Urban Mobility and the Experienced Isolation of Students and Adults*

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Abstract

Do urban children live more isolated lives than urban adults? Using cellphone location data, we measure and compare the experienced racial isolation of students and adults. We find that students in cities experience significantly less integration in their day-to-day lives. The average student experiences 28% more racial isolation outside of the home than the average adult. Even when comparing students and adults living in the same neighborhood, exposure to devices associated with a different race is 21% lower for students. Next, we look at more broad measures of urban mobility and find that students spend more time at home, more time closer to home when they do leave the house, and less time at school than adults spend at work. Finally, we find correlational evidence that neighborhoods with more geographic mobility today also had more intergenerational income mobility in the past. We hope future work will more rigorously test the hypothesis that different geographic mobility patterns can explain why urban density appears to boost adult wages but reduce intergenerational income mobility.

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1 Introduction

Are the lives of urban children more segregated than the lives of urban adults? Athey et al. (2021) find that even where residential segregation is high, white and non-white residents interact during the day as they move around their city.[1] Yet while restaurants, shops, and offices have become less segregated since the 1960s, big city schools have not (Orfield et al., 1994). An adult living in a segregated neighborhood may go to a workplace filled with heterogeneous individuals, but her child may go to a segregated school and return home to play with the children next door.

The experienced isolation of the young is particularly important because isolation appears to harm upward mobility (Cutler and Glaeser, 1997; Chetty and Hendren, 2018). Moreover, the Opportunity Atlas data (Chetty et al., 2018) documents a robust negative correlation between urban density and adult earnings for the children of poor parents – children who grew up in the densest Census tracts end up about five percentiles lower in the adult income distribution than children from moderately dense Census tracts (Glaeser and Tan, 2021). This fact is all the more surprising because wage growth for adults appears to be faster in larger cities (Glaeser and Mare, 2001; Roca and Puga, 2017). One possible explanation for why cities appear to increase human capital accumulation for adults, but not for children, is that students live more isolated lives than adults.

In this paper, we test whether the same metropolis that connects grown-ups also isolates children. We follow the methodology of Athey et al. (2021), who use cell phone Global Positioning System (GPS) data to measure the racial isolation individual experience each day by looking at the mobility of people who live in majority white and majority non-white neighborhoods. We use a similar sample of GPS-enabled devices to examine the diversity of interactions of adults and students in the 100 most populous metropolitan areas in the US. Using these data, we also directly measure other indicators of urban mobility, such as time at school or work, time at home, time spent in neighborhoods with highly educated residents, and the exploration of new places.

[1] The 'experienced isolation' measure in Athey et al. (2021) builds on the 'activity space' literature in sociology (Wong and Shaw, 2011; Shelton et al., 2015; Wang et al., 2018; Beiró et al., 2018). This literature is surveyed in Cagney et al. (2020). Most relevantly, (Moro et al., 2021) use GPS data to compare residential and experienced income segregation.

Our data consists of the location histories for a national longitudinal sample of GPS-enabled devices in 2019.[2] For each device, we infer whether it likely belongs to a student or adult by whether it has a regular presence in a high school during weekdays. For privacy reasons, the data exclude anyone under the age of 16, so our focus is on students aged 16-18. Our school-identified group will also include teachers and other school personnel, which will lead the measured differences between adults and students to be muted since our 'student' sample also contains adults. Like Athey et al. (2021), we do not have data on race, but follow their methodology by looking at devices from neighborhoods with differing racial compositions. We label a 'white device' (WD) as one that lives in a Census block group that is majority white (non-Hispanic) and a 'non-white device' (NWD) as one that lives in a majority non-white block group. Our estimates are therefore an examination of how much individuals from predominantly non-white neighborhoods interact with individuals from predominantly white neighborhoods.

Overall, we estimate experienced isolation of 0.65 for adults, which implies that the average student WD is exposed to 65 percentage points more WDs than the average student NWD. Students, meanwhile, have an estimated experience isolation of 0.73, 12% higher than that of adults. If we exclude time at home—where interactions are primarily with family members of the same race—isolation for both groups declines, while the gap between the students and adults becomes larger. Experienced isolation excluding time at home is 0.29 for adults and 0.37 for children, making students 28% more isolated outside the house than adults. These gaps in experienced isolation are persistent across all large metro areas.

To unpack these figures, we move from these population level isolation estimates to a more detailed look at patterns by race and location. We first look at exposure to diversity, which we define at the device level as the average percent of time spent near devices from neighborhoods of a predominantly different race. The average exposure to diversity is only 0.125, and it is about 30% lower for students than for adults. Even when comparing students and adults living in the same tract, exposure to diversity is lower for students than adults for both WDs and NWDs.

[2]Examples of previous applications of GPS location data include mobility during the COVID-19 pandemic (Chang et al., 2020; Allcott et al., 2020; Couture et al., 2021; Chen et al., 2021), waiting times at voting polls (Chen et al., 2019), knowledge spillovers between employees of different firms (Atkin et al., 2020), and demand for amenities (Athey et al., 2021; Miyauchi et al., 2021).

Looking at more broad measures of urban mobility, we find clear ways in which students live more isolated lives. Students spend more at home and in their neighborhood than adults and spend less time at school than adults spend at work. When they do leave the house, students stay closer to home and spend fewer days traveling outside of their home city. On the other hand, students visit more unique locations in the city, suggesting their less routinized lives lead to more exploration. Students also generally spend their time in more prosperous and better educated neighborhoods, even relative to adults who live in the same neighborhood.

To examine whether our results are the same at the fringes of a city and its center, we turn to the connection between population density and outcomes. Density is both a defining characteristic of urbanism and is negatively associated with children's outcomes in the Opportunity Atlas data (Chetty and Hendren, 2018; Glaeser and Tan, 2021). Adults' time at home declines with density while students' time at home increases with density. Meanwhile, time at work is increasing in density for adults, but time at school decreasing in density for students. We also find that in low density locales, students explore more unique locations than adults, while in high density locales, this pattern is reversed and adults explore more unique locations. Finally, we see that, while students generally spend more of their time than adults in areas with high levels of human capital, this pattern is reversed in the highest density neighborhoods. Taken together, these results suggest that while density enables the employment and exposure of adults to more skilled people, density reduces the time at school for students and their interactions with other educated people.

Finally, we examine the correlation between place-based measures of income mobility from Chetty and Hendren (2018) and several mobility patterns from our data. Although our cellphone data is modern while mobility data refers to a cohort born between 1978 and 1983, there are some clear correlations. Most notably, Census tracts where residents have more exposure to diversity, spend more time outside of the city, and visit more unique locations within the city tend to have higher upward income mobility.

2 Data & Measuring Experienced Isolation

2.1 GPS Mobility Data

Our primary data come from a sample of GPS enabled devices for all of 2019. Access to the data is provided by Replica, an urban data platform. For each device, we observe a unique device identifier and a sequence of 'stays' at different locations.[3] Each stay includes the geographic coordinates, entry time, and exit time. We have no direct information about the device's user, and consequently must infer whether a device is a student and their likely race from the location histories of the device. We provided additional details on the data construction in Appendix A.

2.2 Identifying Likely Student and Adult Devices

For each device-quarter in the data, we identify 'home' as a device's most common overnight location and work as a device's most common daytime non-home location.[4] To focus on urban environments, we look only at devices living within the 100 most populous metropolitan Core-Based Statistical Areas (CBSAs). The smallest CBSA to make the cut is the Spokane-Spokane Valley Area in Washington. The resulting sample includes 12.1 million unique devices with home and work detected.

To label a device as a student, we match 'work' locations to school parcels. We identify the locations of high schools using data from the National Center for Education Statistics (NCES), which is described in Appendix Section A.2. We include only high schools, as our GPS data is meant to exclude individuals under 16 years old. We identify 391,866 devices that are likely high school students at these schools. Appendix Figure A.1 shows that our counts of students at a school are highly correlated with the enrollment reported in the NCES.

Our method of identifying students will also capture teachers and staff. This will add noise and, to the extent adults working at schools are similar to other adults, will bias our measures towards

[3]This data is similar in nature to the data used by Athey et al. (2021); however, rather than observing individual pings each time a device connects to GPS, we observe only these aggregate stays. A consequence of this aggregation is that our data do not include time in transit.

[4]We exclude all devices for which we cannot identify a work location. The majority of these devices have insufficient coverage in the data to confidently identify a work location, but others are either unemployed or employed in occupations without a static work location, such as mailmen or taxi drivers.

finding no differences between students and adults. However, there does appear to be signal in the classification – for example, when examining the types of establishments they visit, we find that 'students' go to far fewer bars and beer/liquor stores than adults.

2.3 Inferring Device 'Race'

Following Athey et al. (2021), we classify devices as either a 'white device' (WD) or 'non-white device' (NWD) based on whether or not their home block group is majority white alone (non-Hispanic) in the American Community Survey (ACS).[5] The average home block group for WDs is 78.5% white, while the average home block group for NWDs is 21.0% white. These assigned races are likely to overestimate true experienced isolation, since the interactions of the minority group of a block will be identified with the majority. However, as long as this misattribution is the same for adults and students, our analysis of differences between these two groups will not be biased.

2.4 Measuring Experienced Isolation and Diversity

We follow Athey et al. (2021) as closely as possible to estimate experienced isolation, but some modifications are required because our data are at the aggregate 'stay' level rather than 'ping' level.[6] Aggregate experienced isolation—setting aside adult and student types for now—is defined as

$$\mathrm{EI}_a = \frac{1}{|\mathrm{WD}_a|} \sum_{i \in \mathrm{WD}_a} \int_{t=0}^{1} s(l(i,t),t)dt - \frac{1}{|\mathrm{NWD}_a|} \sum_{i \in \mathrm{NWD}_a} \int_{t=0}^{1} s(l(i,t),t)dt \tag{2.1}$$

where a is a given CBSA, WD_a is the set of of white devices, NWD_a is the set of non-white devices, and $s(l(i,t),t)$ is the share of individuals in i's location l at time t who are from group WD. In words, this is simply the difference between the average exposure of WDs to other WDs and the average exposure of NWDs to WDs.

[5] We use 2019 ACS block groups rather than 2010 Census blocks as the 2010 Census is now significantly out-of-date. The results are similar if we instead use 2010 blocks.

