020; Courtemanche et al., 2020; Hsiang et al., 2020; Pan et al., 2020). As a result of these policies, aggregate urban mobility reached its lower bound in the United States during the spring of 2020 (Xiong et al., 2020), but significant heterogeneity has been observed among residents of different cities, neighborhoods, and income groups (Basu, Ferreira, 2021a; Chang et al., 2021; Jay et al., 2020; Lee et al., 2020; Ruiz-Euler et al., 2020).

Prior studies exploring the effects of income on pandemic-related behaviors have been limited in the generalizability of their findings on several aspects. First, income alone may not be sufficient to capture the mobility trends of the nation's most vulnerable communities in light of how race, place, and poverty jointly contribute to socioeconomic status in the U.S. (Tung et al., 2017; Williams & Collins, 2016). Such relationships are difficult to observe and explore at smaller, disaggregate spatial scales, due to lack of official data on socio-economic status and mobility outcomes at finer resolutions of Census data. Moreover, prior literature on COVID-19 related mobility changes has largely focused on the frequency of trips as opposed to their diversity, or examined a single destination type at a time, instead of multiple destinations concurrently. There is a need to better understand how widely and to which kinds of destinations different socioeconomic groups traveled to before and during the pandemic, as well as how mobility outcomes for different socio-economic groups may have been influenced by the spatial advantages of their home locations. Can living at a better location help less-privileged communities overcome typical mobility disadvantages and lead to a reduced "mobility gap" between the least and the most privileged?

In this study, we seek to explore the nuances of mobility inequality as laid bare before and during the pandemic, in addition to various approaches to potentially mitigate them. We examine differences in mobility patterns across nine major U.S. cities (Atlanta, Boston, Chicago, Denver, Houston, Los Angeles, Philadelphia, Seattle, and St. Louis – shown in Fig. 1) on a monthly basis before (2019) and during (2020) the COVID-19 pandemic. We use a large longitudinal smartphone dataset to explore (a) how mobility behavior for the least and the most advantaged social groups differed prior to the pandemic, (b) how the pandemic changed these differences, and (c) how mobility inequality varies across cities. In each case, we examine differences in mean trip distances, the spatial extent of city-wide travel, and the proportion of total trips made to three types of destinations (parks, healthcare services, and retail establishments) by socio-economic group. We additionally test whether and how the spatial advantage of residential location may offset the effect of social disadvantage on mobility outcomes.

Instead of comparing mobility outcomes across income groups alone (Jay et al., 2020; Weill et al., 2020), or using a general nation-wide yardstick of social (dis)advantage, we develop a Census Block Group (CBG) level socio-economic index (SEI) (Wheeler et al., 2017) that is uniquely calibrated to each city, allowing us to contrast mobility outcomes for different SEI groups within and across cities. This study is unique in (a) examining empirical mobility records at the CBG scale across nine major U.S. cities using multiple indicators of mobility simultaneously to contrast socio-economic mobility inequality before and during the pandemic in U.S. cities, (b) in using a more comprehensive and contextually sensitive definition of socio-economic status (Jay et al., 2020; Weill et al., 2020), and (c) in controlling for the spatial advantage of residential location and political inclination at the CBG scale.

We first introduce our data for month-to-month mobility behavior analyses and present our socio-economic categorization approach. We then turn to our mobility inequality analyses and findings. The discussion section summarizes our takeaways, presents policy implications, and highlights directions for future research.

2. Data and methods

We obtained mobility data for this study from SafeGraph's COVID-19 Data Consortium, which has made its data freely available to researchers. SafeGraph captures mobility patterns of smartphone users,

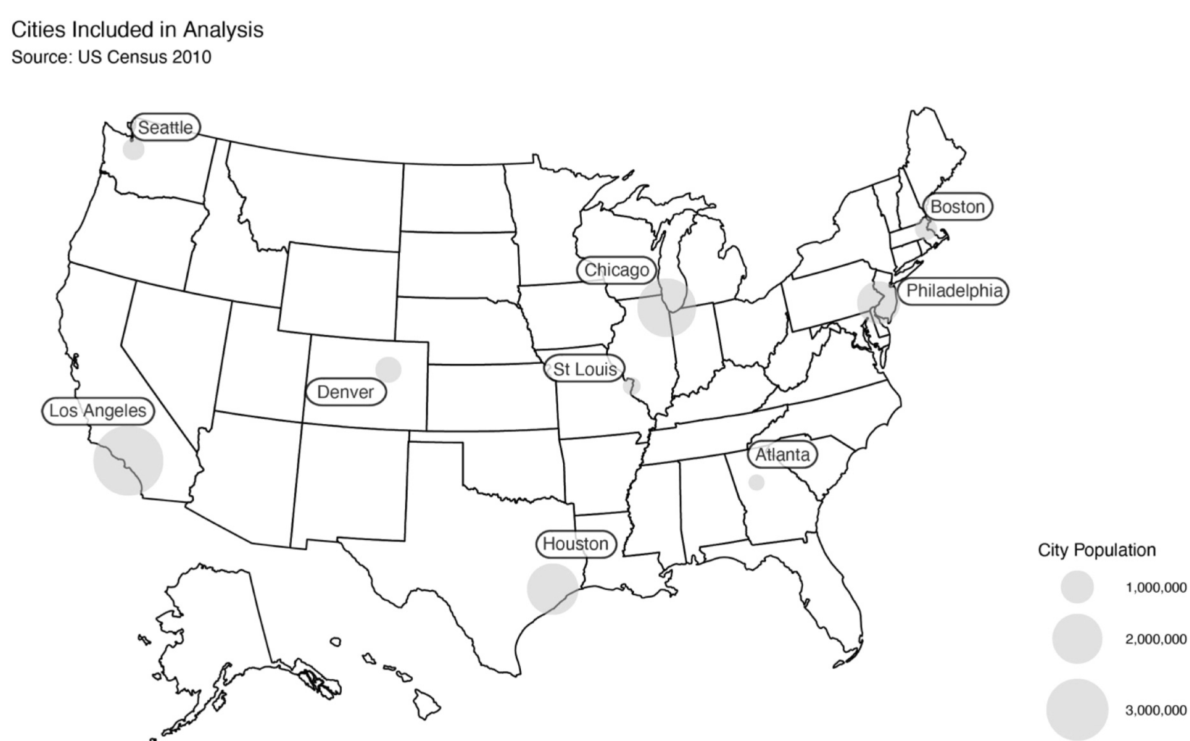

Fig. 1. Geographic coverage of nine cities included in the study. Marker radii are proportional to city population sizes.

sourced from different location-aware applications ("apps"). We used two different SafeGraph datasets: (a) Census Block Group (CBG) to CBG trip data, associated with users whose estimated home-location lies within the origin CBG; and (b) point of interest (POI) trips, indicating the POI destinations visited from each CBG. While CBGs are delineated by official US Census geometry polygons (United States Census Bureau, 2020a), POIs represent point locations for various destination activities included in SafeGraph data—retail stores, parks and playgrounds, health service providers, etc. (SafeGraph, 2022).

Much of the early geographic literature on mobile phone positioning has relied on locating devices based on cell identification or signal-strength triangulation (Masso et al., 2019; Reades et al., 2007; Sevtsuk & Ratti, 2010), which can have a spatial accuracy margin of several hundred meters. More recent studies have used anonymized global positioning technology (GPS) records from smartphones (Ruiz-Euler et al., 2020), location-tagged tweets (Ruiz-Euler et al., 2020), and aggregated mobility reports from Apple and Google (Huang et al., 2021). The SafeGraph data we use are also based on GPS data, where location error is far smaller than cell identification or signal-strength triangulation, typically <10 m (Merry & Bettinger, 2019). This enables SafeGraph data to be used for higher resolution spatial analysis, including visits to specific urban amenities that we explore below.

Average commute time and journey-to-work mode choice information is also published by the US Census as part of the American Community Survey (ACS), but ACS data only reflects work-related trips and general patterns are imputed based on a relatively small randomly collected sample. SafeGraph data are advantageous for their comparatively (and significantly) larger sample and coverage of all trip types, not just work trips. Our data includes over 139 million individual trips in nine cities, covering almost 13 million individuals living in around 9000 Census block groups. Table 1 provides a breakdown of total trip volumes, households, and individuals across all CBGs in our nine cities in our SafeGraph data (Full sample column), as well as by three SEI levels used in our analysis (more on this below).

Despite the large sample, we acknowledge that SafeGraph data are imperfect and may contain biases for illustrating human mobility patterns. The most obvious caveat is that SafeGraph data only detect user movements among people who own a smartphone. In 2021, around 85 % of adults in the U.S. had a smartphone, with lower smartphone penetration levels reported among rural, elderly, and less educated populations (Pew Research, 2021, April 7). Smartphone ownership is also uneven by income: among households with annual incomes higher than $100 k, 97 % of adults owned a smartphone in 2021. Among the $30 k to $99 k earning households, adult smartphone penetration was 87 %, and among the below $30,000 earning households 76 % (Vogels, 2021, June 22). At the same time, the share of adults who use their smartphone as a primary means to go online is higher among the lowest earning group (27 %) than the highest earning group (6 %). SafeGraph data could thus underrepresent the movements of lower income and elderly adults in cities, but the data from those lowest earning adults that are present are likely to be more voluminous and spatially accurate.

