Urban Mobility and the Experienced Isolation of Students*

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Abstract

How isolated are the lives of urban youth from disadvantaged backgrounds? Using detailed GPS location data, we find that students experience more racial and income isolation, spend more time at home, stay closer to home when they do leave, and visit fewer restaurants and retail establishments than adults. Differences in urban mobility are larger across students from different income levels than between students and adults. Students from higher income families visit far more local amenities, spend more time outside of the home, and explore more unique locations than low income students. Combining a number of measures into an individual level index of urban mobility, we find that—even holding fixed household income—urban mobility is positively correlated with a range of neighborhood characteristics such as distance from the urban core, car ownership, upward income mobility, and social capital.

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1 Introduction

For over 50 years, social scientists have hypothesized that segregation in cities has pernicious effects (Kain, 1968; Taeuber and Taeuber, 1969). While Kain (1968) initially emphasized the employment consequences of a spatial mismatch between adults and jobs, social scientists have increasingly focused on the harm inflicted on children who grow up in segregated or poor neighborhoods (Brooks-Gunn et al., 1993; Cutler and Glaeser, 1997; Sampson et al., 2002; Chetty et al., 2016).

Yet while research has typically focused on place of residence, time spent at home represents only a small part of an individual's waking life. Recent work by Athey et al. (2021) finds that "experienced isolation"—measured using the racial mix of where people spend their time, not where they live—is far lower than measures of isolation based only on place of residence.[1] More broadly, the experience of living in a place can vary across different residents depending on how they interact with the local institutions, amenities, and other residents of their city. How and where individuals spend their time can also affect their social network, shaping the ties between people of different socioeconomic backgrounds that appear to be important for intergenerational income mobility (Chetty et al., 2022a).

In this paper, we study the experienced isolation and overall urban mobility of students using a panel of location data from GPS-enabled devices.[2] We first document differences in how isolated students and adults are by both race and income. We then broaden our analyses to include other measures of urban mobility, including visits to local amenities, time spent at home versus work/school, the number of unique locations explored, and characteristics of places visited. In each case, we compare the experience of students to that of adults, as well as the experience of students from families of different income levels.

[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 measure experienced income isolation and explore its connections to device's overall mobility.

[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; Cook, 2023).

We do not directly observe income, race, or student status and must infer them from other patterns in the data. For household income, we follow Cook (2023) and use aspects of a home parcel, including the market value and structure age, to predict the income of the occupants. Among households with volatile earnings, this method may capture permanent income better than annual earnings. The richness of house-specific data allows us to look at income differences within narrow geographic areas. For race, we follow Athey et al. (2021) and create a proxy using the racial composition of a device's home block group. Finally, we infer student status from whether or not the individual's most common weekday location is a high school. For privacy reasons, cellphone record providers take steps to remove anyone under sixteen years of age, and so our sample contains a mixture of older high school students, teachers, and staff; we expect this to attenuate any differences we measure between youth and adults relative to the population differences.

We find that students experience more racial and income isolation than adults do. Excluding time spent at home, the racial isolation of adults is 17% lower than the racial isolation of students in the 100 largest metropolitan areas. Similarly, the income isolation of adults is 12% lower, driven by the high isolation of wealthier students. One potential explanation for why cities provide benefits for adults (Glaeser and Mare, 2001) but offer less upward mobility for students (Chetty and Hendren, 2018) is that urban children lead more isolated lives than urban adults.

We then turn to broader measures of urban mobility and show that, relative to adults, students spend more time at home and in their neighborhood, stay closer to home when they do leave, and visit fewer restaurants and retail establishments. However, students also visit a greater number of unique locations each quarter, spend more time parks and at civil, social, and religious establishments, and spend more time in areas that are richer, more white, less polluted, and have lower crime rates. The differences are often large. For example, students spend nearly 50% more time in their local neighborhood, visit 5% more unique locations each quarter, and go to 10-20% fewer restaurants and retail establishments. The gaps in student and adult urban mobility shrink by about half when we control for a device's home Census tract, demonstrating that younger urbanites live in neighborhoods typically associated with less urban mobility.

The urban mobility gaps between high-income and low-income students are even larger than the urban mobility gaps between students and adults. Student from in the richest quartile of our sample experience 57% more visits to entertainment venues, 34% more visits to restaurants, 38% more visits to parks, and 54% more total unique locations than students in the lowest income quartile. Higher income students also spend 3 percentage points less time at home and, when they leave home, travel further afield. These differences attenuate when we control for tract of residence, but remain both economically and statistically significant. Even within a tract, higher income students are more mobile and take advantage of more urban amenities. These mobility patterns are compatible with the other work documenting a higher willingness to pay for amenities by more educated, richer urban residents (Diamond, 2016; Couture and Handbury, 2020).

Even accounting for differences in household income, we find that urban mobility is correlated with a range of neighborhood characteristics. To simplify our analysis, we aggregate our various measures into a single urban mobility index for each device using principal component analysis. First, urban mobility of students is lower in places that are more densely populated and closer to city hall, paralleling findings that income mobility is also lower in denser neighborhoods and neighborhoods that are closer to the city center (Chetty and Hendren, 2018). Second, urban mobility of students is higher in areas that are higher income or have historically offered greater economic opportunity, as measured by Chetty et al. (2018). Third, urban mobility is higher in areas with greater social capital, as measured by Chetty et al. (2022a,b) using data on Facebook friendships. These results suggest that places with connection across socioeconomic statuses in the virtual world also have residents who are more connected to urban assets in the physical world, supporting the general hypothesis that people benefit more from a city when they connect with a wider swath of its inhabitants.

In Section 2, we discuss our cellphone data and our imputation of income, race, and student status. Section 3 discusses the differences that we document between students and adults. Section 4 presents the results by household income and correlations with neighborhood characteristics. Section 5 concludes.

2 Data

2.1 GPS Mobility Sample

Location data. Our primary dataset is a panel of GPS locations for a sample of cellphones for 2019. Access to the data is provided by Replica, an urban data platform. For each device, we observe a unique identifier and a sequence of 'stays' at different locations. Each stay includes the geographic coordinates, entry time, and exit time. We have no direct information about the device's user, so must infer whether a device is a student and any demographics, such as race and income, using the location histories of the device. Devices are not uniformly sampled across space, so we use sample weights based on a device's home location to correct for unevenness in sampling. We provided additional details on the data construction in Appendix A.

Identifying students. 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.[3] 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 are meant to exclude individuals under 16 years old. 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 invariably captures teachers and staff. This adds noise and, to the extent adults working at schools are similar to other adults, biases our measures towards 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. As further validation, we compare our results to similar statistics from the American Time Use Survey (ATUS) when possible – for example, we find that the GPS data are able to replicate measures in the ATUS on the time spent at home and work/school.

[3]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 postal workers or taxi drivers.

Inferring income and race. We match each device to its home parcel and use parcel level estimates of household income from Cook (2023). The estimates are computed in two stages. First, Cook (2023) uses the American Community Survey (ACS) Public Microdata Sample (PUMS) to predict household income based on characteristics of the parcel, including the market value, building age, type of building (e.g., single versus multi-family), and Public Use Microdata Area (PUMA). Second, each estimate is updated using an empirical Bayes procedure based on the distribution of household income within the device's home block group.[4]

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. If we are willing to assume this misattribution is the same for adults and students, our analysis of differences between these two groups will not be biased.

Final sample. 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 that makes this cut is Spokane-Spokane Valley in Washington. The final sample includes 321,955 students and 9.1 million adults.

2.2 Measuring Experienced Isolation and Exposure to Diversity

To estimate experienced income and racial isolation, we follow the methodology introduced in Athey et al. (2021), which we describe in detail in Appendix Section A.4. Experienced income isolation in an MSA measures the difference between the share of lower income residents interactions with higher income residents and the share of higher income residents interactions that are with other higher income residents. An income isolation measure of 0.5 would imply that lower income

[4]For the full details on the income imputation, refer to Appendix A.2 of Cook (2023).

[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.

devices interact with 50 percentage points fewer higher income devices than do other higher income devices.

