

Supplementary Information for
**Public transit cuts during COVID-19 compound social vulnerability
in 22 US cities**

Armita Kar, Andre L. Carrel, Harvey J. Miller, Huyen T. K. Le*

Table of Contents

1	Transit data sources and time frames.....	3
2	Selection criteria for grocery stores and health care facilities.....	4
3	Measuring transit-based access using average isochrones	5
4	Description of socio-economic variables.....	6
5	Descriptive statistics.....	7
6	Kruskal-Wallis tests for comparing the changes in transit access by socio-economic groups: Accessibility with 30-minute travel time	8
7	Goodness of fit statistics of multilevel models: Accessibility with 30-minute travel time	13
8	Spatial patterns of reductions in transit-based accessibility during off-peak hours	13
9	Sensitivity analysis: Accessibility with 45-minutes travel time	14
	References.....	17

List of Figures

Fig. S1:	Pearson correlation coefficients for the socio-economic variables.....	6
Fig. S2:	Probability of losing transit access in the lockdown and post-lockdown phases (off-peak hours).....	14
Fig. S3:	Social determinants of transit access loss using 45-minutes isochrone measure	15
Fig. S4:	Correlation between urban sprawl index and service cuts using 45-minutes isochrone measure..	16

List of Tables

Table S1	Transit agencies used for each study area and dates used in each study period for measuring accessibility	3
Table S2	Selection criteria for grocery stores	4
Table S3	Selection Criteria for health care facilities	5
Table S4	Socio-economic variables at the block group level	6
Table S5	Descriptive statistics for changes in transit-based access to food during peak hours using a 30-minute total travel time threshold.	7
Table S6	Descriptive statistics for changes in transit-based access to non-urgent healthcare during peak hours using a 30-minute total travel time threshold.	7
Table S7	Descriptive statistics for changes in transit-based access to urgent healthcare during peak hours using a 30-minute total travel time threshold.	7

Table S8 | Kruskal-Wallis test results for changes in transit-based access to food and healthcare during peak and off-peak hours using a 30-minute total travel time threshold.....8

Table S9 | Goodness of fit statistics of the multilevel binary logit models for the changes in transit-based access to food and healthcare during peak hours using a 30-minute total travel time threshold.....12

1 Transit data sources and time frames

We identified the major transit service provider for bus, light rail, and subway services for each city. In addition, we considered multiple agencies for New York and Seattle, where separate transit providers offer bus and rail services. For these two cities, we combined the GTFS datasets and analyzed them as if they were from one single provider. This combination allowed us to determine accessibility for riders who transfer between different transit service providers.

Our study area for each city contains block groups that fall within a half-mile buffer around each transit stop, based on the transit networks during the pre-lockdown period. This ensures that the block groups within our study areas were supported with one or multiple transit services before the pandemic started.

We obtained transit schedule and route information of 22 transit agencies using the static General Transit Feed Specification (GTFS) data from the OpenMobilityData website (Table S1) (GTFS, 2020). GTFS static data provide information regarding transit routes, stops or stations, schedules, transfers, and fares. Assuming that the weekday transit schedule is fixed (i.e., the same for all weekdays in each city), we measured accessibility on a Tuesday (a regular weekday) of each study period. The specific Tuesday was determined with our routes-based date selection criteria.

Table S1 | Transit agencies used for each study area and dates used in each study period for measuring accessibility

Name	Transit agency	Public transit mode(s)	Pre-lockdown phase (highest number of routes between January-February)		Lockdown phase (Lowest number of routes between March-June)		Post-lockdown phase (highest number of routes between November-December)	
			Date	Number of routes	Date	Number of routes	Date	Number of routes
Ann Arbor	The Ride	Bus	28-Jan	34	31-Mar	21	17-Nov	17
Atlanta	MARTA	Bus, subway	7-Jan	115	28-Apr	47	8-Dec	58
Austin	Capital Metro	Bus, light rail	7-Jan	84	31-Mar	56	1-Dec	70
Boston	MBTA	Bus, light rail, subway	7-Jan	235	10-Mar	237	15-Dec	240
Champaign - Urbana	CUMTD	Bus	7-Jan	102	12-May	102	24-Nov	103
Chicago	CTA	Bus, subway	7-Jan	134	21-Apr	134	24-Nov	136
Columbus	COTA	Bus	7-Jan	47	5-May	21	8-Dec	23
Dallas	DART	Bus, light rail, cable tram	7-Jan	161	7-Apr	151	8-Dec	148
Denver	RTD	Bus, light rail	7-Jan	160	26-May	151	24-Nov	110
Los Angeles	LA Metro	Bus, light rail, subway	14-Jan	138	23-Jun	133	1-Dec	134
Louisville	TARC	Bus	28-Jan	47	31-Mar	47	17-Nov	31
Madison	Metro Madison	Bus	4-Feb	126	24-Mar	63	8-Dec	126
Miami	MDC	Bus, light rail	25-Feb	133	28-Apr	119	3-Nov	124
Nashville	MTA	Bus	28-Jan	45	7-Apr	45	24-Nov	42
New York City	MTA, MTABC	Bus, subway	7-Jan	362	5-May	322	1-Dec	364

