

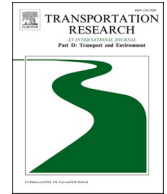


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# Transportation Research Part D

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## Public transit cuts during COVID-19 compound social vulnerability in 22 US cities

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### ABSTRACT

The COVID-19 pandemic has severely impacted public transit services through plummeting ridership during the lockdown and subsequent budget cuts. This study investigates the equity impacts of reductions in accessibility due to transit service cuts during COVID-19 and their association with urban sprawl. We evaluated transit access to food and health care services across 22 US cities in three phases during 2020. We found stark socio-spatial disparities in access to basic services and employment in food and health care. Transit service cuts worsened accessibility for communities with multiple social vulnerabilities, such as neighborhoods with high rates of poverty, low-income workers, and zero-vehicle households, as well as poor neighborhoods with high concentrations of black residents. Moreover, sprawled cities experienced greater access loss during COVID-19 than compact cities. Our results point to policies and interventions to maintain social equity and sustainable urban development while benefiting diverse social groups during disruptions.

### 1. Introduction

For decades, economically and racially marginalized communities in the US have experienced hurdles in accessing basic opportunities such as jobs, schools, health care, food, and other daily activities (Allcott et al., 2019; Elmes, 2018; Mouw and Kalleberg, 2010; Yearby, 2018). The greater vulnerability of these communities exposed them to disproportionate risks during the COVID-19 pandemic (Bowleg, 2020; Patel et al., 2020). Previous studies revealed that marginalized populations are not only at a higher risk of experiencing health-related impacts (e.g., higher infection and death rates) but are also more prone to the socio-economic consequences of the pandemic, such as job losses, food insecurity, and mental stress (Abedi et al., 2020; Bowleg, 2020; Dorn et al., 2020; Kar et al., 2021; McLaren, 2020; Montenovio et al., 2020; Saenz and Sparks, 2020).

Accessibility refers to the ease of reaching destinations (e.g., jobs or services) from key travel origins, such as home (Levinson and Wu, 2020). Transit accessibility measures the ability to do so using transit services, and therefore depends on the transit network, schedules, and urban form (Lei and Church, 2010; Murray and Wu, 2003; O'Sullivan et al., 2000). While most trips in the US are made by car, access to transit is essential for equity, as transit-dependent people are predominantly people with low incomes and minorities

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(Florida, 2019). Good access to transit also raises ridership among people who have limited travel options (Lucas et al., 2018; Pathak et al., 2017; Wang and Woo, 2017) and improves employment outcomes (El-Geneidy et al., 2016; Sanchez, 1999; Stokes and Seto, 2018; Yi, 2006). Therefore, maintaining public transit access to jobs and other essential services is crucial in ensuring sustainable mobility and social equity.

The pandemic negatively affected public transit services of US cities, leaving their survival at stake. According to the National Transit Database (U.S. Department of Transportation, 2019a), transit supply, measured in vehicle revenue miles, increased across the US by an average of 1.5% annually from 2010 through 2018. After a small drop of 2% in 2019, this number dropped by another 10% in 2020 compared to 2019 (U.S. Department of Transportation, 2020, 2019b). While possibly exacerbated by budget cuts that predated the pandemic, this substantial reduction of services in 2020 was most likely a result of the COVID-19 pandemic. Several studies showed that transit use is not a major means of disease transmission if proper sanitization procedures and face mask requirements are in place (Tirachini and Cats, 2020). Yet, transit ridership declined significantly during COVID-19, due to the closure of businesses, teleworking, and fears among transit users of possible transmission, especially those with prior experiences of crowding (Cho and Park, 2021; Hu and Chen, 2021; Liu et al., 2020). In response to lower transit demand and financial constraints, transit agencies adopted various measures, such as limiting service coverage and routes, reducing schedules, and modifying fare collection methods (DeWeese et al., 2020; Tirachini and Cats, 2020). These changes during COVID-19 have reduced the ability of transit systems across the US to provide adequate services and have raised questions about their ability to recover from the current shock and their resilience to future shocks (Quiroz-Gutierrez, 2021; Snyder, 2021).

Few studies have investigated the equity outcomes of transit service cuts during COVID-19 (DeWeese et al., 2020) and their association with urban form. We aim to address this gap while focusing on access to food and health care as indicators of employment opportunities and essential services. Our objectives are to (1) identify social vulnerabilities induced by transit service cuts and the subsequent loss of access to food and health care during COVID-19, and (2) elicit the association between urban sprawl and reduction in accessibility due to transit service cuts. Here, we quantified transit-based access to food and non-urgent and urgent health care within 30 and 45 minutes traveled for all census block groups in the study areas. Our analysis accounts for the peak and off-peak periods separately due to different frequencies of service. To quantify losses in transit-based access, we consider three phases of the pandemic response in 2020, namely, the pre-lockdown (January–February), lockdown (March–June), and post-lockdown phase (November–December). Losing transit access means that a block group had access to a health care or food establishment by transit within 30 or 45 minutes of total travel time before COVID-19 but no longer had this access during or after COVID-19. In addition, we also quantified the percentage of block groups in each study area that lost transit-based access in the lockdown and post-lockdown phases, using the same travel time thresholds to evaluate its relationship with urban sprawl.

## 2. Background

Accessibility is a key performance indicator of urban transportation systems (El-Geneidy and Levinson, 2006). Accounting for mobility within the network and the spatial distribution of opportunities, accessibility is used to measure the ability to reach essential services from travelers' homes, workplaces, or other destinations (Levinson and Wu, 2020). Measuring transit accessibility requires a systematic integration of spatial and temporal coverage of transit services and cost functions associated with its users (e.g., travel time, transit fare) (Lei and Church, 2010). Transit accessibility often considers four key factors: (1) destination attractiveness considering the spatial distribution of opportunity locations and service quality, (2) transit service characteristics (e.g., availability of transit stations, routes, reliability, and cost of using transit service), (3) temporal constraints (e.g., conflicts in transit schedule, operations hours of opportunity locations, and travel time budget of transit users), and (4) socio-economic characteristics of transit users (Malekzadeh and Chung, 2020). Mapping isochrones is a popular network-based space–time approach to quantifying transit accessibility (Higgins et al., 2022; Lei and Church, 2010; O'Sullivan et al., 2000). An isochrone is an area reachable from a specific location given a travel time threshold or other cost parameters and mode-specific criteria (Lei and Church, 2010; Levinson and Wu, 2020; O'Sullivan et al., 2000).

Past studies underscored transit accessibility as an indicator of urban social equity, especially in the context of food and health care access (El-Geneidy et al., 2016; Farber et al., 2016; Lee and Miller, 2019). These two essential services were among the few that were allowed to operate during the pandemic, especially the lockdown periods (Parks et al., 2020). Among all essential workers, 20.6% and 30.2% are employed in food and agriculture and the health care industries (McNicholas and Poydock, 2020). These two industries are also home to many low-to-mid level income jobs (Anderson and Laughlin, 2020; Wolfe et al., 2020). The majority of the workforce employed in food and health care belongs to marginalized communities and earns slightly above the minimum wage (\$11–14 per hour) (Anderson and Laughlin, 2020; McNicholas and Poydock, 2020). Similarly, two-thirds of health care service jobs require low skills, and workers employed in those jobs earn less than \$15 per hour and have no health insurance (Frogner et al., 2016). Given their limited income and other financial barriers, this part of the workforce is more likely to be public transit users whose access to job destinations was affected by changes in transit services during COVID-19.

Many studies have found that a large proportion of low-income and racial minority populations rely on public transit for food shopping and health care services (Hirsch and Hillier, 2013; Shannon and Christian, 2017; Wolfe et al., 2020). For instance, while most people primarily drive, car usage for grocery shopping is significantly low among low-income people and people residing in core urban areas (Shannon and Christian, 2017). Hirsch and Hillier (2013) found that 24% of households who lack access to nearby food stores use public transit for small-scale grocery shopping in Philadelphia, PA. Shannon and Christian (2017) found that households with no vehicle ownership perform only 38% of their food shopping trips using cars in Minneapolis and St. Paul, MN. Similar to food shopping, lack of access to alternative transportation services disproportionately affects recipients of health care services. Approximately 5.8 million people in the US were unable to receive timely treatment in 2017 due to transportation barriers accompanied by physical

health challenges; a majority of this group belongs to the low-income and racial and ethnic minority communities (Wolfe et al., 2020). Hence, public transit access can benefit both employees and consumers of these services.

The vulnerability of public transit to disruption during pandemics and other shocks has greatly affected marginalized populations due to their transportation disadvantages and heavy reliance on transit services. The decline in transit use during COVID-19 was found to be the lowest among low-income, less educated, non-white, and female riders (Brough et al., 2020; Hu and Chen, 2021; Liu et al., 2020); many were essential workers employed in industries such as food and health care that cannot easily accommodate working from home (Parks et al., 2020). As a result, transit service cuts may exacerbate pre-existing social and economic vulnerabilities: on the one hand, service reductions impede work-related travel, increasing the potential for job losses and financial hardship in marginalized communities, as well as a loss of workforce and productivity for society at large (Sanchez, 1999; Stokes and Seto, 2018; Yi, 2006). On the other hand, a lack of access to healthy food and health care can result in nutritional deficiencies, poor health, lack of productivity, and diminished community well-being (Barrett, 2010; Decker and Flynn, 2018; Gundersen and Ziliak, 2015).

In addition, COVID-19 highlights some major deficiencies in US urban systems and current planning practices (Acuto, 2020; Hamidi et al., 2020). Provisioning public transit services is not cost-effective in US cities with sprawled, low-density development, and multi-jurisdictional governance (Burchell and Mukherji, 2003; Carruthers and Ulfarsson, 2003; Gielen et al., 2021). The expansion of highways and continued development outside of urban cores have led to residents, jobs, and services moving to suburbs with more reliance on private vehicles. Moreover, this horizontal expansion of cities resulted in ongoing challenges for transit systems that must contend with declining funding and corresponding needs for cost-cutting to cover an ever-increasing service area (Hortas-Rico, 2014; Richiedei and Tira, 2020; Sakowicz, 2003). Historically, sprawling urban development left low-income and vulnerable populations in deteriorating urban neighborhoods (Ewing et al., 2003), but more recently, less affluent populations have been moving more into suburban areas due to gentrification and decreasing affordability of inner-urban neighborhoods in many jurisdictions (Allen and Farber, 2020a; Schleith et al., 2016). As a consequence, the mobility of marginalized communities is further compromised due to limited transportation options (e.g., lack of public transit services) and longer travel times, in turn limiting access to jobs, services, recreation, and social interaction (Allen and Farber, 2020a; Schleith et al., 2016; Wang et al., 2018).