These measures capture isolation in space, which may not map one-to-one with social segregation nor meaningful interactions between devices sharing a geographic location (White, 1983). For example, students in diverse schools may occupy similar spaces, but still form social cliques split along racial lines. Similarly, higher income devices may visit establishments where they share a space with lower income workers, but may not truly interact with these other individuals.

We compute experienced isolation for both race and income. For racial isolation, we follow Athey et al. (2021) and use the WD and NWD designations based on a device's home neighborhood block group demographics. To be precise, these results give us the isolation between people from predominantly white neighborhoods to those from predominantly non-white neighborhoods. For income isolation, we use the individual income estimate outlined above, and split devices based on whether their estimated income is above the median income in the CBSA ("higher income") or below the median income ("lower income").

Experienced isolation is a population level statistic based on the interactions of all devices within an MSA, so we introduce a complementary individual level measure which we call "exposure to diversity." Exposure to diversity measures how much a given device's interactions are with devices of the *opposite* group. For example, a WD's exposure to diversity is the share of their interactions—proxied by the the places they visit—with NWDs.

3 Urban Mobility of Students and Adults

In this section, we compare individuals whose primary workday location is a school (the "students") with individuals whose primary workday location is otherwise (the "adults"). We first document experienced isolation by race and income and then turn to to urban mobility more broadly.

3.1 Differences in Experienced Isolation

Students experience more racial and income isolation than adults. The first row in Table 1 shows that overall racial isolation is 0.76 for students and 0.71 for adults. The result for students implies that the average white student device is exposed to 76 percentage points more white devices than the average non-white student device. There is a similar gap between students and adults in experienced income isolation; overall experienced income isolation is 0.67 for students and 0.61 for adults. The magnitude of these numbers is partially driven by time at home – recall that for racial segregation, complete isolation at home occurs mechanically, as the racial groups are coded at the block group level. Because the true levels of experienced isolation are hard to assess when race and income is imputed, we focus on the gap between the student and adult populations.[6]

The levels of experienced isolation drop when we restrict to time outside the home, but the gap between student and adults remains similar. The experienced racial isolation of students drops to 0.38 and the racial isolation of adults drops to 0.31, again suggesting that students live more segregated lives than adults. Experienced income isolation drops by a similar magnitude, to 0.26 for students and 0.23 for adults. In other words, students experience 13% more income isolation and 20% more racial isolation than adults.

To help interpret the magnitudes of these results, imagine each person always interacts with exactly one other person. Since we have split income groups at the median, an isolation measure of 0.26 means that a higher income student interacts with another higher income student 63% of the time and with a lower income student 37% of the time. Of course, in reality, individuals can interact with multiple people simultaneously or with no one at all, so time spent interacting with different groups need not sum to one.

The experienced isolation measure discussed so far is defined at the population level. To shift to individual level, we use "exposure to diversity," defined in section 2.2, which captures each individual's exposure to the other group. We restrict each measure to exclude time at home.

[6]While this measure is more precise than our imputation of race because it uses house level data, because we use the block group income distribution to update our estimates of income the isolation measures including time at home will still be mechanically higher.

Conducting the analysis at the individual level allows us to control for residential neighborhoods, testing how much of the difference between students and adults is driven by different home locations.

We find that outside of the home, people on average are in settings where 25% of others are from the opposite racial group and 36% of others are from the opposite income group (Table 1, panel b). Exposure to racial diversity is lower for students than adults, even accounting for differences in home location – the average exposure to racial diversity is 4.7 percentage points lower for students controlling for MSA of residence and 3.4 percentage points controlling for tract of residence. Splitting by imputed race, the typical WD is in a setting where 19% of devices are NWD, while the typical NWD is in a setting where 35% percent of devices are WD. Similarly, students' exposure to income diversity is 3 percentage points lower than that of adults, which shrinks to 2 percentage points when controlling for home tract. The persistence of lower levels of exposure to diversity for students when controlling for home tract suggests that very little of the increased isolation of students is driven by where they live relative to the adult population.

Somewhat surprisingly, splitting by income group shows that lower income students are slightly more exposed to higher income individuals than their adult counterparts are. The average lower income student is exposed to 1.4 percentage points more higher income devices than lower income adults. These estimates suggest that, for students, experienced urban isolation falls along racial lines more than along lines of income.

3.2 Differences in Overall Urban Mobility

Urban neighborhoods provide not just interactions with people, but also interactions with the geographic and economic amenities of cities. To fully understand how the experience of urban youth differs from that their adult counterparts, we now turn to a wider array of outcomes. In particular, we look at four categories of measures: 1) time spent at primary locations (home, work/school, and in the neighborhood); 2) "roaming ranges", or how far devices tend to travel from home and the number of unique places they visit; 3) use of amenities such as restaurants and shops; and 4) characteristics of tracts visited. As in Table 1, Table 2 reports results controlling first for MSA and then for home census tract.

Table 1: Experienced isolation of students and adults

Panel a) Overall experienced isolation (EI)	Aggregate	Students	Adults
All time			
Racial isolation	0.7092	0.7597	0.7075
Income isolation	0.6154	0.6563	0.6136
Excluding time at home			
Racial isolation	0.3134	0.3763	0.3110
Income isolation	0.2338	0.2630	0.2320

Panel b) Individual exposure to diversity	Average	Coefficient on isStudent (Home CBSA controls)	Coefficient on isStudent (Home tract controls)
Racial diversity			
Exposure to racial diversity	0.2519	-0.0468	-0.0337
		(0.0005)	(0.0003)
Exposure to NWD by WD	0.1943	-0.045	-0.0356
		(0.0004)	(0.0003)
Exposure to WD by NWD	0.3484	-0.0282	-0.0311
		(0.0009)	(0.0006)
Income diversity			
Exposure to income diversity	0.3606	-0.0303	-0.0198
		(0.0005)	(0.0004)
Exposure to L by H	0.3091	-0.0458	-0.0388
		(0.0005)	(0.0004)
Exposure to H by L	0.4331	0.0136	0.0145
		(0.0009)	(0.0005)

Note: This table documents overall experienced isolation measures, computed as a weighted average of MSA level measures, with weights corresponding to the MSA population. 'At home' is defined as within 50 meters of home location. Panel b) runs individual-quarter regressions of exposure to diversity on whether the device is a student with either home MSA or home Census tract fixed effects. Exposure to diversity excludes time spent at home. H and L refer to higher and lower income, respectively, while WD and NWD refer to white device and non-white device.

Table 2: Urban mobility of students and adults

	Average (not logged)	Coef. on isStudent (Home CBSA FEs)	Coef. on isStudent (Home tract FEs)
Panel a) Time at primary locations			
Frac. of time at home	0.6573	0.0243	0.0203
		(0.0005)	(0.0004)
Frac. of time at work/school	0.161	-0.0165	-0.0127
		(0.0003)	(0.0002)
Frac. time in neighborhood (excl. home)	0.0488	0.0215	0.0231
		(0.0003)	(0.0002)
Panel b) Roaming ranges			
Log avg miles from home	7.5021	-0.3543	-0.3898
		(0.0019)	(0.0014)
Log # unique locations (geohash7)	42.8904	0.0528	0.0138
		(0.002)	(0.0017)
Panel c) Visits to amenities			
Log # restaurant visits	1.5151	-0.0982	-0.1137
		(0.0023)	(0.0019)
Log # retail visits	1.9806	-0.1948	-0.2181
		(0.0025)	(0.002)
Log # park visits	1.1746	0.0778	0.0577
		(0.0022)	(0.0018)
Log # entertainment visits	1.399	0.0672	0.0318
		(0.0022)	(0.0019)
Log # civil, social, religion visits	0.2523	0.0326	0.025
		(0.0011)	(0.001)
Panel d) Characteristics of tracts visited			
Log median HH income	76386	0.0829	0.0381
		(0.0008)	(0.0006)
Frac. college graduate	0.3924	0.0105	0.0017
		(0.0003)	(0.0002)
Frac. White alone	0.5733	0.0285	0.0071
		(0.0004)	(0.0002)
Air quality (PM25)	8.8084	-0.026	0.0079
		(0.0016)	(0.0012)
Log crimes per sq. mi.	9.711	-0.1973	-0.0709
(Chicago & Los Angeles, 2010-2018)		(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 MSA or 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 50 meters of the location's coordinates, while 'in the neighborhood' is defined as within 1 mile of home. 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.