			Pre-lockdown phase (highest number of routes between January-February)		Lockdown phase (Lowest number of routes between March-June)		Post-lockdown phase (highest number of routes between November-December)	
Philadelphia	SEPTA	Bus, light rail, subway	28-Jan	139	14-Apr	61	17-Nov	138
Phoenix	Valley Metro	Bus, light rail	21-Jan	105	14-Apr	100	1-Dec	104
Portland	TriMet	Bus, light rail	14-Jan	99	21-Apr	94	15-Dec	94
San Francisco	SFMTA	Bus, light rail, cable tram	28-Jan	84	14-Apr	21	1-Dec	37
San Jose	VTA	Bus, light rail	28-Jan	83	31-Mar	46	1-Dec	58
Seattle	King County Metro, Sound Transit	Bus, light rail	4-Feb	225	9-Jun	190	8-Dec	132
Salt Lake City	UTA	Bus, light rail	14-Jan	123	28-Apr	118	24-Nov	109

2 Selection criteria for grocery stores and health care facilities

We obtained data on grocery stores and health care facilities from InfoGroup (InfoGroup, 2019). This dataset contains information on the geographic locations of each facility, their North American Industry Classification System (NAICS) code, and their business characteristics (e.g., sales volume and employee size).

We selected grocery stores based on the NAICS code, retailer brand names, and scale of businesses. Based on distribution across all supermarkets and grocery stores (NAICS 445110) in our selected cities (in descending order), we determined an employee size of 80 and a sales volume of 17.5 million as the threshold representing the top 10th percentile. Our study therefore includes supermarkets and grocery stores with an employee size and sales volume above these threshold values. In addition, we manually selected national-level warehouse clubs, supercenters, and department stores that sell grocery products. Table S2 provides the detailed grocery store selection criteria used in this study.

Table S2 | Selection criteria for grocery stores

Store type	NAICS	Criteria	Example store names
Supermarkets and grocery stores	445110	Employee size > 80 and sales volume > 17.5 million (top 10 th percentile among all stores in our study areas)	Trader Joe’s, Meijer, Whole Food Market, Kroger, Hy-Vee, and Safeway
Warehouse clubs and supercentres	452910	National-level retailer brands that sell groceries	Costco Wholesale, Sam’s Club and BJ’s, and Walmart
Department stores	452111		Target

Similarly, we categorized health care locations into urgent and non-urgent health care facilities based on their NAICS code. Urgent health care includes general hospitals (NAICS 622110) and emergency care services (NAICS 621493). Non-urgent health care includes specialty hospitals (NAICS 622310) and primary care services (NAICS 621111). Table S3 provides the detailed selection criteria for health care facilities. We further applied the DBSCAN clustering approach (Campello et al., 2013; Hahsler et al., 2019) on the primary care and emergency care facilities as they are mostly spatially clustered within our study areas. We chose an epsilon value of 400 meters (approximately 5 minutes walking distance) and a minimum

clustering threshold of 3 points. This means that a group of 3 or more facilities form a cluster (and counted as one location in our analysis) if each facility is located at most 400m away from its neighbors.

Table S3 | Selection Criteria for health care facilities

Type	Facilities included	NAICS	Examples of facilities
Urgent health care	General hospitals	622110	General medical, surgical, and children’s hospital
	Emergency care services	621493	Ambulatory services, trauma centers, urgent medical care
Non-urgent health care	Specialty hospitals (except psychiatric and substance abuse hospitals)	622310	Medical and diagnostic services, chronic disease hospitals, maternity hospitals, neurological services, children’s hospital, eye, ear, nose, and throat hospital
	Primary care physicians	621111	Offices of physicians for independent practices, family physicians’ offices, and health screening services

3 Measuring transit-based access using average isochrones

We generated travel time isochrones to measure accessibility. Isochrones delimit the area reachable from a specific point location given a travel time threshold or other cost parameters and a specific mode of travel. In this study, we generated isochrones using the spatial coverage of transit services (e.g., stop locations and available routes) and travel time as a cost function. We chose travel time thresholds of 30 and 45 minutes, as those are consistent with other accessibility studies and most commute trips are around 30 minutes one way (FRED Economic Data, 2019; Kelobonye et al., 2019; US Census Bureau, 2017).

We considered four criteria for measuring accessibility: destination type (food, urgent, and non-urgent health care), travel time threshold (30 minutes or 45 minutes), transit operation time (peak or off-peak), and pandemic response phase (pre-lockdown, lockdown, and post-lockdown). In addition, we used 9 AM – 10 AM to represent the peak hours and 1 PM – 2 PM to represent the off-peak hours, and sampled isochrones for both hours using 10-minute intervals. We delineated isochrones around each point location using Open Trip Planner on OpenStreetMap and GTFS data as the network inputs (GTFS, 2020; OpenStreetMap, 2020; OpenTripPlanner, 2021) and aggregated them to generate the sample isochrone layers for each combination of accessibility measurement criteria.

Based on the above approach, we generated travel time isochrones to identify the block groups that still had access to food and health care by transit. For each destination and travel time threshold, we had 6 sampled isochrones for each hour (peak or off-peak) in each study area (in the vector format). To average these sampled isochrones, we converted each isochrone layer into a raster format with a 10-meter grid resolution and assigned each cell a value of 1 if it was within the isochrone boundary and 0 otherwise. Then, we overlaid the raster layers and normalized their aggregated values to estimate the probability of a grid cell being within the isochrone. Finally, we used a median threshold value of 0.5 to identify the grid cells that define the average isochrone boundary. We performed this procedure using Python and published the code in a Github public repository. An online map of accessibility changes is available at: <https://arcg.is/05qP5z>.

