Article

Urban mobility and the experienced isolation of students

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Cities provide access to stores, public amenities and other people, but that access may provide less benefit for the lower-income and younger urbanites who lack money and means of easy mobility. Using detailed GPS location data, we measure the urban mobility and experienced racial and economic isolation of the young and the disadvantaged. We find that students in major metropolitan areas 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. Looking across levels of income, students from higher-income families visit more amenities, spend more time outside of the home, and explore more unique locations than low-income students. Combining a number of measures into an index of urban mobility, we find that, conditional on income, urban mobility is positively correlated with home neighborhood characteristics such as distance from the urban core, car ownership and social capital.

For over 50 years, social scientists have documented urban residential segregation[1,2], and its pernicious effects, particularly for children[3–7]. More recently, Athey et al.[8] demonstrated that experiences are not perfectly delineated by place of residence, finding that 'experienced isolation' is far lower than residential segregation, building on the 'activity space' literature in sociology[9–14]. Browning et al.[15] similarly finds that Black youth experience more inter-racial interactions than implied by residential location alone.

Interaction with a diverse set of people is only one potential benefit of urban life. In this Article, we examine a range of outcomes, including racial and income-based experienced isolation, visits to urban amenities, exploration of new places and distance traveled, using a panel of location data from GPS-enabled devices. We are particularly interested in the lives of younger urbanites. Recent work has shown that children in denser urban areas experience less upward economic mobility[16], despite access to a range of amenities, public goods and social infrastructure offered by cities. At the same time, past decades have seen a rise in income segregation for households with children, but not for childless households[17]. Although we cannot identify the sources or consequences of these developments, both are informed by how youth interact with their neighborhood and/or broader urban environment.

In this Article we build a panel of location data from GPS devices and infer three characteristics for each device: household income, race and student status. To infer income, we follow Cook[18] and match

each device to its home parcel, then use characteristics of the home (for example, market value, structure age and location) to predict income. For race, we follow Athey et al.[8] and use whether or not a device is from a majority non-Hispanic white block group to define 'White' and 'non-White' devices. Finally, we define 'students' as 16–18-year-olds attending school and infer student status from whether an individual's most common weekday location is a high school. For privacy reasons, mobile-phone record providers remove anyone under 16 years of age. Importantly, this sample contains a mixture of high-school students, teachers and staff, which probably attenuates the differences we measure between students and adults. Furthermore, US teachers are disproportionately White relative to their students; during the 2017–2018 school year, in public schools where the majority of students were Black, 54% of teachers were White[19]. Nonetheless, we find consistent and meaningful gaps in the urban mobility and isolation of students versus adults. We also perform several robustness checks, as well as a back-of-the-envelopment bias correction that suggests the impact of teachers is small, in Supplementary Sections A and B.

We start by estimating the day-to-day experienced isolation across both race and economic lines. Following the methodology of Athey et al.[8], we find that students experience more racial and income isolation than adults. Excluding time spent at home, the racial isolation of students is 21% higher than that of adults in the 100 largest metropolitan areas. The income isolation of students 13% higher than that of adults, driven

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by the particularly high isolation of high-income students. When we compare the larger and smaller metropolitan areas, we find that the student–adult divide is much starker for the largest metropolitan areas. For example, the racial isolation of students is less than 10% higher than adults in the smallest third of metropolitan areas, but 42% higher in the largest third. One potential explanation for why cities provide benefits for adults[20] but offer less upward mobility for students[16,21] is that urban children lead more isolated lives than urban adults.

We next turn to broader measures of urban mobility and find a more complex picture. 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, but students also explore a greater number of unique locations, spend more time in 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 and go to 10–20% fewer restaurants and retail establishments.

The connection between mobility and income is much stronger than the connection between mobility and student status, with lower-income students appearing far less mobile than wealthier students in every dimension. Students in the richest quartile of our sample make 57% more visits to entertainment venues, 38% more visits to parks, and experience 54% more total unique locations than students in the lowest income quartile. Higher-income students also spend three percentage points less time at home and, when they leave home, travel further afield. These differences attenuate when we control for the tract of residence, but even within a tract, higher-income students are more mobile and take advantage of more urban amenities.

Finally, we investigate the correlation between urban mobility and neighborhood characteristics. To simplify our analysis, we aggregate our various measures into a single urban mobility index. Even holding fixed a device's estimated income, urban mobility is rising for median neighborhood income. Urban mobility is lower in places that are more densely populated and closer to the city center, as well as in places with greater transit access. In its current state, public transit in the United States does not override other factors that limit urban mobility among people experiencing poverty. Urban mobility is also higher in areas with greater social capital, as measured by Chetty et al.[22,23], suggesting that places with residents who are more connected to urban assets in the physical world also have greater connection across socioeconomic statuses in the virtual world.

Although this Article cannot speak to the long-run costs of urban isolation, we have documented that students appear to live more isolated lives than their adult counterparts, especially in the largest cities. Moreover, lower-income urbanites appear to make far less use of urban amenities, which are themselves core benefits of urban life[24,25]. Wealth appears to be a complement, rather than a substitute, for enjoying the pleasures of urban life.