Table 1
Sample characteristics.

Variable	Low SEI (SEI < 20% ile)	20–80 % SEI	High SEI (SEI > 80% ile)	Full sample
Census block groups	1817	5435	1808	9060
Individuals	2,392,647	8,135,270	2,401,327	12,929,244
Individuals per block group	1316 (677)	1497 (764)	1328 (718)	1427 (743)
Households	809,877	2,989,277	1,087,011	4,886,165
Households per block group	446 (227)	550 (302)	601 (374)	539 (309)
Smartphone devices (All trips)	25,833,615	87,078,842	26,673,937	139,586,394
Smartphone devices per block group (All trips)	14,218 (17,728)	16,022 (17,572)	14,753 (15,500)	15,407 (17,226)
Smartphone devices (POI trips)	682,986	2,570,138	820,302	4,073,425
Smartphone devices per block group (POI trips)	376 (449)	473 (581)	454 (605)	450 (563)

Note: Counts are provided by socioeconomic status (SEI) quintile groups (Q1, Q2–4, Q5) and the full sample for Census block groups, individuals, households, and smartphone devices. Means (standard deviations) are reported for per-block-group variables. Smartphone device counts cover a two-year period from Jan 2019 to Dec 2020.

We computed the average monthly travel distance for trips originating from each origin CBG in the nine cities ($n = 9062$) by observing the volume of trips going to all other CBGs in the same city according to network driving distances between CBG centroids using Mapbox Directions API (Mapbox, 2021) (weighted by the number of trips to each destination). Beyond average monthly travel time, we also characterized typical spatial extents of trips originating from each CBG by computing the average monthly proportion of city-wide CBGs visited, which allowed us to compare how the geographic extent of travel from each CBG may differ across socio-economic groups. We also examined the average monthly percent of trips from each CBG that were headed to parks, retail amenities, and health-related amenities. We chose these three destination types as specific categories of interest that have been shown to affect travel behavior during the COVID-19 pandemic in the literature (Basu, Ferreira, 2021a; Chang et al., 2021; Jay et al., 2020; Lee et al., 2020; Ruiz-Euler et al., 2020; Xiong et al., 2020).

We categorized each CBG in the nine cities by five SEI quintiles using the methodology proposed by Wheeler et al. (Wheeler et al., 2017). Socioeconomic status is typically a composite variable, constructed from a number of input parameters, including income, housing, employment, and educational attainment, with coefficients assigned to each component based on equal weighting, factor analysis, or principal component analysis (Cabrera-Barona et al., 2015; Diez-Roux et al., 2001). However, these approaches do not consider the relationship between the outcome and the socioeconomic variables when constructing the index. Following (Wheeler et al., 2017), we used a weighted quantile sum (WQS) regression to estimate a city-specific socioeconomic index (SEI) for each CBG, using the monthly mean difference in trip distance between 2020 and 2019 as the dependent variable. Demographic variables for CBGs inside cities' administrative boundaries, including income, race, and educational attainment, were obtained from the American Community Survey 2015–2019 five-year estimates by the US Census Bureau (United States Census Bureau, 2020b). The key advantages of this approach are that (a) SEI categories are constructed specifically to examine mobility behaviors, and (b) the particular weights of socio-economic characteristics (e.g., income, race, education, etc.) can vary by city, outlining how attributes of relative privilege differ by context. Table 2 shows best fitting SEI weights for the nine cities included in our study, using aggregate difference in mean distance traveled per month as the dependent variable of the WQS regression. In Chicago, Philadelphia and Seattle, for instance, SEI is primarily determined by race, in Atlanta mostly by income, and in Boston by educational attainment. Though we also explored using the same category weights for SEI groupings across all cities, the weights reported in Table 2 affirmed that the social attributes that predict mobility privilege differ by city.

Access to jobs by transit from each CBG was obtained from the University of Minnesota's Accessibility Observatory (University of Minnesota Center for Transportation Studies, 2019). The Accessibility Observatory publishes worker-weighted transit accessibility by using transit schedule data and measuring the number of jobs reached from CBG centroids within a 30-minute travel time between 7:00 AM and 8.59 AM on workdays. A walkability rating for each CBG was obtained from the WalkScore API (WalkScore, 2021), which rates walkability levels of individual address points in cities on a 0–100 scale based on the

Table 2
Best fitting SEI weights for the nine cities, using aggregate difference in mean distance traveled per month as the dependent variable of a weighted quantile sum regression model.

City	% White	Median HH Income	% college educated	Population density	% renters * Income	% 30-min commutes
All	0.353	0.034	0.551	0.059	0.003	0.001
Atlanta	0.105	0.503	0.059	0.211	0.098	0.024
Boston	0.058	0.069	0.513	0.296	0.039	0.026
Chicago	0.439	0.008	0.43	0.091	0.021	0.011
Denver	0.216	0.028	0.468	0.139	0.001	0.148
Houston	0.266	0.16	0.463	0.095	0.009	0.007
Los Angeles	0.267	0.046	0.59	0.072	0.011	0.015
Philadelphia	0.446	0.078	0.384	0.003	0.07	0.019
Seattle	0.395	0.091	0.145	0.189	0.149	0.03
St. Louis	0.295	0.242	0.275	0.041	0.066	0.082

Cell colorcoding is row-standardized to highlight factor weights specific to each city:

Low	Average	High

Note: The variables used to construct the socio-economic index (SEI) of a Census Block Group (CBG) are: (a) % Non-Hispanic White individuals, (b) Median household income, (c) % adults (aged 25 or more) with at least a college degree, (d) Population density, (e) % renter-occupied housing units interacted with median household income, and (f) % workers (aged 16 or more, not working at home) with at-most 30 minute-long commutes. The weights are proportionally adjusted such that they sum to one across each row. Table is color-coded by row, where red indicates higher and green lower weights for each city separately.

availability and diversity of pedestrian destinations within walking range. Table 3 illustrates how both transit access to jobs and WalkScore values are distributed among the lowest (0–20%ile), middle (20–80% ile) and highest (80–100%ile) SEI groups across all CBGs in the nine cities in our dataset, highlighting that the highest SEI groups tend to reside in more transit accessible and walkable neighborhoods, and the lowest SEI groups in the least transit accessible and walkable neighborhoods. On average, highest SEI groups can reach 2.5 times more jobs by 30-minute transit ride on a typical weekday morning than the lowest SEI groups and their neighborhoods tend to be 15 % more walkable, on average.

3. Analyses and findings

We start by describing the differences in these outcome variables between the lowest and the highest SEI groups in each city before the pandemic, and then turn to the question of how the COVID-19 pandemic may have affected changes in travel behavior outcomes across socio-economic groups.

3.1. Social and spatial determinants of pre-pandemic mobility

In order to establish a baseline for mobility patterns in 2019, we present the results of explanatory models of monthly-averaged pre-pandemic travel outcomes in Table 4, where variations in five different dependent variables are explained with socio-economic differences between CBGs, as well as two mobility-related spatial advantages of the travelers' locations—transit accessibility to jobs and WalkScore. We additionally include some interaction effects between the two categories of variables. The middle SEI groups (20%ile – 80%ile) are used as a reference to compare high- and low-SEI differences in outcome variables.

Comparing the dummy coefficients for Lowest SEI and Highest SEI across each of the outcome variables (rows two and three of Table 4), we find that residents of block groups in the highest SEI quintile traveled longer distances than residents of the lowest SEI block groups ($-0.101^{***} < -0.301^{***}$), which corroborates prior literature on U.S. travel statistics (Memmott & Bureau of Transportation Statistics, 2007). The negative signs suggest that both the highest and the lowest SEI groups traveled less distance and visited a smaller percentage of city-wide destinations than the middle SEI groups in the nine cities on average, though the lowest SEI groups had wider travel extents than the highest SEI groups ($-0.077^{***} > -0.238^{***}$). We also find that people from high SEI blocks made significantly more trips to parks ($0.246^{***} > -0.086^{***}$) and healthcare destinations ($0.067^{***} > 0.037$) and fewer trips ($-0.115^{***} < 0.246^{***}$) to retail destinations than people from the lowest-SEI blocks in 2019. This broadly corroborates that mobility outcomes of relatively low and high SEI groups significantly differed even before the pandemic started.

Table 4 also provides insight into how location advantages—living in relatively amenity-rich neighborhoods (with high WalkScore values), or living in more public transit served areas—could impact mobility outcomes before the pandemic. Averaged across all SEI groups, we find that living in high WalkScore neighborhoods implied shorter average trip lengths (-0.502^{***}) and fewer city-wide CBGs visited overall (-0.069^{***}), likely due to the availability of more destinations nearby. Living in more walkable neighborhoods also implied a larger proportion of trips made to retail destinations (0.324^{***}), likely due to having a larger choice of smaller stores within walking distance rather than driving to big-box general stores further way—but a smaller proportion of trips to parks (-0.100^{***}) and health services (-0.032^{***}), which may be lacking in denser urban areas.