Students and adults differ in the amount of time spent at home, work/school, and in the neighborhood (Table 2, panel a). The average device spends 66% of time at home, 16% of time at work/school and 5% of time in their home neighborhood.[7] Students spend more time at home and in the neighborhood than adults, and less time at school than adults spend at work. Controlling for home tract, students spend 2.3 percent more of their time in their neighborhood, which means that they are spending almost 50% more time near to their home. This fact highlights the importance of highly local amenities, for example safe residential streets, for youth relative to adults. Finally, students also spend about 10% less time at school than adults spend at work.

When outside the home, students and adults also differ in how far they "roam" (Table 2, panel b). The average distance from home is 7.5 miles across all devices; this distance is about 35% smaller for students, a gap that persists even when comparing students and adults living in the same tract. Although students travel shorter distances, relative to adults, their travel patterns are also less routine. The average device in our sample is observed in 43 unique 'places' (approximately 500ft×500ft squares). Students travel to 5% more unique locations controlling for MSA, and 1.4% percent controlling for tract. The drop in the effect when controlling for tract suggests the majority of students' greater exploration comes from differences between the neighborhoods children grow up in and the neighborhoods working adults live in.

The modest connection between student-status and unique places masks a much larger shift in the nature of the locations visited (Table 2, panel c). Controlling for home tract, students visit 11% fewer retail shops and 22% fewer restaurants, but 3% more entertainment venues and 6% more parks. Students also visit more civic, religious and social venues, but the overall number of such visits among both students and adults are small. These visits exclude those to any location identified as a device's work place, so the differences are not driven by adults being more likely to work at restaurants and shops. The differences are similar when we control for MSA and for tract, suggesting that these differences in consumption patterns are not tied to differences in access from home to urban amenities.

[7] We compare this with the time-use results in the American Time Use Survey (ATUS). Averaging across the 2009 to 2019 period to increase sample size (to around 4,000 high school students), we find high school students in the ATUS report spending 66% of their time at home and 18% of their time at school – remarkably similar to our results.

Finally, when outside of home and work/school, students visit Census tracts that are on average richer, better educated, have a higher white population share, less pollution, and less crime (Table 2, panel d). To evaluate this, we compute the time a device spends in each Census tract and regressed characteristics of the tract on student-status, weighting by the time spent in the tract. While the gaps between average education, pollution, and white share of the population of tracts visited by students compared to adults are quite small, the gap in the crime rate is large. Our crime data are limited to Chicago and Los Angeles due to data availability, but in those cities, students visit tracts with 20% fewer crimes per square mile. The gap in crime rate falls to 7% when controlling for home tract, suggesting that students live in lower-crime neighborhoods on average, perhaps because childless adults may take more locational risks when deciding where to live than adults with children.

Overall, these results suggest that while students experience more isolation than adults—especially along racial lines—the overall experience of urban youth differs from that of urban adults in predictable ways. Students generally go to somewhat nicer neighborhoods and are exposed to slightly less crime. They go to fewer restaurants and shops, but more parks and entertainment venues. Yet this overall picture of teenage live in cities masks considerable heterogeneity among the student population. We now turn to differences among students by household income.

4 Household Income and the Urban Mobility of Students

In this penultimate section, we first look at mobility by imputed income and then the relationship between mobility and neighborhood characteristics. Higher income students have greater urban mobility across a range of measures, but neighborhoods also play a role, holding fixed the household income of a device. We focus on students in the main text, but Appendix Figure C.4 reproduce these results for the adult population, where the results are similar, though attenuated.

To document differences by income, we divide devices into quartiles of predicted household income and compare a range of mobility measures across each quartile.[8] For each measure, we

[8] We believe that measurement error in income would likely to attenuate the estimated relationship between income and mobility; however, families who spend more on their housing, relative to permanent income, may be more interested in consuming urban amenities.

present two versions. The first controls only for a device's home MSA, so captures differences driven both by neighborhood and the direct effect of income. The second version controls for home tract to isolate the effect of income, holding fixed home location.

First, relative to the baselines from Table 2, students in the highest income quartile spend about 5% less time at home and 18% more time in the neighborhood than students in the lowest income quartile (Figure 1, panels a and b). The effects declines substantially when we control for home tract, suggesting a large part of the reason lower income students spend more time at home and less time in their neighborhood is due to the neighborhood itself.

Second, richer students both visit more unique locations and tend to travel further from home when they leave the house (Figure 1, panels c and d). The relationship between income and number of locations visited is strong and monotonic. Students in the highest income quartile visit 54% more unique locations than students in the lowest income quartile. The link between distance from home and income is non-monotonic, although the bottom quartile of income stays the closest to home. Students in the third quartile spend their time 15% further from their homes than those in the bottom quartile, but student in the richest quartile only stray 6% further from home than the lowest-income students. When controlling for home tract, the coefficients drop by about half, but the relationship between income and number of unique places visited remains strong.

Third, there are stark differences by income in students' consumption of various local amenities such as restaurants, shops, and parks (Figure 1, panels e and f). The strongest relationship is between income and visits to entertainment venues – controlling for home MSA, students from the top income quartile visit 57% more entertainment locations than those in the bottom income quartile. The impact of income on park and restaurant visits is smaller, but still large. Students in the highest-income quartile take 35% more visits to restaurants and 38% more visits to parks than students in the lowest-income quartile. Students in the top quartile also take 26% more trips to retail stores than those in the bottom quartile. The impact of income on visits to civic, social and religious locations is smaller, which is unsurprising given the rarity of such trips. On average, the gap between the top and bottom quartiles attenuates by 45% when controlling for home tract, but again remain large.

Finally, there is a weak relationship between household income and exposure to both income and racial diversity (Figure 1, panels g and h). Exposure to income diversity is unsurprisingly lowest for the middle of the distribution, as people with incomes slightly above the median income are likely to interact with people whose incomes are below the median. As we move out to the top and bottom quartiles, however, we see some asymmetries: students from the highest-income households are more isolated from below median income households than the lowest-income households are from above median income households, echoing our results from Table 1. The connection between income exposure and income remains large when we control for tract of residence, suggesting this trend is not a function of where families live in a metro area, but a more fundamental characteristic of household travel patterns. Racial exposure to diversity declines with income, though the effects are small and, once we control for tract, the relationship becomes economically insignificant.