4 Description of socio-economic variables

We extracted socio-economic information at a census block group level from American Community Survey (ACS) 5-year estimates (2014-2018) and the Environmental Protection Agency (EPA) Smart Location Database (Ramsey and Bell, 2014; US Census Bureau, 2020). Table S4 provides a list of socio-economic variables used in this study.

Table S4 | Socio-economic variables at the block group level

Variable name	Description	Unit	Data Source
Poverty rate	Percentage of households living below the poverty level (determined by householder's age, family size, and number of children)	Percentage	ACS 5-year estimates 2014-2018
Black or African American	Percentage of Black or African American populations	Percentage	
Other races	Percentage of people who are not non-Hispanic White or Black	Percentage	
No-vehicle households	Percentage of households with no car ownership	Percentage	
Low-income workers	Percentage of workers with income below \$1,250 per month	Percentage	EPA Smart Location Database

We examined the Pearson correlation coefficients among the socio-economic variables to ensure that the models were not affected by multicollinearity. As shown in Fig. S1, the absolute correlation coefficient values between all model variables are below 0.5, which confirms that no strong correlation effects among the model parameters were present.

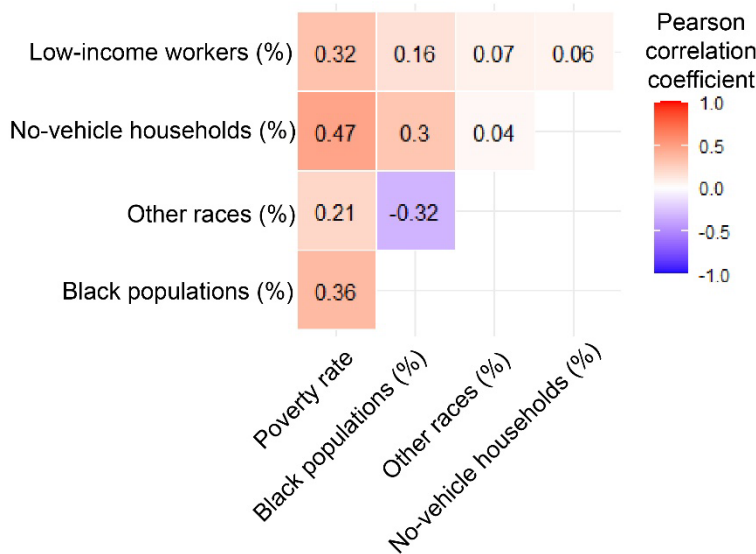


Fig. S2 | Pearson correlation coefficients for the socio-economic variables. The cells colored in red shades represent positive correlation and the cells colored in purple shades represent negative correlation between the respective variables on the x and y axis.

5 Descriptive statistics

Table S5 | Descriptive statistics for changes in transit-based access to food during peak hours using a 30-minute total travel time threshold.

		Block groups with no access		Block groups with access	
		Lockdown	Post-lockdown	Lockdown	Post-lockdown
Poverty rate	Mean	12.91	13.10	16.50	16.50
	Median	8.82	9.00	12.95	12.94
	Std.	12.83	13.13	14.01	14.00
Percentage of black populations	Mean	15.94	14.66	17.88	17.98
	Median	4.86	3.87	4.84	4.93
	Std.	24.35	23.55	27.08	27.13
Percentage of other races	Mean	34.36	39.67	41.59	41.02
	Median	26.05	32.68	35.67	34.80
	Std.	27.65	28.60	28.86	28.84
Percentage of no-vehicle households	Mean	8.93	8.72	22.56	22.56
	Median	4.48	4.61	12.89	12.85
	Std.	12.60	11.96	24.21	24.24
Percentage of low-income workers	Mean	0.24	0.25	0.24	0.24
	Median	0.23	0.24	0.24	0.24
	Std.	0.08	0.08	0.08	0.08
Total area	Sum	1.54E+09	1.24E+09	1.14E+10	1.18E+10

Table S6 | Descriptive statistics for the in transit-based access to non-urgent healthcare during peak hours using a 30-minute total travel time threshold.

		Block groups with no access		Block groups with access	
		Lockdown	Post-lockdown	Lockdown n	Post-lockdown
Poverty rate	Mean	12.47	10.64	15.96	16.08
	Median	7.84	6.93	12.35	12.45
	Std.	13.65	11.41	13.88	13.96
Percentage of black populations	Mean	19.46	15.04	17.59	17.85
	Median	4.60	3.47	4.73	4.79
	Std.	29.76	25.93	26.83	27.05
Percentage of other races	Mean	24.86	30.89	40.61	40.09
	Median	19.44	24.45	34.13	33.49
	Std.	21.70	25.30	28.86	28.74
Percentage of no-vehicle households	Mean	10.06	6.22	20.49	20.86
	Median	4.12	3.07	10.89	11.28
	Std.	14.83	9.17	23.37	23.50
Percentage of low-income workers	Mean	0.23	0.23	0.24	0.24
	Median	0.23	0.22	0.24	0.24
	Std.	0.07	0.08	0.08	0.08
Total area	Sum	8.52E+08	1.00E+09	1.63E+10	1.59E+10

Table S7 | Descriptive statistics for changes in transit-based access to urgent healthcare during peak hours using a 30-minute total travel time threshold.