Living in neighborhoods with better public transit access to jobs also implied shorter trip lengths on average (-0.130^{***}), but a higher proportion of city-wide CBGs visited (0.179^{***}), and a larger proportion of total trip-making to parks (0.125^{***}), retail destinations (0.172^{***}), and healthcare destinations (0.061^{***}) alike. Prior to the pandemic, walkability and transit access thus both contributed to reducing mean trip distances. While living in walkable neighborhoods primarily increased retail visits, transit access provided residents better access to city-wide destinations overall and increased proportional visits to all three destination types.

However, the effects of advantageous home location—residing in more walkable or transit served areas—on travel behavior were not the same for high and low SEI groups even in pre-pandemic times. Interestingly, higher-SEI groups living in more transit-accessible neighborhoods actually had longer average trip distances (0.077^{***}) and visited significantly more city-wide destinations (0.116^{***}) than the middle SEI control group. Given that transit trips are typically shorter in distance and more spatially constrained than automobile trips, this likely points to more automobile use by high SEI groups even when living near transit. Prior research has pointed to a phenomenon of "transit-induced gentrification", whereby high-income households who move into transit-oriented developments actually end up using more automobiles and not relying on transit (Basu, Ferreira, 2021a; Basu, Ferreira, 2021b). Among low SEI groups, we find that living in more transit-served areas is correlated with lower average trip lengths (-0.056) and fewer city-wide CBGs visited (-0.148^{***}), suggesting greater reliance on transit services.

Living in more walkable neighborhoods also affected travel behavior of low and high SEI block group residents differently. In addition to the overall walkability effect reported above, high SEI groups living in more walkable areas traveled less to other parts of the city—they made shorter

Table 3
Mean transit access to jobs and mean WalkScore by SEI groups across nine cities.

	Avg. nr of jobs reached by transit within 30 min on a weekday morning.	Avg. WalkScore (0–100)
Lowest SEI	1,204,974	64.0
Middle SEI	1,401,554	66.2
Highest SEI	3,084,827	73.7

Note: The averages reflect all 9063 CBGs across nine cities; they are therefore disproportionately affected by larger cities such as LA, Chicago and Houston.

Table 4
Explanatory models of pre-pandemic mobility outcomes.*

Mobility outcomes (Jan-Dec 2019)					
Dependent variable					
	Avg. monthly trip length	Avg. monthly proportion of city-wide CBGs visited	Avg. monthly park trip proportion	Avg. monthly retail trip proportion	Avg. monthly health trip proportion
	(1)	(2)	(3)	(4)	(5)
Constant	0.064*** (0.044, 0.084)	0.055*** (0.030, 0.080)	−0.046*** (−0.069, −0.022)	−0.008 (−0.032, 0.017)	−0.043*** (−0.065, −0.021)
	$t = 6.308$	$t = 4.350$	$t = -3.846$	$t = -0.597$	$t = -3.783$
	p = 0.000	$p = 0.00002$	$p = 0.0002$	$p = 0.551$	p = 0.0002
Lowest-SEI	−0.301*** (−0.343, −0.259)	−0.077*** (−0.130, −0.025)	−0.086*** (−0.135, −0.037)	0.246*** (0.194, 0.298)	0.037 (−0.009, 0.084)
	$t = -14.048$	$t = -2.898$	$t = -3.444$	$t = 9.213$	$t = 1.576$
	p = 0.000	$p = 0.004$	$p = 0.001$	p = 0.000	$p = 0.116$
Highest-SEI	−0.101*** (−0.143, −0.060)	−0.238*** (−0.290, −0.186)	0.246*** (0.198, 0.295)	−0.115*** (−0.167, −0.063)	0.067*** (0.021, 0.113)
	$t = -4.776$	$t = -9.023$	$t = 9.959$	$t = -4.360$	$t = 2.854$
	$p = 0.00001$	$p = 0.000$	p = 0.000	p = 0.00002	$p = 0.005$
Transit access to jobs	−0.130*** (−0.162, −0.098)	0.179*** (0.139, 0.219)	0.125*** (0.088, 0.163)	0.172*** (0.132, 0.212)	0.061*** (0.026, 0.097)
	$t = -7.957$	$t = 8.749$	$t = 6.565$	$t = 8.443$	$t = 3.372$
	$p = 0.000$	$p = 0.000$	p = 0.000	p = 0.000	$p = 0.001$
WalkScore	−0.502*** (−0.524, −0.480)	−0.069*** (−0.096, −0.041)	−0.100*** (−0.126, −0.074)	0.324*** (0.297, 0.351)	−0.032*** (−0.057, −0.008)
	$t = -44.719$	$t = -4.903$	$t = -7.613$	$t = 23.146$	$t = -2.582$
	p = 0.000	p = 0.00000	p = 0.000	p = 0.000	$p = 0.010$
% Democratic votes	−0.132*** (−0.149, −0.115)	−0.144*** (−0.165, −0.123)	0.163*** (0.144, 0.183)	0.084*** (0.063, 0.104)	0.144*** (0.126, 0.163)
	$t = -15.597$	$t = -13.636$	$t = 16.493$	$t = 7.920$	$t = 15.358$
	p = 0.000	$p = 0.000$	p = 0.000	p = 0.000	p = 0.000
Lowest-SEI X Transit access to jobs	−0.056 (−0.123, 0.011)	−0.148*** (−0.232, −0.064)	0.040 (−0.039, 0.118)	−0.011 (−0.095, 0.073)	0.041 (−0.033, 0.116)
	$t = -1.634$	$t = -3.460$	$t = 0.986$	$t = -0.255$	$t = 1.082$
	$p = 0.103$	$p = 0.001$	$p = 0.325$	$p = 0.800$	$p = 0.280$
Highest-SEI X Transit access to jobs	0.077*** (0.024, 0.129)	0.116*** (0.050, 0.181)	−0.155*** (−0.216, −0.093)	−0.069** (−0.134, −0.003)	0.014 (−0.045, 0.072)
	$t = 2.858$	$t = 3.462$	$t = -4.942$	$t = -2.060$	$t = 0.455$
	p = 0.005	p = 0.001	p = 0.00000	$p = 0.040$	$p = 0.649$
Lowest-SEI X WalkScore	0.008 (−0.041, 0.056)	−0.027 (−0.088, 0.033)	−0.030 (−0.087, 0.027)	−0.014 (−0.074, 0.047)	−0.034 (−0.088, 0.020)
	$t = 0.311$	$t = -0.880$	$t = -1.038$	$t = -0.440$	$t = -1.242$
	$p = 0.757$	$p = 0.380$	$p = 0.300$	$p = 0.661$	$p = 0.215$
Highest-SEI X WalkScore	−0.059*** (−0.099, −0.020)	−0.118*** (−0.167, −0.069)	0.025 (−0.021, 0.071)	−0.114*** (−0.163, −0.065)	−0.058*** (−0.102, −0.014)
	$t = -2.944$	$t = -4.711$	$t = 1.077$	$t = -4.554$	$t = -2.602$
	p = 0.004	$p = 0.00001$	$p = 0.282$	p = 0.00001	p = 0.010
Observations	9062	9061	9062	9062	9062
R^2	0.397	0.057	0.048	0.143	0.034
Adjusted R^2	0.397	0.056	0.047	0.142	0.033
Residual Std. Error	0.736 (df = 9052)	0.918 (df = 9051)	0.860 (df = 9052)	0.917 (df = 9052)	0.816 (df = 9052)
F Statistic	663.501*** (df = 9; 9052)	60.988*** (df = 9; 9051)	51.097*** (df = 9; 9052)	168.151*** (df = 9; 9052)	35.151*** (df = 9; 9052)

Note: Data for all 12 months of 2019 are used. We standardized all variables within each city to obtain city-standardized z-scores that were used as explanatory variables in the model. This was done to address the different distributions of sociodemographic variables within each city, e.g., the mean Non-White population proportion is much higher in St. Louis than in Boston.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

trips (−0.059***) and visited fewer city-wide CBGs overall (−0.118***), but allocated a smaller proportion of their travel to retail destinations (−0.114***) than middle SEI groups (our reference group). For low SEI blocks, living in walkable neighborhoods did not significantly alter travel behavior compared to the middle SEI control group levels (all Lowest-SEI * WalkScore coefficients are statistically insignificant). This suggests that high SEI groups were able to take more advantage of highly walkable neighborhoods than low SEI groups, in terms of reducing trip distances, but were less likely to patronize local retailers than the middle SEI group, possibly because of higher reliance on e-commerce. At the same time, low SEI households may not have been be able to afford goods and services in highly walkable areas, or the destinations they needed may be have been under provisioned at the neighborhood scale.