[6] A ping is recorded each time a GPS device shares its location, while stays are aggregates of pings into individual stops at a location (with entry and exit times). For example, a visit to a grocery store may generate hundreds of pings but would only result in a single stay. We use the duration of a stay as a weight to approximate for the number of pings that were emitted during the stay. This still excludes time spent traveling between stays, which is included in ping-level measures from Athey et al. (2021).

We make several assumptions in order to estimate Equation 2.1. First, we assume that $s(l(i,t),t)$ does not vary by time for a given location.[7] Second, we assume that the full population of visits can be approximated using the device sample, re-weighted accordingly. Finally, we discretize locations by geohash7s (approximately 500×500 feet).

To estimate Equation 2.1, we first construct leave-one-out estimates of $s(\cdot)$ for each individual-location as:

$$\hat{s}_l^{-i} = \frac{\sum_{j \in P_l^{-i,\text{WD}}} \gamma_j d_j}{\sum_{j \in P_l^{-i}} \gamma_j d_j} \tag{2.2}$$

where P_l^{-i} is the set of stays in location l by devices besides i, $P_l^{-i \cap \text{WD}}$ is the set of stays in location l by WDs, and d_j is the duration of stay j.[8] Next, for each device-quarter in our sample we measure aggregate exposure as:

$$\hat{S}_{iq} = \frac{1}{\sum_{j \in P_{iq}} d_j} \sum_{j \in P_{iq}} \hat{s}_l^{-i} d_j \tag{2.3}$$

where P_{iq} is the set of all stays by device i in quarter q.

Finally, we estimate experienced isolation for a CBSA a as:

$$\hat{\text{EI}}_a = \frac{1}{|\text{WD}_a|} \sum_{i \in \text{WD}} \sum_{q \in Q_i} \lambda_{iq} \hat{S}_{iq} - \frac{1}{|N\text{WD}_a|} \sum_{i \in \text{NWD}} \sum_{q \in Q_i} \lambda_{iq} \hat{S}_{iq} \tag{2.4}$$

where Q_i is the set of quarters in which device i is observed and we abuse notation slightly to let WD_a be the set of all white device-quarters (rather than just devices) in geography a and NWD_a be the corresponding set of non-white device-quarters. We use sample weights λ_{iq} to correct for unevenness in the home locations of GPS sample compared to the ACS. We provide more details on these sample weights, which are used for all results in the paper, in Appendix Section A.4.

To estimate experienced isolation for students and adults, we estimate Equation 2.4 separately for each type. Note that the leave-one-out estimates of exposure remain the same, but only devices of a given type are used to aggregate exposure in Equation 2.4 – consequently, our experienced isolation measure for students measures exposure to both students and adults.

[7] This is most clearly violated in residential areas, where daytime and nighttime populations will differ substantially.
[8] We weight by duration in the location to approximate the ping-level measure used in Athey et al. (2021).

Experienced isolation is defined at the population level. An experienced isolation score of 0.1 would imply a gap of 10 percentage points in the exposure to WDs by other WDs and NWDs. We also define a companion measure at the individual level, which we call experienced diversity. Experienced diversity for a given device is the average exposure to devices of the *opposite* imputed race and is estimated as

$$\hat{\text{ED}}_{iq} = \frac{1}{\sum_{j \in P_{iq}} d_j} \sum_{j \in P_{iq}} \mathbb{1}\{\text{NWD}_{iq}\} \hat{s}_l^{-i} d_j + \mathbb{1}\{\text{WD}_{iq}\}(1 - \hat{s}_l^{-i}) d_j \tag{2.5}$$

where $\mathbb{1}\{\text{WD}_{iq}\}$ and $\mathbb{1}\{\text{NWD}_{iq}\}$ are indicators for whether the device's imputed race is white or non-white. As before, $\hat{s}_l^{-1}$ is the leave-one-out estimate of location l's share white, d_j is the duration of stay j, and P_{iq} is the set of all stays for device i in quarter q. The two measures are closely linked – experienced isolation is a transformation of the average experienced diversity in a CBSA.[9]

We want to highlight that these measures capture geographic isolation, which may not map one-to-one with social segregation White (1983). Devices occupying the same geographic space may not meaningfully interact – for example, students in diverse schools may occupy similar spaces, but form social cliques split along racial lines.

3 Experienced Isolation and Diversity of Students and Adults

In this section, we first discuss overall experienced isolation and then turn to experienced diversity, our individual level component of experienced isolation. We end by discussing the broader patterns of mobility and interaction that we observe for adults and students.

3.1 Experienced Isolation

The leftmost column of panel (a) in Table 1 shows that overall experienced isolation is 0.65, meaning that the average WD spends their time (on average) with 65 percentage points more WDs than the average NWD spends with WDs. The bulk of this isolation comes from the home – aggregate experienced isolation outside the home drops to below 0.3.

[9] Experienced isolation can be computed from experienced diversity as $\text{EI} = (1 - \bar{\text{ED}}_{\text{WD}}) - \bar{\text{ED}}_{\text{NWD}}$, where $\bar{\text{ED}}_{\text{WD}}$ is the average experienced diversity of white devices and $\bar{\text{ED}}_{\text{NWD}}$ is the average experienced diversity of NWDs.

The second and third columns show the different experienced isolation of students and adults. Overall student isolation is 0.73 and adult isolation is 0.65. When we exclude nighttime hours, the experience isolation of both groups falls, but there is still a significant difference between the groups. When we just look at isolation outside the home, the experienced isolation of adults is 0.288 and the experienced isolation of students is 0.368. Excluding time at home, students experience roughly 28% more isolation than adults.

Panel (b) documents the time allocations of students and adults at different types of locations. Students spend 65% of their time at home, while adults spend 61% of their time at home. Students also spend additional time in their home neighborhood, outside of the house. By contrast, adults spend 17% of their time at work while students spend 14% of their time at school.[10] The other time use categories all represent much smaller time allocations. Adults spend more time at shops, restaurants, parks and entertainment venues. Students appear to spend more time at religious establishments. Adults also spend more time in the 'other' category, which can include travel, outdoor activities, or time visiting friends in other neighborhoods.

Panel (b) also shows the experienced isolation for adults and students in each one of these categories. Every category is more isolated for students than adults. Time at home and in the home neighborhood is particularly isolating for both students and adults. The isolation of students at home is 0.9 and the isolation of adults at home is 0.85. In some cases, such as restaurants and entertainment venues, the experienced isolation gaps are relatively small (0.02 or less). In other areas, such as schools/workplaces or the other category, the gaps are quite sizable (0.06 or more). The higher aggregate isolation of students partially reflects the fact that adults spend more time at work than students spend at school, and that (childless) adults are more likely to live in areas that have visitors from different race neighborhoods.

In the Appendix, we document how these measures vary across individual CBSAs – Figure B.6 maps the overall experienced isolation and gap between students and adults for all CBSAs and Table B2 provides the raw numbers. While the levels of experienced isolation differ substantially

[10] The American Time Use Survey (ATUS) reports that adults spent 14% of their time working. The discrepancy can be explained by the fact that we identify place of work as an individual's most common daytime destination, and so everyone in our sample has a place of work.

across CBSAs, the experienced isolation of students is higher than that of adults in nearly all of the largest CBSAs.[11] The gap between student and adult experienced isolation is especially high—about 10 percentage points—in the CBSAs of the largest American cities, including New York City, Chicago, and Los Angeles. In Appendix Section B.3, we also discuss the relationship between our measures and enrollment-based school isolation measures from Logan et al. (2017).

3.2 Exposure to Diversity

Table 1, Panel (c), focuses on the individual-level measure, exposure to diversity. This is useful for decomposing the difference between students and adults into a residential location component and a within neighborhood component. Overall exposure to diversity is 0.125, meaning 12.5% of the average device's geographic interactions are with devices of the opposite inferred race.[12] The second and third rows break this measure out for WDs and NWDs. White exposure to diversity is 0.10, while non-white exposure to diversity is 0.16. This large gap partially reflects the fact that there are many more devices that we categorize as white.

In the middle and right columns, we report the coefficient on whether a device is a 'student' in two separate regressions. In the regressions associated with the middle column, we control for metropolitan area fixed effects. In those for the right column, we control for tract fixed effects. The middle column therefore answers the question of whether students are disproportionately isolated relative to adult residents of their metropolitan area. The right column asks if students are more isolated that adults who live in their neighborhoods. The middle column reveals more about the overall isolation of students, since conditioning on place of residence is essentially controlling for a major determinant of individual isolation.

All six coefficients in these columns are significant and negative. In the first row of the panel, we find that exposure to diversity is 0.039 points lower for students than for adults, which is approximately 30% of the sample mean. The estimated student coefficient drops in magnitude

[11] The three exceptions are El Paso, TX, McAllen-Edinburg-Mission, TX, and Durham-Chapel Hill, NC

[12] If both WDs and NWDs experienced a diversity exposure of 0.125, then the implied isolation measure is 0.75, which is higher than our measure of isolation. Experienced isolation is computed at the CBSA-level and then aggregated by taking the population weighted average, which yields slightly different results than averaging exposure to diversity at the individual-level as smaller metropolitan areas are generally less segregated than larger areas.

Table 1: Experienced isolation of students and adults

Panel a) Overall experienced isolation (EI)	Aggregate	Students	Adults
All hours	0.6535	0.7321	0.6512
Excluding night time (12am-6am)	0.5677	0.6243	0.5661
Excluding time at home (<150m)	0.2910	0.3679	0.2883
Excluding time in home tract	0.2631	0.3325	0.2605

Panel b) EI by location category	Students		Adults	
	% of hours	EI	% of hours	EI
Home	65.371	0.900	60.996	0.851
Neighborhood (excl. home)	5.267	0.645	4.141	0.604
School/work	14.182	0.354	17.223	0.282
Retail	0.296	0.190	0.493	0.205
Restaurant	0.288	0.170	0.403	0.151
Entertainment	0.410	0.130	0.442	0.117
Park	0.435	0.212	0.501	0.176
Religious organization	0.067	0.291	0.054	0.249
Other	13.298	0.286	15.469	0.227

Panel c) Individual exposure to diversity	Average	Coefficient on isStudent (Home CBSA controls)	Coefficient on isStudent (Home tract controls)
All			
Exposure to diversity	0.125	-0.0386	-0.0264
		(0.0002)	(0.0002)
Exposure to NWD by WD	0.1001	-0.0353	-0.0239
		(0.0002)	(0.0002)
Exposure to WD by NWD	0.1645	-0.0341	-0.0294
		(0.0003)	(0.0003)
Excluding time at home			
Exposure to diversity	0.2631	-0.0529	-0.0377
		(0.0003)	(0.0003)
Exposure to NWD by WD	0.2087	-0.0534	-0.0411
		(0.0003)	(0.0003)
Exposure to WD by NWD	0.3496	-0.0303	-0.0309
		(0.0005)	(0.0004)

Note: This table documents overall experienced isolation measures, computed as a weighted average of CBSA-level measures, with weights corresponding to the CBSA population. Panel a) documents the overall level of experienced isolation. 'At home' is defined as within 150 meters of home location. 'Neighborhood' is defined as within a mile of home, but not at home. Panel b) splits the experienced isolation measures by categories of locations visited. Panel c) runs individual-quarter regressions of exposure to diversity on whether the device is a student with either home CBSA or home Census tract fixed effects.

to -0.026 when we include tract of residence fixed effects. This fact suggests that one-third of the difference in exposure to diversity between students and adults is due to the different home locations of students. Outside the home, students have about 20% less exposure to devices of the opposite race than adults. In the second and third rows, we split up the sample by imputed race and find quite similar results.