Results

We start by examining students' urban mobility in comparison to adults using a panel of location data from GPS-enabled devices (details about the data and methods are provided in the Methods). We document experienced isolation by race and income and then turn to broader measures of travel, urban amenity consumption, and time use. We then look within the student population to see who benefits from cities and dense urban areas. We focus in particular on differences in household income, both because we hypothesize that income plays a critical role in urban mobility and because our data allow us uniquely to explore differences in income while holding fixed narrow neighborhoods of residence. In the last section, we look at correlates with the component of urban mobility that are explained by neighborhood.

Table 1 | Experienced isolation of students and adults

(a) Overall experienced isolation, EI	Aggregate	Students	Adults
Outside of home			
Racial isolation	0.3134	0.3763	0.3110
Income isolation	0.2338	0.2630	0.2320
Including time at home			
Racial isolation	0.7092	0.7597	0.7075
Income isolation	0.6154	0.6563	0.6136

(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 (0.0005)	−0.0337 (0.0003)
Exposure to NWD by WD	0.1943	−0.045 (0.0004)	−0.0356 (0.0003)
Exposure to WD by NWD	0.3484	−0.0282 (0.0009)	−0.0311 (0.0006)
Income diversity			
Exposure to income diversity	0.3606	−0.0303 (0.0005)	−0.0198 (0.0004)
Exposure to L by H	0.3091	−0.0458 (0.0005)	−0.0388 (0.0004)
Exposure to H by L	0.4331	0.0136 (0.0009)	0.0145 (0.0005)

This table documents overall experienced isolation measures, computed as a weighted average of Metropolitan Statistical Area (MSA) level measures, with weights corresponding to the MSA population. 'At home' is defined as within 50 m 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, higher and lower income, respectively; WD, White device; NWD, non-White device; CBSA, core-based statistical area.

Student and adult differences in experienced isolation

We find that students experience 21% greater experienced racial isolation and 13% greater experienced income isolation than adults. Experienced isolation measures the difference between the share of group A's (for example, lower-income residents) interactions with members of group B (for example, higher-income residents) and the share of group B's interactions with other members of group B. For details on the measure, see the section Measuring experienced isolation and exposure to diversity.

The first row in Table 1 shows that racial isolation outside the home is 0.38 for students, compared to 0.31 for adults, which is similar to the difference between the 25th and 75th percentiles of cities when ranked by overall experienced isolation. Results are similar when using a continuous definition of race (Supplementary Section B.1 presents details). Experienced income isolation outside the home is also larger for students (0.26) than for adults (0.23). To facilitate interpretation, imagine everyone always interacts with exactly one other person. Because 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 (for a difference of 26 percentage points). The levels of experienced isolation rise when we include time within the home (partly mechanically due to our inference strategies for race and income), but the student–adult gap remains similar. In Supplementary Section B.4, we perform a simple back-of-the-envelope calculation to account for bias from including teachers in the 'student' sample and find the student estimates change by less than one percentage point.

As experienced isolation is defined at the population level, we shift to an analogous individual level, 'exposure to diversity' (defined in detail in the section Measuring experienced isolation and exposure to diversity), which captures each individual's exposure to the other

Table 2 | Experienced isolation and urban mobility by city size

City size	Experienced racial isolation		Experienced income isolation	
	Students	Adults	Students	Adults
Big: rank 1–33	0.384	0.271	0.314	0.237
Medium: rank 34–66	0.327	0.263	0.294	0.251
Small: rank 67–100	0.272	0.248	0.278	0.249

This table documents average differences in experienced isolation and urban mobility across cities of different sizes. Cities are ranked based on their 2010 population. Each statistic is computed at the city level and then averaged across all cities within a given size group.

group. Outside the home, adults are in settings where, on average, 25% of others are from the other racial group and 36% of others are from the other income group (Table 1b). The average exposure to racial diversity is 4.7 percentage points lower for students, which reduces to 3.4 percentage points once controlling for tract of residence. We can split these results by imputed race. We find the typical White device (WD) is in a setting where 19% of devices are non-White devices (NWDs), and the typical NWD is in a setting where 35% of devices are WD. For students, these numbers are again substantially lower, at 15% and 32%. The result of greater exposure to racial diversity for Black devices parallels the findings in ref. 15. However, while Browning et al.[15] emphasizes that difference, our focus is on the fact that all students are more isolated than their adult counterparts. Similarly, students' exposure to income diversity is three percentage points lower than that of adults at baseline; perhaps surprisingly, this difference is driven primarily by higher-income students, who are notably more isolated by income than their adult counterparts.

These estimates suggest that, for students, experienced urban isolation may fall along racial lines more than along lines of income. When we control for the home tract, average exposure to income diversity is two percentage points lower for students than adults. The persistence of students' lower levels of exposure to diversity by both race and income when controlling for home tract refutes the notion that the increased isolation of students relative to working adults is mainly driven by the neighborhoods in which students live.

Experienced isolation by city size
We now compare the experienced isolation of students and adults in cities of different sizes. Our main sample pools the one hundred most populous US cities, and Table 2 splits this sample based on whether individuals live in the largest, middle or smallest third of our sample of cities. The first two columns in Table 2 examine experienced racial isolation for students and adults. Students in our biggest cities experience 41% more racial isolation than students in our smallest cities, and adults in our biggest cities experience just 9% more racial isolation than adults in our smallest cities. Student racial isolation is 42% higher than adult racial segregation in the biggest cities, and student isolation is less than 10% higher than adult segregation in the smallest cities. A similar pattern emerges for income isolation. In large cities, income isolation is 32% higher for students than for adults, but in small cities, income segregation is only 12% higher for students than for adults. Both measures suggest that urban size increases the isolation of our student sample relative to the population as a whole.