3.2. Changes in mobility outcomes by socioeconomic status from 2019 to 2020

In order to explore how the COVID-19 pandemic shifted mobility outcomes for different socioeconomic groups in 2020, we first present descriptive statistics of monthly aggregated mobility outcomes for both 2019 and 2020 by SEI quintiles in Table 5. While mean raw trip distances for the lowest and highest SEI groups were statistically indistinguishable in 2019 ($t = 1.6$, $p = 0.12$), the lowest-SEI group traveled 695 m more than the highest-SEI group following the outbreak in 2020 ($t = 33.0$, $p < 0.001$), on average across nine cities and all CBGs within them.

Table 5
Differences in monthly-aggregated mobility outcomes by SEI quintiles.

Mobility outcomes (monthly average)	Quintile 1 [Q1: *Lowest SEI*] mean (std. dev.)	Quintiles 2–4 mean (std. dev.)	Quintile 5 [Q5: *Highest SEI*] mean (std. dev.)	Q1 vs. Q5 Diff. in mean (95 % CI) t-stat (residual d.f.)
Trip distance (2019) [meters]	4467 (1841)	4882 (1890)	4433 (2135)	34 (−9, 78) 1.556 (31,865)
Trip distance (2020) [meters]	3736 (1802)	3735 (1771)	3041 (1965)	695 (653, 736) 33.035*** (31,837)
% of within-city non-home CBGs visited (2019)	3.1 % (3.3 %)	3.3 % (3.3 %)	3.0 % (3.1 %)	0.1 % points (0.07 %, 0.21 %) 4.079*** (32,461)
% of within-city non-home CBGs visited (2020)	1.6 % (2.0 %)	1.7 % (1.8 %)	1.3 % (1.9 %)	0.3 % points (0.28 %, 0.37 %) 15.042*** (32,160)
% of trips made to parks (2019)	6.4 % (7.8 %)	6.2 % (6.8 %)	7.2 % (7.1 %)	−0.8 % points (−1.0 %, −0.6 %) −9.813*** (32,328)
% of trips made to parks (2020)	5.5 % (9.2 %)	6.5 % (9.9 %)	10.2 % (13.8 %)	−4.7 % points (−5.0 %, −4.5 %) −36.193*** (27,658)
% of trips made to retail establishments (2019)	64.9 % (11.1 %)	63.2 % (10.4 %)	63.1 % (11.4 %)	1.8 % points (1.5 %, 2.0 %) 14.140*** (32,540)
% of trips made to retail establishments (2020)	67.6 % (15.0 %)	64.7 % (15.2 %)	64.6 % (19.8 %)	3.0 % points (2.6 %, 3.4 %) 15.310*** (29,746)
% of trips made to healthcare centers (2019)	4.2 % (5.7 %)	3.8 % (4.4 %)	3.9 % (4.7 %)	0.3 % points (0.2 %, 0.4 %) 5.350*** (31,459)
% of trips made to healthcare centers (2020)	3.1 % (6.2 %)	3.2 % (6.5 %)	4.0 % (9.3 %)	−0.9 % points (−1.2 %, −0.8 %) −11.166*** (27,704)

Note: Data for April through December are summarized to provide monthly statistics for 2019 and 2020; *** indicates $p < 0.001$. January and February are omitted because the pandemic had not yet affected mobility outcomes in Jan-Feb 2020, while March is omitted because of precipitous mobility changes implying a transition period (see Fig. 2). April is the first 'stable' post-outbreak month in 2020.

Additionally, while the lowest SEI group traveled to 0.1 % points more city-wide CBGs per month than the high SEI group in 2019 ($t = 4.1$, $p < 0.001$), this gap widened to 0.3 % points during the pandemic in 2020 ($t = 15.0$, $p < 0.001$).

Regarding destination types, we find that the lowest-SEI group made 0.8 % points fewer trips to parks ($t = -9.8$, $p < 0.001$) than the highest-SEI group in 2019, reflecting the lower tendency of recreational trip-making from lower-SEI CBGs during 'normal' times. The pandemic substantially widened this disparity to 4.7 % points ($t = -36.2$, $p < 0.001$) in 2020. Given that only 5.5 % of all trips were headed to parks for lowest SEI residents in 2020 overall, this suggests that high SEI residents dedicated almost double the proportion of their overall journeys to green spaces. Similar inequities regarding park visits during COVID-19 have been reported elsewhere in the literature (Jay et al., 2020; Jay et al., 2021; Larson et al., 2021). Lower-SEI groups also made 1.8 % points more retail trips in 2019 than high SEI groups and this gap increased to a 3.0 % difference ($t = 15.3$, $p < 0.001$) in 2020. Finally, in 2019 the lowest-SEI group made 0.3 % points *more* trips to healthcare centers than the highest-SEI group ($t = 5.4$, $p < 0.001$). However, this difference flipped during the pandemic, when the lowest-SEI group made 0.9 % points *fewer* healthcare trips than the highest-SEI group ($t = -11.2$, $p < 0.001$). These descriptive statistics suggest that during the public health crisis, the lowest-SEI group reduced healthcare trips significantly (from 4.2 % to 3.1 %), while the highest-SEI group saw a marginal increase (from 3.9 % to 4.0 %).

3.3. Social and spatial determinants of pandemic-induced mobility changes from 2019 to 2020

The descriptive differences reported above become more pronounced when we examine the factors that explain *changes* in mobility outcomes at the CBG level across the two time periods as presented in Table 6. Unlike the average 2019 outcome variables modeled in Table 4, here the dependent variables in each of the five columns reflect changes from 2019 to 2020. For instance, column one in Table 6 illustrates the average monthly percent change in trip length at the CBG level, calculated as (2020 monthly average value – 2019 monthly average value) / (2020 monthly average value) further averaged over nine months (April through December) to account for seasonal differences in mobility outcomes.

Even though mobility behavior was additionally affected by business closures and government shut-down policies, which varied across cities during the pandemic, we standardized all modeled variables by each city's mean to address unobserved city-level fixed effects that could not be included at the CBG resolution. Using city-level standardization thus also eliminated the need for separate city-level dummy variables. However, we acknowledge that some unobserved variables could also vary by SEI group. For instance, unemployment has been reported to have affected the lowest SEI groups the most severely during the pandemic. The differences we report between highest and lowest SEI group travel patterns can therefore reflect behavior changes, policy effects, and additional unobserved covariates concurrently. We recognize the challenge in isolating these three effects and acknowledge this as a limitation of our work.

A positive coefficient for lowest SEI groups (0.453***) suggests that the percent change in average trip length from 2019 to 2020 was around 45 % smaller for the lowest SEI group compared to the middle SEI control group, affirming a much smaller reduction in travel among the least privileged residents. The lowest SEI groups also witnessed a 21.2 % smaller reduction in the proportion of city-wide CBGs visited than the middle SEI group. The highest-SEI group experienced the opposite: their average trip length decreased 47.6 % more than the middle SEI group and they reduced their city-wide visits to other CBGs 46.2 % more than the middle SEI group. This indicates that the lowest-SEI group had to travel further to access necessary goods, services and jobs during the pandemic, whereas higher SEI groups were more likely to be able to work from home and turn to e-commerce for subsistence deliveries.

Additionally, the lowest-SEI group reduced the proportion of their total trip-making dedicated to parks (−0.229***) and healthcare (−0.125***) and increased the proportion of trips to retail establishments (0.109***) during the pandemic. The highest-SEI group, in contrast, increased the proportion of their trips dedicated to parks (0.572***) and healthcare (0.180***), and did not show a significant change in retail trip-making. This indicates that more socioeconomically advantaged groups were able to limit their mandatory travel (e.g., commuting to work) and instead increase their recreational and maintenance travel (e.g., to parks and healthcare) during the pandemic.

Similar to our pre-pandemic observations, we find differences across neighborhood contexts as well. Residents of CBGs with better transit access to jobs reduced their trip distances significantly less than residents of CBGs that were further away from transit access. We noted in

Table 6
Explanatory models of pandemic-induced mobility changes.