In the bottom of Table 1, Panel (c), we report results on exposure to diversity outside the home. Since race is imputed based on residential location, exposure to diversity is artificially low within the home as all residents are assigned the same race. When we exclude time spent at home, exposure to diversity increases to 0.26 in aggregate (0.21 for WDs and 0.35 for NWDs). The overall student exposure to diversity outside the home is 20% lower than adult exposure to diversity when we control for metropolitan area, and 14% lower when we control for tract of residence. In the bottom two rows, we find that exposure outside the home is lower for WDs than for NWDs. For WDs, student exposure to diversity is over 25% lower than adult exposure to diversity when we control for metropolitan area and 20% lower than adult exposure when we control for tract of residence. The gap between adult and student exposure to diversity is lower for NWDs, but it is still statistically significant and economically meaningful. Controlling for either tract or metropolitan area, we find that the exposure of NWDs to diversity is about 8% lower for students than for adults.

4 Broader Mobility Patterns of Students and Adults

We now turn to broader patterns of urban mobility between adults and students. We report measures of the distances they travel, the time spent at home and work/school, and the characteristics of the areas that they visit. We then turn to the links between density and urban mobility.

4.1 Broader Mobility Patterns of Students and Adults

Table 2 looks at patterns of mobility between students and adults. We document a general pattern of adults being more mobile than students. The first two rows of Panel (a) mirror results that have already been shown in Table 1 – adults spend less time at home than students and more time at work than students spend at school. The results with home tract controls show that the time gaps found in Table 1 are not the result of residential location.

Rows (3)-(5) show that adults are generally more mobile than students. Students are more likely to spend time close to their homes, even when they are not in their homes, while adults are more likely to travel $>$ 50 miles away from home. Even when we restrict to days when devices remain within 50 miles of their residence, adult devices travel further afield than student devices. These facts could be explained by the greater prevalence of car ownership among adults and by adults commuting further for work than students commute for school.

The final row of Panel (a) reports the number of unique locations (geohash7s) visited in a quarter. We observe student phones going to about 8% more unique locations than adults, holding metropolitan areas fixed. When we control for Census tract of residents, the gap drops to about 4%, suggesting that students live in places where people tend to be more mobile. Even though students spend more time in the house, they go to more unique places when they do travel, which is compatible with a view that students' lives are less routinized than adults.

In bottom panel, we look at the characteristics of the Census tracts where adults and children travel, excluding time at home or work. The first three rows show demographic characteristics of residents. All three demographic variables show a similar pattern. Students are generally exposed to richer, better educated, and whiter neighborhoods. For all three of these outcomes, however, the coefficients fall by more than half once we control for tract of residence. Indeed, the coefficients for both race and education become quite small with these controls.

The fourth row shows air pollution, measured by the presence of particulates with diameters smaller than 2.5 micrometers. The air pollution regressions show that children typically face less pollution than adults in their metropolitan area, but more pollution than adults who live in their Census tract, although the magnitudes are small in both cases. In the last row, we look at exposure to crime, although we can do this only for Chicago and Los Angeles where we have neighborhood-level crime data. Adults are exposed to far more crime than children, but the coefficient drops by more than half when we control for tract of residence. Again, both results may be explained by parents choosing somewhat healthier (and often suburban) neighborhoods than other adults.

These results looked at aggregate differences in urban mobility of students and adults living in the top 100 CBSAs. We now turn to differential patterns by geography – specifically, by density of residence within a CBSA. We focus on density, because it is the defining feature of cities and because density is a strong negative correlate of upward mobility for urban children (Glaeser and Tan, 2021).

Table 2: Urban mobility of students and adults

	Average (not logged)	Coef. on isStudent (Home CBSA FEs)	Coef. on isStudent (Home tract FEs)
Device-quarter level outcomes			
Frac. of time at home	0.6395	0.0391	0.0345
		(0.0003)	(0.0003)
Frac. of time at work/school	0.1738	-0.027	-0.0231
		(0.0002)	(0.0002)
Frac. time <1mi from home (excl. home)	0.0552	0.0164	0.0186
		(0.0002)	(0.0002)
Frac. of days over 50mi from home	0.0697	-0.0254	-0.0263
		(0.0002)	(0.0002)
Avg miles from home	7.4075	-0.3238	-0.3639
		(0.0011)	(0.0011)
Log # unique locations (geohash7)	41.2958	0.081	0.0379
		(0.0014)	(0.0013)
Characteristics of tracts visited			
Log median HH income	75845	0.0829	0.0381
		(0.0008)	(0.0006)
Frac. college graduate	0.3902	0.0102	0.0012
		(0.0004)	(0.0002)
Frac. White alone	0.5794	0.0315	0.0078
		(0.0004)	(0.0003)
Air quality (PM25)	8.6467	-0.026	0.0079
		(0.0016)	(0.0012)
Log crimes per sq. mi. (Chicago & Los Angeles)	9.711	-0.1973	-0.0709
		(0.0159)	(0.0085)

Note: The table documents coefficients from regressions of mobility metrics on whether the device is a student with fixed effects for either the device's home CBSA of Census tract. Miles from home is the average distance of stays outside of the home on days the device stayed within 50 miles of home, weighted by the stay duration. 'At home/work/school' is defined as within 150 meters of the location's coordinates. We use data on the average estimated tract-level air pollution in 2019 from the Environmental Protection Agency (EPA). For the crime outcomes, we subset to just devices that live within those city boundaries and measure crime as the sum of all crimes reported between 2010-2018 in a tract. The characteristics of tracts visited results exclude time spent at home or work/school. To handle zeros, we use the inverse hyperbolic sine instead of the logarithm. Both the averages and regressions use the device weights; for tract outcomes, the regressions are also weighted by time spent in the tract. Standard errors are clustered at the device-quarter level.

4.2 Density and urban mobility

To examine the relationship between population density and mobility, we use the within-CBSA density decile for each device's home block group. Consequently, we are not estimating a constant treatment effect of physical density but rather the impact of a relatively higher density level within a metropolitan area. Notably, in both our sample of GPS devices as well as in the ACS, students disproportionately live in the less dense, more suburban parts of cities. 3.7% of devices in the least dense decile are students compared to 2.4% in the most dense decile (see Appendix Figure A.2).

Figure 1 plots how certain mobility outcomes vary by within-CBSA density. To construct the figure, we regress each outcome on home density decile interacted with whether the device is a student, controlling for metropolitan area fixed effects. We also control for the log household median income and fraction white alone in the device's home tract to narrow in on the correlation with home density, holding fixed race and income.[13] We normalize the intercept for adults at the first decile to be the mean outcome for adults at that decile.

The first panel shows that adults who live in denser areas spend less time at home than adults in less dense areas. This fits the view that in urban areas, apartments are smaller and people are more likely to go out to eat or drink or find entertainment or work longer hours. The opposite is true for children, who spend more of their time at home when they live in denser areas. Panel (b) shows the mirror of this result for time spent at work or school. Density is associated with more time at work for adults and less time at school for students, while students in the densest block groups spend about one percentage point less time at school than those in the least dense.

Panel (c) shows the number of unique locations visited, which declines with density for both students and adults. The decline with density is quite dramatic for students and quite mild for adults. In the least decile, students visit far more unique locations than adults. In the most dense decile, however, adults visit more unique locations than students. Density seems associated with living more geographically compact lives, especially for students.

Finally, panel (d) shows the education of residents of the tracts in which students and adults spend time outside of the home. This increases for both students and adults generally; however, in

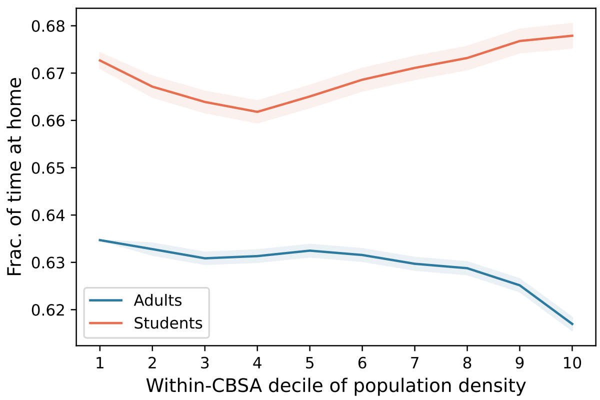
[13] Appendix Figure B.5 repeats these regressions without controls for income and race.

the densest of areas of the cities, there is a sizeable drop for students relative to adults.

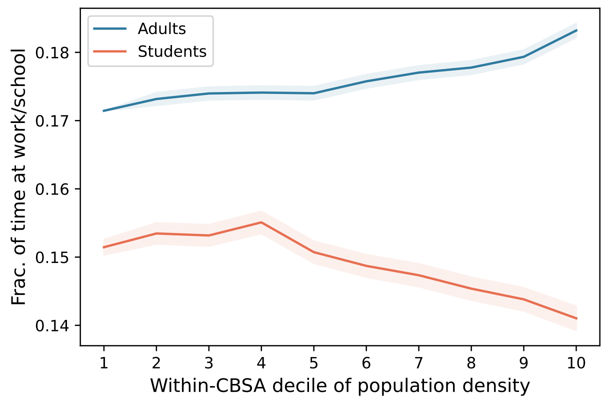
Appendix Figure B.4 includes the relationship between mobility and density for additional outcomes. Overall, we find that geographic mobility varies substantially with density within metropolitan areas, that trends often differ between students and adults, and that the densest deciles often have trend reversals. We now turn to the final section of the paper that concerns the correlation between geographic mobility and income mobility.