		Block groups with no access		Block groups with access	
		Lockdown	Post-lockdown	Lockdown	Post-lockdown
Poverty rate	Mean	10.38	8.82	16.19	16.24
	Median	6.91	5.95	12.59	12.64
	Std.	11.42	9.77	13.99	14.00
Percentage of black populations	Mean	16.70	12.27	17.83	18.06
	Median	3.19	2.53	4.84	4.90
	Std.	28.02	23.25	26.99	27.20
Percentage of other races	Mean	25.12	30.19	40.87	40.53

		Block groups with no access		Block groups with access	
		Lockdown	Post-lockdown	Lockdown	Post-lockdown
	Median	18.65	23.99	34.56	34.09
	Std.	22.18	24.29	28.86	28.87
	Mean	6.25	5.20	21.00	21.01
Percentage of no-vehicle households	Median	2.92	2.66	11.42	11.45
	Std.	9.07	7.03	23.54	23.52
	Mean	0.23	0.23	0.24	0.24
Percentage of low-income workers	Median	0.22	0.22	0.24	0.24
	Std.	0.06	0.08	0.08	0.08
	Mean	0.22	0.22	0.24	0.24
Total area	Sum	1.08E+09	9.29E+08	1.52E+10	1.53E+10

6 Kruskal-Wallis tests for comparing the changes in transit access by socio-economic groups: Accessibility with 30-minute travel time

Table S8 | Kruskal-Wallis test results for changes in transit-based access to food and healthcare during peak and off-peak hours using a 30-minute total travel time threshold.

	Grocery				Health non-urgent				Health urgent			
	Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down
Ann Arbor												
Number of observations	141	141	142	144	156	161	156	169	127	139	127	137
Variables	p-value											
Poverty rate	0.278	0.015	0.224	0.002	0.010	0.036	0.004	0.101	0.068	0.000	0.036	0.008
Black population (%)	0.014	0.973	0.022	0.951	0.959	0.956	0.712	0.207	0.873	0.647	0.909	0.479
Other races (%)	0.066	0.477	0.058	0.514	0.301	0.304	0.603	0.550	0.612	0.736	0.483	0.852
Owner of no vehicle (%)	0.001	0.000	0.001	0.000	0.049	0.103	0.060	0.074	0.207	0.002	0.067	0.047
Low-income workers (%)	0.094	0.000	0.097	0.000	0.016	0.001	0.010	0.001	0.014	0.001	0.011	0.028
Atlanta												
Number of observations	581	611	593	614	814	801	801	786	771	796	762	798
Variables	p-value											
Poverty rate	0.327	0.038	0.636	0.069	0.000	0.001	0.000	0.034	0.013	0.000	0.006	0.006
Black population (%)	0.001	0.014	0.019	0.004	0.001	0.073	0.020	0.016	0.001	0.250	0.002	0.219
Other races (%)	0.185	0.431	0.870	0.383	0.019	0.111	0.109	0.472	0.411	0.406	0.181	0.153
Owner of no vehicle (%)	0.127	0.010	0.105	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.001	0.025	0.004	0.004	0.000	0.001	0.000	0.001	0.001	0.000	0.001	0.000
Austin												
Number of observations	367	353	364	354	457	449	457	461	432	435	430	434
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.431	0.272	0.458	0.324	0.810	0.931	0.972	0.568	0.604	0.208	0.478	0.276
Other races (%)	0.845	0.495	0.819	0.390	0.820	0.853	0.845	0.757	0.816	0.859	0.973	0.994
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Boston												

	Grocery				Health non-urgent				Health urgent			
	Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down
Number of observations	1522	1488	1503	1496	1735	1714	1715	1699	1691	1653	1688	1625
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.018	0.008	0.005	0.001	0.001	0.000	0.003	0.003	0.001	0.001	0.020	0.004
Urbana- Champaign												
Number of observations	72	77	72	77	92	93	92	92	89	90	89	90
Variables	p-value											
Poverty rate	0.439	0.009	0.420	0.013	0.126	0.002	0.107	0.001	0.522	0.065	0.577	0.074
Black population (%)	0.407	0.043	0.454	0.033	0.350	0.778	0.320	0.751	0.563	0.117	0.436	0.061
Other races (%)	0.027	0.018	0.024	0.028	0.832	0.399	0.794	0.545	0.890	0.376	0.904	0.280
Owner of no vehicle (%)	0.268	0.119	0.318	0.147	0.123	0.050	0.122	0.018	0.430	0.357	0.756	0.272
Low-income workers (%)	0.757	0.828	0.680	0.867	0.085	0.063	0.091	0.097	0.090	0.684	0.114	0.611
Chicago												
Number of observations	2458	2434	2456	2435	2572	2570	2573	2571	2557	2556	2558	2558
Variables	p-value											
Poverty rate	0.005	0.005	0.024	0.001	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.066	0.021	0.007	0.073	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.010	0.056	0.259	0.037	0.004	0.001	0.009	0.000	0.012	0.000	0.003	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.003	0.001	0.001	0.002
Columbus												
Number of observations	533	555	539	553	700	698	701	702	650	655	641	667
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.029	0.043	0.042	0.184	0.118	0.024	0.010	0.074	0.287	0.193	0.180	0.008
Other races (%)	0.493	0.785	0.577	0.749	0.908	0.956	0.872	0.984	0.684	0.907	0.994	0.961
Owner of no vehicle (%)	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dallas												
Number of observations	1287	1316	1273	1301	1443	1425	1459	1448	1409	1397	1395	1369
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.902	0.727	0.934	0.986	0.440	0.037	0.318	0.510	0.894	0.855	0.657	0.954
Other races (%)	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Denver												