Student and adult differences in overall urban mobility
Urban neighborhoods provide not just interactions with people, but also interactions with the geographic and economic amenities of cities. We now look at the additional mobility outcomes. See the section Defining urban mobility for a detailed description of these measures. As in Table 1, Table 3 reports results controlling first for Metropolitan Statistical Area (MSA) and then for home census tract.

Students and adults differ in the amount of time spent at home, work/school and in the neighborhood (Table 3a). The average device spends 66% of time at home, 16% of time at work/school and 5% of time in the home neighborhood. We compare this with the time-use results in the American Time Use Survey (ATUS). Averaging across the 2009–2019 period (for a sample size of around 4,000 high-school students), we find that high-school students in the ATUS report spend 66% of their time at home and 18% of their time at school—remarkably similar. Students spend less time at school than adults spend at work, and more time at home and in the neighborhood than adults. In particular, controlling for home tract, students spend nearly 50% more time in their surrounding neighborhood.

When outside the home, students and adults differ in how far they 'roam' (Table 3b). The average distance from home is 7.5 miles across all devices; this distance is ~35% smaller for students, a gap that persists even when comparing students and adults living in the same tract. Although students travel shorter distances, their travel patterns are less routine. The average student visits 5% more unique locations—defined by 500 ft × 500 ft squares—than the average adult, although much of this difference in exploration can be explained by differences in where students live.

The somewhat modest connection between student status and unique locations masks a large shift in the nature of the locations visited (Table 3c). 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 is small. These visits exclude those to any location identified as a device's workplace, so the differences are not driven by adults being more likely to work at restaurants and shops.

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 3d). To evaluate this, we compute the time a device spends in each census tract and regress characteristics of the tract on student status, weighting by the time spent in the tract. Although 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 although students experience more isolation than adults—especially along racial lines—in other ways, the overall experience of urban youth differs from that of urban adults predictably. 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 life in cities masks considerable heterogeneity by levels of income among the student population.

Household income and the urban mobility of students
We now look at the relationship between urban mobility, household income and home neighborhood characteristics. Not only do we hypothesize that income plays a critical role in urban mobility, but our data allow us uniquely to explore differences in income while holding fixed narrow neighborhoods of residence. Furthermore, our measure of income based on a device's home parcel is less susceptible to measurement error than our measure of race. Other work in this literature has instead focused more prominently on differences in mobility and neighborhood level exposure by race[26–29].

We find that both play a role—higher-income students have greater urban mobility across a range of measures holding neighborhood

Table 3 | Urban mobility of students and adults

	Average (not logged)	Coefficient on isStudent (home CBSA FEs)	Coefficient on isStudent (home tract FEs)
(a) Time at primary locations			
Fraction of time at home	0.6573	0.0243 (0.0005)	0.0203 (0.0004)
Fraction of time at work/school	0.161	−0.0165 (0.0003)	−0.0127 (0.0002)
Fraction of time in neighborhood (excl. home)	0.0488	0.0215 (0.0003)	0.0231 (0.0002)
(b) Roaming ranges			
log average miles from home	7.5021	−0.3543 (0.0019)	−0.3898 (0.0014)
log no. of unique locations (geohash7)	42.8904	0.0528 (0.002)	0.0138 (0.0017)
(c) Visits to amenities			
log no. of restaurant visits	1.5151	−0.0982 (0.0023)	−0.1137 (0.0019)
log no. of retail visits	1.9806	−0.1948 (0.0025)	−0.2181 (0.002)
log no. of park visits	1.1746	0.0778 (0.0022)	0.0577 (0.0018)
log no. of entertainment visits	1.399	0.0672 (0.0022)	0.0318 (0.0019)
log no. of civil, social, religion visits	0.2523	0.0326 (0.0011)	0.025 (0.001)
(d) Characteristics of tracts visited			
log median HH income	76386	0.0829 (0.0008)	0.0381 (0.0006)
Fraction college graduate	0.3924	0.0105 (0.0003)	0.0017 (0.0002)
Fraction White alone	0.5733	0.0285 (0.0004)	0.0071 (0.0002)
Air quality (PM25)	8.8084	−0.026 (0.0016)	0.0079 (0.0012)
log crimes per square mile	9.711	−0.1973 (0.0159)	-0.0709 (0.0085)
(Chicago & Los Angeles, 2010–2018)			

This table documents coefficients from regressions of mobility metrics on whether the device is a student with fixed effects (FEs) for either the device's home MSA or census tract. Miles from home is the average distance of stays outside 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 m of the location's coordinates, and '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 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 and 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.

fixed, but also, even for students with similar income, neighborhood characteristics matter. We continue to focus on students in the main text, but Supplementary Fig. C.3 reproduces these results for the adult population.

To document differences by income, we divide devices into quartiles of predicted household income and compare a range of mobility measures across each quartile. For each measure, we present versions controlling only for a device's home MSA and a version controlling for home tract.