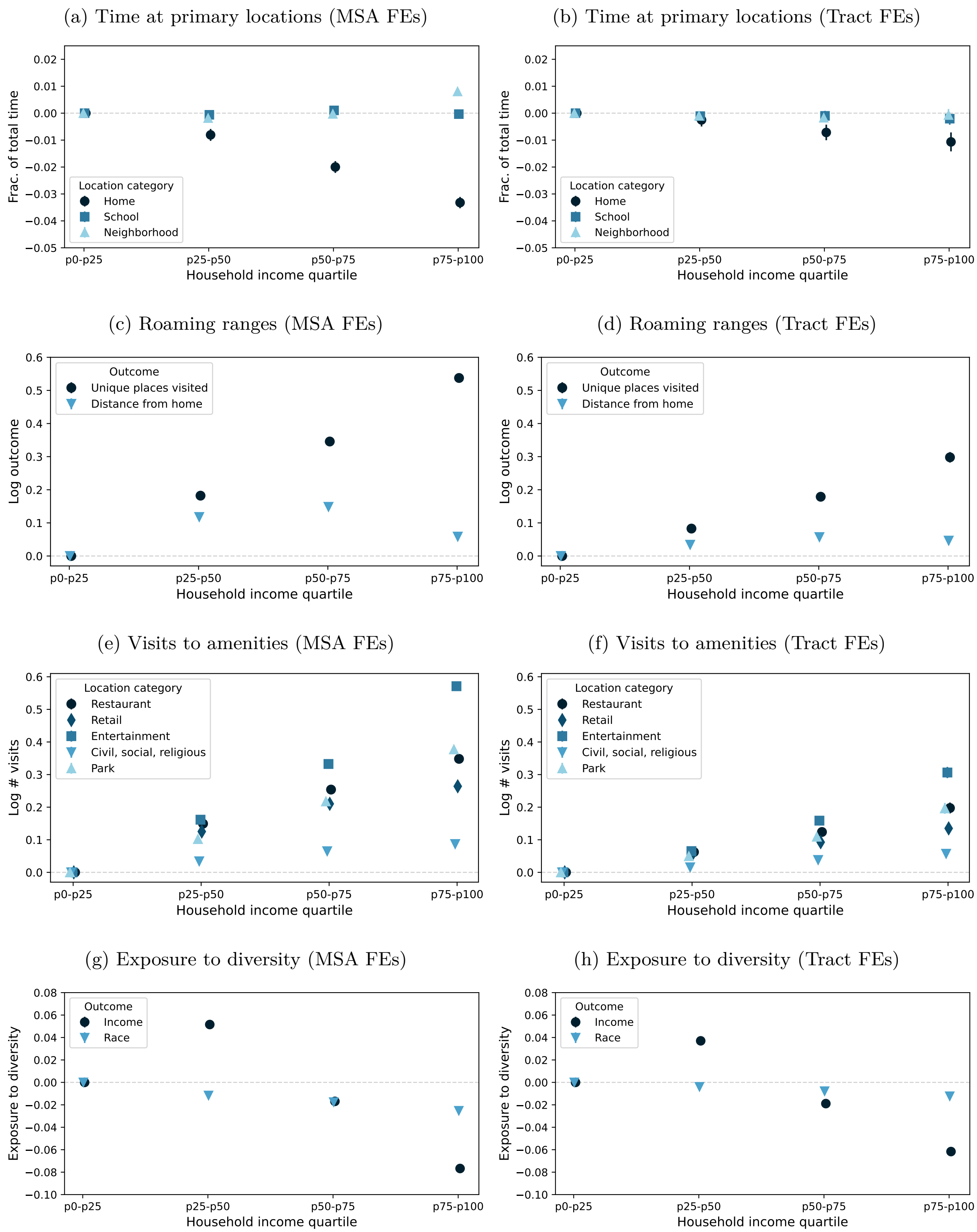
4.1 Correlation of urban mobility with neighborhood characteristics

In this section, we focus on the component of urban mobility tied characteristics of the neighborhood itself by investigating the correlation between features of a tract and the level of urban mobility of its residents. To facilitate an analysis of the connection between neighborhoods and urban mobility, we collapse our mobility measures down to a single mobility index. Specifically, we first standardize each individual measure using the cross-device mean and standard deviations of the variables, then use Principal Component Analysis (PCA) to collapse the measures into a single measure of urban mobility.[9] Finally, for interpretability we transform the first principal component into a z-score, which we use as our final index of urban mobility. Appendix Table B2 shows the correlation between this index and each of the component parts; our urban mobility index is increasing in visits to amenities and roaming range and decreasing in the time spent at routine locations such as home and work.

The first panel of Figure 2 shows, as discussed before, that urban mobility increases steeply with the predicted household income of the device. The linear coefficient when the mobility index is regressed on income is 0.46, implying that a 10% increase in the median household income in a

[9] To put similar weight on amenities, time at locations, and roaming ranges, we first use PCA within each category of mobility and then use PCA across the components estimate for each category.

Figure 1: Urban mobility of students by income



tract corresponds to around a half standard deviation increase in the urban mobility of that tract. In all subsequent panels, we show results with controls for just MSA as well as with controls for the log of device household income, given how fundamental the relationship is between income and urban mobility. Appendix Table B3 reports the coefficients from linear regressions with and without a linear income control, which we will report in the text because they provide a simple way of assessing how much of the relationship between income and mobility is reduced by controlling for place-based attributes, and, similarly, how much the relationship between place and urban mobility is reduced by controlling for household income.

There is a persistent positive relationship between urban mobility and neighborhood median household income, even controlling for device level income (Figure 2, panel b). Without controls, the coefficient is 0.46, which is almost as large in magnitude as the coefficient on individual income. When we include both variables in a regression, the coefficient on neighborhood income attenuates to 0.31. Provided our individual measure is a less noisy proxy for income than the neighborhood median income would be, the persistence of a significant coefficient on neighborhood income suggests a persistent neighborhood effect even within devices of a similar income level.

Urban mobility is also decreasing in measures of "urbanity", such as population density and proximity to city hall (Figure 2, panels c and d). The linear coefficient for urban mobility regressed on log population density is -0.11, which falls in magnitude to -0.08 when we control for individual income. While denser areas have more nearby amenities to visit, devices living in these areas have lower urban mobility on average, perhaps because they are less likely to own a car. Similarly, mobility rises with the log distance from city hall. The coefficient without income controls is 0.17, which falls to 0.11 when we control for income. The finding may help explain why proximity to city centers is also slightly negatively associated with income mobility (Chetty et al., 2018). Controlling for either density and proximity to city hall does relatively little to reduce relationship between urban mobility and imputed income, however. That coefficient falls from 0.46 to 0.42 when we control for density and 0.43 when we control for proximity to city hall.

One obvious reason urban students might have lower mobility is that they might be less likely to have access to a car, even controlling for income. looks at the share of households in the tract that own a car. The coefficient is 1.37, meaning that as the share of households with a car increases by 10 percentage points, urban mobility increases by 0.14 standard deviations. This is a reasonably large effect, given that a standard deviation is 12 percentage points (driven by the long left tail, as the median is 0.95). The estimated coefficient falls by 65% to 0.48 when we control for household income, as richer devices live in areas with higher levels of car ownership.

Panel f) documents a small positive correlation between geographic mobility and upward economic mobility as measured by the Opportunity Atlas (Chetty et al., 2018). Chetty et al. (2018) define upward mobility as the income percentile of children born to parents at 25th percentile, based on Americans born in a tract between 1978-1983. Despite the time gap, the raw correlation is strong. However, the estimated coefficient drops from 2.19 to 0.52 when we control for household income. We interpret this to mean that there is less urban mobility in places where there has historically been less income mobility, but much of this correlation is driven by the fact that lower income households have less of both types of mobility.

Finally, urban mobility is positively correlated with measures of neighborhood social capital (Figure 2, panels g and h). Panel g) looks at the link between geographic mobility and economic connectedness, which is a measure of Facebook connections between lower income individuals and higher income individuals (Chetty et al., 2022a). Specifically, it is the average share of above-median socioeconomic status friends among below-median socioeconomic status residents of the zipcode. The linear coefficient is 0.89, which falls to 0.41 when we control for individual income. Panel h) shows a somewhat weaker positive link between urban mobility and how clustered social connections are for neighborhood residents ("network clustering"), another measure produced by Chetty et al. (2022a) that captures the rate at which two friends of a resident are also friends with each other. This finding is consistent with the hypothesis that virtual connections rely on physical ones; links between different groups happen when people traverse their city, such that areas with higher urban mobility generate more bridging social connections. Of course, it is possible that causality goes the other way, in that greater social capital leads to greater urban mobility, as all our findings are only correlations.

In this section, we have documented that higher income areas have higher urban mobility, even when we control for household income. Urban mobility is lower in areas with more population density, fewer cars, and closer to the city center. Finally, we find a correlation between urban mobility and both social and upward income mobility, suggesting that physical mobility has the potential to be an important way in which social connections are made and economic advancement for youth from low-income households is achieved.