	Grocery				Health non-urgent				Health urgent			
	Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down
Number of observations	1247	1171	1215	1176	1548	1564	1546	1558	1514	1523	1513	1529
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.000	0.516	0.001	0.360	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Los Angeles												
Number of observations	4200	4107	4192	4069	4816	4401	4818	4329	4685	4617	4668	4487
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.000	0.001	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.001	0.112	0.004	0.162	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Louisville												
Number of observations	288	277	284	279	428	425	428	429	371	391	370	392
Variables	p-value											
Poverty rate	0.596	0.008	0.447	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.107	0.597	0.251	0.529	0.000	0.000	0.000	0.000	0.001	0.000	0.007	0.000
Other races (%)	0.535	0.096	0.540	0.205	0.285	0.139	0.096	0.144	0.487	0.195	0.429	0.322
Owner of no vehicle (%)	0.800	0.019	0.601	0.046	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.394	0.178	0.432	0.416	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Madison												
Number of observations	151	155	156	155	168	172	172	176	155	160	160	160
Variables	p-value											
Poverty rate	0.000	0.000	0.002	0.000	0.005	0.000	0.014	0.001	0.001	0.003	0.001	0.002
Black population (%)	0.405	0.914	0.063	0.781	0.428	0.812	0.234	0.648	0.493	0.213	0.630	0.091
Other races (%)	0.042	0.574	0.057	0.518	0.136	0.224	0.047	0.127	0.920	0.756	0.745	0.173
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.001	0.008	0.008	0.024	0.004	0.003	0.002	0.002
Low-income workers (%)	0.002	0.000	0.001	0.000	0.001	0.001	0.000	0.002	0.000	0.001	0.000	0.001
Miami												
Number of observations	1340	1358	1318	1351	1468	1439	1486	1447	1462	1428	1441	1414
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.756	0.653	0.468	0.950	0.283	0.003	0.025	0.011	0.025	0.240	0.001	0.033
Other races (%)	0.391	0.001	0.167	0.003	0.000	0.003	0.000	0.003	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nashville												

	Grocery				Health non-urgent				Health urgent			
	Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down
Number of observations	207	219	209	217	327	334	327	332	307	311	307	308
Variables	p-value											
Poverty rate	0.068	0.035	0.066	0.039	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.238	0.561	0.257	0.519	0.464	0.044	0.615	0.069	0.089	0.133	0.108	0.279
Other races (%)	0.520	0.607	0.694	0.610	0.209	0.055	0.233	0.076	0.214	0.267	0.237	0.154
Owner of no vehicle (%)	0.004	0.013	0.006	0.023	0.000	0.000	0.000	0.000	0.004	0.002	0.003	0.010
Low-income workers (%)	0.021	0.008	0.018	0.029	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
New York City												
Number of observations	5993	5970	5925	5906	6348	6355	6348	6349	6330	6332	6327	6330
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.000	0.000	0.000	0.000	0.014	0.027	0.001	0.005	0.000	0.011	0.000	0.004
Other races (%)	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Philadelphia												
Number of observations	2027	2068	2040	2094	2244	2251	2258	2278	2196	2233	2201	2217
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phoenix												
Number of observations	1651	1646	1652	1641	1806	1789	1811	1784	1755	1758	1765	1772
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.032	0.005	0.006	0.085	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Portland												
Number of observations	776	775	773	769	814	830	820	821	825	823	826	828
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.008	0.006	0.003	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Other races (%)	0.760	0.688	0.570	0.198	0.293	0.649	0.414	0.287	0.291	0.279	0.250	0.175
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
San Jose												

	Grocery				Health non-urgent				Health urgent			
	Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down	Lock-down	Post-lock down
Number of observations	851	841	840	843	955	968	970	974	915	923	915	934
Variables	p-value											
Poverty rate	0.000	0.017	0.001	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.527	0.312	0.487	0.381	0.392	0.174	0.371	0.463	0.026	0.119	0.007	0.081
Other races (%)	0.081	0.009	0.018	0.000	0.008	0.013	0.023	0.040	0.392	0.108	0.501	0.246
Owner of no vehicle (%)	0.002	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.007	0.272	0.018	0.069	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Seattle												
Number of observations	856	849	859	844	1128	1115	1125	1110	1150	1139	1142	1129
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.934	0.675	0.860	0.649	0.206	0.299	0.383	0.567	0.090	0.010	0.033	0.065
Other races (%)	0.000	0.000	0.000	0.000	0.039	0.000	0.036	0.000	0.057	0.122	0.174	0.015
Owner of no vehicle (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.132	0.184	0.061	0.145	0.012	0.066	0.034	0.028	0.001	0.006	0.090	0.155
San Francisco												
Number of observations	592	591	591	591	596	596	595	596	595	596	594	595
Variables	p-value											
Poverty rate	0.034	0.012	0.042	0.022	0.002	0.003	0.002	0.001	0.011	0.021	0.009	0.032
Black population (%)	0.373	0.543	0.387	0.399	0.206	0.148	0.185	0.138	0.689	0.220	0.652	0.288
Other races (%)	0.109	0.101	0.100	0.249	0.373	0.740	0.544	0.631	0.384	0.771	0.357	0.818
Owner of no vehicle (%)	0.000	0.038	0.000	0.023	0.001	0.131	0.000	0.085	0.000	0.061	0.000	0.049
Low-income workers (%)	0.192	0.667	0.094	0.823	0.007	0.230	0.028	0.198	0.114	0.110	0.090	0.155
Salt Lake City												
Number of observations	551	586	560	590	935	927	940	931	901	906	894	902
Variables	p-value											
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black population (%)	0.045	0.007	0.055	0.014	0.095	0.008	0.324	0.013	0.057	0.013	0.161	0.025
Other races (%)	0.002	0.000	0.037	0.000	0.005	0.000	0.039	0.000	0.015	0.002	0.289	0.005
Owner of no vehicle (%)	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low-income workers (%)	0.125	0.924	0.804	0.957	0.002	0.007	0.004	0.002	0.001	0.000	0.010	0.017