### 3. Methods

#### 3.1. Data

##### 3.1.1. Public transit data

We selected 22 cities for this study based on the availability of General Transit Feed Specification (GTFS) data and with the goal of obtaining a mix of cities of different sizes. The cities include Ann Arbor (MI), Atlanta (GA), Austin (TX), Boston (MA), Champaign-Urbana (IL), Chicago (IL), Columbus (OH), Dallas (TX), Denver (CO), Los Angeles (CA), Louisville (KY), Madison (WI), Miami (FL), Nashville (TN), New York City (NY), Philadelphia (PA), Phoenix (AZ), Portland (OR), San Jose (CA), Seattle (WA), San Francisco (CA), and Salt Lake City (UT). In each city, we included all transit modes (i.e., bus, subway, light rail, and cable tram) for which data were available. We integrated data for bus and rail networks in the same city to generate a multimodal transportation network for the estimation of travel isochrones. This approach ensured that we captured transit connectivity where riders had the option to transfer between modes. We obtained static GTFS data with information about transit routes, stops or stations, schedules, and transfers from the OpenMobilityData website (GTFS, 2020), and road network data from OpenStreetMap (OSM) (OpenStreetMap, 2020).

Based on the changes in transit services in 2020, we defined three phases of pandemic response, namely pre-lockdown, lockdown, and post-lockdown, to examine the temporal variation of transit service coverage. The pre-lockdown phase extends from January to February, as all states in our study began issuing official stay-at-home orders in March 2020, except for the states of Massachusetts and Texas (Moreland et al., 2020). However, the goal of this study is to evaluate pandemic-induced changes in transit supply, not in transit demand. We designated March to June as the lockdown phase since the transit services in the study areas, measured by their number of routes, experienced the largest declines during this time window and therefore were least accessible to their users. Also, the official stay-at-home orders ended by June 2020 in most states (Moreland et al., 2020; USA Today, 2021). During June 2020, some social distancing restrictions were still in effect, and states adopted phase-based reopening plans. Considering these reopening plans, businesses and services in different states took different amounts of time to reopen and become operational. Therefore, our post-lockdown phase extends from November to December, allowing for sufficient time after the lockdown phase for transit agencies to adopt recovery measures (if any) and adjust to the post-pandemic environment.

We used the same time windows for the lockdown and post-lockdown phases for all cities to ensure consistency. These same time windows also allowed us to consider the geographically varying rates of COVID-19 transmission and fluctuating numbers of cases, as well as delayed responses from agencies in light of the uncertainty. However, we used the number of routes as an indication of transit supply during all phases. Within the three time windows, we set some criteria to choose specific dates separately for each agency to quantify their transit service in the respective phase. These criteria are as follows: (1) pre-lockdown period: a date on which the highest number of transit routes were served, (2) lockdown period: a date on which the lowest number of transit routes were served, and (3) post-lockdown period: a date on which the highest number of transit routes was served. To measure accessibility provided by transit on a regular weekday, we selected a Tuesday, assuming that all weekdays followed the same transit schedule. If multiple Tuesdays fulfilled the criteria, we used the first such Tuesday to perform our analysis. Table S1 in the Supplemental Information (SI) provides the full information on transit agencies and dates used in this study.

### 3.1.2. Food and health care location data

In this study, access to food represents peoples' ability to reach grocery stores that carry a wide assortment of fresh and healthy food products. We obtained the locations and business data of grocery stores for each city from InfoGroup (InfoGroup, 2019). We filtered grocery stores based on the North American Industry Classification System (NAICS) code, retailer brand names, and scale of businesses. The grocery stores used in this study represent the top 10th percentile of supermarkets and grocery stores based on the employee size and sales volume of each store across 22 cities (SI Table S2). We also included warehouse clubs, supercenters, and department stores that sell grocery products, namely, Walmart, Target, Costco Wholesale, Sam's Club, and BJ's. We collected health care locations from InfoGroup as well. We classified the locations into urgent (general hospital and emergency care services) and non-urgent health care facilities (specialty hospitals and primary care services) based on their NAICS code (SI Table S3). Our study areas contain many primary care and emergency care facilities that are spatially clustered. To reduce the computational burden, we generated clusters using the DBSCAN clustering approach (Campello et al., 2013; Hahsler et al., 2019) on these two datasets. The detailed food and health care location selection criteria are discussed in SI Section 2.

### 3.2. Measuring accessibility to food and health care

We analyzed changes in transit-based accessibility to food, urgent, and non-urgent health care across the 22 cities. We generated a half-mile buffer around each transit stop (approximately 10 minutes walking distance), based on the local transit network during the pre-lockdown period. We defined the following criteria to generate isochrones of travel time (i.e., accessibility): (1) travelers only use transit and walking, and walk no more than half a mile to and from transit stops, and (2) travelers transfer no more than once, with transfers lasting no more than 5 minutes.

For each city, we generated 30 and 45-minute isochrones around each grocery store and urgent or non-urgent health care facility for the peak and off-peak hours of each study phase. We used 9 AM – 10 AM as the time window representing peak hours and 1 PM – 2 PM for the off-peak hours, and sampled isochrones for both hours using 10-minute intervals. Finally, we represented accessibility as a geometric average of the sample isochrones for peak or off-peak hours for each destination to account for variation in transit frequencies and wait times. The process of generating and processing isochrones is discussed in SI Section 3.

### 3.3. Quantifying equity impacts of public transit service changes

We extracted socio-economic information at the census block group level from American Community Survey (ACS) 5-year estimates (2014–2018) and the Environmental Protection Agency's Smart Location Database (Ramsey and Bell, 2014; US Census Bureau, 2020) (SI section 4).

For each city, we examined the individual effects of each socio-economic variable on the changes in transit-based access to food and health care during peak and off-peak hours of lockdown and post-lockdown phase. First, we estimated the percent change in accessible area compared to the total block group area for each block group in the study areas. The data follow a highly skewed distribution with zero values accounting for 56–67% of the total observations. We applied Kruskal-Wallis (KW) test, a non-parametric equivalent to one-way ANOVA, to compare the mean rank of the variable of interest (i.e., percent change of accessible area in each block group) across socio-demographic groups. As socio-demographics are continuous variables, we used the quartile values to categorize each socio-economic variable into four groups. We ran the tests separately for each city given their difference in socio-demographic compositions.

KW tests have several limitations: (1) they do not accommodate interaction terms, (2) they rely on the assumption that the distributions of the compared groups follow the same shape, which did not hold in many cases in our dataset, (3) the categorization of socio-economic variables into quartile leads to unavoidable information loss, and (4), the significant results only mean that at least one group is different from the other groups, but do not identify which one. Therefore, we conducted additional analyses to investigate the interacting effects between multiple socio-economic hardships and overcome the potential bias that was introduced by the violation of the KW test assumption.

Specifically, we used separate multilevel binary logit models to estimate the equity impacts of transit cuts during peak and off-peak hours in the lockdown and post-lockdown phases. In all cases, the reference was the pre-lockdown phase. We estimated separate models for each period of transit operation (peak and off-peak), destination type (groceries, urgent health care, and non-urgent health care), and phases of the pandemic response (lockdown and post-lockdown) using travel time thresholds of 30 (for main analysis) and 45 minutes (for sensitivity analysis). In each model, our dependent variable was a binary variable denoting whether a block group lost accessibility to the specific destination type during the specified period. While the binary measure may lead to some information loss, it allows us to overcome the complication of modeling zero-inflated, highly-skewed data in the multilevel regression framework.

We assigned a binary value of accessibility loss (0 or 1) for each block group. A block group received a value of 0 (no loss in accessibility) if more than 30% of the block group area had access to the specific destination type during the pertinent transit operation hours (e.g., peak hour) and pandemic response phase (e.g., lockdown phase), and 1 (loss in accessibility) otherwise. The two-level multilevel models include block group-level socio-economic variables for level 1, along with several interaction terms: *low-income workers* with *no-vehicle households*, *poverty rate* with *no-vehicle households*, *poverty rate* with *black populations*, and *black populations* with *no-vehicles* as independent variables. Cities were coded as group-level factors (level 2), using random intercepts to examine the differences in the probability of losing access among cities. Each independent variable was normalized to a z-score value.

The model applies a logit link function to estimate the probability  $p$  of losing access  $y$  for a block group  $i$  in a city  $j$ . The dependent variable (transit access loss) is:

$$y_{ij} = \text{logit}(p_{ij}) = \log\left[\frac{p_{ij}}{1 - p_{ij}}\right]$$

Equation (1) is the first level of the multilevel model:

$$y_{ij} = \beta_{0j} + \beta_i X_{ij} + e_{ij}, \quad e_{ij} \sim N(0, \sigma^2) \tag{1}$$

where,  $\beta_{0j}$  is the random intercept that varies by city  $j$ ;  $\beta_i$  is the coefficient for the block-group-level socio-economic variables  $X_{ij}$ ; the error term  $e_{ij}$  is assumed to be normally distributed with a mean value of 0 and variance  $\sigma^2$ .

Equation (2) is the second level of the multilevel model:

$$\beta_{0j} = \gamma_0 + \gamma_j, \quad \gamma_j \sim N(0, \tau^2) \tag{2}$$

where  $\gamma_0$  is the overall intercept of the model; the error term  $\gamma_j$  represents the deviation in intercept for city  $j$  and follows a normal distribution with a mean value of 0 and variance  $\tau^2$ .