Figure 1: Mobility outcomes and density

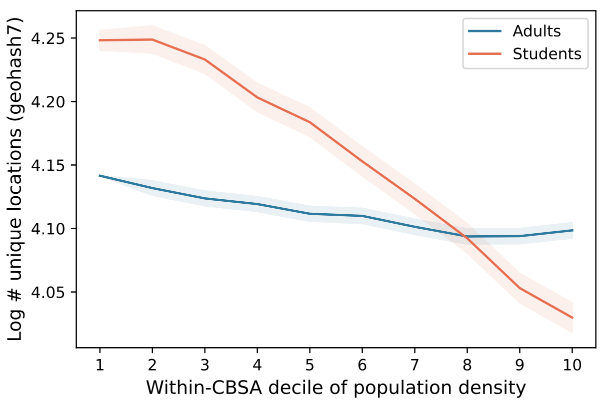
(a) Frac. time at home



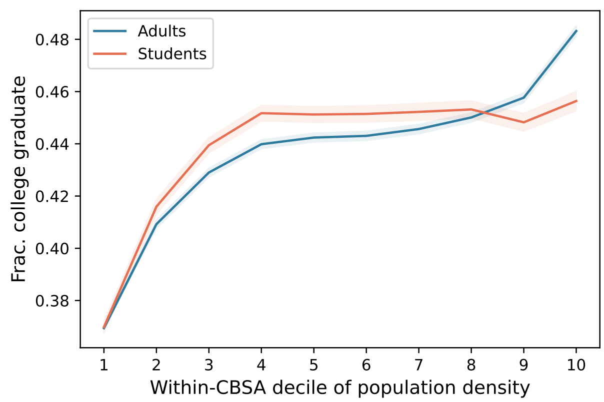
(b) Frac. time at work/school



(c) Log # unique locations



(d) Frac. college grad of visited tracts



Note: This figure plots the relationship between urban mobility and density. We regress each outcome on the interaction between within-CBSA decile of home block group density and whether the device is a student, with fixed effects for the CBSA and controls for log median household income and fraction white alone. Panels a)-c) use device-quarter level data, while panel d) uses data on all tracts visited within a given device-quarter. Coefficients are computed relative to adults in the least dense decile and the Y-axis is shifted by the average outcome for adults in the least dense decile. Standard errors are clustered at the device-quarter level. The shaded region represents a 95% confidence interval.

5 Correlations with Upward Mobility

We use data on upward mobility from the Opportunity Atlas, which is detailed in Chetty et al. (2018). We first focus on majority non-white tracts, and we use the estimated income mobility for children whose parents were at the 25th percent of the income distribution at the time of the child's birth. There is a significant temporal mismatch of more than 20 years between our data and the Opportunity Atlas data, which capture people who would have been 17 years old around 1997. Consequently, these results could easily reflect the impact of income mobility on geographic mobility rather than of geographic mobility on income mobility.

Our results are summarized in Figure 2. In all cases, we report results where absolute income mobility is regressed on geographic mobility. Each panel shows 12 coefficients taken from 12 separate regressions, for six different types of geographic mobility. Panel (a) shows regression results for majority non-white tracts and include CBSA fixed effects but no other tract-level controls. Panel (b) adds controls for tract characteristics, including fraction white in the tract, log of population density, log of median age, and the share of residents enrolled in school. Panel (c) reports results for all tracts, not just those that are majority non-white.

In almost every case, the coefficient on mobility of students is closer to zero than the coefficient on the mobility of adults. The most natural explanation for this fact is that there are far fewer students than adults and consequently our tract-level measures of the mobility of students have more measurement error, which would lead to attenuation bias.

The share of time spent at home, work and school are largely uncorrelated with upward mobility. The time that adults spend in the neighborhood, however, is negatively associated with upward mobility. While we have controlled for density in panels (b) and (c), this variable may still be capturing aspects of suburban life which appear to be positively associated with opportunity the Opportunity Atlas data.

The last three measures of geographic mobility—days spent outside the city, unique locations visited, and exposure to diversity—are each positively correlated with income mobility in all three figures, using data for both adults and students. In the first two panels, exposure to diversity has the strongest correlation with upward mobility. This echos earlier research finding that residential segregation is negatively associated with upward mobility (Chetty and Hendren, 2018). The correlation between exposure to diversity and income mobility in Figure 2 provides suggestive evidence that experienced isolation is also associated with less upward mobility. The number of unique locations visited by adults is also strongly associated with upward mobility in all three panels. These facts are compatible with the view that mixing is associated with escaping poverty, but future work will need to address the possibility that the causality is running in the opposite direction.

6 Conclusion

In this paper, we address the hypothesis that adults and students experience different levels of segregation, even if they live in the same neighborhood. We follow the methods of Athey et al. (2021) to measure 'experienced isolation' of students and adults. Our primary innovation is to look at the experienced isolation and overall urban mobility of adults and students separately.

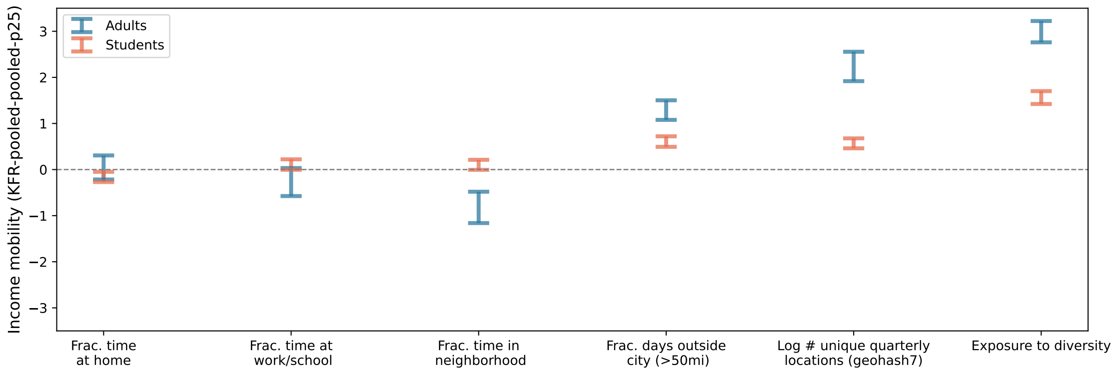
We find significant differences in the experienced isolation and urban mobility of adults and students. Overall isolation is 12% higher for students than for adults and isolation when outside the home is 28% higher for students. Overall exposure to diversity is 32% lower for students than for adults when controlling for metropolitan areas. Even when comparing devices who live in the same tract, exposure to diversity is 21% lower for students. These results support the hypothesis that the urban young live far more isolated lives than adults, which may explain why cities appear to increase wage growth for adults but reduce upward mobility for children (Glaeser and Tan, 2021).

Looking at broader measures of urban mobility, we find that students spend more time at home than adults, especially when they live in the densest parts of metropolitan areas. Moreover, even when outside the home, students spend their time closer to home and travel outside the city on fewer days. Adults spend more time at work than students spend at school, and their workplaces tend to be more integrated than students' high schools. Students do, however, spend their time in more prosperous and better-educated—but also less diverse—neighborhoods than adults.

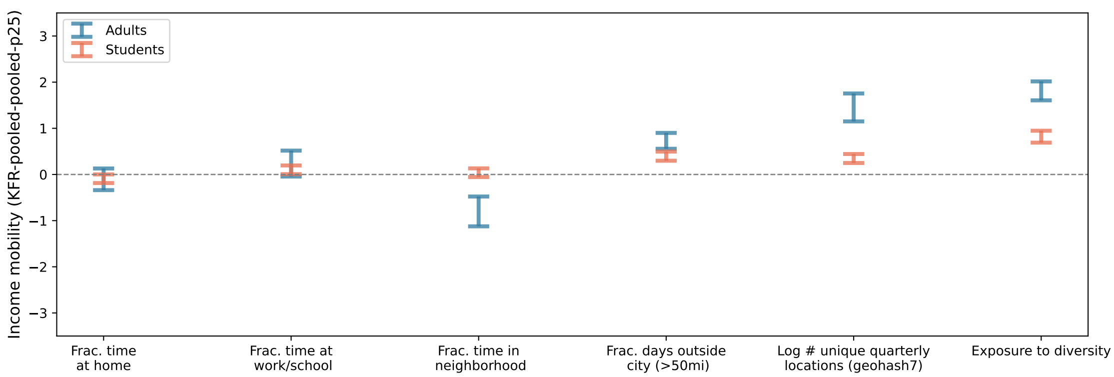
Finally, we find the slightest suggestion of evidence that these forms of isolation are associated with lower levels of upward income mobility. Using measures of income mobility from Chetty and Hendren (2018), we find positive correlations between upward income mobility and exposure to

Figure 2: Income mobility and urban mobility

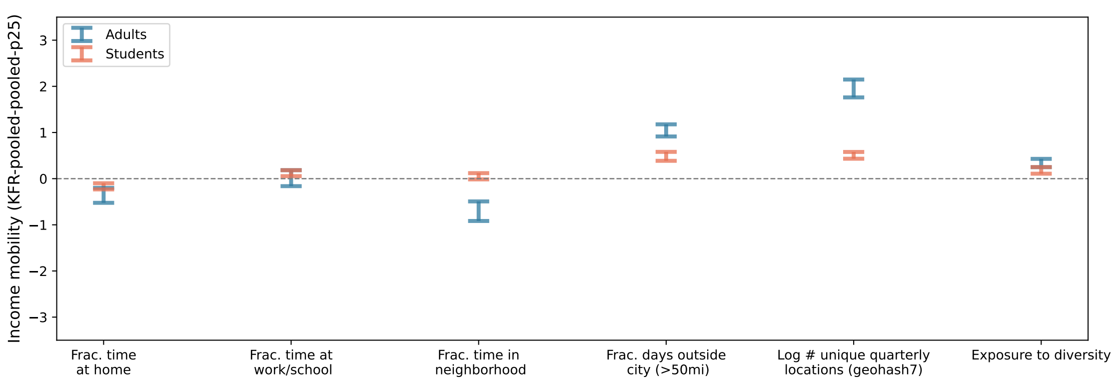
(a) Majority non-white tracts. Controls: CBSA FEs



(b) Majority non-white tracts. Controls: CBSA FEs and tract characteristics



(c) All tracts. Controls: CBSA FEs and tract characteristics



Note: This figure plots coefficients from tract-level regressions of opportunity and urban mobility measures for students and adults, with fixed effects for CBSAs. Controls for tract characteristics include fraction white alone, log population density, log median age, and the fraction of residents enrolled in school. The regressions for students and results are run separately and exclude any tracts with 5 or fewer student devices. Opportunity is measured by the absolute income mobility for students born to parents in the 25th percentile of income – a value of 1 implies an increase of one percentage point in the income distribution. Each regression is weighted by the number of households in that tract who are below the 25th nationwide income percentile. Effects are standardized to be for a one standard deviation increase in the urban mobility measure for each groups. Each bar represents a 95% confidence interval.

diversity, time spent away from the city, and number of unique locations visited. However, we caution that these correlations are stronger for the adult measures than for the student measures, and income mobility is assessed for a cohort that is roughly forty years old at the time of our geographic mobility measures. We hope that future research will assess the connection between urban mobility and income mobility more thoroughly.