Change in mobility outcomes (Apr-Dec 2019 VS Apr-Dec 2020)					
Dependent variable					
	Avg. monthly % change in trip length (2020–2019)	Avg. monthly change in destination proportion	Avg. monthly change in park trip proportion	Avg. monthly change in retail trip proportion	Avg. monthly change in health trip proportion
	(1)	(2)	(3)	(4)	(5)
Constant	−0.003 (−0.027, 0.020)	0.036*** (0.014, 0.059)	−0.075*** (−0.099, −0.052)	−0.035*** (−0.061, −0.009)	−0.026** (−0.049, −0.002)
	$t = -0.291$	$t = 3.133$	$t = -6.325$	$t = -2.639$	$t = -2.119$
	$p = 0.772$	$p = 0.002$	$p = 0.000$	$p = 0.009$	$p = 0.035$
Lowest-SEI	0.453*** (0.404, 0.502)	0.212*** (0.164, 0.260)	−0.229*** (−0.278, −0.180)	0.109*** (0.054, 0.164)	−0.125*** (−0.174, −0.075)
	$t = 18.037$	$t = 8.672$	$t = -9.107$	$t = 3.892$	$t = -4.905$
	p = 0.000	$p = 0.000$	p = 0.000	p = 0.0002	p = 0.00000
Highest-SEI	−0.476*** (−0.525, −0.428)	−0.462*** (−0.509, −0.415)	0.572*** (0.523, 0.620)	0.011 (−0.043, 0.066)	0.180*** (0.131, 0.229)
	$t = -19.212$	$t = -19.162$	$t = 23.016$	$t = 0.415$	$t = 7.159$
	p = 0.000	p = 0.000	p = 0.000	$p = 0.679$	p = 0.000
Job access by transit	0.051*** (0.013, 0.088)	−0.148*** (−0.185, −0.112)	0.102*** (0.065, 0.140)	−0.090*** (−0.131, −0.048)	0.033* (−0.005, 0.071)
	$t = 2.644$	$t = -7.964$	$t = 5.329$	$t = -4.209$	$t = 1.688$
	p = 0.009	p = 0.000	$p = 0.00000$	$p = 0.00003$	$p = 0.092$
WalkScore	−0.046*** (−0.072, −0.020)	−0.174*** (−0.199, −0.149)	−0.040*** (−0.065, −0.014)	−0.023 (−0.052, 0.006)	0.043*** (0.017, 0.069)
	$t = -3.473$	$t = -13.582$	$t = -3.007$	$t = -1.568$	$t = 3.217$
	p = 0.001	p = 0.000	p = 0.003	$p = 0.117$	p = 0.002
% Democratic votes	0.016 (−0.003, 0.036)	−0.239*** (−0.257, −0.220)	−0.015 (−0.034, 0.005)	−0.011 (−0.032, 0.011)	−0.004 (−0.023, 0.016)
	$t = 1.618$	$t = -24.729$	$t = -1.489$	$t = -0.962$	$t = -0.359$
	$p = 0.106$	p = 0.000	$p = 0.137$	$p = 0.336$	$p = 0.720$
Lowest-SEI X Job access	0.033 (−0.046, 0.112)	0.074* (−0.003, 0.151)	−0.104** (−0.183, −0.025)	0.043 (−0.045, 0.131)	0.059 (−0.021, 0.139)
	$t = 0.816$	$t = 1.895$	$t = -2.576$	$t = 0.963$	$t = 1.442$
	$p = 0.415$	$p = 0.059$	$p = 0.011$	$p = 0.336$	$p = 0.150$
Highest-SEI X Job access	0.040 (−0.021, 0.102)	0.072** (0.012, 0.132)	−0.016 (−0.077, 0.046)	0.052 (−0.017, 0.121)	0.024 (−0.039, 0.086)
	$t = 1.281$	$t = 2.341$	$t = -0.498$	$t = 1.485$	$t = 0.748$
	$p = 0.201$	$p = 0.020$	$p = 0.619$	$p = 0.138$	$p = 0.455$
Lowest-SEI X WalkScore	0.040 (−0.017, 0.096)	−0.014 (−0.069, 0.041)	0.061** (0.004, 0.118)	−0.118*** (−0.181, −0.054)	0.023 (−0.035, 0.080)
	$t = 1.363$	$t = -0.491$	$t = 2.109$	$t = -3.643$	$t = 0.778$
	$p = 0.173$	$p = 0.624$	$p = 0.036$	$p = 0.0003$	$p = 0.437$
Highest-SEI X WalkScore	−0.099*** (−0.146, −0.053)	−0.069*** (−0.114, −0.024)	−0.032 (−0.079, 0.014)	0.034 (−0.018, 0.085)	0.001 (−0.045, 0.048)
	t = −4.209	$t = -2.993$	$t = -1.374$	$t = 1.283$	$t = 0.057$
	p = 0.00003	$p = 0.003$	$p = 0.170$	$p = 0.200$	$p = 0.955$
Observations	9061	9060	9059	9059	9059
R^2	0.116	0.211	0.094	0.009	0.023
Adjusted R^2	0.115	0.21	0.093	0.008	0.022
Residual Std. Error	0.863 (df = 9051)	0.838 (df = 9050)	0.863 (df = 9049)	0.960 (df = 9049)	0.873 (df = 9049)
F Statistic	132.064*** (df = 9; 9051)	268.411*** (df = 9; 9050)	104.532*** (df = 9; 9049)	9.540*** (df = 9; 9049)	23.714*** (df = 9; 9049)

Note: Dependent variables measure observed change from expected levels in 2020 (during the pandemic). All variables are city-level standardized; Data for Apr-Dec 2019–2020 are used.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3 that more transit accessible neighborhoods are typically populated by higher SEI groups. That households living close to transit traveled longer distances during the pandemic than households without transit likely reflects that middle income groups who relied on transit prior to the pandemic, left their neighborhoods on longer car-based trips to access green spaces and other amenities during the pandemic. Residents living in areas without good transit connections likely had bigger suburban homes with yards, without much need to leave their neighborhoods to access green spaces during the pandemic. Residents of walkable CBGs had more favorable outcomes during the pandemic due to their proximity to amenities within the neighborhood, which was reflected through shorter trips to fewer destinations and a higher proportion of healthcare trips than usual.

We also tested whether and how political inclination—captured as the percent of votes for President Biden in the 2020 presidential election—explains pandemic-induced changes in mobility behavior in Table 6. The 2020 U.S. Presidential election data, showing percent of votes for President Biden, were obtained from The Upshot (The Upshot, 2021) and matched to CBGs featured in our sample. Given that most large U.S. cities are Democratically leaning overall, we did not divide CBGs into Republican versus Democrat groups, but rather used a continuous variable showing the percent of votes for President Biden in the 2020 election from each CBG. SafeGraph mobility data were linked with demographic data of the associated home CBG. We see in Table 6 that more Democratically leaning CBGs traveled to significantly fewer other CBGs in their city during 2020 (−0.239***). A 1 % increase in democratic leaning at the CBG level produced a 0.24 % percent decrease in city-wide travel extent in 2020, compared to pre-pandemic travel levels. Left-leaning neighborhoods thus exhibited more cautious travel behavior during the pandemic.

To examine whether spatial advantage may offset socioeconomic disadvantage during the pandemic, we again interacted job accessibility and WalkScore with dummy variables for the lowest and the highest SEI groups in Table 6. The results suggest that both high and low SEI groups increased the percent of city-wide CBGs visited when living in better transit-served areas compared to the middle SEI control group (0.074* for lowest SEI; 0.072** for highest SEI). Again, this likely signals a shift from transit use to automobile use during the pandemic compared to a "normal" year before. While high-SEI groups already traveled to more city-wide destinations when living in transit-served areas before the pandemic, that was not the case for low-SEI groups in 2019—the latter actually visited a smaller proportion of city-wide CBGs when living near transit prior to the pandemic (see Table 4). The SEI-specific trip destination proportions in Table 6 suggest that when living in transit served areas, higher SEI-groups left these inner-city areas more for park access, while the lowest SEI groups left more for sustenance travel to retail destinations. The last two coefficient estimates in Table 6 suggest that living in walkable neighborhoods enabled high SEI groups to have shorter average journeys (−0.099***) and to travel to fewer city-wide destinations (−0.069***) during the pandemic. There was no significant effect of highly walkable areas on these outcomes for the lowest SEI groups.

3.4. Differences among cities

We supplement our general findings presented above with explorations of the differences in mobility outcomes for trip distance and travel extent across the nine cities in our study. Fig. 2 compares how average monthly trip lengths changed in 2020 within each city by SEI category. The dashed line in the middle of each graph represents pre-pandemic mean trip distance for each month in 2019. We observe two commonalities across all cities: (a) there was a sharp decrease in trip lengths observed in March and April, and (b) the relationship between SEI category and trip length reduction is directly proportional. The highest-SEI groups were able to reduce their trip lengths more than the lowest-SEI groups across all cities observed. Chicago, Houston, and Philadelphia exhibited the largest "mobility gap" between the highest and lowest-SEI groups, while Seattle and Atlanta showed a much more moderate gap. Trip distances for the lowest-SEI group recovered to pre-pandemic levels in Denver and St. Louis in June and Chicago in December 2020. For other groups, trip distances remained well below pre-pandemic levels throughout 2020, with the largest sustained reductions observed in Boston and Seattle.

The pooled regression models for changes in trip length and percent of city-wide CBGs visited presented in the previous section were estimated on combined data from the nine cities to extract general findings, but some differences in these outcomes are expected across the various cities. We therefore estimated sub-models with the same specification for each city separately. City-specific changes in trip lengths and percentages of city-wide CBGs visited between 2019 and 2020 are presented in Fig. 3 (comparative charts for 2019 are presented in Supplementary Materials). Large differences between mobility behaviors of the highest and lowest SEI groups can be seen in seven of the nine cities (excluding Atlanta and Seattle), where higher-SEI groups reduced both trip lengths and the number of destinations they traveled to during the pandemic, while the lowest SEI groups did not (Fig. 3a and d). The biggest differences between the highest and lowest SEI groups' travel behavior is seen in Chicago, Denver, Houston, Los Angeles and Philadelphia. Atlanta, along with Seattle to a lesser extent, stands out as an exception, where both the pandemic-induced changes in trip lengths and city-wide CBGs visited were similar and statistically indistinguishable between the highest and lowest SEI groups. Seattle and Atlanta thus have the least inequitable pandemic-induced changes in travel behavior among their most and the least privileged residents. Although this raises an interesting question about which particular spatial, social, and economic qualities of cities may contribute to relatively smaller or larger "mobility gaps" between the highest and lowest SEI groups, an answer is beyond the scope of this paper and will have to remain a subject of future research.