First, relative to the baselines from Table 3, students in the highest income quartile spend ~5% less time at home and 18% more time in the neighborhood than students in the lowest income quartile (Fig. 1a,b). The effect 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 when they leave the house (Fig. 1c,d). The relationship between income and the 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. When controlling for home tract, the coefficients drop by about half, but the relationship between income and the 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 (Fig. 1e,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 make 35% more visits to restaurants and 38% more visits to parks than students in the lowest income quartile. On average, the gap between the top and bottom quartiles attenuates by 45% when controlling for home tract, but again remains large.

Finally, there is a weak relationship between household income and exposure to both income and racial diversity (Fig. 1g,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 home tract, suggesting that 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.

As a validation check, we conduct a similar exercise using the 2017 National Household Transportation Survey (NHTS) in Supplementary Table B4. Although the NHTS does not allow us to look at detailed destination types or to control for neighborhood differences, we can look at some trends by income. Similar to our results, we find that both travel for amenities and time away from the home are rising in household income.

Urban mobility and neighborhood characteristics

How does the urban mobility of students relate to the characteristics of their home neighborhood? To facilitate an analysis of the connection between neighborhoods and urban mobility, we also collapse our mobility measures down to a single mobility index for each device using principal component analysis (PCA) (see the section Defining urban mobility for details). The first panel of Fig. 2 shows that, as shown above for the component parts, urban mobility increases steeply with the predicted household income of the device. The linear coefficient when the mobility index is regressed on log predicted income is 0.41, suggesting that a twofold increase in predicted income increases urban mobility by nearly half of a standard deviation. In all subsequent panels, we show results with controls for just MSA as well as with controls for the log of predicted income, to isolate the correlation that persists beyond the impact of household income. Supplementary Table B3 reports the coefficients from analogous linear regressions, which we report in the main text to summarize the graphs.