The combined multilevel model is:

$$y_{ij} = \gamma_0 + \gamma_j + \beta_i X_{ij} + e_{ij} \tag{3}$$

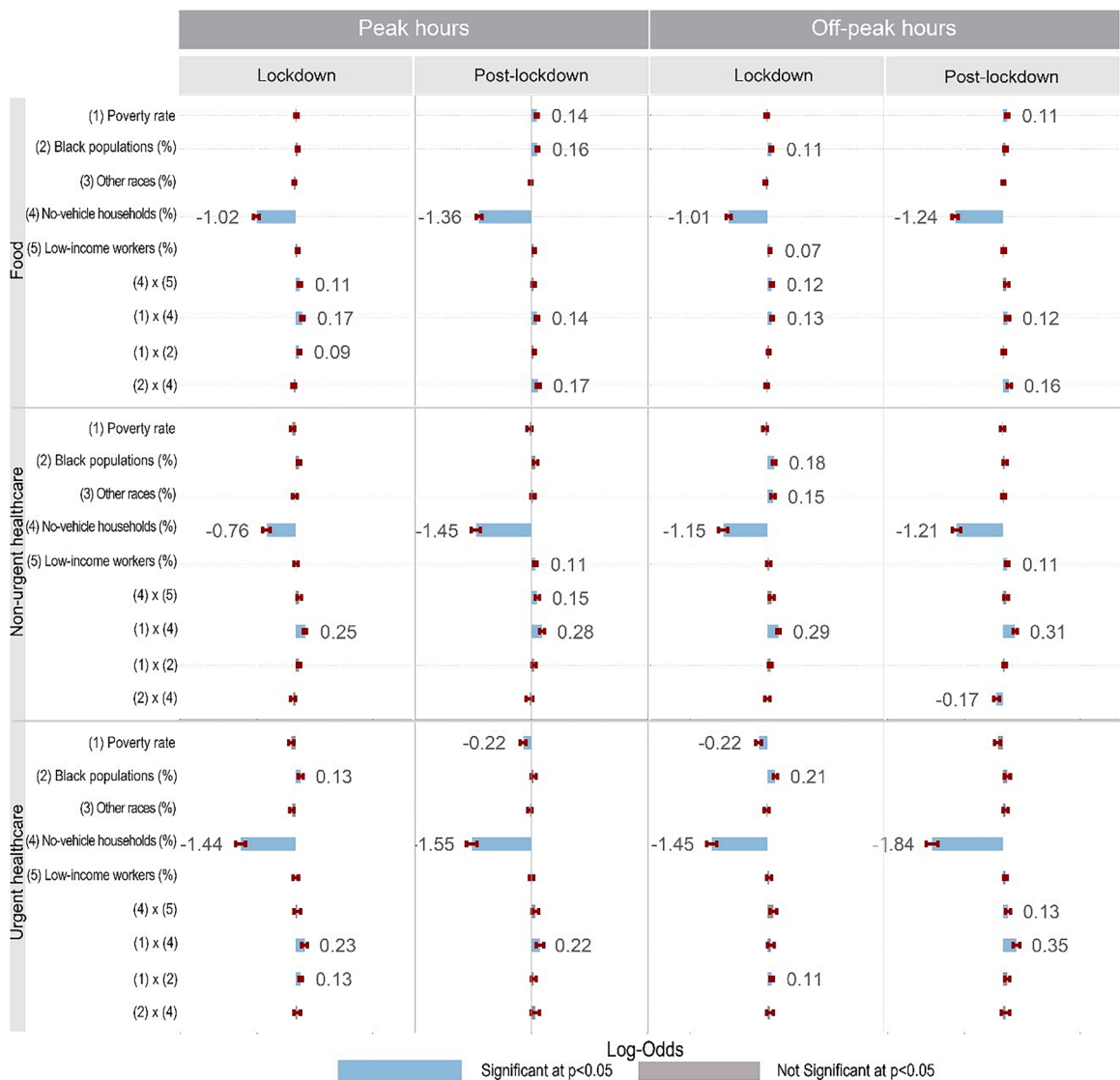


Fig. 1. Likelihood of losing transit access to food and health care facilities during COVID-19. Notes: Coefficients were estimated from multilevel binary logit models using a travel time threshold of 30-minutes from food and health care facilities. Red bars represent confidence intervals.

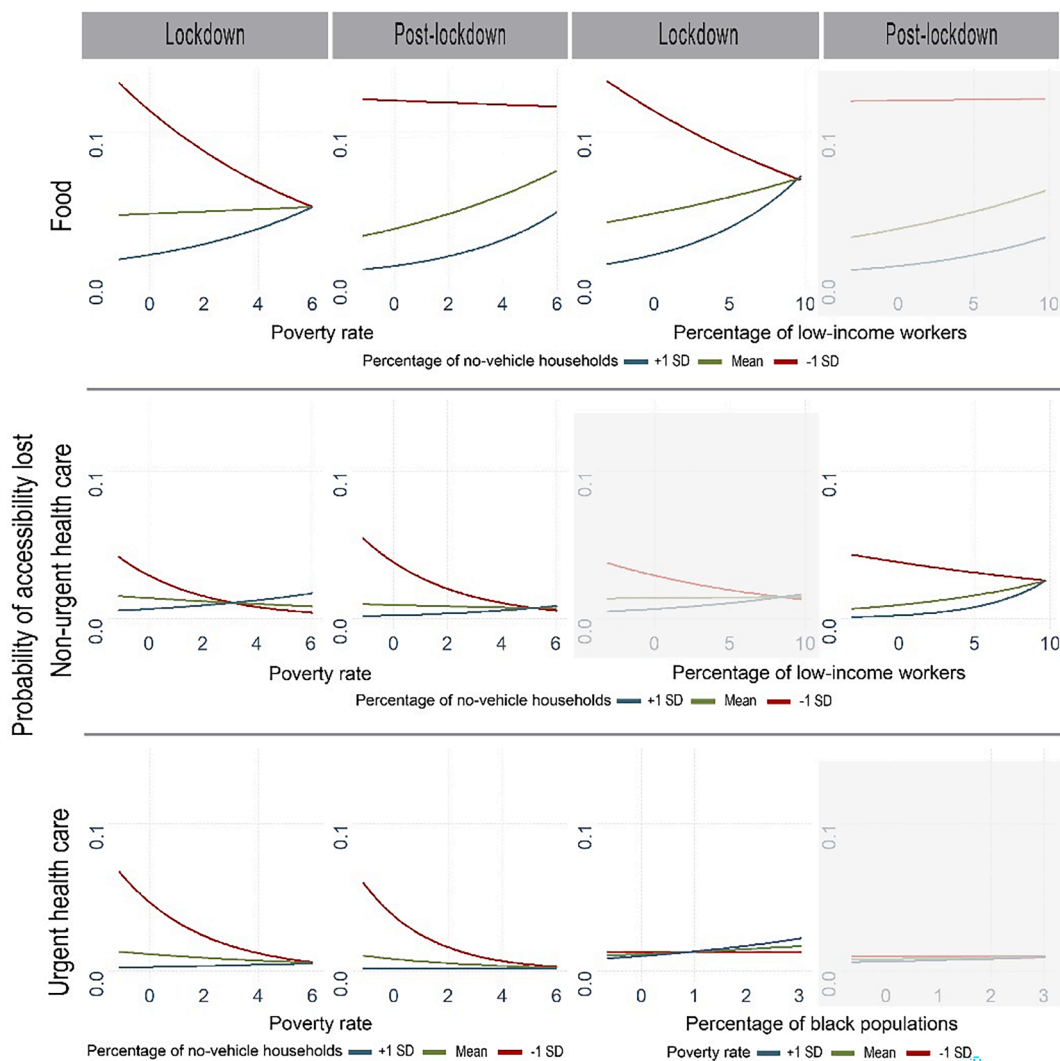
### 3.4. Evaluating the relationship between urban sprawl and accessibility reduction

Our study areas somewhat deviate from administrative city boundaries, as they are the service areas covered by each transit agency. We derived the urban sprawl index for each study area as an inverse of the area-weighted average of county-level compactness data (Ewing and Hamidi, 2014).

We acquired the urban compactness dataset from the National Cancer Institute (NCI) (Ewing and Hamidi, 2014). The NCI used the following indicators to determine a compactness factor: development density, land use mix, population and employment centering, and street accessibility. In the NCI dataset, the value of the compactness factor is converted to a composite compactness index with a mean of 100 and a standard deviation of 25. Here, a composite value greater than 100 indicates a higher level of compactness, while an index less than 100 indicates more sprawl. We obtained these NCI composite compactness indices at a county level and calculated their area-weighted average for each study area  $j$  as shown in equation (4):

$$C_j = \frac{\sum_{i=1}^n C_i A_i}{\sum_{i=1}^n A_i} \tag{4}$$

where  $C_j$  denotes the area-weighted composite compactness index for study area  $j$ ,  $n$  denotes the number of counties with service coverage in the pre-lockdown phase,  $C_i$  represents the composite index of county  $i$ , and  $A_i$  represents the total block group area within



**Fig. 2.** Peak period: Interactions between socio-economic variables in predicting the probability of decreased accessibility during peak hours in the lockdown and post-lockdown phases. Notes: Vertical axes show the likelihood of reductions in accessibility, given different combinations of socio-economic variables in the x-axes. Variables on the x-axis are calculated as the normalized z-score at the census block group level. Grey boxes represent insignificant interactions for one out of two phases (lockdown and post-lockdown). Significance is indicated at the  $p < 0.05$  level. Insignificant interactions for both phases are not shown.

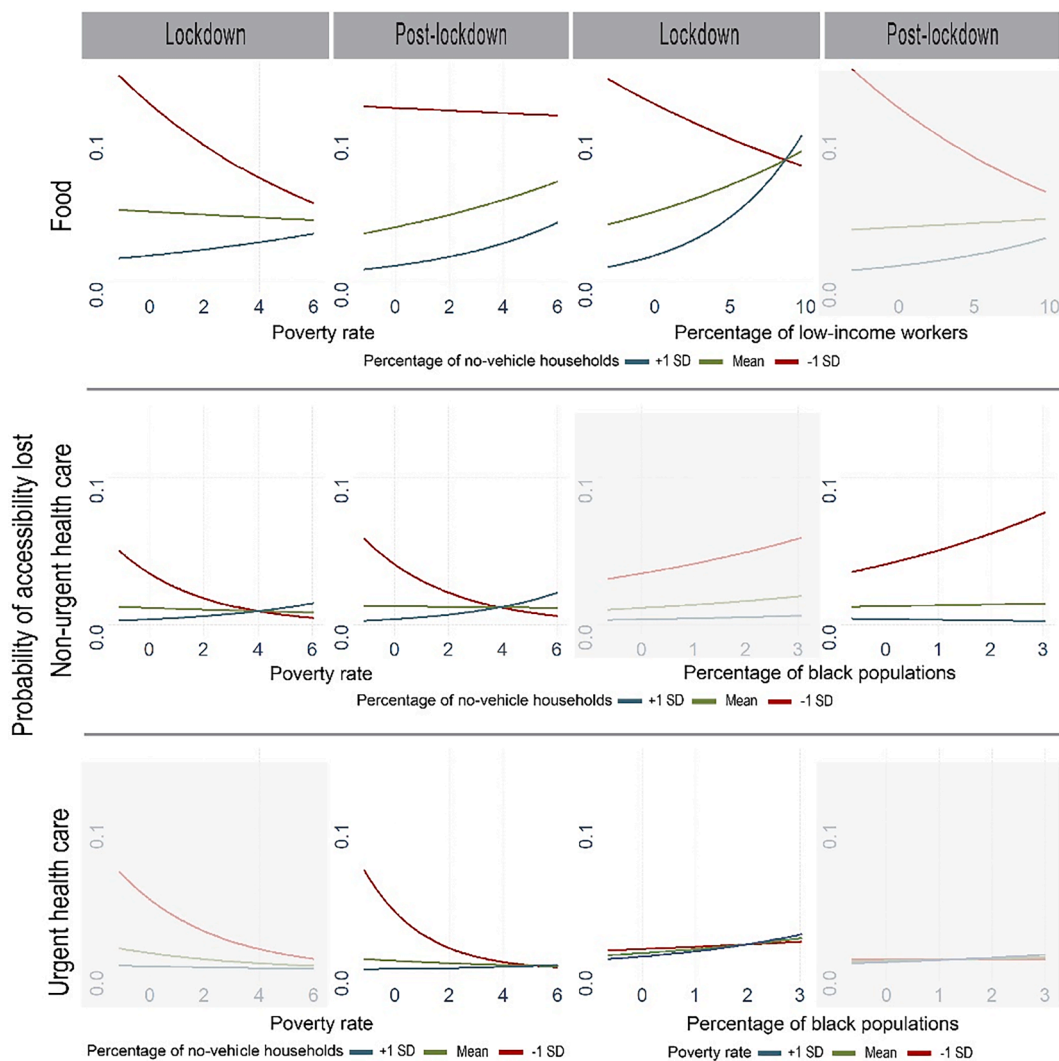
county  $i$  with service coverage in the pre-lockdown phase.