Finally, we also examined how political leaning towards a Democratic presidential nominee in the 2020 election impacted the extent of city-wide travel in each of the nine cities separately (Fig. 4). Residents of Democratically leaning CBGs traveled to fewer non-home CBGs in each of the nine cities individually (all coefficients in Fig. 4 are significant at

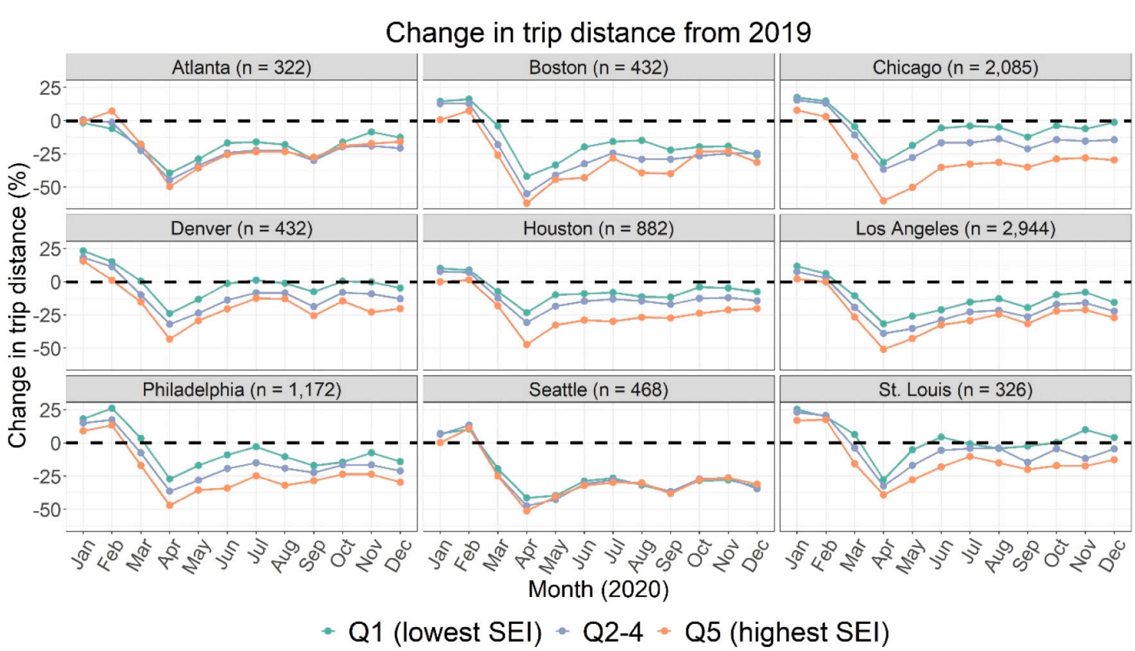

Fig. 2. Deviation in monthly-averaged 2020 trip distances from 2019. Actual monthly trip lengths in 2020 are compared to 2019 trip lengths. Block groups in each city are clustered into one of three groups - Q1 (lowest SEI), Q2-4 (combination of SEI quintiles 2, 3, and 4), and Q5 (highest SEI). Point estimates represent the monthly means.

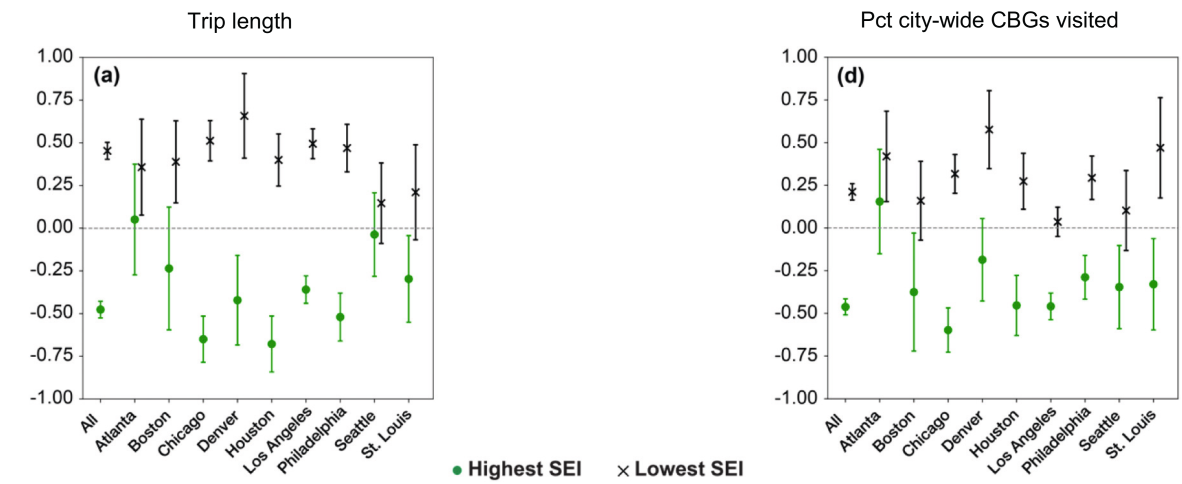

Fig. 3. (a) City-specific standardized coefficient estimates for average changes in trip length between April–December 2020 for highest and lowest SEI quintile CBGs, (d) City-specific standardized coefficient estimates for average changes in proportion of non-home CBGs visited in the city between April–December 2020 for highest and lowest SEI quintile CBGs. Whiskers denote 95 % confidence intervals.

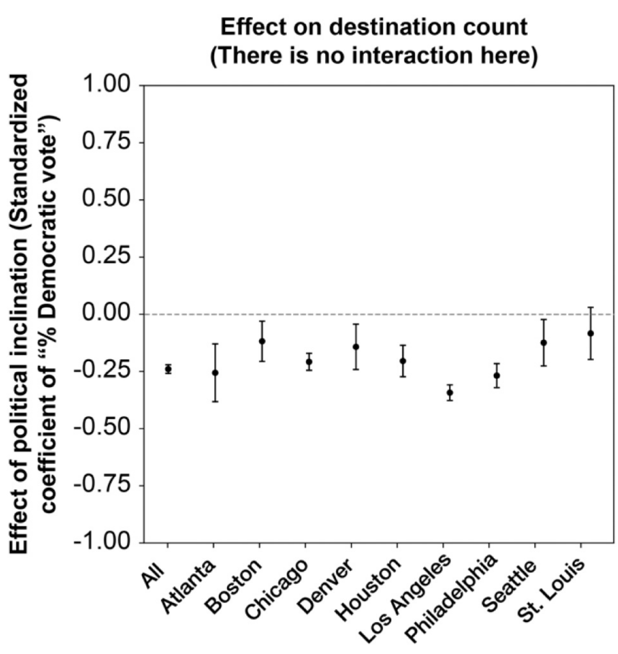

Fig. 4. City-specific standardized estimates of the effect of political inclination on pandemic-induced change in destination count between April–December 2019–2020.
Note: Whiskers denote 95 % confidence intervals.

95 % confidence, except for 90 % in St. Louis). This suggests that political ideology does not merely impact travel in strongly Democratic cities, such as Boston or Los Angeles, but even within cities that have an overall Republican leaning. Houston TX, for instance, had an overall 74 % support for Trump in the 2020 election, but those CBGs within Houston that were leaning more towards Biden, exhibited a more cautionary travel behavior according to our data.

4. Discussion

Despite city-specific heterogeneity in the highest and lowest SEI groups' mobility prior to the pandemic, our findings highlight that during the pandemic, lowest-SEI groups universally traveled the largest distances and visited the most destinations in each of the nine cities we analyzed. During extraordinary circumstances, mobility privilege that comes with higher SEI is manifested by a greater freedom to choose whether and where to travel. Longer trips to more destinations among lower SEI groups during the pandemic, including a higher rate of retail visits, and a lower rate of park and healthcare visits, aligns with prior work suggesting that essential- and service-sector workers continued to travel for employment, family-care, and sustenance during the public-health emergency, while middle- and higher-income populations could more readily work and organize childcare from home (Dimke et al., 2020; Ruiz-Euler et al., 2020).