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A Data appendix

A.1 GPS data

The GPS data come from an unbalanced panel of GPS-enabled devices in 2019. Home and work locations are identified by Replica based on heuristics for when individuals tend to be at home versus work. Home location is generally the most common overnight location in a quarter, while work locations is generally the most common non-home daytime location.[14]

To identify stays at different types of establishments, we use data from SafeGraph on the locations of various Points of Interest (POIs). The establishments data include the polygon describing the establishment's footprint. We use this polygon to identify when a device visits a given establishments. For establishments located within a larger, parent location (e.g., a restaurant within a mall), we assign the parent location rather than trying to disambiguate the individual establishment.

We categorize establishments according to their North American Industry Classification System (NAICS) code. Restaurants are those with NAICs codes beginning with '722'. Retail locations are those establishments with NAICS codes beginning with '44' or '45'. Parks, while not establishments, are identified in SafeGraph with a NAICS codes of '712190'. Entertainment locations are all non-park POIs with a NAICS code beginning with '71'. Finally, religious organizations are those with NAICS codes beginning with '8131'.

A.2 Building a sample of schools

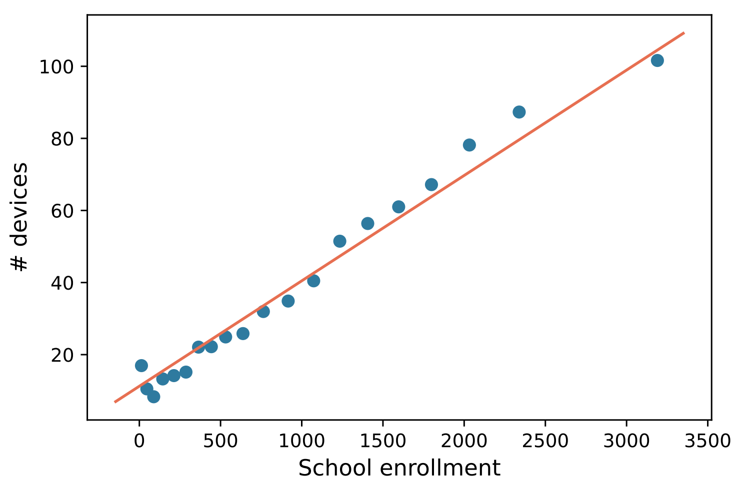
The schools data comes from the National Center for Education Statistics (NCES). However, NCES data only includes the school address, name, grades served, and enrollment. Moreover, the address is often a PO box or simply the town center rather than the actual school location. To match NCES schools to parcels, we first match each school to Safegraph data on schools using the school's name and location. The Safegraph data includes precise coordinates for each school as well as polygons. Unfortunately, the Safegraph polygons—which are often automatically generated from satellite imagery—are inaccurate for schools; for large schools with multiple building, the polygon

[14] We require devices to have at least 8 overnights and 5 days at work in the quarter to make the sample.

will generally only include a single building. We instead match the Safegraph coordinates to parcel-level data from LandGrid. These parcels come from local municipalities and provide more accurate boundaries for school locations. In total, 82% of schools representing 88% of enrollment are successfully matched to a parcel.

Figure A.1 plots the relationship between a school's enrollment and the number of devices we label as a student at that school – the two counts of students are highly correlated. Figure A.2 plots the percent of residents who are students in the GPS sample as well as the percent who are in grades 9-12 in the 2019 5-year ACS. Students predominantly live in the less dense areas of the city. The overall trend is true in both the ACS and GPS, although we consistently find fewer high school (HS) students in the GPS data than in the ACS. This could be due to a number of factors, including 1) many HS students are under 16 years old and 2) we cannot match all schools to parcel polygons.

Figure A.1: NCES school enrollment & number of devices in sample

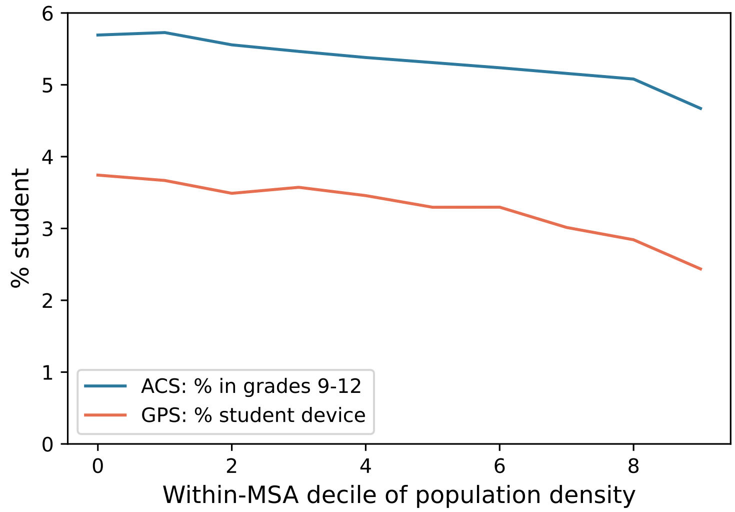


Note: This figure plots the relationship between the enrollment of a school as reported by the NCES and the number of devices labeled as a student of that school.

A.3 Sample quality

Figure A.3 plots the fraction of devices who live in each decile of tract characteristics – if sampling were orthogonal to tract characteristics, 10% of devices would be sampled from each decile. Instead,

Figure A.2: Percent of residents who are students by density



Note: This figure plots the percent of residents who are students by within-CBSA home block group density. We separately plot the percent student in the GPS sample as well as the percent in grades 9-12 in the 2019 5-year ACS.

we can see that devices are over-sampled from poorer, less white, less educated, and more dense areas.

Figure A.4 plots the distribution of block group fraction white-alone (non-Hispanic). The average block group of white devices is 78.5% white, while the average block group of non-white devices is 21.0% white.

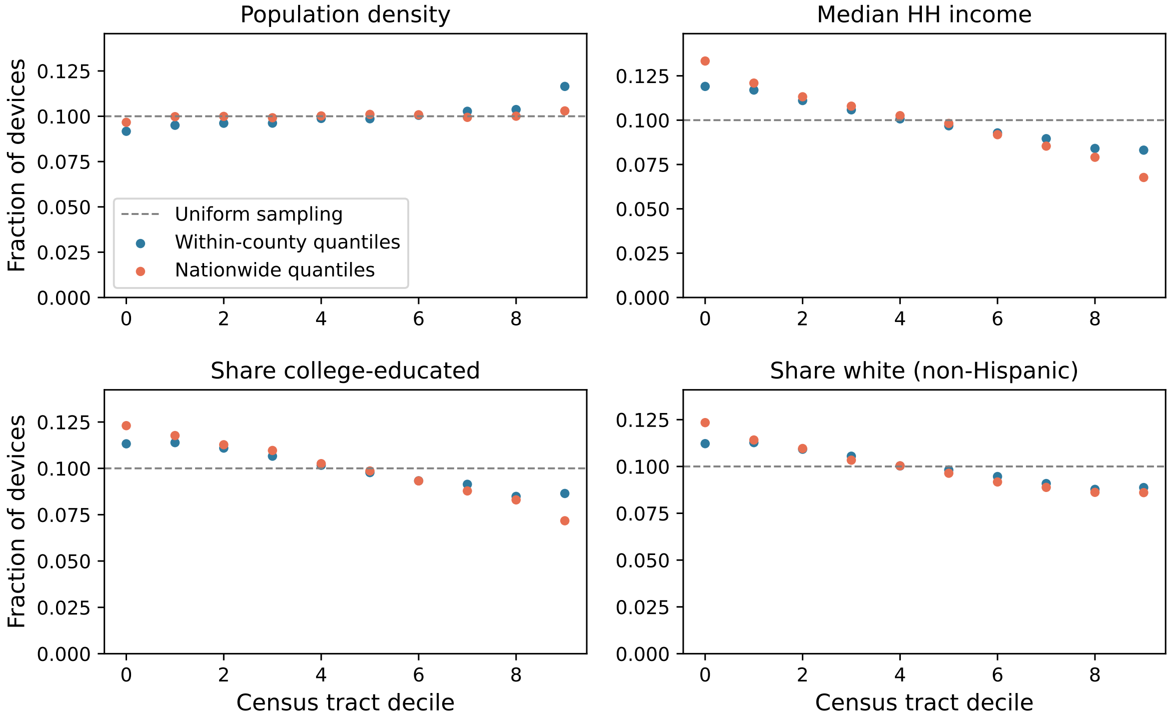
A.4 Sample Weights

GPS devices in our sample tend to be slightly over-sampled from poorer, less white, less educated, and more dense areas (see Appendix Figure A.3). To address the uneven sampling of devices, we re-weight home locations to match the distribution of the 2019 5-year ACS by using the following sample weights

$$\lambda_{iq} = \frac{N_{g(iq)}}{\tilde{N}_{g(iq)}}$$

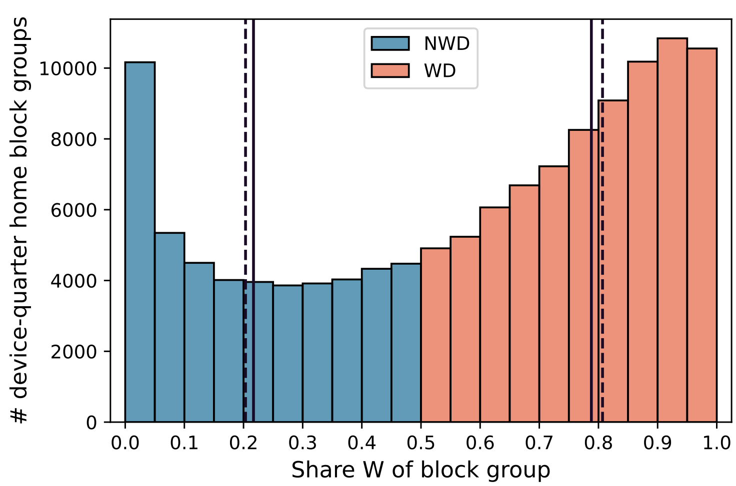
where $N_{g(iq)}$ is the ACS population of a device's home tract g and $\tilde{N}_{g(iq)}$ is the total number of devices observed in tract g in quarter q. The average device weight is 20.2 (standard deviation of 12.9). We use these weights for all results.