We estimated the urban sprawl index for each study area as an inverse of the area-weighted composite compactness index. Hence, the urban sprawl indices in our study areas vary from 0.004 to 0.009, where a higher value indicates greater sprawl and a lower value refers to compact study areas.

Finally, we estimated the percentage of block groups of each study area that experienced a reduction in accessibility during the peak and off-peak periods of the lockdown and post-lockdown phases compared to the pre-lockdown phase using travel time thresholds of 30 and 45 minutes. We then tested the association between the urban sprawl index and the percentage of block groups with reduced accessibility for our study areas using Spearman's rank-order correlation test.

### 3.5. Robustness check

The methods discussed in sections 3.2 to 3.4 was performed using two travel time thresholds of 30 and 45 minutes. We used our accessibility measures using a 30-minute threshold for the main analysis and compared the results with accessibility measures of a 45-minute threshold for checking the robustness of our study findings.



**Fig. 3.** Off-peak period: Interactions between socio-economic variables in predicting the probability of decreased accessibility during off-peak hours in the lockdown and post-lockdown phases. Notes: Vertical axes show the likelihood of reductions in accessibility, given different combinations of socio-economic variables in the x-axes. Variables on the x-axis are calculated as the normalized z-score at the census block group level. Grey boxes represent insignificant interactions for one out of two phases (lockdown and post-lockdown). Significance is indicated at the  $p < 0.05$  level. Insignificant interactions for both phases are not shown.



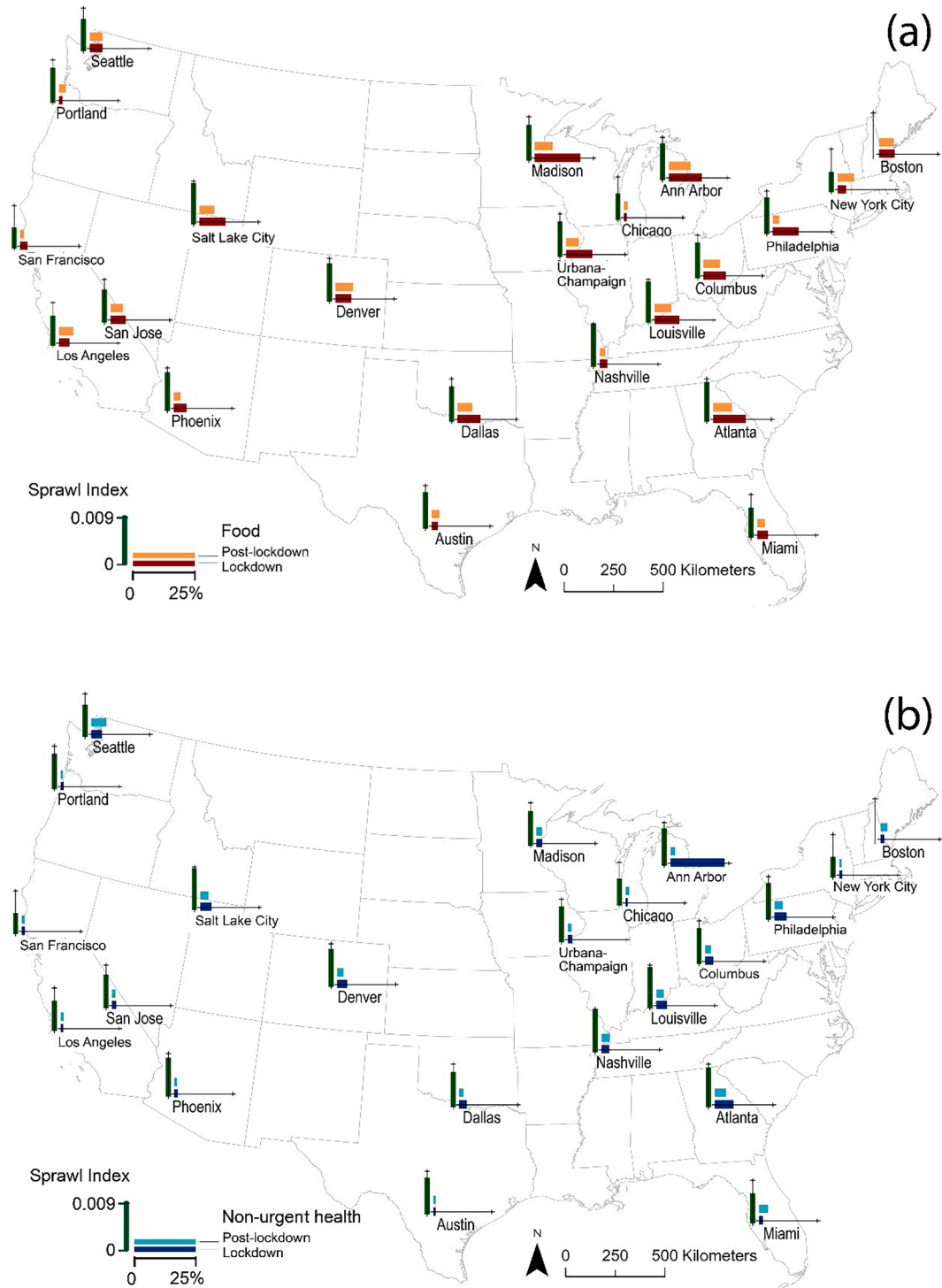


Fig. 4. Probability of losing transit access in the lockdown and post-lockdown phases (peak hours). Notes: Horizontal bars on the right represent the probability of losing access to food (a), non-urgent (b), and urgent health care (c). Vertical green bars represent the urban sprawl index. Whiskers on both axes represent the maximum values of urban sprawl and the probability of losing transit access. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



Fig. 4. (continued).

## 4. Results

### 4.1. Social vulnerabilities induced by transit service cuts

Descriptive statistics are shown in Table S5–S7 in the SI. According to the KW tests, the mean percentage changes of accessible area significantly vary across the four quartile groups of most socio-economic variables (Table S8), especially for large cities such as Boston, Chicago, Dallas, Denver, Los Angeles, Miami, New York, Philadelphia, and Phoenix. For the rest of the mid-size and small-scale cities, block groups categorized by poverty rates, percentages of black populations, and zero-vehicle ownership indicate significant differences in their losses in transit access for most cases.

Fig. 1 shows the results from the multilevel binary logit models of access loss from food and health care facilities within 30 minutes travel time. All variables were measured at the census block group level. The goodness of fit statistics of these models are discussed in SI Table S9. The models indicate a high likelihood of losing transit access to food and health care services for vulnerable populations, especially when considering the interaction effects (Fig. 1). Figs. 2 and 3 further elaborate the interactions between socio-economic variables in predicting the probability of decreased accessibility during peak and off-peak hours in the lockdown and post-lockdown phases. The direction, magnitude, and interaction patterns of these variables during peak and off-peak hours are similar. It is noteworthy that this loss of access affects not only grocery customers and health care patients, but also employees who operated these essential services during the pandemic. A web map of accessibility changes in all cities during the study periods is available at <https://arcg.is/05qP5z>.

Block groups with socio-economic disadvantages, such as high poverty rates and large shares of black populations, were more likely to lose access overall (Fig. 1). Additionally, social vulnerabilities appeared to compound: block groups with multiple social disadvantages experienced a higher likelihood of losing accessibility during both peak and off-peak hours (Figs. 1, 2 and 3). The likelihood of losing access was higher in block groups with two socio-economic factors in play, such as poverty, low incomes, high shares of black populations, and lack of a vehicle (Figs. 2 and 3). Although the percentages of zero-vehicle households alone imply a negative effect on transit-based access loss (Fig. 1), increases in its share in high poverty block groups were associated with a higher likelihood of losing transit services during the peak and off-peak hours of all study phases (Figs. 2 and 3). Similarly, block groups with high percentages of low-income households and zero-vehicle ownership were more vulnerable considering their access to food during peak and off-peak hours of the lockdown phase (Figs. 2 and 3) and access to non-urgent health care during post-lockdown peak hours (Fig. 2).

Interestingly, neighborhoods with more black populations and fewer zero-vehicle households were more likely to lose access to non-urgent health care during off-peak hours compared to black-dominant neighborhoods with lower vehicle ownership (Fig. 3). On the other hand, poverty rates exacerbated the vulnerability of black populations of losing transit access in the case of urgent care in both transit operation time of lockdown phase (Figs. 2 and 3).

#### 4.2. Spatial patterns of reductions in transit-based accessibility

Here we explored the service cut and recovery patterns across cities. Fig. 4 presents the probability of losing transit access in the lockdown and post-lockdown phases during peak hours (from the multilevel logit models). In the first phase of the pandemic (lockdown), transit cuts resulted in greater loss of access to food than to health care during peak hours (Fig. 3). In the second phase (post-lockdown), however, most cities showed similar recovery patterns in transit access to both food and health care. The cities with a greater loss of transit access during lockdown (i.e., have more block groups that lost access) also showed significant recovery of access during the post-lockdown phase (i.e., fewer block groups that lost access post-lockdown). This recovery pattern was visible in Philadelphia, Salt Lake City, Dallas, Denver, Atlanta, Madison, and Ann Arbor. Meanwhile, some cities, such as Los Angeles and Seattle, experienced additional losses instead of recovering post-lockdown: while they had fewer block groups that lost access during the lockdown phase, they had more block groups that saw additional losses of access post-lockdown. This pattern is also noticeable in New York and Portland, considering their access to food, and in Boston and Miami, considering their access to health care.