7 Goodness of fit statistics of multilevel models: Accessibility with 30-minute travel time

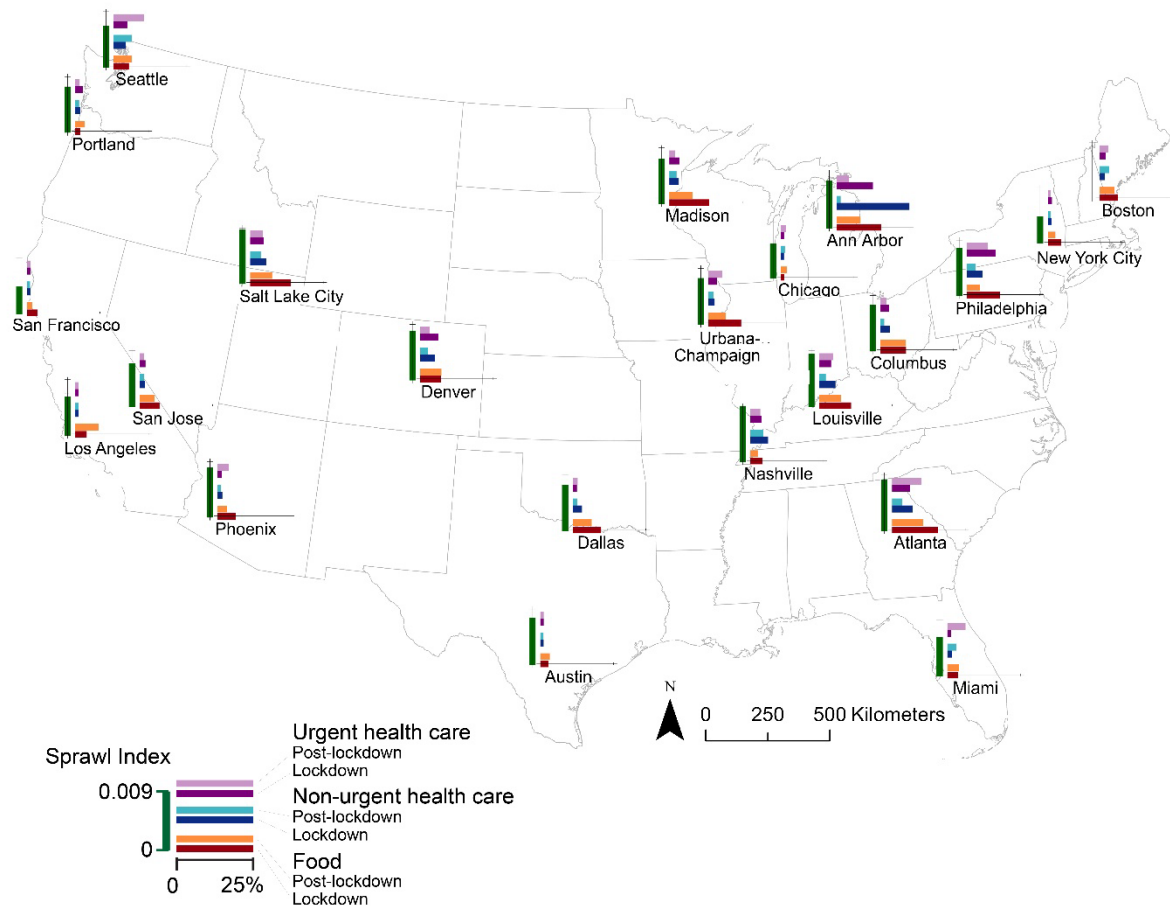
Table S9 | Goodness of fit statistics of the multilevel binary logit models for the changes in transit-based access to food and healthcare during peak hours using a 30-minute total travel time threshold.

		Peak		Off-peak	
		Lockdown	Post-lockdown	Lockdown	Post-lockdown
Grocery	Number of obs.	27691	27588	27556	27499
	Number of groups	22	22	22	22
	Goodness of fit	LL: -6186.9 AIC: 12395.9	LL: -6086.7 AIC: 12195.3	LL: -6158.0 AIC: 12338.0	LL: -6052.4 AIC: 12126.8
Health non-urgent	Number of obs.	31550	31077	31598	31042
	Number of groups	22	22	22	22
	Goodness of fit	LL: -3428.1 AIC: 6878.2	LL: -3500.5 AIC: 7023.0	LL: -3300.8 AIC: 6623.6	LL: -3937.8 AIC: 7897.5
Health urgent	Number of obs.	30887	30861	30813	30675
	Number of groups	22	22	22	22
	Goodness of fit	LL: -3570.9 AIC: 7163.9	LL: -3370.9 AIC: 6763.8	LL: -3525.8 AIC: 7073.6	LL: -3341.6 AIC: 6705.1

Notes: LL: Log-likelihood; AIC: Akaike information criterion

8 Spatial patterns of reductions in transit-based accessibility during off-peak hours

Fig. S2 represents the percentages of block groups with loss of accessibility during off-peak hours using a travel time threshold of 30 minutes. Most cities showed a similar pattern of accessibility loss and recovery from the lockdown to the post-lockdown phase, regardless of whether peak or off-peak hours were considered. However, a few cities had some deviations between peak and off-peak hours. In terms of access to food, cities with differences between peak and off-peak hours include New York, Columbus, Philadelphia, Madison, Salt Lake City, Atlanta, and Los Angeles. Again, Philadelphia, Seattle, Phoenix, Ann Arbor, and Atlanta exhibited differences in accessibility losses to non-urgent and urgent health care facilities between peak and off-peak hours. For the rest of the cities, the differences in the probability of losing access to food and health care between peak and off-peak hours were less than 1%.