Figure A.3: Sampling of devices by block group characteristics



Note: This figure plots the relationship between the enrollment of a school as reported by the NCES and the number of devices labeled as a student of that school.

Figure A.4: Distribution of block group level fraction white



Note: This figure plots a histogram of the number of the number of devices sampled from different bins of home block group fraction white alone (non-Hispanic). The solid line represents the mean fraction white for each WD and NWD; the dashed line is the median.

B Additional results on the mobility of students & adults

B.1 Experienced isolation with continuous race

Our baseline measure of experienced isolation uses a binary measure of race—as in Athey et al. (2020)—based on whether a device's home block group is majority white non-Hispanic or not. We also explore assigning devices a continuous measure of race using the percent of their home block group that is white. Using this continuous measure of race, we can estimate experienced isolation as

$$\hat{EI}_a^C = \frac{1}{|W_a|} \sum_i \sum_{q \in Q_i} \rho_{iq} \lambda_{iq} \hat{S}_{iq} - \frac{1}{|NW_a|} \sum_i \sum_{q \in Q_i} (1 - \rho_{iq}) \lambda_{iq} \hat{S}_{iq} \tag{B.1}$$

where ρ_{iq} is the continuous measure of race, $|W_a| = \sum_i \sum_{q \in Q_i} \lambda_{iq} \rho_{iq}$, and $|NW_a| = \sum_i \sum_{q \in Q_i} \lambda_{iq}(1 - \rho_{iq})$

The results are in Table B1. Using this measure, students are 4.12% more isolated in aggregate and 17.6% more isolated when outside of the home. However, the levels are dramatically different.

Experienced isolation with continuous race will be biased downwards relative to 'true' exposure to diversity. Imagine a device whose true exposure to white individuals is 100%. When using a continuous measure of race, each exposure to a white individual will not count as a fully segregated exposure but instead will assume the device is exposed to the average percent white in the individual's home block group, making it look like the device has more diverse exposures than it does. Similarly, a device whose true exposure is 0% white will have a positive estimated exposure.

Table B1: Experienced isolation using continuous measure of race

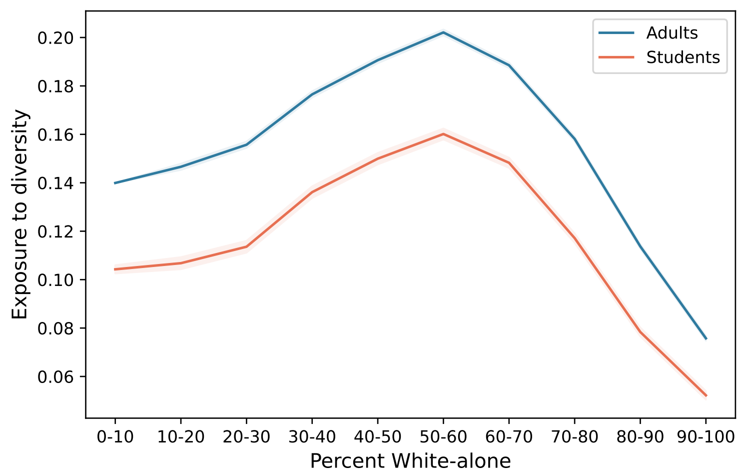
Panel a: experienced isolation	Aggregate	Student	Adult
All	0.2134	0.2248	0.2123
Excluding time at home	0.1141	0.1370	0.1129
Excluding time in home tract	0.1060	0.1274	0.1050

Note: This table documents a few basic measures of experienced isolation using a continuous measure of race based on the percent non-white in a device's home block group

B.2 Exposure to diversity and home block group race

Figure B.1 plots the relationship between percent white in a device's home block group and the device's exposure to diversity. This figure is constructed in a similar manner to those in Figure 1, by regressing exposure to diversity for a given device-quarter on whether the device is a student, interacted with the percent of their home block group's residents who are white (truncated to nearest 10%). Recall that exposure to diversity uses WD and NWD, rather than true race; as such, devices in racially mixed block groups still have exposure to diversity well below 50%.

Figure B.1: Exposure to diversity by home block group percent white

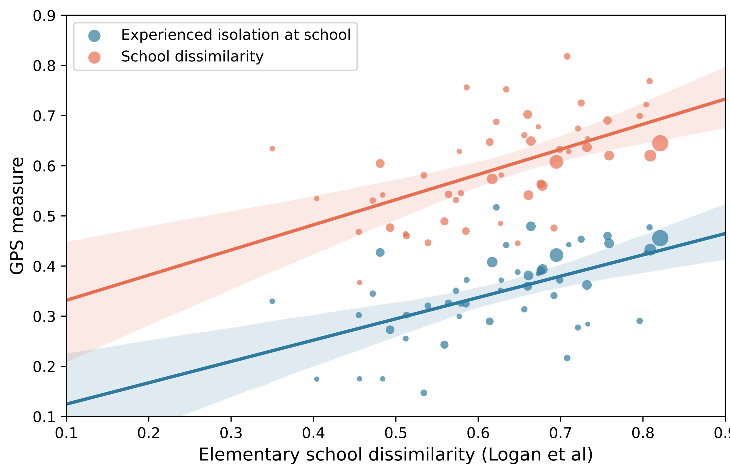


Note: This figure documents how exposure to diversity varies by the racial composition of a device's home block group. The figure is constructed by regressing exposure to diversity for a given device-quarter on whether the device is a student, interacted with the percent of their home block group's residents who are white (truncated to nearest 10%). The shaded region represents a 95% confidence interval

B.3 Experienced isolation and school dissimilarity

Figure B.2 compares measures of segregation from GPS data at the MSA-level to the dissimilarity indices from Logan et al. (2012, 2017) for the top 50 MSAs. The first measure is the experienced isolation of students while at school, while the second is the dissimilarity of WD/NWD school populations within a CBSA, intended to be analogous to the measure in Logan et al. Dissimilarity is defined as the percentage of students in one group who would have to move to a different school to achieve a racial balance representative of the MSA. The GPS measures and the Logan measure are positively correlated, which is encouraging, but there are also clear differences. These differences are perhaps expected for a number of reasons: 1) the dissimilarity indices are based on 2010 elementary school enrollment while the experienced isolation is based on 2019 high school students; 2) the dissimilarity indices compare white students and either Black or Hispanic, while we are comparing students from majority white and non-white neighborhoods; 3) our data will include some teachers; 4) the dissimilarity indices are defined either for MSAs or PMSAs instead of CBSAs, so the geographic match is imperfect (e.g., the results for Chicago are comparing the Chicago PMSA and the Chicago-Joiliet-Naperville CBSA).

Figure B.2: GPS measures vs. elementary school dissimilarity



Note: Figure B.2 compares MSA-level experienced isolation of students while at school and dissimilarity of school populations of WD/NWD to the dissimilarity indices from Logan et al. (2012, 2017) . The dissimilarity indices are based on 2010 elementary school enrollment from NCES. Correlation for EI is 0.55 and for dissimilarity is 0.56.

B.4 Experienced isolation and residential isolation

Figure B.3 plots the relationship between an CBSA's experienced and residential isolation, splitting experienced isolation by whether or not a device is within its home tract. The relationship is plotted for both binary and continuous race and can help highlight the differences of each type of race assignment. For binary race, the time at home is estimated to be extremely isolated—generally far above residential isolation—because devices are spending the majority of their time in a home parcel where all other devices have the same, binary race. Meanwhile, for continuous race, experienced isolation is approximately equal to residential isolation while in the home tract. This is because experienced isolation with continuous race and residential are making a similar underlying assumption – interactions in the home tract are (approximately) with the average race of that location.[15]

For the majority of CBSAs, we estimate that experienced isolation is *higher* than residential isolation. This is counter to the findings in Athey et al. (2020). We believe that the discrepancies stem from differences in data construction. Athey et al. (2020) use raw GPS pings, which are recorded each time an app on the device connects to GPS, while we use staypoints, which are aggregations of pings into 'stays' in a given location. In Athey et al. (2020), a unit of 'exposure' to a neighborhood is therefore at the ping level, while in our measure we weight by staypoint minutes in a location.

The use of stays instead of pings leads to larger estimates of experienced isolation for two reasons, both related to how time spent at home affects the aggregate measure. First, using pings puts less weight on time spent at home. Devices are less likely to ping overnight while the holder is sleeping; however, a staypoint is still formed from the evening to the morning. Athey et al. (2020) report that 42.5% of pings are at home for the average device (their Table A3), while devices in our sample are at home for 63.9% of minutes observed. Excluding night time stays, for example, substantially reduces our measure of experienced isolation, although it remains higher than residential isolation (Table 1).

The second reason is that exposure when using pings will include devices walking/driving through the location, while staypoints include only those devices that stop for at least 5 minutes in a location. This difference is particularly noticeable for residential locations – the experienced isolation in Athey et al. (2020) of 'at home' pings is 0.672 (Table A9), which is lower than expected given that, by definition, all devices who live in that geohash7 are assigned the same race. This low number is likely due to devices who walk/drive through the location during the day, who are more diverse than the residents. The assumption that the time people visit a location is independent

[15] The measures differ for two reasons: 1) with experienced isolation, race is measured at the block group rather than tract level and 2) interactions in the home block group include outside visitors, although for residential tracts the majority of interactions are with other residents.