5 Conclusion

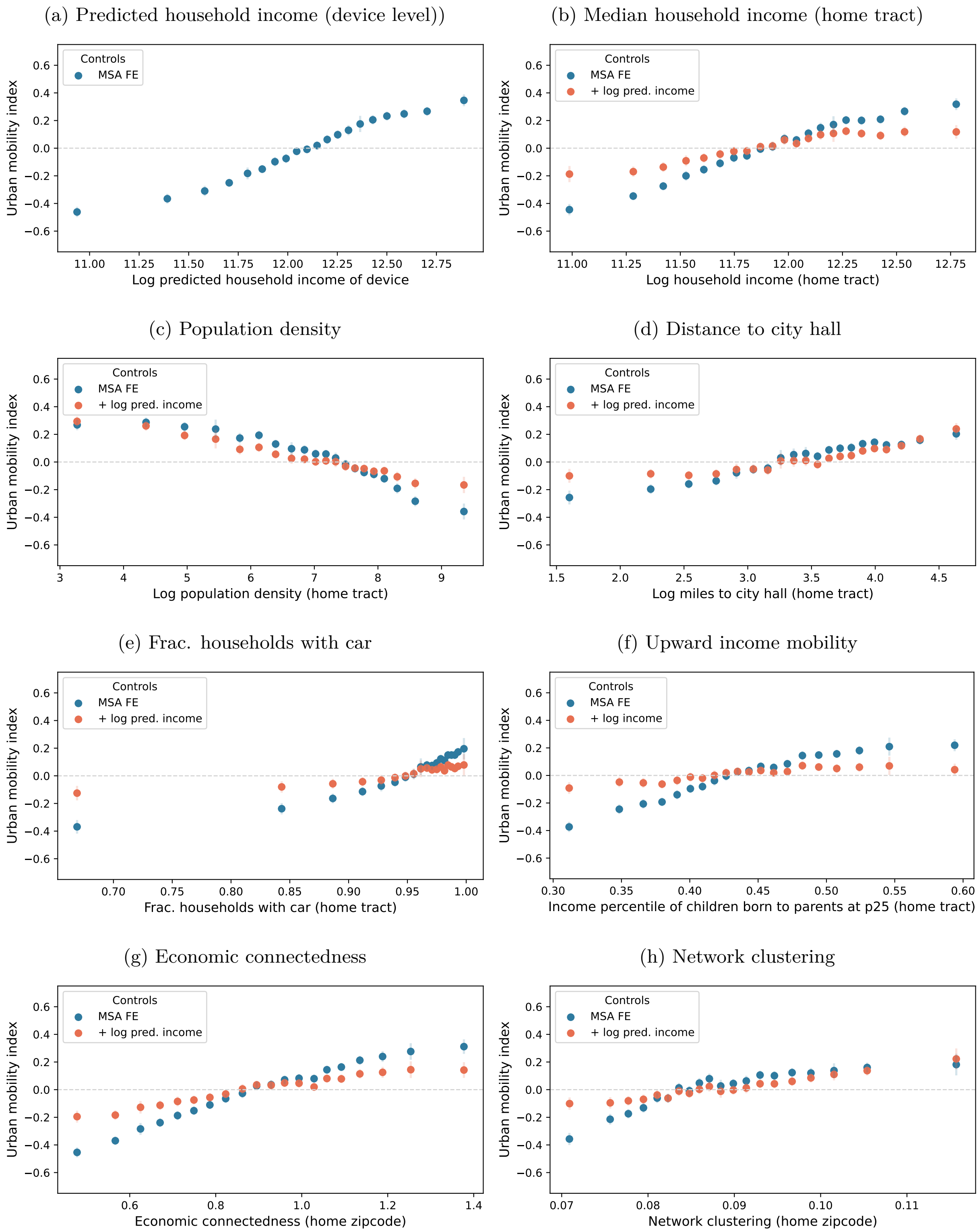
This paper used cell phone records to investigate the lives of urban youth. We find that students in our sample experience greater income and racial isolation than adults, spend more time at home and in their neighborhood, stay closer to home when they are outside of the house, and lead less routinized lives, visiting more unique locations.

Differences in urban mobility are even larger *within* the population of students across different levels of income. High income students are much more likely to visit every form of local amenity, visit more unique locations, spend less time at home, and roam further from home when they do leave the house. In each case, the differences attenuate when comparing students who live within the same neighborhood, but often remain large. On average, home neighborhood can explain about half of the gap between the mobility differences of higher versus lower income students.

Urban mobility is correlated with a range of neighborhood characteristics, even controlling for a device's predicted income. Areas that have higher car ownership, are less dense, and higher neighborhood income all have higher levels of urban mobility. Urban mobility is also higher for students living in tracts that have higher economic mobility and greater social capital, lending some support to the idea that face-to-face connection is important in building the relationships that can be helpful for long-run success.

This work highlights a central paradox of urban America. Lower income residents living in urban areas, where amenities and public goods are dense, appear to be getting the least out of urban life. Income seems to strongly condition the benefits of urban living. We hope that future work will help us to understand why lower income residents seem to get so much less out of cities.

Figure 2: Correlates of urban mobility



References

Allcott, Hunt, Levi Boxell, Jacob Conway, Billy Ferguson, Matthew Gentzkow, and Benny Goldman, "What Explains Temporal and Geographic Variation in the Early US Coronavirus Pandemic?," Technical Report w27965, National Bureau of Economic Research, Cambridge, MA October 2020.

Athey, Susan, Billy Ferguson, Matthew Gentzkow, and Tobias Schmidt, "Experienced Segregation," Technical Report w27572, National Bureau of Economic Research, Cambridge, MA July 2020.

_ , _ , _ , and _ , "Estimating experienced racial segregation in US cities using large-scale GPS data," *Proceedings of the National Academy of Sciences*, 2021, *118* (46).

Atkin, David, Keith Chen, and Anton Popov, "The Returns to Serendipity: Knowledge Spillovers in Silicon Valley," 2020, p. 49.

Beiró, Mariano G, Loreto Bravo, Diego Caro, Ciro Cattuto, Leo Ferres, and Eduardo Graells-Garrido, "Shopping mall attraction and social mixing at a city scale," *EPJ Data Science*, 2018, *7*, 1–21.

Brooks-Gunn, Jeanne, Greg J Duncan, Pamela Kato Klebanov, and Naomi Sealand, "Do neighborhoods influence child and adolescent development?," *American journal of sociology*, 1993, *99* (2), 353–395.

Cagney, Kathleen A, Erin York Cornwell, Alyssa W Goldman, and Liang Cai, "Urban mobility and activity space," *Annual Review of Sociology*, 2020, *46*, 623–648.

Chang, Serina, Emma Pierson, Pang Wei Koh, Jaline Gerardin, Beth Redbird, David Grusky, and Jure Leskovec, "Mobility network models of COVID-19 explain inequities and inform reopening," *Nature*, November 2020.

Chen, M Keith, Judith A Chevalier, and Elisa F Long, "Nursing home staff networks and COVID-19," *Proceedings of the National Academy of Sciences*, 2021, *118* (1).

_ , Kareem Haggag, Devin G Pope, and Ryne Rohla, "Racial disparities in voting wait times: evidence from smartphone data," *The Review of Economics and Statistics*, 2019, pp. 1–27.

Chetty, Raj and Nathaniel Hendren, "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1107–1162.

_ **, John N Friedman, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter**, "The opportunity atlas: Mapping the childhood roots of social mobility," Technical Report, National Bureau of Economic Research 2018.

_ **, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt**, "Social capital I: measurement and associations with economic mobility," *Nature*, August 2022.

_ , **and** _ , "Social capital II: determinants of economic connectedness," *Nature*, August 2022.

_ **, Nathaniel Hendren, and Lawrence F Katz**, "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment," *American Economic Review*, 2016, *106* (4), 855–902.

Cook, Cody, "Heterogeneous Preferences for Neighborhood Amenities: Evidence from GPS data," *Available at SSRN 4212524*, 2023.

Couture, Victor and Jessie Handbury, "Urban revival in America," *Journal of Urban Economics*, 2020, *119*, 103267.

_ **, Jonathan I Dingel, Allison Green, Jessie Handbury, and Kevin R Williams**, "JUE Insight: Measuring movement and social contact with smartphone data: a real-time application to COVID-19," *Journal of Urban Economics*, 2021, p. 103328.

Cutler, David M. and Edward L. Glaeser, "Are Ghettos Good or Bad?*," *The Quarterly Journal of Economics*, August 1997, *112* (3), 827–872.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000," *American Economic Review*, March 2016, *106* (3), 479–

524.

Glaeser, Edward L and David C Mare, "Cities and skills," *Journal of labor economics*, 2001, *19* (2), 316–342.

Kain, John F., "Housing Segregation, Negro Employment, and Metropolitan Decentralization*," *The Quarterly Journal of Economics*, May 1968, *82* (2), 175–197.

Logan, John R, Elisabeta Minca, and Sinem Adar, "The geography of inequality: Why separate means unequal in American public schools," *Sociology of education*, 2012, *85* (3), 287–301.

_ , Weiwei Zhang, and Deirdre Oakley, "Court orders, white flight, and school district segregation, 1970–2010," *Social Forces*, 2017, *95* (3), 1049–1075.