Other cities (Austin, Chicago, Nashville, Columbus, San Francisco, and San Jose) had lower yet persistent changes in transit accessibility throughout all study periods. Cities such as Urbana-Champaign, Louisville, and Phoenix, showed a recovering pattern considering their access to food and non-urgent health care and experienced more losses in transit access to urgent care. The differences in transit access changes between peak and off-peak hours are minor (SI Fig. S2).

#### 4.3. Impacts of urban sprawl on accessibility reduction

We investigated the association between reduction in transit access and the urban form of these cities. Fig. 5 shows Spearman's rank-order correlation ( $\rho$ ) between the urban sprawl index and changes in transit access to food and health care. Higher values of  $\rho$  indicate a stronger correlation between urban sprawl and the percentage of block groups with transit service cuts. Boston was excluded from this analysis due to the missing sprawl index.

We found that the percentage of block groups that lost transit accessibility was positively correlated with the level of sprawl of the cities. This means that both employees and customers of grocery stores and health care facilities in sprawled cities were more likely to lose transit access to these services than those living in compact cities. Additionally, the correlation between the percentage of block groups with access loss and the urban sprawl index shows a stronger effect in the lockdown phase than in the post-lockdown phase, especially for food and urgent health care. Transit agencies in some cities resumed some of their services in the post-lockdown phase. Therefore, the service gaps between this phase and the pre-lockdown phase are smaller than the gap between the lockdown and pre-lockdown phases. As a result, the reductions in access measured in the post-lockdown phase were not as extensive as in the lockdown phase, resulting in weaker correlation coefficients.

Figs. 6 and 7 show the detailed scatterplots of the correlations between urban sprawl indices and the percentages of block groups with reduced transit access to food and health care in 21 cities (except Boston). The x-axis indicates the urban sprawl index, and the y-axis is the percentage of block groups with reduced transit accessibility to food and health care in the respective phases. Very few study areas fall in the high-low or low-high quadrants when the correlation coefficients are significant. Most study areas are in either high-high or low-low quadrants, indicating higher declines in transit services in highly sprawled urban areas.

#### 4.4. Findings from robustness check

Our robustness checks using a 45-minute travel time threshold show that the results above are robust. The models with 30 and 45-minute travel times yielded similar directions of effects for most variables, with few deviations in significance and magnitude (SI Fig. S3). Similarly, our findings on the correlation between urban sprawl and reduction in accessibility remained consistent when the travel time threshold was increased (SI Fig. S4).

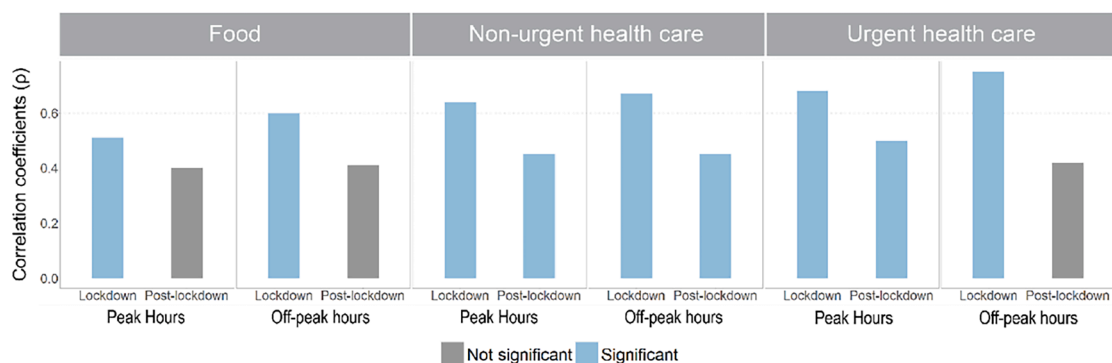


Fig. 5. Correlation between urban sprawl index and the percentage of block groups that lost accessibility in the respective phases. Notes: The y-axis represents Spearman's rank-order correlation coefficient ( $\rho$ ). Blue bars represent significant  $\rho$ 's (at  $p < 0.05$ ), and grey bars represent insignificant  $\rho$ 's. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

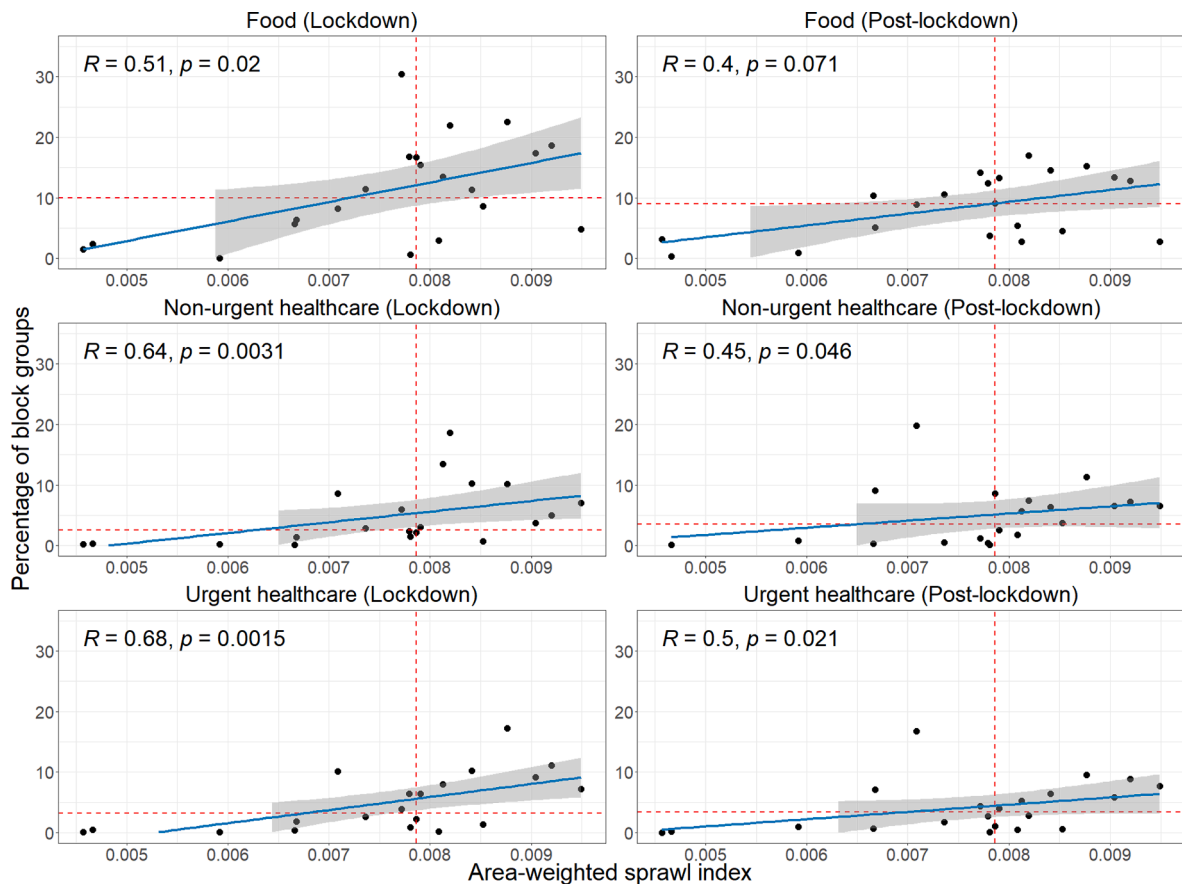


Fig. 6. Correlation between urban sprawl index and the percentage of block groups that lost accessibility during peak hours, using a travel time threshold of 30 minutes.

## 5. Discussion

### 5.1. Equity implications of accessibility lost during COVID-19

Access to food and health care is indispensable in everyday life, and they are especially important during a pandemic such as COVID-19. Limited access to such essential services may have particularly adverse effects on disadvantaged populations. For example, limited food access is linked to food insecurity and indirectly connected to nutrition deficiencies, higher susceptibility to chronic diseases, and poor physical and mental health (Barrett, 2010; Decker and Flynn, 2018; Gundersen and Ziliak, 2015). Similarly, limited health care access is linked to negative physical and psychological health consequences and may also affect medical care expenses, mortality rates, life expectancy, community well-being, and productivity (Bradley et al., 2011). In addition, grocery stores and health care facilities are basic community services providing employment opportunities for many low-income essential workers (Anderson and Laughlin, 2020; Frogner et al., 2016; Parks et al., 2020).

Our study highlights inequalities in access to essential services and jobs because of transit service cuts during the COVID-19 pandemic, thereby complementing results from recent studies on COVID-19 and social equity (Bowleg, 2020; Dorn et al., 2020; Patel et al., 2020). Our results show that transit services were more severely cut for the communities that needed them the most, particularly in neighborhoods with a large share of low-income and black populations. Additionally, communities with multiple disadvantages, such as high poverty rate, no vehicle ownership, and a high share of low-income workers, suffered the most from these reductions in accessibility due to transit service cuts. It is particularly important to understand and alleviate these impacts since budget cuts may result in service reductions that outlast the pandemic.