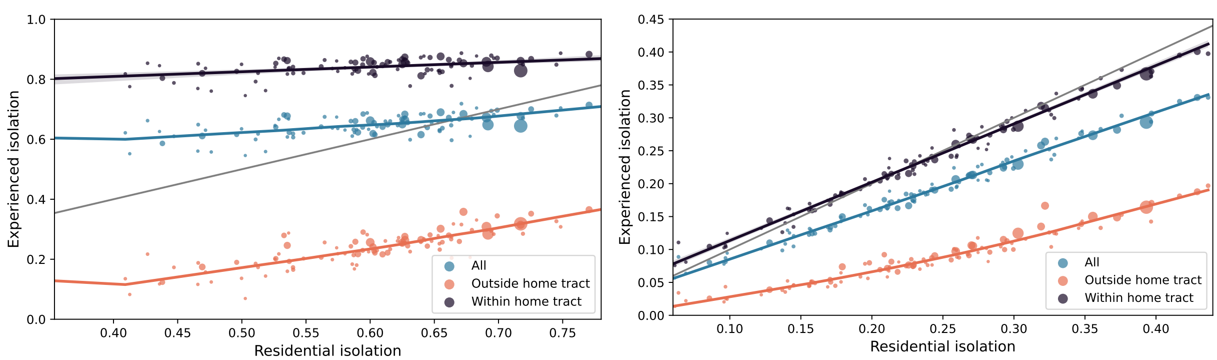
of their race is violated in the case of residences where night-time and day-time populations differ substantially.

While the home-based assignment of race makes it difficult to compare experienced and residential isolation directly, much like Athey et al. (2020) we find that individuals experience far less isolation outside of the home tract than they do within their home tract and that experienced isolation outside of the home tract is also substantially lower than residential isolation. In many ways, this is the core insight of their paper: residential isolation overstates the isolation that individual experience in their day-to-day lives, as time outside of the home is empirically less isolating. Finally, while comparisons of residential and experienced isolation are complicated by the home-based assignment of race, we do not belief the issue affects the relative differences in either measure of isolation for students and adults.

Figure B.3: Experienced vs. residential isolation

(a) Binary race

(b) Continuous race

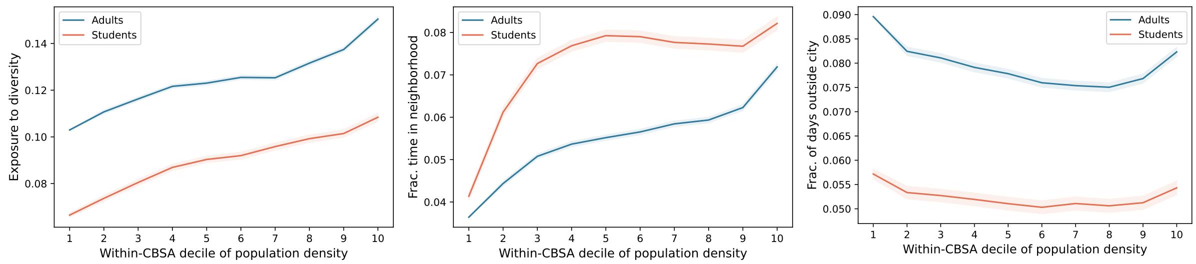


Note: Each figure plots the relationship between experienced isolation and residential isolation at the MSA level. Residential isolation is estimated to be consistent with the method of estimating experienced isolation; it uses either binary block-group level race or continuous race.

B.5 Additional tables and figures

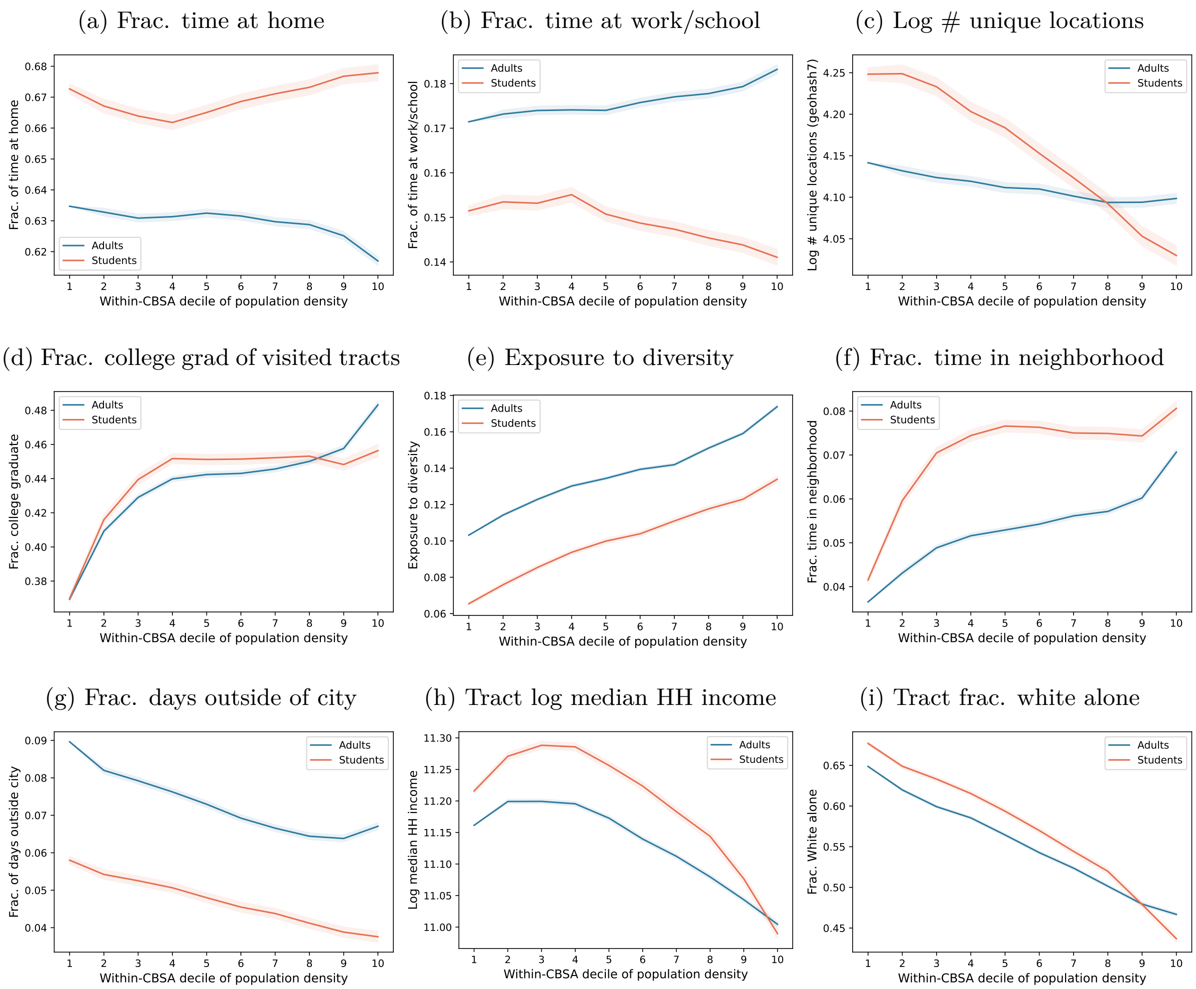
Figure B.4: Mobility outcomes and density – other outcomes

(a) Exposure to diversity (b) Frac. time in neighborhood (c) Frac. days outside of city



Note: This figure extends Figure 1 to additional mobility outcomes. To deal with zeros, we use an inverse hyperbolic sine transformation rather than logarithm.

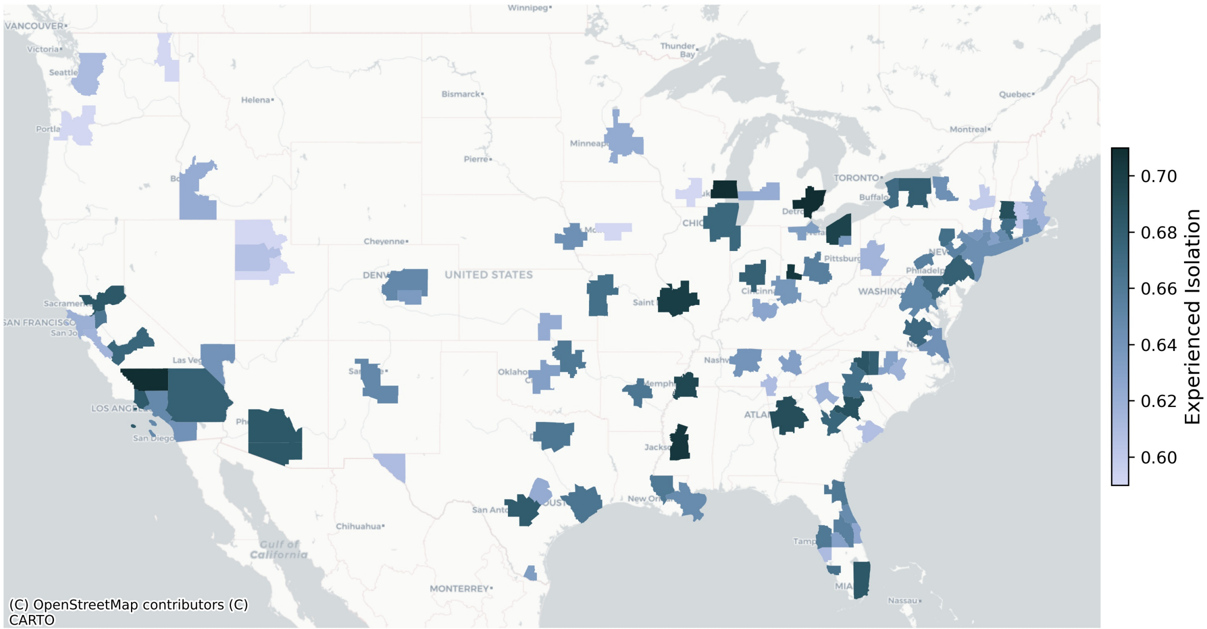
Figure B.5: Mobility outcomes and density – no controls