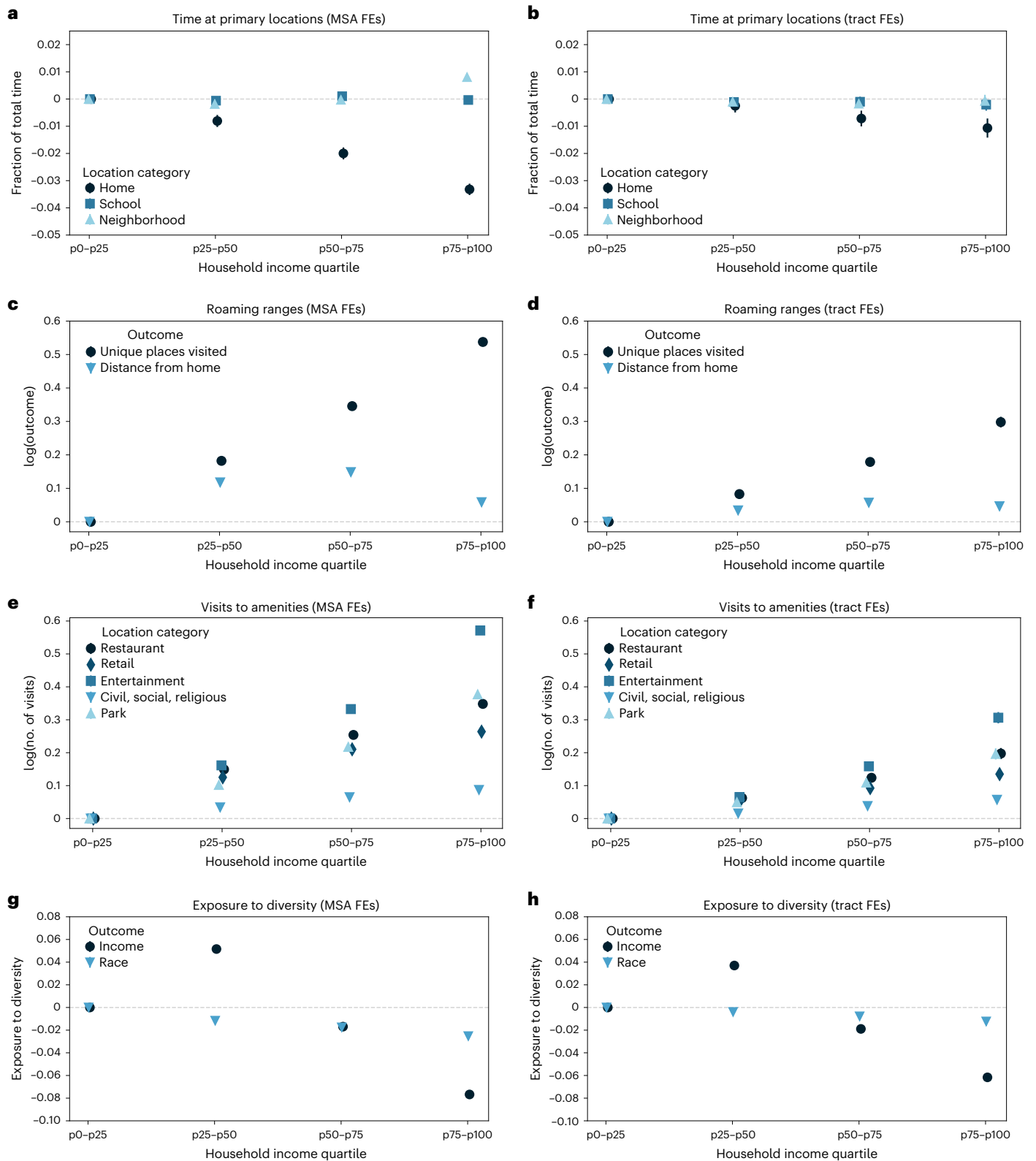
Fig. 1 | Urban mobility of students by income. a–h, The relationships between student income and various measures of urban mobility. Sample size *n* = 398,472 for all graphs. **a,c,e,g,** Time at primary locations (MSA FEs; **a**), roaming ranges (MSA FEs; **c**), visits to amenities (MSA FEs; **e**) and exposure to diversity (MSA FEs; **g**) plotted as a coefficient from a linear regression of the specified device-quarter level mobility measure on indicators for the quartile of a device's predicted income with MSA fixed effects. **b,d,f,h,** Time at primary locations (tract FEs; **b**), roaming ranges (tract FEs; **d**), visits to amenities (tract FEs; **f**) and exposure to diversity (tract FEs; **h**) plotted as analogous coefficients with tract fixed effects. 95% confidence intervals are represented by bars around each point (although they are often covered by the point itself).
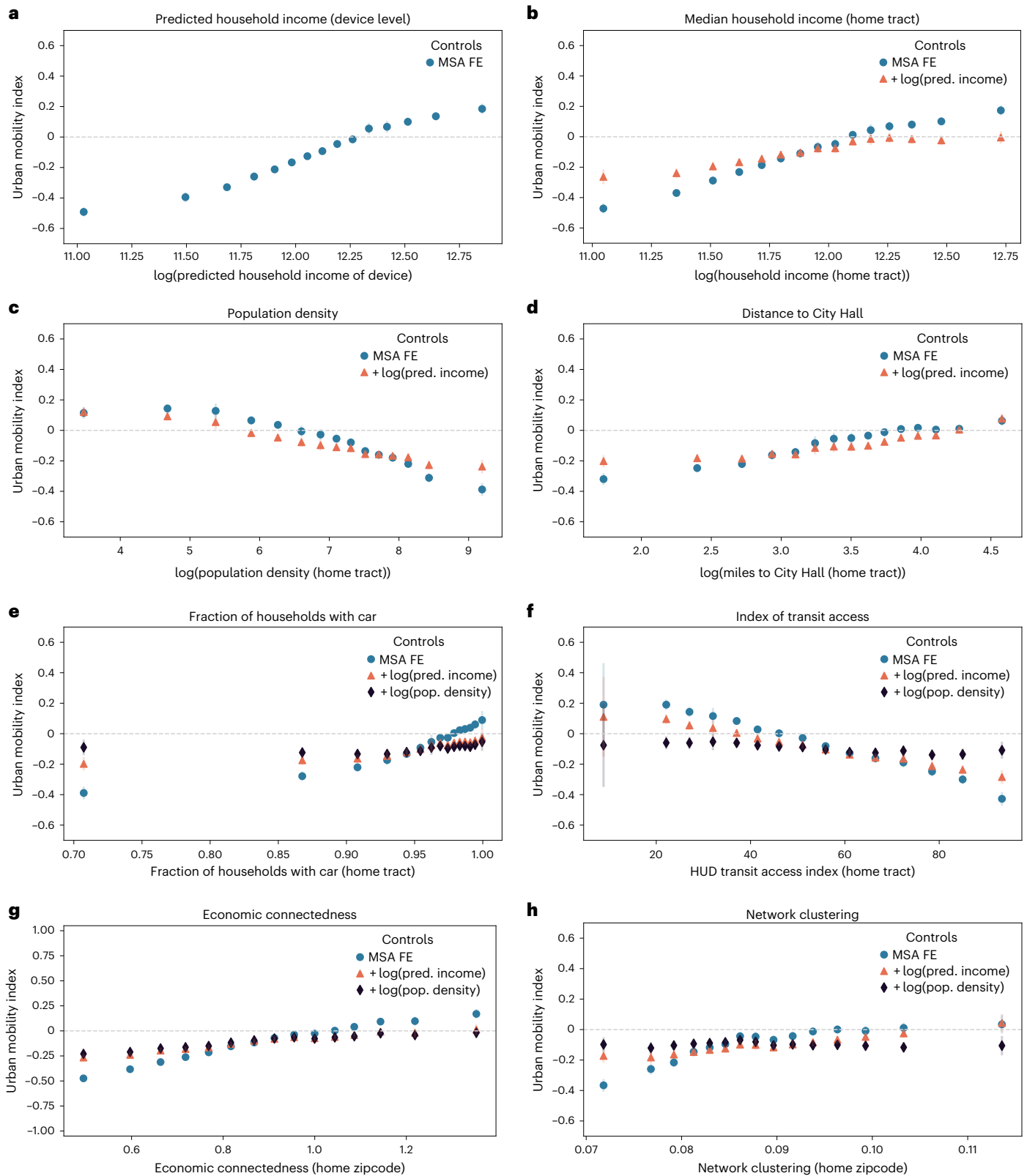
Fig. 2 | Correlates of urban mobility. a–h, The relationships between urban mobility and various correlates using a series of binscatters. **a**, Predicted household income (device level) with the data ordered by the device's predicted income, plotting the average urban mobility index within binned groups. **b**, Median household income (home tract) bins by median household income of the census tract. **c**, Population density by population density. **d**, Distance to City Hall by distance to City Hall. **e**, Fraction of households with a car by the fraction of households with a car. **f**, Index of transit access by an index published

by the Department of Housing and Urban Development (HUD). **g**, Economic connectness by a measure of friendships across income groups based on the Facebook social graph[22]. **h**, Network clustering by a measure of how likely it is that any two friends of a given person are themselves friends on Facebook[22]. All plots control for MSA fixed effects, and for some we additionally control for the log of a device's predicted income. Sample size n = 398,472 for all graphs. 95% confidence intervals are represented by bars around each point (although they are often covered by the point itself).