Our study also underscores a critical planning issue in US cities: the compromised resilience and inefficiency in providing crucial community services, including transportation, food, and health care, as a result of urban sprawl. The results suggest that sprawled study areas underwent greater reductions in transit-based food and health care access as compared to compact areas. This is an equity issue: significant numbers of low-income households are forced to live in the suburbs due to gentrification, housing unaffordability, segregation, and decentralization of employment (Barton and Gibbons, 2017; Kneebone, 2017; Redding, 2021). While a larger percentage of low-income suburban residents owns a car compared to their urban counterparts, they still face considerable transportation

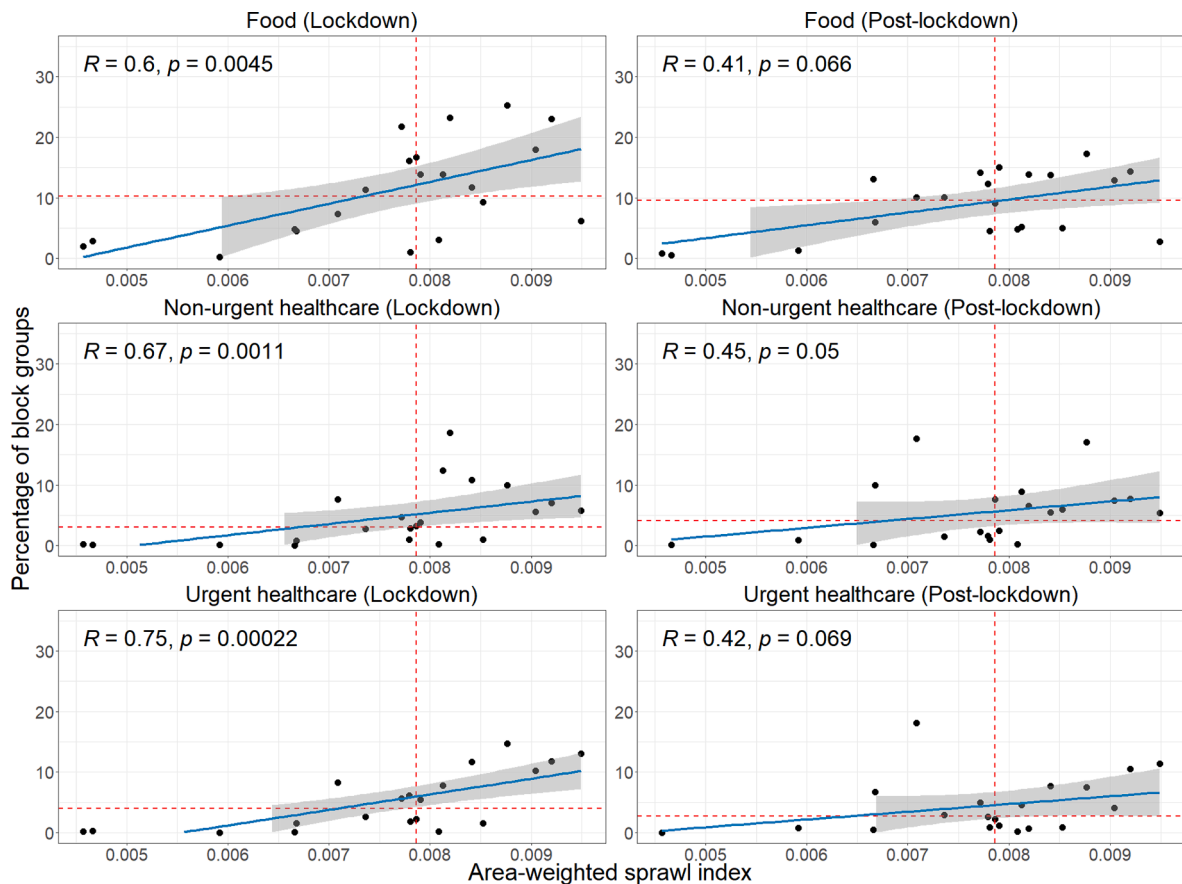


Fig. 7. Correlation between urban sprawl index and the percentage of block groups that lost accessibility during the off-peak hours, using a travel time threshold of 30-minutes.

barriers due to insufficient car access, poor vehicle quality, and high maintenance and operation costs for such vehicles (Blumenberg et al., 2020). Consequently, low-income suburban residents also tend to rely heavily on public transit when this option is available (Lucas et al., 2018; Pathak et al., 2017; Wang and Woo, 2017). Many of them belong to the essential workforce employed in the food and health care industries, whose mobility was impeded by pandemic-related transit service changes. Thus, household car ownership alone does not guarantee access. Transit, as well as other transportation services, need to be restored and strengthened to protect and prioritize the mobility of these marginalized populations.

Our results suggest that transit agencies that went through larger reductions during the lockdown phase are recovering at a better pace. In contrast, agencies with lower service reductions in the lockdown phase were mostly forced to maintain those cuts or make additional cuts in the post-lockdown phase. It is possible that transit agencies of these cities experienced a slower recovery due to pandemic-induced budget shortages or low ridership. Regardless of the causes, this poor recovery pattern is alarming, as its continuation may put the viability of transit systems at stake. Hence, the resilience of the transportation system and basic community services need to be systematically and organizationally strengthened by means of resource allocation, fiscal policies, a skilled workforce, state, and federal support and coordination, and preparedness plans for future shocks.

## 5.2. Policy implications

Our study has significant implications for understanding equity issues and the future recovery of public transit, which has historically functioned as a social stabilizer. Reductions in transit services decrease access to jobs, basic services, and social connections. If these service cuts persist after the lockdown, the consequences will persist as well. Our findings further illustrate the outside impacts of COVID-19 on disadvantaged populations and the risk of backsliding on social and economic equity. Greater government assistance for transit agencies in such a time of crisis, and continued updates to planning policies to reduce urban sprawl, are a means to empower affected communities with improved mobility and access to basic services.

Besides, services in both urban and suburban low-income areas are essential to prioritize equity over efficiency (Allen and Farber, 2020a, 2020b). Some policies adopted during COVID-19 could be strengthened and applied more widely to promote transportation equity. For instance, on-demand shared mobility services such as micro-transit became a popular alternative to traditional transit

services during the pandemic. In response to low ridership, some cities, such as Detroit, MI, supplemented their suburban transit routes with micro-transit services (American Public Transportation Association, 2022). Other cities such as Los Angeles, CA, Seattle, WA, Columbus, OH, Houston, TX, Jacksonville, FL, and Grand Rapids, MI launched micro-transit as a complement to their existing services to improve transportation to essential destinations such as homes, jobs, health care services, groceries, and schools (American Public Transportation Association, 2022). Local agencies can maintain these additional routes and services as a supplement to the existing public transit network. Continuation and expansion of these services can enhance transit coverage, eliminate car dependency, solve the first-mile last-mile problem, and promote affordable mobility for all (Wong, 2020; Zhou et al., 2021). Besides, the US federal government provided support for transit agencies' operation costs through COVID-19 relief packages, in addition to aid focusing on infrastructure and maintenance costs (TransitCenter, 2021). These short-term funding efforts should be expanded in the long run to enable the restoration, enhancement, and operational efficiency of transit services (He et al., 2021; TransitCenter, 2021).

Additionally, transit agencies should prioritize people with acute mobility disadvantages, such as essential workers, economically marginalized population groups, and people with disabilities while restoring transit service post-lockdown (He et al., 2021). Some of these initiatives are already in progress. Many transit agencies have attempted to balance cost-cutting measures and the provision of services to frequent riders and essential job destinations while limiting overall transit routes and services during the pandemic (Vock, 2020). Given the multiple facets of service cut impacts, as illustrated by our study, multi-agency cooperation and a holistic consideration of social impacts of transit service adjustments would be beneficial (SPUR, 2015).

Prior to the pandemic, various initiatives were undertaken to increase transportation-related financial support for low-income households. Examples included ride offers by the nationwide taxicab and livery service program (Harmon, 2020), transportation vouchers distributed by the US federal program titled, Temporary Assistance to Needy Families (TANF) (Center on Budget and Policy Priorities, 2021), and many financial support programs facilitating car ownership and maintenance (Blumenberg et al., 2020; Mendenhall et al., 2012; Rubiner, 2006). However, given the diverse needs of household members and the operating expenses of cars, these population groups still tend to experience constraints on their automobile access to services and rely on public transit for their day-to-day mobility, underscoring the need for a multimodal transportation system encompassing both automobiles and public transit (Blumenberg et al., 2020; Pendall et al., 2021).

It is worth noting that restructuring our transportation systems should be done alongside reconfiguring land use patterns. Cities should use the opportunity presented by the COVID-19 disruption to rethink and redesign urban areas in more resilient ways. In the long run, changes to the built environment are imperative, as none of the current urban or suburban settings provide an affordable solution to marginalized populations (Kramer, 2018). Potential strategies include, but are not limited to, updating zoning ordinances to allow mixed land use, removing minimum parking requirements, building affordable housing, updating eviction regulations, attracting businesses to underserved neighborhoods, and promoting urban infill development. Transit-oriented development and urban densification should also be promoted, although policies need to be in place to reduce the impacts of gentrification.

COVID-19 creates additional challenges and uncertainty regarding the effectiveness of improving accessibility through land use reconfiguration. Due to widespread teleworking, demand for suburban homes has increased. While this leads to potential investments and the opening of new businesses in these areas (Bayraktarian and Armstrong, 2021; Winkler and Gordon, 2021), which might increase accessibility in suburban areas, it may also cause gentrification in areas that were affordable before COVID-19. At the same time, the low housing stock pushes rents and housing prices up and makes housing less affordable to low-income populations (Mari, 2021; Olick, 2021). This means that vulnerable populations have even fewer residential choices than before and may be forced to accept higher transportation costs to reduce their housing expenses. Therefore, policies that promote housing affordability are important to ensure transportation equity.

## 6. Conclusions

Our study investigates the equity impacts of reductions in accessibility to essential services due to transit service cuts during COVID-19. We found compounding effects of social vulnerabilities, such as income, race, lack of vehicle ownership, and neighborhood type, further exacerbating the negative impacts of the loss of transit-based access to food and health care. This study has important implications for designing a systematic method of evaluating temporal changes in public transit services. Future studies may build on this research to evaluate the resilience of other sustainable forms of transportation (e.g., walking and biking) during the COVID-19 pandemic. Future research should also study the transit agencies where slower recovery patterns were observed to identify the underlying social, financial, and institutional mechanisms affecting their resilience. In addition, researchers may investigate the various service adjustment strategies employed by agencies to identify approaches with fewer negative equity impacts and apply that knowledge to devise policies for faster recoveries from future disruptions.

Our study has several limitations. First, although we applied an average isochrone measure to account for transit service frequency, the service changes we measured with our approach may deviate to a small degree from the actual changes. Second, our analysis of the relationship between urban sprawl and reductions in accessibility is based on a simple correlation measure and does not reveal a causal relationship. The correlations found in this study might be an outcome of external effects that future studies can explore. Third, our measure of transit-based accessibility during the lockdown phase does not distinguish between pandemic-induced transit service cuts and service cuts that were already planned prior to the pandemic. Fourth, although our study intended to select a mix of cities of different sizes, the proportions of big, mid-sized, and small cities are not equal in our selection and are not representative for all US cities. This may limit the generalizability of our results. Finally, our study evaluates the supply of transit services, that is, how much transit service was available and who was able to use it. The study does not provide any measurement of transit demand. Future studies may adopt mode-specific analyses and measure changes in transit demand and consumption due to the pandemic-related changes in transit

supply, and use this study as a basis for evaluating the demand–supply mismatch.

## 7. Data and code availability

Data and codes are available at: <https://osf.io/95qj6/>.

## Author contributions

AK and HTKL designed research; AK collected data and conducted analyses; AK, ALC, HJM, and HTKL interpreted the results; AK and HTKL wrote the manuscript; AK, ALC, HJM, and HTKL edited the manuscript; HTKL supervised the project.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

<https://osf.io/95qj6/>

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.trd.2022.103435>.