Our results also highlight that the mobility gap is more complex than simply the higher income group traveling more before the pandemic and less during the pandemic. Spatial characteristics of neighborhoods such as higher levels of walkability and transit accessibility impact travel outcomes beyond income or socio-economic status and the directionality of such impacts was further affected by the pandemic. In 2019, before the pandemic, we observed that living in a transit-served neighborhood was related to lower trip lengths and a higher proportion of city-wide CBGs reached, on average across all SEI groups, but *longer* trip lengths among the high SEI groups. This suggested that high SEI residents living in transit-rich areas may be benefitting from other attractive neighborhood qualities that come with density and transit access, while still using private automobiles for most of their travel. During the pandemic, even average residents living in a transit-served neighborhood reduced their trip distance less than an average resident in a transit-poor area, suggesting a broader shift to automobile travel in transit-oriented areas during the public health emergency. This signals a long-term challenge to regain trust and re-establish habits of using public transportation in U.S. cities across income and class spectra.

Residing in more walkable and amenity-rich neighborhoods, on the other hand, was correlated with overall reductions in trip lengths and travel extents before the pandemic, but again the effect clearly differed by socio-economic class—living in a more walkable area further reduced trip lengths and city-wide travel for high SEI residents, who could afford to patronize local amenities. We did not observe any WalkScore effect for trip lengths and city-wide travel extents for lowest SEI residents, who may be priced out of more expensive amenities in walkable neighborhoods or because their amenity-needs are under-represented in walkable neighborhoods, and whose mobility range thus remained unaffected. The same difference persisted during the pandemic—we found that living in more walkable areas further reduced travel for the highest SEI residents during the pandemic, but not the lowest SEI residents. Among the latter, living in high WalkScore areas was in fact related to a larger reduction in retail trips than for other lowest SEI residents who do not live in walkable neighborhoods. Our findings suggest that while living at a more walkable location does generally benefit higher-SEI groups by reducing their need to travel further to access destinations, it does not necessarily benefit lower-SEI groups in a similar way. Given that our data shows aggregated CBG-level outcomes, it is possible that individual low-SEI persons residing in high SEI blocks, or vice versa, could experience different outcomes. However, the idea of simply affording a home in "high-opportunity" neighborhoods may not equalize local accessibility and mobility outcomes without other supportive policies, such as affordable commercial amenities. The unaffordability of smaller-scale neighborhood amenities could push low SEI residents to travel further to big-box retail destination. Such mitigating neighborhood influences on mobility outcomes of different socio-economic groups have been under-examined so far and our findings call for more research.

In line with prior research that has explored the effect of political ideologies and religious beliefs on compliance with COVID-19 related mobility reduction policies (Chan et al., 2020; Hill et al., 2020a; Hill et al., 2020b), we found that residents of more Democratically leaning CBGs traveled to fewer non-home CBGs in their respective cities city during the pandemic across all nine cities (Table 6), and in each of the cities individually (all coefficients are significant at 95 % confidence, except for 90 % in St. Louis – see Fig. 4). Unlike prior studies, our estimates control for both SEI and location effects, thereby affirming that the pandemic's impact on travel behavior is shaped by social standing, spatial context, and political ideology simultaneously.

Travel behavior outcomes also differed by city—the biggest socio-economic mobility gaps between high and low SEI group during the pandemic were observed in Chicago, Denver, Houston, Los Angeles and Philadelphia, while Seattle and Atlanta exhibited relatively small differences between the highest and lowest SEI groups' travel behavior. Future research could particularly examine why mobility behavior between the highest and lowest SEI groups is remarkably similar in some cities and starkly contrasting in others. Although our descriptive analysis does not identify causal mechanisms that determine mobility gaps within and across American cities, the large datasets on urban mobility and place quality explored here can facilitate further research on such mechanisms.

For urban policy making, our findings suggest that strategic policies and targeted investment are needed to combat mobility inequality in cities. Our findings indicate that lowest SEI groups traveled less than highest SEI groups before the pandemic, largely due to higher reliance on public transportation. This does not suggest corrective policies that would lead to more driving and longer travel distances among the urban poor—quite the opposite. In light of urban climate change goals, policy innovation is needed to reduce driving and longer trip distances among the highest SEI groups in American cities, instead increasing public transit use among them. Our data showed that while living near transit before the pandemic generally explained lower trip distances but wider city-wide travel extents, this was not the case for high SEI CBGs, who instead exhibited longer, likely car-based trips from transit-oriented areas. To counter transit gentrification and achieve more transit ridership across socio-economic class lines, two types of policies are needed: (a) policies that guarantee affordable housing options for lower-income residents—who are already most likely to use transit—close to transit stations, including preservation of existing low rent homes; and (b) policies that induce middle- and higher-income populations to shift from automobile use to transit use. The latter entail more investments into the spatial coverage, frequency and quality of transit services along with more restrictive parking and congestion fees near transit-served inner-city neighborhoods. The COVID-19 pandemic has further reduced transit ridership among all income groups, suggesting that more immediate campaigns and fare incentives to regain trust and re-establish habits for bus and rail travel may be needed.

Our analysis also showed uneven mobility behaviors between the highest and lowest SEI groups who live in more walkable, amenity-rich neighborhoods. While the availability of diverse local destinations in such areas tend to reduce the need for longer journey distances and wider city-wide travel for higher SEI groups, that was not the case for the lowest SEI groups. To address this, affordable housing policies need to be extended to commercial space as well. Ensuring that a certain proportion of commercial space in highly walkable areas is available to community-servicing businesses at below-market rates can help broaden local accessibility to goods and services among lower-income households, thus helping extend the benefits of walkable neighborhoods to more constituents (Sevtsuk, 2020).

Furthermore, since a great deal of travel for households with children involves care-related trips (de Madariaga & Zucchini, 2019), it is also important to ensure public investments into childcare, local public schools and social institutions, such as public libraries, sports and recreational facilities, freely accessible for all. Our analysis showed that higher SEI groups dedicate a higher proportion of trips to parks and health-related destinations than lowest SEI groups, and that this gap notably widened during the pandemic. Ensuring more local access to high-quality parks, health- and social institutions can address mobility inequality at the neighborhoods scale.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.104006.

CRediT authorship contribution statement

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Declaration of competing interest

Authors have no conflicts of interest to declare.

Acknowledgements

We thank SafeGraph for donating data for research purpose and consulting on the use of the dataset. This research was supported by the Bloomberg Harvard City Leadership Initiative, funding by Bloomberg Philanthropies. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of Harvard City Leadership Initiative or Bloomberg Philanthropies. The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

References

Agrawal, A. W., Blumenberg, E. A., Abel, S., Pierce, G., & Darrah, C. N. (2011). *Getting around when you're just getting by: the travel behavior and transportation expenditures of low-income adults (No. CA-MTI-10-2806)*. Mineta Transportation Institute.
Basu, R., & Ferreira, J. (2021). Sustainable mobility in auto-dominated Metro Boston: Challenges and opportunities post-COVID-19. *Transport Policy, 103*, 197–210.
Basu, R., & Ferreira, J. (2021). Planning car-lite neighborhoods: Does bikesharing reduce auto-dependence? *Transportation Research Part D: Transport and Environment, 92*, Article 102721. https://doi.org/10.1016/j.trd.2021.102721
Block, P., Hoffman, M., Raabe, I. J., Dowd, J. B., Rahal, C., Kashyap, R., & Mills, M. C. (2020). Social network-based distancing strategies to flatten the COVID-19 curve in a post-lockdown world. *Nature Human Behaviour, 4*(6), 588–596.
Cabrera-Barona, P., Murphy, T., Kienberger, S., & Blaschke, T. (2015). A multi-criteria spatial deprivation index to support health inequality analyses. *International Journal of Health Geographics, 14*, 11. https://doi.org/10.1186/s12942-015-0004-x. PMID: 25888924.
Cartenì, A., Di Francesco, L., & Martino, M. (2020). How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study. *Science of the Total Environment, 741*, Article 140489.

Chan, H. F., Brumpton, M., Macintyre, A., Arapoc, J., Savage, D. A., Skali, A.Torgler, B., … (2020). How confidence in health care systems affects mobility and compliance during the COVID-19 pandemic. *PloS one, 15*(10), Article e0240644.

Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature, 589*(7840), 82–87.

Chen, J. T., & Krieger, N. (2021). Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county versus zip code analyses. *Journal of Public Health Management and Practice, 27*(1), S43–S56.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S. Vespignani, A., … (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science, 368*(6489), 395–400.

Chowkwanyun, M., & Reed, A. L., Jr. (2020). Racial health disparities and COVID-19—Caution and context. *New England Journal of Medicine, 383*(3), 201–203.

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong social distancing measures in the United States reduced the COVID-19 growth rate: study evaluates the impact of social distancing measures on the growth rate of confirmed COVID-19 caSEI across the United States. *Health Affairs, 39*(7), 1237–1246.

de Madariaga, I. S., & Zucchini, E. (2019). Measuring mobilities of care, a challenge for transport agendas. In *Integrating gender into transport planning* (pp. 145–173). Springer International Publishing. https://doi.org/10.1007/978-3-030-05042-9_7.

De Vos, J., Schwanen, T., Van Acker, V., & Witlox, F. (2013). Travel and subjective well-being: A focus on findings, methods and future research needs. *Transport Reviews, 33*(4), 421–442.