Miyauchi, Yuhei, Kentaro Nakajima, and Stephen J Redding, "Consumption access and agglomeration: evidence from smartphone data," Technical Report, National Bureau of Economic Research 2021.

Moro, Esteban, Dan Calacci, Xiaowen Dong, and Alex Pentland, "Mobility patterns are associated with experienced income segregation in large US cities," *Nature communications*, 2021, *12* (1), 1–10.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley, "Assessing "neighborhood effects": Social processes and new directions in research," *Annual review of sociology*, 2002, *28* (1), 443–478. Publisher: Annual Reviews 4139 El Camino Way, PO Box 10139, Palo Alto, CA 94303-0139, USA.

Shelton, Taylor, Ate Poorthuis, and Matthew Zook, "Social media and the city: Rethinking urban socio-spatial inequality using user-generated geographic information," *Landscape and urban planning*, 2015, *142*, 198–211.

Taeuber, Karl E. and Alma F. Taeuber, *Negroes in Cities: Residential Segregation and Neighborhood Change*, Atheneum, 1969. Google-Books-ID: x3MqAAAAYAAJ.

Wang, Qi, Nolan Edward Phillips, Mario L Small, and Robert J Sampson, "Urban mobility and neighborhood isolation in America's 50 largest cities," *Proceedings of the National Academy of Sciences*, 2018, *115* (30), 7735–7740.

White, Michael J, "The measurement of spatial segregation," *American journal of sociology*, 1983, *88* (5), 1008–1018.

Wong, David WS and Shih-Lung Shaw, "Measuring segregation: An activity space approach," *Journal of geographical systems*, 2011, *13* (2), 127–145.

A Data appendix

A.1 GPS Data

The GPS data come from an unbalanced panel of GPS-enabled devices in 2019. The raw data consist of 'stays' at different locations and include an entry/exit time and GPS coordinates.

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.[10]

To identify visits to 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

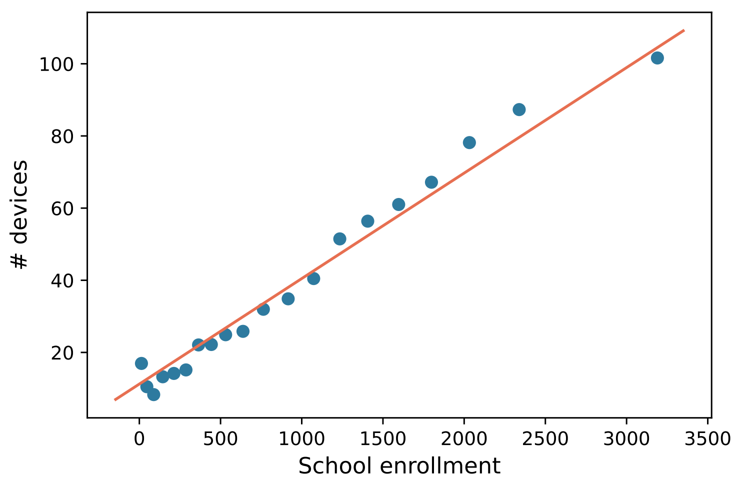
The schools data comes from the National Center for Education Statistics (NCES). However, NCES data only includes the school address, name, grades served, and enrollment. Moreover, the address is often a PO box or simply the town center rather than the actual school location. To match NCES schools to 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

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

from satellite imagery—are inaccurate for schools; for large schools with multiple building, the polygon 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 that many HS students are under 16 years old and that we cannot match all schools to parcel polygons.

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

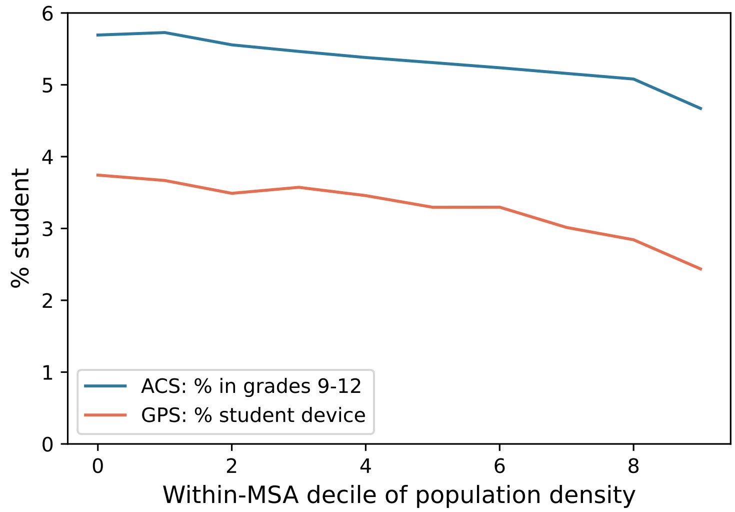


Note: This figure plots the relationship between the enrollment of a school as reported by the NCES and the number of devices labeled as a student of that school.

A.3 Sample Quality and Sample Weights

Figure A.3 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

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.

devices is 21.0% white.

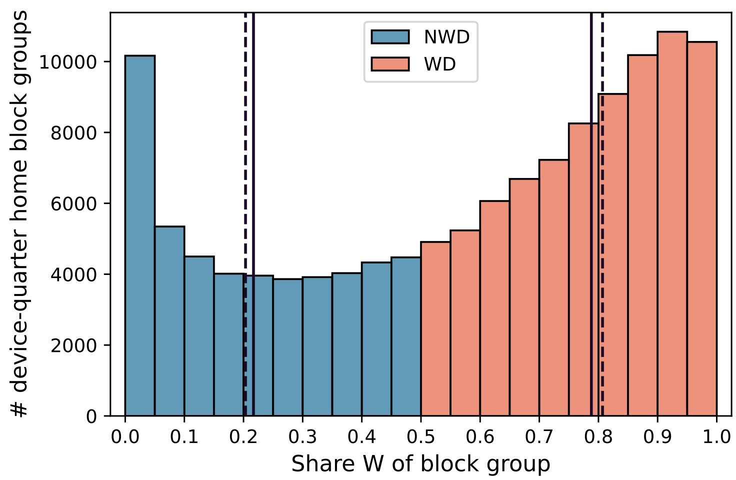
Figure A.4 plots the fraction of devices who live in each decile of tract characteristics. If sampling were orthogonal to tract characteristics, 10% of devices would be sampled from each decile. Instead, we can see that devices are over-sampled from poorer, less white, less educated, and more dense areas.

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

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

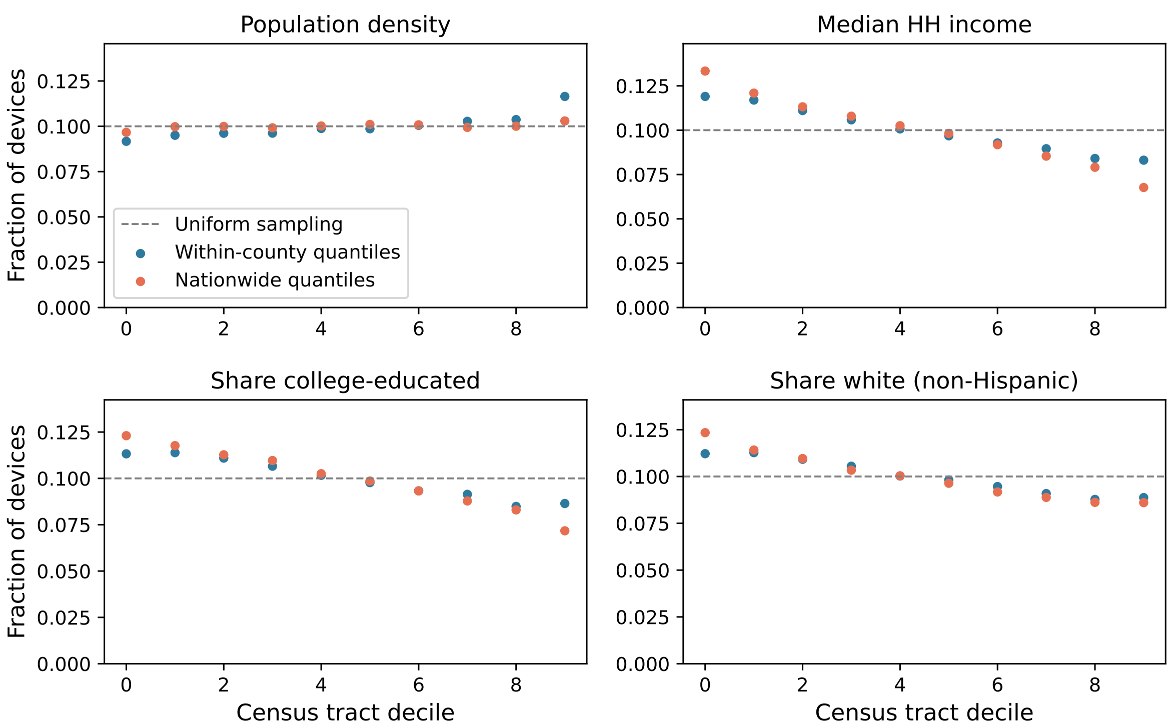
where $N_{g(iq)}$ is the ACS population of a device's home tract g and $\tilde{N}_{g(iq)}$ is the total number of devices observed in tract g in quarter q. The average device weight is 20.2 (standard deviation of 12.9). We use these weights for all results.