## References

- Abedi, V., Olulana, O., Avula, V., Chaudhary, D., Khan, A., Shahjouei, S., Li, J., Zand, R., 2020. Racial, Economic, and Health Inequality and COVID-19 Infection in the United States. *J. Racial and Ethnic Health Disparities*. <https://doi.org/10.1007/s40615-020-00833-4>.
- Acuto, M., 2020. COVID-19: Lessons for an Urban(izing) World. *One Earth* 2 (4), 317–319. <https://doi.org/10.1016/j.oneear.2020.04.004>.
- Allcott, H., Diamond, R., Dubé, J.-P., Handbury, J., Rahkovsky, I., Schnell, M., 2019. Food Deserts and the Causes of Nutritional Inequality. *The Quarterly Journal of Economics* 134, 1793–1844. <https://doi.org/10.1093/qje/qjz015>.
- Allen, J., Farber, S., 2020a. Suburbanization of transport poverty. *Annals of the American Association of Geographers* 1–18.
- Allen, J., Farber, S., 2020b. Planning transport for social inclusion: An accessibility-activity participation approach. *Transportation Research Part D: Transport and Environment* 78, 102212.
- Anderson, D.A., Laughlin, L., 2020. Retail workers: 2018. American Community Survey Reports.
- American Public Transportation Association, 2022. Microtransit. American Public Transportation Association. URL <https://www.apta.com/research-technical-resources/mobility-innovation-hub/microtransit/> (accessed 5.13.22).
- Barrett, C.B., 2010. Measuring Food Insecurity. *Science* 327 (5967), 825–828.
- Barton, M.S., Gibbons, J., 2017. A stop too far: How does public transportation concentration influence neighbourhood median household income? *Urban Studies* 54 (2), 538–554. <https://doi.org/10.1177/0042098015593462>.
- Bayraktarian, K., Armstrong, K., 2021. Why Some Suburban Businesses Are Thriving During the Pandemic. *The New York Times*.
- Blumenberg, E., Brown, A., Schouten, A., 2020. Car-deficit households: determinants and implications for household travel in the U.S. *Transportation* 47 (3), 1103–1125. <https://doi.org/10.1007/s11116-018-9956-6>.
- Bowleg, L., 2020. We're Not All in This Together: On COVID-19, Intersectionality, and Structural Inequality. *Am J Public Health* 110, 917–917. 10.2105/AJPH.2020.305766.
- Bradley, E.H., Elkins, B.R., Herrin, J., Elbel, B., 2011. Health and social services expenditures: associations with health outcomes. *BMJ Quality & Safety* 20 (10), 826–831. <https://doi.org/10.1136/bmjqs.2010.048363>.
- Brough, R., Freedman, M., Phillips, D.C., 2020. Understanding Socioeconomic Disparities in Travel Behavior during the COVID-19 Pandemic (No. #20202), CPIP Working Paper Series. UCI Center for Population, Inequality, and Policy.
- Burchell, R.W., Mukherji, S., 2003. Conventional Development Versus Managed Growth: The Costs of Sprawl. *Am J Public Health* 93 (9), 1534–1540. <https://doi.org/10.2105/AJPH.93.9.1534>.
- Campello, R.J.G.B., Moulavi, D., Sander, J., 2013. Density-Based Clustering Based on Hierarchical Density Estimates, in: Pei, J., Tseng, V.S., Cao, L., Motoda, H., Xu, G. (Eds.), *Advances in Knowledge Discovery and Data Mining, Lecture Notes in Computer Science*. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 160–172. 10.1007/978-3-642-37456-2\_14.
- Carruthers, J.I., Ulfarsson, G.F., 2003. Urban Sprawl and the Cost of Public Services. *Environ Plann B Plann Des* 30 (4), 503–522. <https://doi.org/10.1068/b12847>.
- Center on Budget and Policy Priorities, 2021. Policy Basics: Temporary Assistance for Needy Families [WWW Document]. Center on Budget and Policy Priorities. URL <https://www.cbpp.org/research/family-income-support/temporary-assistance-for-needy-families> (accessed 11.25.21).
- Cho, S.-H., Park, H.-C., 2021. Exploring the Behaviour Change of Crowding Impedance on Public Transit due to COVID-19 Pandemic: Before and After Comparison. *Transportation Letters* 13 (5-6), 367–374. <https://doi.org/10.1080/19427867.2021.1897937>.
- Decker, D., Flynn, M., 2018. Food Insecurity and Chronic Disease: Addressing Food Access as a Healthcare Issue. *Rhode Island Medical Journal* 101, 28–30.
- DeWeese, J., Hawa, L., Demyk, H., Davey, Z., Belikov, A., El-geneidy, A., 2020. A Tale of 40 Cities: A Preliminary Analysis of Equity Impacts of COVID-19 Service Adjustments across North America. *Findings*, 10.32866/001c.13395.
- Dorn, A.V., Cooney, R.E., Sabin, M.L., 2020. COVID-19 exacerbating inequalities in the US. *The Lancet* 395 (10232), 1243–1244. [https://doi.org/10.1016/S0140-6736\(20\)30893-X](https://doi.org/10.1016/S0140-6736(20)30893-X).
- El-Geneidy, A.M., Levinson, D.M., 2006. Access to Destinations: Development of Accessibility Measures.
- El-Geneidy, A., Levinson, D., Diab, E., Boisjoly, G., Verbich, D., Loong, C., 2016. The cost of equity: Assessing transit accessibility and social disparity using total travel cost. *Transportation Research Part A: Policy and Practice* 91, 302–316. <https://doi.org/10.1016/j.tra.2016.07.003>.