Even controlling for household income, there is a persistent positive relationship between urban mobility and neighborhood median household income (Fig. 2b). Without controls, the coefficient on neighborhood income is 0.40, 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 0.17 – even for devices of a similar income level, those in higher-income neighborhoods exhibit greater urban mobility.

Urban mobility is decreasing in measures of 'urbanity', such as population density and proximity to City Hall (Fig. 2c,d). The linear coefficient for urban mobility regressed on log population density is −0.09, which falls in magnitude to −0.07 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. Similarly, mobility rises with the log distance from City Hall. The coefficient without income controls is 0.15, which falls to 0.10 when we control for income. One obvious reason students in dense neighborhoods might have lower mobility is that they might be less likely to have access to a car. Figure 2e looks at the share of households in the tract that own a car. There is a strong relationship between urban mobility and car ownership: for each ten-percentage-point increase in car ownership (approximately one standard deviation), urban mobility increases by 0.16 standard deviations. In contrast, urban mobility is slightly lower in neighborhoods that the Department of Housing and Urban Development (HUD) identifies as having greater transit access. This relationship between urban mobility and transit access, however, is primarily driven by population density; once controlling for population density, there is no meaningful relationship between urban mobility and transit access.

Finally, urban mobility is positively correlated with measures of neighborhood social capital as measured by connections on social media (Fig. 2g,h). Figure 2g looks at the link between geographic mobility and economic connectedness, which is a measure of Facebook connections between lower- and higher-income individuals[22]. Specifically, it is the average share of above-median socioeconomic status friends among below-median socioeconomic status residents of the zip code. The linear coefficient is 0.76, which falls to 0.32 when we control for individual income. Figure 2h shows a weaker positive link between urban mobility and how clustered social connections are for neighborhood residents ('network clustering'), another measure produced by ref. 22 that captures the rate at which two friends of a resident are also friends with each other. The relationship between mobility and network clustering is attenuated when controlling for population density, but the relationship with economic connectedness persists. 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 equally possible that causality goes the other way, and that greater social capital leads to greater urban mobility, as our findings are only correlations.

Conclusion

Density provides city-dwellers with access to amenities, yet proximity does not necessarily translate into use, particularly for lower-income youth, who lack funds and cars and whose highly local amenities may differ substantially from those in wealthy neighborhoods. An alternate view is that those with a lower opportunity cost of time are able to travel more and spend more time interacting with their urban environment.

We find that students experience greater income and racial isolation than adults, and this gap is much larger in the biggest metropolitan areas. Students also spend more time at home and in their neighborhood, stay closer when they leave the home, 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. Higher-income students are much more likely to visit every form of local amenity,

explore more unique locations, spend less time at home, and roam further from home. In each case, the differences attenuate when comparing students who live within the same neighborhood, but often remain large. On average, home neighborhoods 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 income. Areas that have higher car ownership, are less dense and have a higher neighborhood income all have higher levels of urban mobility. Urban mobility is also higher for students living in tracts that have greater social capital, perhaps because physical connection increases social capital.

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

Methods

GPS mobility sample

Location data. Our primary data are a panel of GPS locations for a sample of mobile phones from 2019. Examples of previous applications of GPS location data include mobility during the COVID-19 pandemic[30–33], waiting times at voting polls[34], knowledge spillovers between employees of different firms[35] and demand for amenities[8,18,36]. 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 various locations[37]. 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 Supplementary Section A. To assuage concerns about the representativeness of the GPS sample, we document in the section Student and adult differences in overall urban mobility that our sample replicates time-use patterns for students in ATUS, and in the section Household income and the urban mobility of students that we replicate travel patterns for youth in the National Household Transportation Survey (NHTS). Both surveys have very small youth samples relative to our data. Our data are also able to add considerable detail on mobility patterns.

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. We exclude devices for which we observe insufficient data to identify a work location. The majority of devices have insufficient coverage in the data to identify a work location confidently; these devices are either unemployed or employed in occupations without a static work location, such as postal workers or taxi drivers. Devices excluded from the sample live in tracts that are slightly more non-Hispanic White (68.8% versus 67.1%) and tracts with higher median household income (US$79,653 versus US$75,397). To label a device as a student, we match 'work' locations to the geographic parcels of public schools. We identify the locations of high schools using data from the National Center for Education Statistics (NCES). Supplementary Section A.2 describes the matching process. We include only high schools, as our GPS data are meant to exclude individuals under 16 years old. Supplementary Fig. 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 establishment they visit, we find that 'students' go to far fewer bars and beer/liquor stores than adults. We have also done a back-of-the-envelope bias correction for some results, which suggests that the impact of teachers is small, in Supplementary Section B.