Notes: Horizontal bars on the right represent the probability of losing access to food and health care. Vertical green bars represent urban sprawl index. Whiskers on both axes represent the maximum values of urban sprawl and the probability of losing transit access.

Fig. S2 | Probability of losing transit access in the lockdown and post-lockdown phases (off-peak hours).

9 Sensitivity analysis: Accessibility with 45-minutes travel time

We obtained similar results in terms of the direction of effects for most variables when conducting a similar analysis with a 45-minutes travel time threshold (Fig. S3). However, the magnitude and significance of the model coefficients differ between these two sets of models in some cases. For instance, the effects of the poverty rate and populations of other races vary between models generated with 30-minute and 45-minute travel time thresholds. Meanwhile, other results were consistent with the main analysis: block groups with high shares of black populations and low-income workers were more likely to experience transit service cuts regardless of the travel time threshold used for measuring accessibility. The interactions between socio-economic variables show that the influences on accessibility losses during the lockdown and post-lockdown phases were similar to those found in the main analysis with a 30-minute travel time threshold.

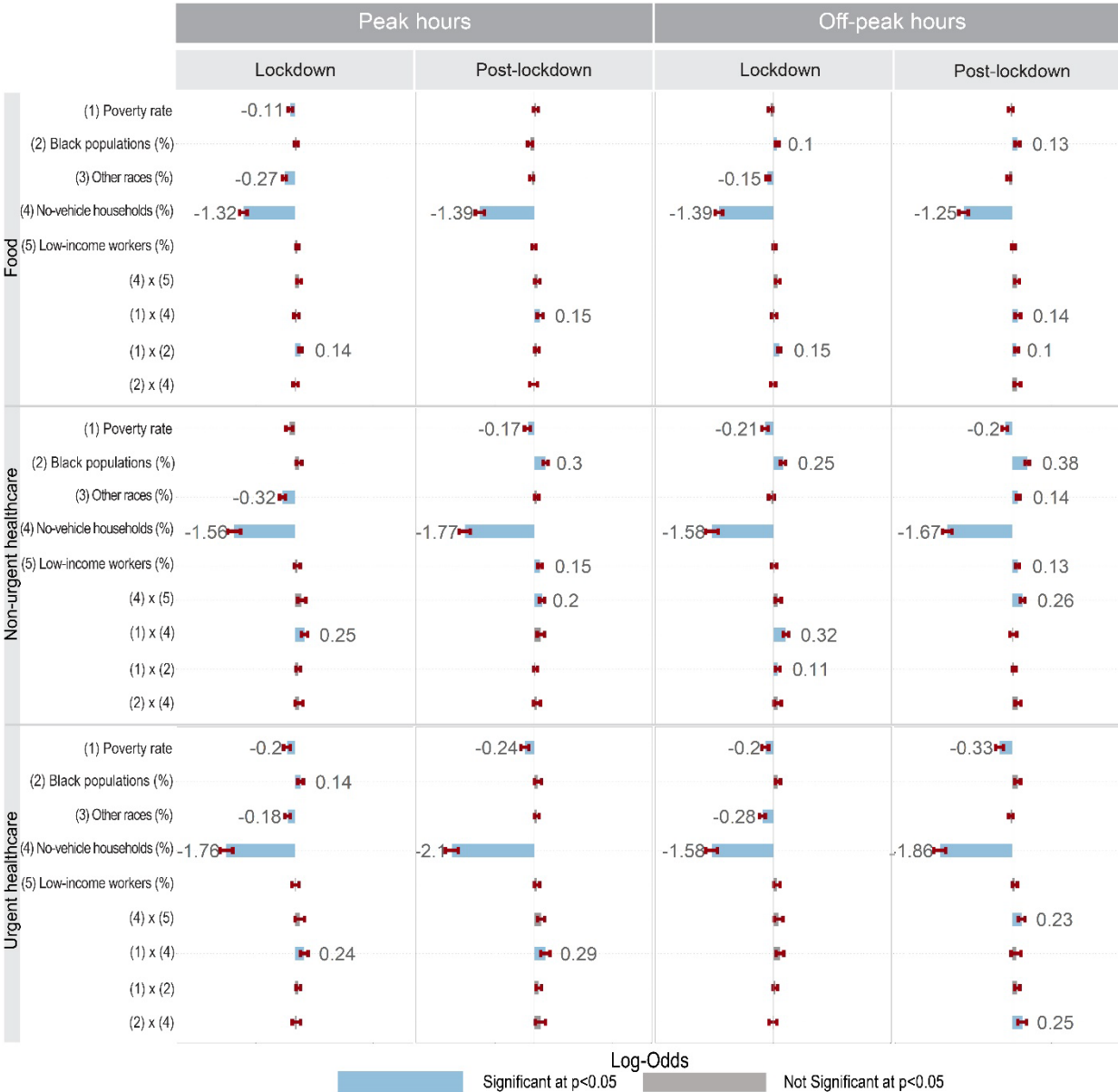


Fig. S3 | Influence of variables on losing transit-based access to food, urgent health care, and non-urgent health care during the peak and off-peak hours of the lockdown and post-lockdown phases, compared to the pre-lockdown phase, using a travel time threshold of 45 minutes. All variables were measured at the census block group level. Blue and grey bars respectively represent the significant and non-significant coefficients of multilevel binary logit models. Significance is indicated at the p<0.05 level. The values of significant coefficients are mentioned beside the blue bars. Red lines represent 95% confidence intervals. Dependent variable: loss of access (yes/no). Socio-demographic and urban form variables were extracted from the American Community Survey 5-year estimates 2014-2018 and Smart Location Database.