Diez-Roux, A. V., Kiefe, C. I., Jacobs, D. R., Jr., Haan, M., Jackson, S. A., Nieto, F. J., et al. (2001). Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies. *Annals of Epidemiology, 11*, 395–405. PMID: 11454499.

Dimke, C., Lee, M. C., & Bayham, J. (2020). *Working from a distance: Who can afford to stay home during COVID-19? Evidence from mobile device data*. medRxiv.

Gross, C. P., Essien, U. R., Pasha, S., Gross, J. R., Wang, S. Y., & Nunez-Smith, M. (2020). Racial and ethnic disparities in population-level COVID-19 mortality. *Journal of General Internal Medicine, 35*(10), 3097–3099.

Hill, T., Gonzalez, K. E., & Davis, A. (2020). The nastiest question: Does population mobility vary by state political ideology during the novel coronavirus (COVID-19) pandemic? *Sociological Perspectives, 64*(5), 786–803. https://doi.org/10.1177/0731121420979700, 0731121420979700.

Hill, T. D., Gonzalez, K., & Burdette, A. M. (2020). The blood of Christ compels them: State religiosity and state population mobility during the coronavirus (COVID-19) pandemic. *Journal of Religion and Health, 59*(5), 2229–2242.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T.Wu, T., … (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature, 584*(7820), 262–267.

Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the US during the COVID-19 pandemic. *International Journal of Digital Earth*, 1–19.

Jay, J., Bor, J., Nsoesie, E. O., Lipson, S. K., Jones, D. K., Galea, S., & Raifman, J. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour, 4*(12), 1294–1302.

Jay, J., Heykoop, F., Hwang, L., de Jong, J., & Kondo, M. (2021). *Effects of the COVID-19 pandemic on park use in U.S. cities*. https://doi.org/10.1101/2021.04.23.21256007

Jia, J. S., Lu, X., Yuan, Y., Xu, G., Jia, J., & Christakis, N. A. (2020). Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature, 582*(7812), 389–394.

King, D. A., Smart, M. J., & Manville, M. (2019). The poverty of the carless: Toward universal auto access. *Journal of Planning Education and Research, 42*(3), 464–481. https://doi.org/10.1177/0739456X18823252, 0739456X18823252.

Klein, N. J., & Smart, M. J. (2017). Car today, gone tomorrow: The ephemeral car in low-income, immigrant and minority families. *Transportation, 44*(3), 495–510.

Larson, L. R., Zhang, Z., Oh, J. I., Beam, W., Ogletree, S. S., Bocarro, J. N., Lee, K. J., Casper, J., Stevenson, K. T., Hipp, J. A., Mullenbach, L. E., Carusona, M., & Wells, M. (2021). Urban park use during the COVID-19 pandemic: Are socially vulnerable communities disproportionately impacted? *Frontiers in Sustainable Cities, 3*. https://doi.org/10.3389/frsc.2021.710243

Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLoS One, 15*(11), Article e0241468.

Lucas, K. (2012). Transport and social exclusion: Where are we now? *Transport Policy, 20*, 105–113.

Mapbox. (2021). Mapbox Directions API. https://docs.mapbox.com/api/navigation/directions/.

Martens, K. (2016). *Transport justice: Designing fair transportation systems*. Routledge.

Masso, A., Silm, S., & Ahas, R. (2019). Generational differences in spatial mobility: A study with mobile phone data. *Population, Space and Place, 25*(2), Article e2210. https://doi.org/10.1002/psp.2210

Memmott, J., & Bureau of Transportation Statistics. (2007). Trends in personal income and passenger vehicle miles. Bureau of Transportation Statistics special report. Https://Www.Bts.Gov/Archive/Publications/Special_reports_and_issue_briefs/Special_report/2007_10_03/Entire.

Merry, K., & Bettinger, P. (2019). Smartphone GPS accuracy study in an urban environment. *PLoS ONE, 14*(7), Article e0219890. https://doi.org/10.1371/journal.pone.0219890

Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., & Zhang, L. (2020). Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. *Scientific Reports, 10*(1), 1–9.

Pentland, S. (2014). *Social physics*. Penguin Books.

Pew Research. (2021, April 7). Mobile fact sheet. https://www.pewresearch.org/internet/fact-sheet/mobile/.

Reades, J., Calabrese, F., Sevtsuk, A., & Ratti, C. (2007). Cellular census: Explorations in urban data collection. *IEEE Pervasive Computing, 6*(3). https://doi.org/10.1109/MPRV.2007.53

Ruiz-Euler, A., Privitera, F., Giuffrida, D., Lake, B., & Zara, I. (2020). *Mobility patterns and income distribution in times of crisis: US urban centers during the COVID-19 pandemic*. Available at SSRN 3572324.

SafeGraph. (2022). *Determining points of interest visits from location data: A technical guide to visit attribution*. SafeGraph Resources. https://resources.safegraph.com/c/technical-guide-visit-attribution?x=v8-RYh&lx=UFM2aY&dest_url=https%3A%2F%2Fwww.safegraph.com%2Fvisit-attribution&ref_url=https%3A%2F%2Fwww.google.com%2F&dest_url=https%3A%2F%2Fwww.safegraph.com%2Fpost%2Fbeginners-guide-to-census%2F%3Futm_source%3Dcontent%26utm_medium%3Dreferral%26utm_campaign%3Dcolabnotebook%26utm_content%3Dbeginners_census_guide&ref_url=https%3A%2F%2Fcolab.research.google.com%2F.

Sevtsuk, A. (2020). Street commerce. In *Creating vibrant urban sidewalks*. Penn Press.

Sevtsuk, A., & Ratti, C. (2010). Does Urban mobility have a daily routine? Learning from the aggregate data of mobile networks. *Journal of Urban Technology, 17*(1). https://doi.org/10.1080/10630731003597322

Taylor, B. D., & Ong, P. M. (1995). Spatial mismatch or automobile mismatch? An examination of race, residence and commuting in US metropolitan areas. *Urban Studies, 32*(9), 1453–1473. https://doi.org/10.1080/00420989550012348

The Upshot. (2021). Presidential precinct map 2020. https://github.com/TheUpshot/presidential-precinct-map-2020.

Tung, E. L., Cagney, K. A., Peek, M. E., & Chin, M. H. (2017). Spatial context and health inequity: Reconfiguring race, place, and poverty. *Journal of Urban Health, 94*(6), 757–763.

United States Census Bureau. (2020). 2019 TIGER/Line® Shapefiles: Block Groups. https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2019&layergroup=Block+Groups.

United States Census Bureau. (2020). American Community Survey 5-Year Data (2009-2019). https://www.census.gov/data/developers/data-sets/acs-5year.html.

University of Minnesota Center for Transportation Studies. (2019). *Access across America: Transit 2019 Data*. Available at. Accessibility Observatory https://access.umn.edu/data/datasets/index.html. (Accessed 22 June 2021).

Van Dorn, A., Cooney, R. E., & Sabin, M. L. (2020). COVID-19 exacerbating inequalities in the US. *Lancet, 395*(10232), 1243 (London, England).

Vogels, E. A. (2021, June 22). *Digital divide persists even as Americans with lower incomes make gains in tech adoption*. Pew Research Center. https://www.pewresearch.org/fact-tank/2021/06/22/digital-divide-persists-even-as-americans-with-lower-incomes-make-gains-in-tech-adoption/.

Wachs, M., & Taylor, B. D. (1998). Can transportation strategies help meet the welfare challenge? *Journal of the American Planning Association, 64*(1), 15–19. https://doi.org/10.1080/01944369808975952

WalkScore. (2021). Walk Score API. Available at https://www.walkscore.com/professional/api.php. (Accessed 22 June 2021).

Weill, J. A., Stigler, M., Deschenes, O., & Springborn, M. R. (2020). Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proceedings of the National Academy of Sciences, 117*(33), 19658–19660.

Wheeler, D. C., Czarnota, J., & Jones, R. M. (2017). Estimating an area-level socioeconomic status index and its association with colonoscopy screening adherence. *PloS One, 12*(6). https://doi.org/10.1371/journal.pone.0179272. e0179272- e0179272.

Williams, D. R., & Collins, C. (2016). Racial residential segregation: A fundamental cause of racial disparities in health. *Public Health Reports, 116*(5), 404–416. https://doi.org/10.1093/phr/116.5.404

Xiong, C., Hu, S., Yang, M., Younes, H., Luo, W., Ghader, S., & Zhang, L. (2020). Mobile device location data reveal human mobility response to state-level stay-at-home orders during the COVID-19 pandemic in the USA. *Journal of the Royal Society Interface, 17*(173), Article 20200344.

Yancy, C. W. (2020). COVID-19 and African Americans. *JAMA, 323*(19), 1891–1892.

Zhao, H., Harris, R. J., Ellis, J., & Pebody, R. G. (2015). Ethnicity, deprivation and mortality due to 2009 pandemic influenza A (H1N1) in England during the 2009/2010 pandemic and the first post-pandemic season. *Epidemiology & Infection, 143*(16), 3375–3383.