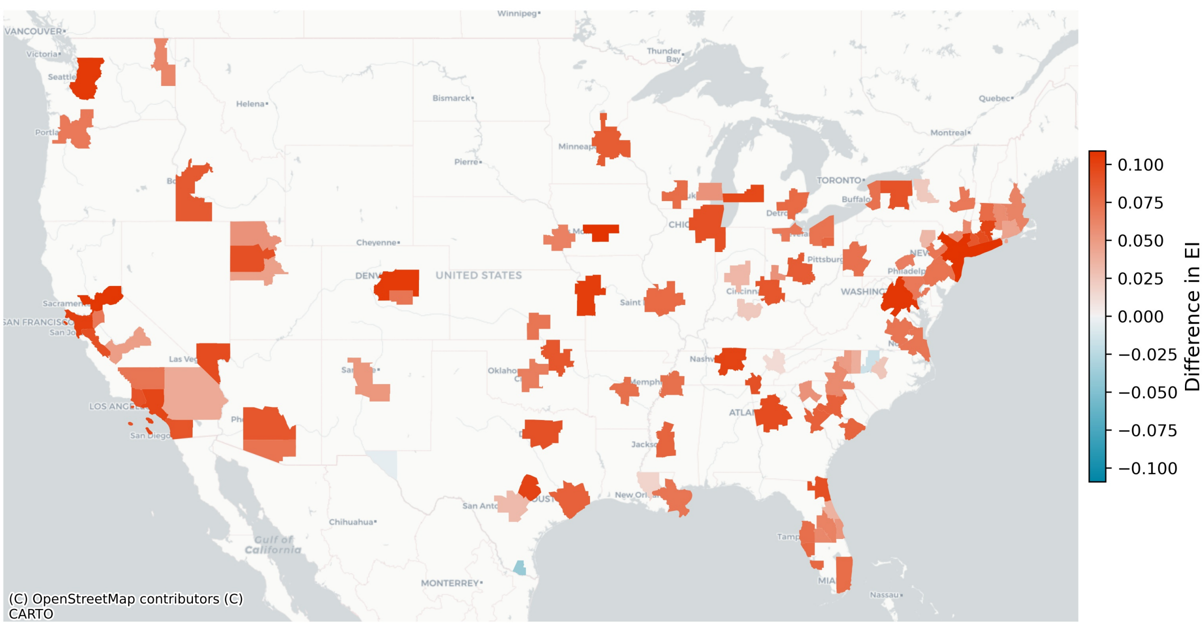
Note: This figure replicates Figures 1 and B.4 without any controls for home characteristics, except home CBSA. This figure also includes two other tract-level outcomes (without controls). To deal with zeros, we use an inverse hyperbolic sine transformation rather than logarithm.

Figure B.6: Experienced isolation by CBSA

(a) Aggregate



(b) Difference between students and adults



Note: These figures map aggregate experienced isolation and the difference between student and adult isolation for each of the top 100 CBSAs.

Table B2: Experienced and residential isolation for all MSAs

	Experienced isolation			Residential isolation
CBSA	Aggregate	Student	Adult	Aggregate
New York-Newark-Jersey City, NY-NJ-PA	0.644	0.750	0.641	0.717
Los Angeles-Long Beach-Anaheim, CA	0.648	0.744	0.646	0.692
Chicago-Naperville-Elgin, IL-IN-WI	0.673	0.763	0.670	0.691
Dallas-Fort Worth-Arlington, TX	0.662	0.750	0.658	0.600
Houston-The Woodlands-Sugar Land, TX	0.664	0.744	0.662	0.627
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.650	0.753	0.647	0.625
Miami-Fort Lauderdale-Pompano Beach, FL	0.684	0.758	0.682	0.673
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.677	0.748	0.676	0.717
Atlanta-Sandy Springs-Alpharetta, GA	0.690	0.780	0.686	0.655
Boston-Cambridge-Newton, MA-NH	0.615	0.676	0.614	0.640
Phoenix-Mesa-Chandler, AZ	0.683	0.769	0.681	0.627
San Francisco-Oakland-Berkeley, CA	0.619	0.718	0.616	0.602
Riverside-San Bernardino-Ontario, CA	0.677	0.718	0.676	0.535
Detroit-Warren-Dearborn, MI	0.714	0.789	0.712	0.771
Seattle-Tacoma-Bellevue, WA	0.611	0.713	0.609	0.469
Minneapolis-St. Paul-Bloomington, MN-WI	0.623	0.706	0.620	0.590
San Diego-Chula Vista-Carlsbad, CA	0.641	0.728	0.639	0.610
Tampa-St. Petersburg-Clearwater, FL	0.661	0.733	0.658	0.588
Denver-Aurora-Lakewood, CO	0.649	0.750	0.646	0.614
St. Louis, MO-IL	0.700	0.775	0.698	0.725
Baltimore-Columbia-Towson, MD	0.672	0.738	0.670	0.661
Charlotte-Concord-Gastonia, NC-SC	0.667	0.724	0.665	0.625
Orlando-Kissimmee-Sanford, FL	0.655	0.717	0.653	0.603
San Antonio-New Braunfels, TX	0.681	0.711	0.680	0.533
Portland-Vancouver-Hillsboro, OR-WA	0.586	0.653	0.584	0.438
Pittsburgh, PA	0.615	0.687	0.614	0.604
Sacramento-Roseville-Folsom, CA	0.684	0.788	0.681	0.594
Cincinnati, OH-KY-IN	0.639	0.726	0.637	0.645
Las Vegas-Henderson-Paradise, NV	0.640	0.732	0.638	0.526
Kansas City, MO-KS	0.667	0.768	0.665	0.669
Austin-Round Rock-Georgetown, TX	0.623	0.718	0.619	0.537

Columbus, OH	0.655	0.739	0.653	0.629
Cleveland-Elyria, OH	0.697	0.767	0.695	0.699
Indianapolis-Carmel-Anderson, IN	0.677	0.711	0.677	0.647
San Jose-Sunnyvale-Santa Clara, CA	0.616	0.705	0.613	0.496
Nashville-Davidson–Murfreesboro–Franklin, TN	0.640	0.738	0.637	0.594
Virginia Beach-Norfolk-Newport News, VA-NC	0.642	0.711	0.640	0.562
Providence-Warwick, RI-MA	0.637	0.677	0.632	0.656
Milwaukee-Waukesha, WI	0.722	0.774	0.720	0.782
Jacksonville, FL	0.661	0.751	0.659	0.585
Oklahoma City, OK	0.632	0.696	0.630	0.587
Memphis, TN-MS-AR	0.694	0.767	0.693	0.694
Raleigh-Cary, NC	0.619	0.643	0.618	0.540
Richmond, VA	0.672	0.741	0.670	0.627
New Orleans-Metairie, LA	0.647	0.716	0.645	0.663
Louisville/Jefferson County, KY-IN	0.627	0.650	0.627	0.654
Hartford-East Hartford-Middletown, CT	0.669	0.766	0.666	0.679
Salt Lake City, UT	0.606	0.697	0.605	0.540
Buffalo-Cheektowaga, NY	0.670	0.741	0.668	0.719
Rochester, NY	0.679	0.768	0.677	0.745
Grand Rapids-Kentwood, MI	0.622	0.716	0.619	0.548
Tucson, AZ	0.684	0.754	0.682	0.639
Tulsa, OK	0.660	0.746	0.658	0.616
Urban Honolulu, HI	0.597	0.687	0.595	0.663
Fresno, CA	0.675	0.720	0.672	0.565
Bridgeport-Stamford-Norwalk, CT	0.631	0.716	0.628	0.654
Worcester, MA-CT	0.599	0.655	0.598	0.511
Omaha-Council Bluffs, NE-IA	0.643	0.705	0.640	0.605
Albuquerque, NM	0.649	0.699	0.648	0.466
Greenville-Anderson, SC	0.618	0.671	0.617	0.513
Bakersfield, CA	0.719	0.787	0.716	0.671
Albany-Schenectady-Troy, NY	0.598	0.665	0.596	0.631
New Haven-Milford, CT	0.646	0.739	0.644	0.621
McAllen-Edinburg-Mission, TX	0.633	0.594	0.634	0.104
Baton Rouge, LA	0.660	0.676	0.659	0.612
Knoxville, TN	0.632	0.644	0.631	0.589

Oxnard-Thousand Oaks-Ventura, CA	0.682	0.769	0.678	0.696
El Paso, TX	0.610	0.605	0.610	0.447
Allentown-Bethlehem-Easton, PA-NJ	0.654	0.723	0.652	0.648
Columbia, SC	0.688	0.767	0.684	0.598
North Port-Sarasota-Bradenton, FL	0.611	0.687	0.609	0.586
Dayton-Kettering, OH	0.704	0.756	0.702	0.748
Charleston-North Charleston, SC	0.608	0.686	0.606	0.535
Greensboro-High Point, NC	0.679	0.716	0.677	0.622
Stockton, CA	0.662	0.728	0.659	0.427
Cape Coral-Fort Myers, FL	0.666	0.742	0.664	0.529
Little Rock-North Little Rock-Conway, AR	0.662	0.734	0.661	0.663
Colorado Springs, CO	0.635	0.704	0.633	0.500
Boise City, ID	0.621	0.706	0.620	0.409
Akron, OH	0.637	0.715	0.635	0.571
Springfield, MA	0.689	0.764	0.687	0.665
Lakeland-Winter Haven, FL	0.630	0.689	0.629	0.472
Des Moines-West Des Moines, IA	0.559	0.672	0.555	0.518
Poughkeepsie-Newburgh-Middletown, NY	0.636	0.693	0.634	0.575
Winston-Salem, NC	0.685	0.732	0.683	0.642
Ogden-Clearfield, UT	0.558	0.610	0.556	0.476
Madison, WI	0.560	0.635	0.559	0.466
Deltona-Daytona Beach-Ormond Beach, FL	0.646	0.681	0.645	0.526
Toledo, OH	0.633	0.700	0.632	0.599
Wichita, KS	0.622	0.691	0.620	0.588
Durham-Chapel Hill, NC	0.631	0.617	0.632	0.580
Provo-Orem, UT	0.552	0.598	0.551	0.413
Syracuse, NY	0.643	0.666	0.642	0.643
Augusta-Richmond County, GA-SC	0.674	0.754	0.671	0.574
Jackson, MS	0.704	0.782	0.702	0.683
Palm Bay-Melbourne-Titusville, FL	0.626	0.678	0.624	0.436
Harrisburg-Carlisle, PA	0.655	0.719	0.654	0.653
Chattanooga, TN-GA	0.610	0.699	0.608	0.678
Scranton–Wilkes-Barre, PA	0.667	0.700	0.667	0.536
Spokane-Spokane Valley, WA	0.546	0.604	0.544	0.503