Inferring income and race. We match each device to its home parcel and use parcel-level estimates of household income from ref. 18. The estimates are computed in two stages. First, ref. 18 matches each parcel to data on housing characteristics from Corelogic, including building age, type of building (for example, single versus multi-family) and a prediction of its current market value. Based on the relationship between housing characteristics and household income in the American Community Survey (ACS) Public Microdata Sample (PUMS), an initial estimate of household income is formed for each device. One limitation of the ACS PUMS data is that only the Public Use Microdata Area (PUMA) of each home is observed, rather than more granular geographic identifiers such as home block group. To improve estimates using the more granular geographic data available in the GPS data, a second step is performed in which each estimate is updated using an empirical Bayes procedure based on the distribution of household income within the device's home block group. For full details on the income imputation, see appendix A.2 of ref. 18.

Following Athey et al.[8], we classify devices as either WD or NWD based on whether or not their home block group is majority White (non-Hispanic). We use 2019 ACS block groups rather than 2010 Census blocks, as the 2010 Census is now substantially out of date. However, the results are similar if we instead use 2010 blocks to identify WDs and NWDs. Using only these two broad classifications of race will mask substantial heterogeneity by race and ethnicity; however, because of the measurement error inherent in using home geography to impute race, we do not attempt to further divide devices based on ethnicity or more granular races. Even with this broad classification of race, our measure will frequently misclassify White individuals as NWDs and vice versa; the average home block group for WDs is 78.5% White, and the average home block group for NWDs is 21.0% White.

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.

Measuring experienced isolation and exposure to diversity
To estimate experienced income and racial isolation, we follow the methodology introduced in ref. 8, which we describe in detail in Supplementary 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 with other higher-income residents. Using GPS data, we define each device's exposure to members of each race and income group based on the time it spends in each location and the race and income distributions of other devices in that location. An income isolation measure of 0.5 would imply that lower-income 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 or meaningful interactions between devices sharing a geographic location[38]. 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 ref. 8 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 from those from predominantly non-White neighborhoods. As a robustness check, in Supplementary Section B.2 we document a positive correlation between measures of segregation from GPS data and the school dissimilarity indices from refs. 39,40. In Supplementary Section B.3, we discuss the relationship between experienced isolation and residential isolation. 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 places they visit—with NWDs.

Defining urban mobility
In addition to experienced isolation, we look at four other categories of urban mobility: (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.

To facilitate an analysis of the connection between neighborhoods and urban mobility, we also collapse our mobility measures down to a single mobility index for each device. Specifically, we first standardize each measure using the cross-device mean and standard deviations of the variables, then use PCA to collapse the measures into a single measure. 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. The individual measures included are the time at home, work/school and in the neighborhood, the number of visit to each category of amenity, the number of unique locations visited, and the average miles traveled from home. Finally, for interoperability, we transform the first principal component into a z-score, which we use as our final index of urban mobility. Supplementary Table B2 shows the correlation between this index and each of the component parts.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
The primary data that support the findings are provided by Replica, an urban data platform, and are provided under a restricted agreement for the current study. Therefore, it is not publicly available. Other data in the study come from the census and are accessed via IPUMS, a database of census and survey data housed at the University of Minnesota, as well as from Opportunity Insights, an economics research laboratory at Harvard.

Code availability
The primary data that support the findings are provided by Replica, an urban data platform, and are provided under a restricted agreement for the current study and are thus not publicly available. As running the code for this Article requires proprietary data, it is also not publicly available, but can be provided upon request.