- Elmes, M.B., 2018. Economic Inequality, Food Insecurity, and the Erosion of Equality of Capabilities in the United States. *Business & Society* 57 (6), 1045–1074. <https://doi.org/10.1177/0007650316676238>.
- Ewing, R., Hamidi, S., 2014. *Measuring urban sprawl and validating sprawl measures*. National Cancer Institute, National Institutes of Health.
- Ewing, R., Pendall, R., Chen, D., 2003. Measuring Sprawl and Its Transportation Impacts. *Transportation Research Record* 1831 (1), 175–183. <https://doi.org/10.3141/1831-20>.
- Farber, S., Ritter, B., Fu, L., 2016. Space–time mismatch between transit service and observed travel patterns in the Wasatch Front, Utah: A social equity perspective. *Travel Behaviour and Society* 4, 40–48. <https://doi.org/10.1016/j.tbs.2016.01.001>.
- Florida, R., 2019. *The New American Divide: Driving to Work Alone vs. Bloomberg.com, Anything Else*.
- Frogner, B.K., Skillman, S.M., Patterson, D.G., Snyder, C.R., 2016. Comparing the Socioeconomic Well-Being of Workers Across Healthcare Occupations 13.
- Gielen, E., Riutort-Mayol, G., Miralles i Garcia, J.L., Palencia Jiménez, J.S., 2021. Cost assessment of urban sprawl on municipal services using hierarchical regression. *Environment and Planning B: Urban Analytics and City Science* 48 (2), 280–297. <https://doi.org/10.1177/2399808319869345>.
- GTFSS, 2020. *OpenMobilityData - Public transit feeds from around the world* [WWW Document]. URL <https://transitfeeds.com/> (accessed 5.3.21).
- Gundersen, C., Ziliak, J.P., 2015. Food Insecurity And Health Outcomes. *Health Affairs* 34 (11), 1830–1839. <https://doi.org/10.1377/hlthaff.2015.0645>.
- Hahsler, M., Piekenbrock, M., Doran, D., 2019. dbSCAN: Fast Density-Based Clustering with R. *J. Stat. Soft.* 91. 10.18637/jss.v091.i01.
- Hamidi, S., Sabouri, S., Ewing, R., 2020. Does Density Aggravate the COVID-19 Pandemic?: Early Findings and Lessons for Planners. *Journal of the American Planning Association* 86 (4), 495–509. <https://doi.org/10.1080/01944363.2020.1777891>.
- Harmon, E., 2020. *Transportation Partnership Grants Program*. MAPC. URL <https://www.mapc.org/resource-library/taxipartnerships/> (accessed 11.25.21).
- He, Q., Rowangould, D., Karner, A., Palm, M., LaRue, S., 2021. *Covid-19 Pandemic Impacts on Essential Transit Riders: Findings from a U.S. Survey* (preprint). *SocArXiv*. 10.31235/osf.io/3km9y.
- Higgins, C., Palm, M., DeJohn, A., Xi, L., Vaughan, J., Farber, S., Widener, M., Miller, E., 2022. Calculating place-based transit accessibility: Methods, tools and algorithmic dependence. *JTLU* 15 (1). <https://doi.org/10.5198/jtlu.15.110.5198/jtlu.2022.2012>.
- Hirsch, J., Hillier, A., 2013. Exploring the Role of the Food Environment on Food Shopping Patterns in Philadelphia, PA, USA: A Semiquantitative Comparison of Two Matched Neighborhood Groups. *IJERPH* 10, 295–313. <https://doi.org/10.3390/ijerph10010295>.
- Hortas-Rico, M., 2014. Urban sprawl and municipal budgets in Spain: A dynamic panel data analysis. *Papers in Regional Science* 93 (4), 843–864. <https://doi.org/10.1111/pirs.12022>.
- Hu, S., Chen, P., 2021. Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. *Transportation Research Part D: Transport and Environment* 90, 102654. <https://doi.org/10.1016/j.trd.2020.102654>.
- InfoGroup, 2019. *InfoGroup* [WWW Document]. InfoGroup. <https://www.infogroup.com/our-data/>.
- Kar, A., Motoyama, Y., Carrel, A.L., Miller, H.J., Le, H.T.K., 2021. COVID-19 exacerbates unequal food access. *Applied Geography* 134, 102517. <https://doi.org/10.1016/j.apgeog.2021.102517>.
- Kneebone, E., 2017. *The changing geography of US poverty*. Brookings Institutions, February.
- Kramer, A., 2018. The unaffordable city: Housing and transit in North American cities. *Cities* 83, 1–10. <https://doi.org/10.1016/j.cities.2018.05.013>.
- Lee, J., Miller, H.J., 2019. Analyzing collective accessibility using average space-time prisms. *Transportation Research Part D: Transport and Environment* 69, 250–264.
- Lei, T.L., Church, R.L., 2010. Mapping transit-based access: integrating GIS, routes and schedules. *International Journal of Geographical Information Science* 24 (2), 283–304. <https://doi.org/10.1080/13658810902835404>.
- Levinson, D.M., Wu, H., 2020. Towards a general theory of access. *JTLU* 13, 129–158. <https://doi.org/10.5198/jtlu.2020.1660>.
- Liu, L., Miller, H.J., Scheff, J., 2020. The impacts of COVID-19 pandemic on public transit demand in the United States. *PLoS ONE* 15, e0242476. <https://doi.org/10.1371/journal.pone.0242476>.
- Lucas, K., Philips, I., Mulley, C., Ma, L., 2018. Is transport poverty socially or environmentally driven? Comparing the travel behaviours of two low-income populations living in central and peripheral locations in the same city. *Transportation Research Part A: Policy and Practice* 116, 622–634.
- Malekzadeh, A., Chung, E., 2020. A review of transit accessibility models: Challenges in developing transit accessibility models. *International Journal of Sustainable Transportation* 14, 733–748. <https://doi.org/10.1080/15568318.2019.1625087>.
- Mari, F., 2021. *Will Real Estate Ever Be Normal Again?* *The New York Times*.
- McLaren, J., 2020. *Racial Disparity in COVID-19 Deaths: Seeking Economic Roots with Census data*. (No. w27407). National Bureau of Economic Research, Cambridge, MA. 10.3386/w27407.
- McNicholas, C., Poydock, M., 2020. Who are essential workers?: A comprehensive look at their wages, demographics, and unionization rates. accessed 2.3.22. *Economic Policy Institute*. <https://www.epi.org/blog/who-are-essential-workers-a-comprehensive-look-at-their-wages-demographics-and-unionization-rates/>.
- Mendenhall, R., Edin, K., Crowley, S., Sykes, J., Tach, L., Kriz, K., Kling, J.R., 2012. The Role of Earned Income Tax Credit in the Budgets of Low-Income Households. *Social Service Review* 86, 367–400. <https://doi.org/10.1086/667972>.
- Montenovo, L., Jiang, X., Rojas, F.L., Schmutte, I., Simon, K., Weinberg, B., Wing, C., 2020. Determinants of Disparities in Covid-19 Job Losses (No. w27132). National Bureau of Economic Research, Cambridge, MA. 10.3386/w27132.
- Moreland, A., Herlihy, C., Tynan, M.A., Sunshine, G., McCord, R.F., Hilton, C., Poovey, J., Werner, A.K., Jones, C.D., Fulmer, E.B., Gundlapalli, A.V., Strosnider, H., Pottvien, A., Garcia, M.C., Honeycutt, S., Baldwin, G., CDC Public Health Law Program, CDC COVID-19 Response Team, Mitigation Policy Analysis Unit, CDC Public Health Law Program, Clodfelter, C., Howard-Williams, M., Jeong, G., Landsman, L., Shelburne, J., CDC COVID-19 Response Team, Mitigation Policy Analysis Unit, Brown, A., Cramer, R., Gilchrist, S., Hulkower, R., Limeres, A., Popoola, A., 2020. Timing of State and Territorial COVID-19 Stay-at-Home Orders and Changes in Population Movement — United States, March 1–May 31, 2020. *MMWR Morb. Mortal. Wkly. Rep.* 69, 1198–1203. 10.15585/mmwr.mm6935a2.
- Mouw, T., Kalleberg, A.L., 2010. Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s. *Am Sociol Rev* 75, 402–431. <https://doi.org/10.1177/0003122410363564>.
- Murray, A.T., Wu, X., 2003. Accessibility tradeoffs in public transit planning. *Journal of Geographical Systems* 5, 93–107. <https://doi.org/10.1007/s101090300105>.
- O’Sullivan, D., Morrison, A., Shearer, J., 2000. Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach. *International Journal of Geographical Information Science* 14, 85–104. <https://doi.org/10.1080/136588100240976>.
- Olick, D., 2021. *America is short more than 5 million homes, and builders can’t make up the difference* [WWW Document]. CNBC. URL <https://www.cnbc.com/2021/09/14/america-is-short-more-than-5-million-homes-study-says.html> (accessed 11.30.21).
- OpenStreetMap, 2020. *OpenStreetMap* [WWW Document]. OpenStreetMap. URL <https://www.openstreetmap.org/> (accessed 6.17.21).
- Parks, C.A., Nugent, N.B., Fleischhacker, S.E., Yaroch, A.L., 2020. Food System Workers are the Unexpected but Under Protected COVID Heroes. *The Journal of Nutrition* 150, 2006–2008. <https://doi.org/10.1093/jn/nxaa173>.
- Patel, J.A., Nielsen, F.B.H., Badiani, A.A., Assi, S., Unadkat, V.A., Patel, B., Ravindran, R., Wardle, H., 2020. Poverty, inequality and COVID-19: the forgotten vulnerable. *Public Health* 183, 110–111. <https://doi.org/10.1016/j.puhe.2020.05.006>.
- Pathak, R., Wyczalkowski, C.K., Huang, X., 2017. Public transit access and the changing spatial distribution of poverty. *Regional Science and Urban Economics* 66, 198–212. <https://doi.org/10.1016/j.regsciurbeco.2017.07.002>.
- Pendall, R., Hayes, C., Dawkins, C., Jeon, J.S., Knaap, E., Blumenberg, E., Pierce, G., 2021. *Driving to Opportunities* 33.
- Quiroz-Gutierrez, M., 2021. *Public transit systems won’t recover for nearly a decade* [WWW Document]. accessed 12.6.21 *Fortune*. <https://fortune.com/2021/11/02/covid-public-transportation-pre-pandemic-levels/>.
- Ramsey, K., Bell, A., 2014. *Smart location database*. Washington, DC.
- Redding, S., 2021. *Suburbanization in the United States 1970-2010* (No. w28841). National Bureau of Economic Research, Cambridge, MA. 10.3386/w28841.
- Richiiedi, A., Tira, M., 2020. *Municipal Budget Management and the Generation of Urban Sprawl. A Case Study of the Lombardy Region (Italy)*. *Planning Practice & Research* 35, 169–184. <https://doi.org/10.1080/02697459.2020.1726132>.
- Rubiner, B., 2006. *Temporary Assistance to Needy Families (TANF) program*. The Annie E. Casey Foundation.



- Saenz, R., Sparks, C., 2020. The Inequities of Job Loss and Recovery Amid the COVID-19 Pandemic. 10.34051/p/2021.3.
- Sakowicz, J.C., 2003. Urban Sprawl: Florida's and Maryland's Approaches. *J. Land Use & Envtl. L.* 19, 377.
- Sanchez, T.W., 1999. The Connection Between Public Transit and Employment: The Cases of Portland and Atlanta. *Journal of the American Planning Association* 65, 284–296. <https://doi.org/10.1080/01944369908976058>.
- Schleith, D., Widener, M., Kim, C., 2016. An examination of the jobs-housing balance of different categories of workers across 26 metropolitan regions. *Journal of Transport Geography* 57, 145–160. <https://doi.org/10.1016/j.jtrangeo.2016.10.008>.
- Shannon, J., Christian, W.J., 2017. What is the relationship between food shopping and daily mobility? A relational approach to analysis of food access. *GeoJournal* 82, 769–785.
- Snyder, T., 2021. Policy Hackathon: Can public transit recover from Covid-19? [WWW Document]. accessed 12.6.21 POLITICO. <https://www.politico.com/news/2021/05/27/covid-public-transit-hackathon-489983>.
- Spur, 2015. Seamless Transit: How to make Bay Area public transit function like one rational, easy-to-use system. SPUR, San Francisco Bay Area.
- Stokes, E.C., Seto, K.C., 2018. Tradeoffs in environmental and equity gains from job accessibility. *Proc Natl Acad Sci USA* 115, E9773–E9781. <https://doi.org/10.1073/pnas.1807563115>.
- Tirachini, A., Cats, O., 2020. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. *JPT* 22. <https://doi.org/10.5038/2375-0901.22.1.1>.
- USA Today, 2021. Coronavirus closures: Map of where US states are tightening restrictions [WWW Document]. accessed 11.10.21. <https://www.usatoday.com/storytelling/coronavirus-reopening-america-map/>.
- TransitCenter, 2021. Envisioning a Federal Program to Increase Transit Service [WWW Document]. URL <http://transitcenter.org/envisioning-a-federal-program-to-increase-transit-service/> (accessed 11.11.21).
- U.S. Department of Transportation, 2019a. National Transit Summaries and Trends 2018: Appendix.
- U.S. Department of Transportation, 2019b. National Transit Database National Transit Summaries & Trends.
- U.S. Department of Transportation, 2020. 2020 National Transit Summaries and Trends.pdf.
- US Census Bureau, 2020. 2014–2018 American Community Survey 5-Year Estimates [WWW Document]. accessed 7.31.20. <https://data.census.gov/cedsci/>.
- Vock, C.D., 2020. Transit in Crisis [WWW Document]. American Planning Association. URL <https://www.planning.org/planning/2020/dec/transit-in-crisis/> (accessed 11.11.21).
- Wang, Q., Phillips, N.E., Small, M.L., Sampson, R.J., 2018. Urban mobility and neighborhood isolation in America's 50 largest cities. *Proc Natl Acad Sci USA* 115, 7735–7740. <https://doi.org/10.1073/pnas.1802537115>.
- Wang, K., Woo, M., 2017. The relationship between transit rich neighborhoods and transit ridership: Evidence from the decentralization of poverty. *Applied Geography* 86, 183–196. <https://doi.org/10.1016/j.apgeog.2017.07.004>.
- Winkler, D.T., Gordon, B.L., 2021. COVID-19 and the Single-Family Home Market: One City's Experience. *THE COUNSELORS OF REAL ESTATE, Real Estate Issues*, p. 45.
- Wolfe, M.K., McDonald, N.C., Holmes, G.M., 2020. Transportation Barriers to Health Care in the United States: Findings From the National Health Interview Survey, 1997–2017. *American Journal of Public Health* 110, 815–822. <https://doi.org/10.2105/AJPH.2020.305579>.
- Wong, S.A.S., PhD And Stephen D., 2020. Public Transit and Shared Mobility COVID-19 Recovery: Policy Options and Research Needs. 10.7922/G2DV1H5G.
- Yearby, R., 2018. Racial Disparities in Health Status and Access to Healthcare: The Continuation of Inequality in the United States Due to Structural Racism. *American Journal of Economics and Sociology* 77, 1113–1152. <https://doi.org/10.1111/ajes.12230>.
- Yi, C., 2006. Impact of Public Transit on Employment Status: Disaggregate Analysis of Houston, Texas. *Transportation Research Record* 1986, 137–144. <https://doi.org/10.1177/0361198106198600117>.
- Zhou, Y., Liu, X.C., Grubestic, T., 2021. Unravel the impact of COVID-19 on the spatio-temporal mobility patterns of microtransit. *Journal of Transport Geography* 97, 103226. <https://doi.org/10.1016/j.jtrangeo.2021.103226>.