Figure A.3: 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.

Figure A.4: Sampling of devices by block group characteristics



Note: This figure 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.

A.4 Experienced Income and Racial Isolation Measures

Aggregate experienced isolation between any two groups A and B is defined as the difference between the average exposure of group A to other members of group A and the average exposure of group B to members of group A. Specifically, we define

$$\mathrm{EI}_g = \frac{1}{|\mathrm{A}_g|} \sum_{i \in \mathrm{A}_g} \int_{t=0}^{1} s(l(i,t),t)dt - \frac{1}{|\mathrm{B}_g|} \sum_{i \in \mathrm{B}_g} \int_{t=0}^{1} s(l(i,t),t)dt, \tag{A.1}$$

where g indicates a geographic unit such as CBSA, A_g is the set of devices in group A, B_g is the set of devices in group B, and $s(l(i,t),t)$ is the share of devices in individual i's location l at time t who are from group A.

We make several assumptions in order to estimate Equation A.1. First, we assume that $s(l(i,t),t)$ does not vary by time for a given location.[11] 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 A.1, we first construct leave-one-out estimates of $s(\cdot)$ for each individual and location pair as:

$$\hat{s}_l^{-i} = \frac{\sum_{j \in P_l^{\mathrm{A},-i}} d_j}{\sum_{k \in P_l^{-i}} d_k}, \tag{A.2}$$

where P_l^{-i} is the set of stays in location l by devices excluding i, $P_l^{\mathrm{A},-i}$ is the set of stays in location l by members of group A, and d_j is the duration of stay j. Weighting by duration in the location approximates the ping-level measure used in Athey et al. (2021). Next, for each individual-quarter in our sample we measure aggregate exposure as the duration weighted average $\hat{s}_l^{-i}$:

$$\hat{S}_{iq} = \frac{\sum_{j \in P_{iq}} \hat{s}_{l(j)}^{-i} d_j}{\sum_{k \in P_{iq}} d_k} \tag{A.3}$$

where P_{iq} is the set of all stays by device i in quarter q and $l(j)$ is the location corresponding to stay j.

[11] This is most clearly violated in residential areas, where daytime and nighttime populations will differ substantially.

Finally, we estimate experienced isolation for CBSA g as:

$$\widehat{\mathrm{EI}}_g = \frac{1}{|\mathrm{A}_g|} \sum_{i \in \mathrm{A}_g} \sum_{q \in Q_i} \hat{S}_{iq} - \frac{1}{|\mathrm{B}_g|} \sum_{i \in \mathrm{B}_g} \sum_{q \in Q_i} \hat{S}_{iq} \tag{A.4}$$

where Q_i is the set of quarters in which device i is observed and we abuse notation slightly to let A_g be the set of all device-quarters (rather than just devices) of group A in geography g and B_g be the corresponding set of device-quarters of group B.[12] To estimate experienced isolation for students and adults, we estimate Equation A.4 separately for each type. Note that the leave-one-out estimates of exposure remain the same for both groups – consequently, our experienced isolation measure for students measures exposure to both students and adults.

We also define a new companion measure to facilitate individual-level regressions, which we call experienced diversity. Experienced isolation is a population-level statistic; for example, an experienced isolation score of 0.1 implies a gap of 10 percentage points in the exposure to members of group A by other members of group A relative to members of group B. Experienced diversity, in contrast, is the average exposure to devices of the *opposite* group and is estimated as

$$\widehat{\mathrm{ED}}_{iq} = \frac{1}{\sum_{j \in P_{iq}} d_j} \sum_{j \in P_{iq}} \mathbf{1}\{i \in \mathrm{B}\} \times \hat{s}_{l(j)}^{-i} d_j + \mathbf{1}\{i \in \mathrm{A}\} \times (1 - \hat{s}_{l(j)}^{-i}) d_j \tag{A.5}$$

The two measures are closely linked – experienced isolation is a transformation of the average experienced diversity by each group in a city.

B Additional results

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

[12] We weight all statistics using device-quarter weights that correct for unevenness in the home locations of the GPS sample compared to the ACS. We provide more details on these weights, which are used for all results in the paper, in Appendix Section A.3.

group that is white. Using this continuous measure of race, we can estimate experienced racial isolation as

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

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

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

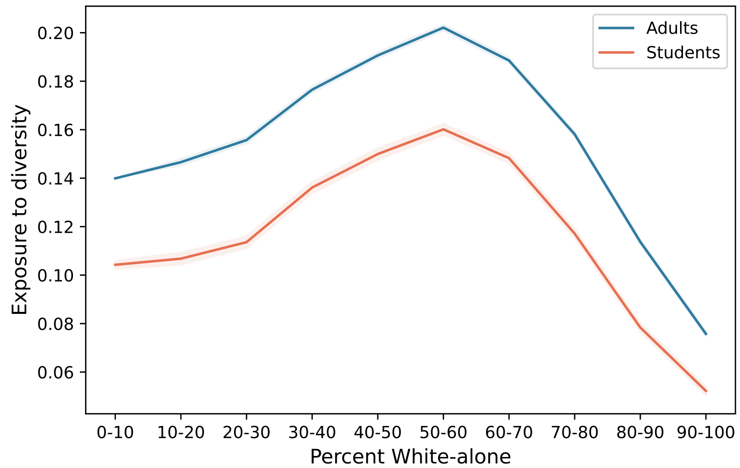
Panel a: experienced isolation	Aggregate	Student	Adult
All	0.2134	0.2248	0.2123
Excluding time at home	0.1141	0.1370	0.1129
Excluding time in home tract	0.1060	0.1274	0.1050

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 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

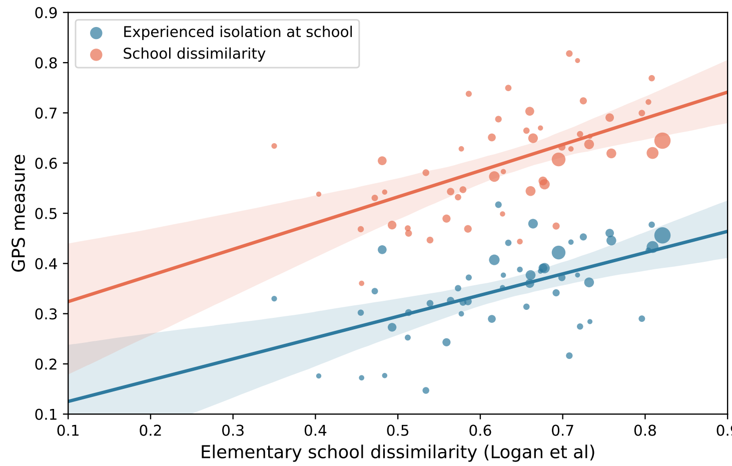


Note: This figure documents how exposure to diversity varies by the racial composition of a device's home block group. The figure is constructed by regressing exposure to diversity for a given device-quarter on whether the device is a student, interacted with the percent of their home block group's residents 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. (2012, 2017). 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.[13]

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. (2021). We believe that the discrepancies stem from differences in data construction. Athey et al. (2021) use raw GPS pings, which are

[13]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.