The correlations between urban sprawl index and percentages of block groups that lost access show similar results for both the 30-minute and 45-minute travel time thresholds (Fig. S4). In other words, sprawled cities were more likely to experience transit service cuts and subsequent reductions in food and health care access regardless of the travel time thresholds used for the analysis. In addition, the correlations for the 45-minute travel time also appear to be statistically significant during the post-lockdown phase in terms of access to food, whereas this was not the case with the 30-minute travel time threshold.

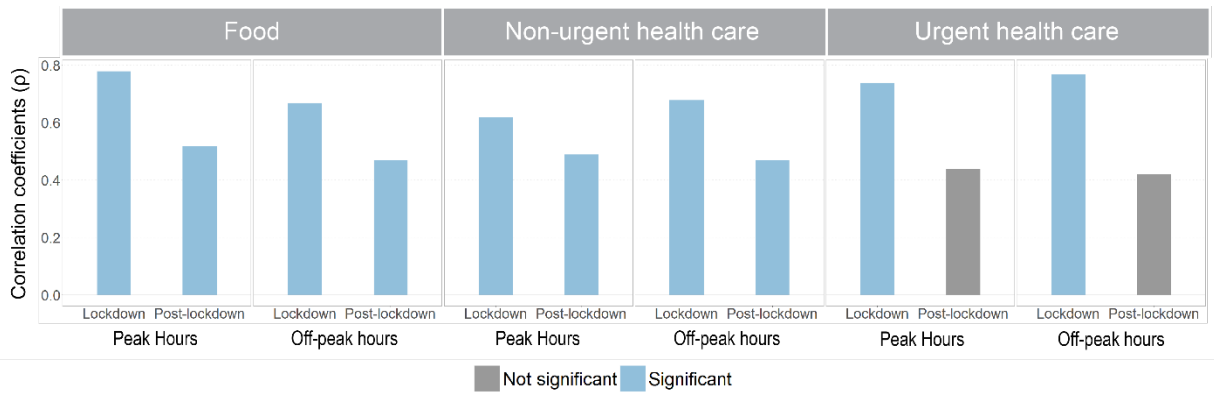


Fig. S4 | Correlation between urban sprawl index and the percentage of block groups that lost accessibility in the various phases, using a travel time threshold of 45 minutes. The y-axis shows Spearman's rank-order correlation coefficient (ρ). Blue bars represent significant ρ 's (at $p < 0.05$) and grey bars represent insignificant ρ 's. Higher values of ρ indicate a stronger correlation between urban sprawl and the percentage of block groups where transit service was cut. Boston was excluded from this analysis due to the missing sprawl index.

References

- 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. https://doi.org/10.1007/978-3-642-37456-2_14
- FRED Economic Data, 2019. Mean Commute Time [WWW Document]. FRED Economic Data. URL <https://fred.stlouisfed.org/release?rid=415> (accessed 8.24.21).
- GTFS, 2020. OpenMobilityData - Public transit feeds from around the world [WWW Document]. URL <https://transitfeeds.com/> (accessed 5.3.21).
- Hahsler, M., Piekenbrock, M., Doran, D., 2019. dbSCAN: Fast Density-Based Clustering with R. *J. Stat. Soft.* 91. <https://doi.org/10.18637/jss.v091.i01>
- InfoGroup, 2019. InfoGroup [WWW Document]. Infogroup. URL <https://www.infogroup.com/our-data/>
- Kelobonye, K., McCarney, G., Xia, J. (Cecilia), Swapan, M.S.H., Mao, F., Zhou, H., 2019. Relative accessibility analysis for key land uses: A spatial equity perspective. *Journal of Transport Geography* 75, 82–93. <https://doi.org/10.1016/j.jtrangeo.2019.01.015>
- OpenStreetMap, 2020. OpenStreetMap [WWW Document]. OpenStreetMap. URL <https://www.openstreetmap.org/> (accessed 6.17.21).
- OpenTripPlanner, 2021. Open Trip Planner: Multimodal Trip Planning [WWW Document]. URL <https://www.opentripplanner.org/> (accessed 8.12.21).
- Ramsey, K., Bell, A., 2014. Smart location database. Washington, DC.
- US Census Bureau, 2020. 2014-2018 American Community Survey 5-Year Estimates [WWW Document]. URL <https://data.census.gov/cedsci/> (accessed 7.31.20).
- US Census Bureau, 2017. Average One-Way Commuting Time by Metropolitan Areas [WWW Document]. The United States Census Bureau. URL <https://www.census.gov/library/visualizations/interactive/travel-time.html> (accessed 8.24.21).