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. (2021), 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. In their earlier working paper version, 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).

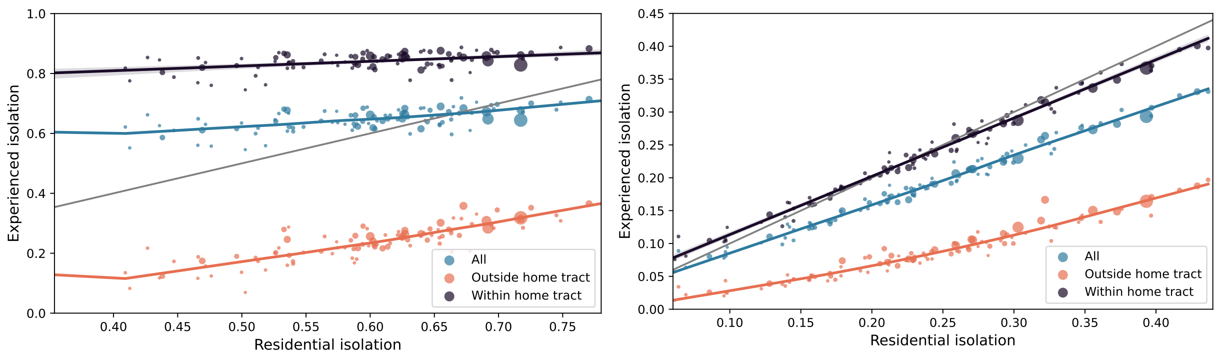
The second reason is that exposure when using pings will include devices walking/driving through the location, while staypoints include only those devices that stop for at least 5 minutes in a location. This difference is particularly noticeable for residential locations – the experienced isolation in 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 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. (2021) 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.

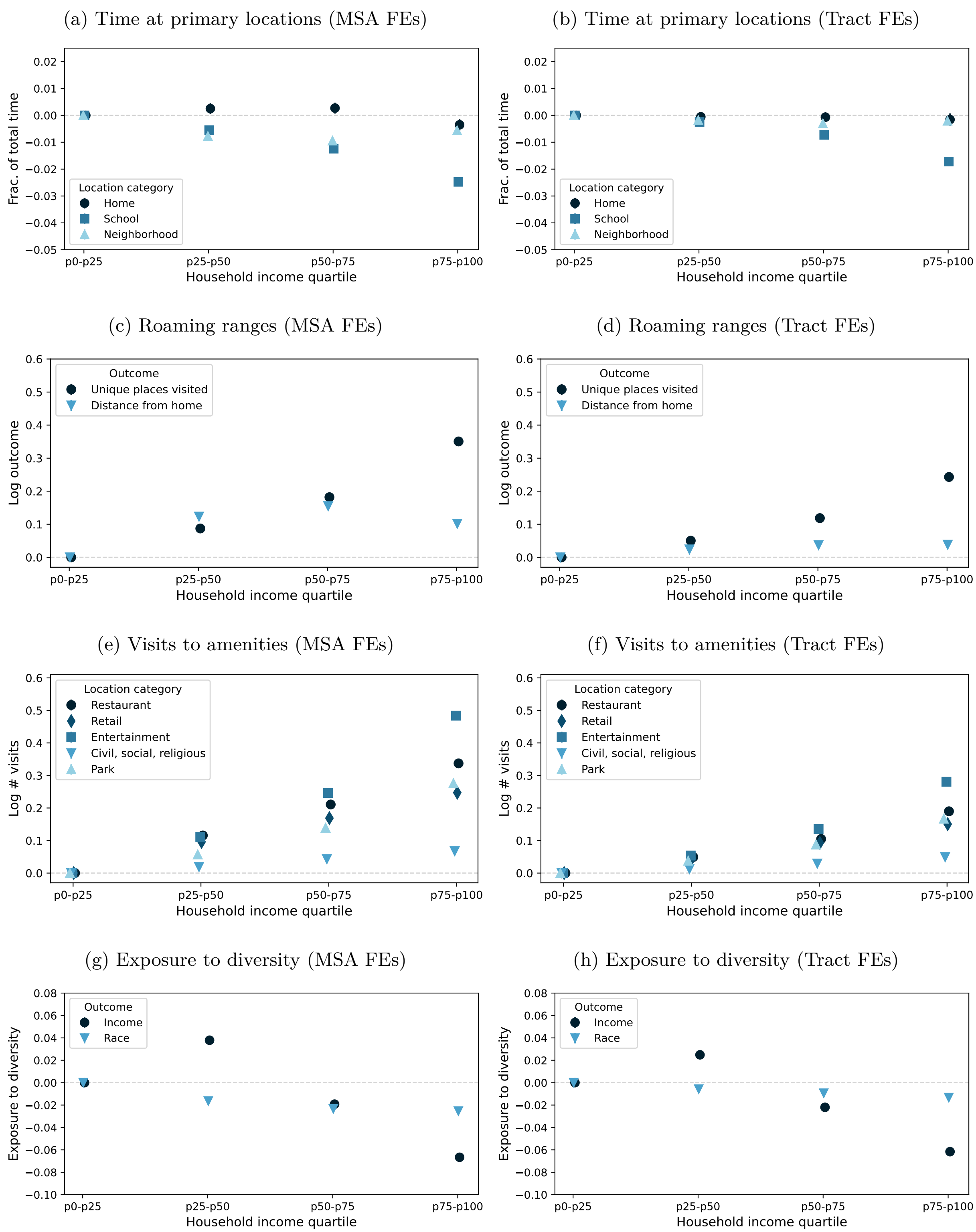
C Supplementary tables and figures

Table B2: Correlation between urban mobility index and its components

Measure (z-score)	Corr. with urban mobility index
Urban mobility index	1.0
# restaurant visits	0.649
# retail visits	0.638
# park visits	0.49
# entertainment visits	0.561
# civil, social, religous visits	0.255
Frac. time at home	-0.229
Frac. time at work	-0.093
Frac. time in neighborhood	-0.036
# unique locations	0.773
Avg. miles from home (hxcl. home)	0.394

Note: This table plots the correlation between the single urban mobility index and each of its component parts. Each component is z-scored. To construct the index, we first do PCA on each of the three groups: amenity visits, fraction of time in primary locations, and roaming ranges. We then do a PCA on the resulting principal components and take the z-score to get our final measure.

Figure C.4: Urban mobility of adults by income



(a) Time at primary locations (MSA FEs)

(b) Time at primary locations (Tract FEs)

(c) Roaming ranges (MSA FEs)

(d) Roaming ranges (Tract FEs)

(e) Visits to amenities (MSA FEs)

(f) Visits to amenities (Tract FEs)

(g) Exposure to diversity (MSA FEs)

(h) Exposure to diversity (Tract FEs)

Table B3: Correlates of urban mobility

Outcome: urban mobility index	Univariate	Multivariate	
	Covariate	Covariate	Log pred. income
Device covariates			
Log pred. device household income	0.471		
	(0.006)		
Home tract covariates			
Log median household income	0.458	0.199	0.307
	(0.007)	(0.013)	(0.012)
Log pop. density	-0.109	-0.08	0.418
	(0.002)	(0.002)	(0.007)
Log miles to city hall	0.168	0.111	0.432
	(0.005)	(0.005)	(0.007)
Frac. households with car	1.368	0.478	0.424
	(0.037)	(0.038)	(0.008)
Upward income mobility	2.188	0.525	0.425
	(0.052)	(0.066)	(0.009)
Home zipcode covariates			
Economic connectedness	0.889	0.414	0.345
	(0.018)	(0.026)	(0.011)
Network clustering	10.217	6.982	0.452
	(0.527)	(0.423)	(0.008)

Note: This table plots linear coefficients corresponding to the relationships shown in Figure 2. The data device-quarter level (students only) and include 371,243 observations. The first column regresses the urban mobility index on the listed covariate and documents. The second and third column report coefficients on the covariate and on log predicted device household income from a regression of urban mobility on both. All regressions additionally control for city fixed effects and are weighted by the device sample weights. Standard errors are clustered at the home tract level, except for the zipcode covariates where they are instead clustered at the home zipcode level.