References

1. Kain, J. F. Housing segregation, negro employment, and metropolitan decentralization. *Q. J. Econ.* **82**, 175–197 (1968).
2. Taeuber, K. E. & Taeuber, A. F. *Negroes in Cities: Residential Segregation and Neighborhood Change* (Atheneum, 1969).
3. Brooks-Gunn, J., Duncan, G. J., Klebanov, P. K. & Sealand, N. Do neighborhoods influence child and adolescent development? *Am. J. Sociol.* **99**, 353–395 (1993).
4. Cutler, D. M. & Glaeser, E. L. Are ghettos good or bad?. *Q.J. Econ.* **112**, 827–872 (1997).
5. Sampson, R. J., Morenoff, J. D. & Gannon-Rowley, T. Assessing 'neighborhood effects': social processes and new directions in research. *Ann. Rev. Sociol.* **28**, 443–478 (2002).
6. Chyn, E. & Katz, L. F. Neighborhoods matter: assessing the evidence for place effects. *J. Econ. Perspect.* **35**, 197–222 (2021).
7. Chyn, E., Collinson, R. & Sandler, D. The long-run effects of residential racial desegregation programs: evidence from gautreaux. Working paper (2023).
8. Athey, S., Ferguson, B., Gentzkow, M. & Schmidt, T. Estimating experienced racial segregation in US cities using large-scale GPS data. *Proc. Natl Acad. Sci. USA* **118**, e2026160118 (2021).
9. Wong, D. W. & Shaw, S.-L. Measuring segregation: an activity space approach. *J. Geograph. Syst.* **13**, 127–145 (2011).
10. Shelton, T., Poorthuis, A. & Zook, M. Social media and the city: rethinking urban socio-spatial inequality using user-generated geographic information. *Landsc. Urban Plan.* **142**, 198–211 (2015).
11. Wang, Q., Phillips, N. E., Small, M. L. & Sampson, R. J. Urban mobility and neighborhood isolation in America's 50 largest cities. *Proc. Natl Acad. Sci. USA* **115**, 7735–7740 (2018).
12. Beiró, M. G. et al. Shopping mall attraction and social mixing at a city scale. *EPJ Data Sci.* **7**, 28 (2018).
13. Cagney, K. A., York Cornwell, E., Goldman, A. W. & Cai, L. Urban mobility and activity space. *Ann. Rev. Sociol.* **46**, 623–648 (2020).
14. Moro, E., Calacci, D., Dong, X. & Pentland, A. Mobility patterns are associated with experienced income segregation in large US cities. *Nat. Commun.* **12**, 4633 (2021).
15. Browning, C. R., Pinchak, N. P., Boettner, B., Calder, C. A. & Tarrence, J. Geographic isolation, compelled mobility, and everyday exposure to neighborhood racial composition among urban youth. *Am. J. Sociol.* **128**, 914–961 (2022).
16. Chetty, R. & Hendren, N. The impacts of neighborhoods on intergenerational mobility I: childhood exposure effects*. *Q. J. Econ.* **133**, 1107–1162 (2018).
17. Owens, A. Inequality in children's contexts: income segregation of households with and without children. *Am. Sociol. Rev.* **81**, 549–574 (2016).
18. Cook, C. *Heterogeneous Preferences for Neighborhood Amenities: Evidence from GPS Data* (SSRN, 2023); https://ssrn.com/abstract=4212524
19. Spiegelman, M. *Race and Ethnicity of Public School Teachers and Their Students* (NCES, 2020); https://nces.ed.gov/pubs2020/2020103/index.asp
20. Glaeser, E. L. & Mare, D. C. Cities and skills. *J. Labor Econ.* **19**, 316–342 (2001).
21. Chetty, R. & Hendren, N. The impacts of neighborhoods on intergenerational mobility II: county-level estimates. *Q. J. Econ.* **133**, 1163–1228 (2018).
22. Chetty, R. et al. Social capital I: measurement and associations with economic mobility. *Nature* **608**, 108–121 (2022).
23. Chetty, R. et al. Social capital II: determinants of economic connectedness. *Nature* **608**, 122–134 (2022).
24. Couture, V., Gaubert, C., Handbury, J. & Hurst, E. *Income Growth and the Distributional Effects of Urban Spatial Sorting*. Technical Report w26142 (National Bureau of Economic Research, 2019); http://www.nber.org/papers/w26142.pdf
25. Couture, V. & Handbury, J. Neighborhood change, gentrification and the urbanization of college graduates. *J. Econ. Perspect.* **37**, 29–52 (2023).
26. Levy, B. L., Phillips, N. E. & Sampson, R. J. Triple disadvantage: neighborhood networks of everyday urban mobility and violence in US cities. *Am. Sociol. Rev.* **85**, 925–956 (2020).
27. Candipan, J., Phillips, N. E., Sampson, R. J. & Small, M. From residence to movement: the nature of racial segregation in everyday urban mobility. *Urban Studies* **58**, 3095–3117 (2021).
28. Brazil, N. Environmental inequality in the neighborhood networks of urban mobility in us cities. *Proc. Natl Acad. Sci. USA* **119**, e2117776119 (2022).
29. Xu, W. The contingency of neighbourhood diversity: variation of social context using mobile phone application data. *Urban Studies* **59**, 851–869 (2022).
30. Chang, S. et al. Mobility network models of COVID-19 explain inequities and inform reopening. *Nature* **589**, 82–87 (2020).
31. Allcott, H. et al. *What Explains Temporal and Geographic Variation in the Early US Coronavirus Pandemic?* Technical Report w27965 (National Bureau of Economic Research, 2020); http://www.nber.org/papers/w27965.pdf
32. Couture, V., Dingel, J. I., Green, A., Handbury, J. & Williams, K. R. JUE insight: measuring movement and social contact with smartphone data: a real-time application to COVID-19. *J. Urban Econ.* **127**, 103328 (2021).
33. Chen, M. K., Chevalier, J. A. & Long, E. F. Nursing home staff networks and COVID-19. *Proc. Natl Acad. Sci. USA* **118**, e2015455118 (2021).
34. Chen, M. K., Haggag, K., Pope, D. G. & Rohla, R. Racial disparities in voting wait times: evidence from smartphone data. *Rev. Econ. Stat* **104**, 1341–1350 (2022).
35. Atkin, D., Chen, K. & Popov, A. *The Returns to Serendipity: Knowledge Spillovers in Silicon Valley*. Working Paper 30147 (National Bureau of Economic Research, 2020).
36. Miyauchi, Y., Nakajima, K. & Redding, S. J. *Consumption Access and Agglomeration: Evidence from Smartphone Data*. Working Paper 28497 (National Bureau of Economic Research, 2021).
37. Birant, D. & Kut, A. ST-DBSCAN: an algorithm for clustering spatial-temporal data. *Data Knowl. Eng.* **60**, 208–221 (2007).
38. White, M. J. The measurement of spatial segregation. *Am. J. Sociol.* **88**, 1008–1018 (1983).
39. Logan, J. R., Minca, E. & Adar, S. The geography of inequality: why separate means unequal in American public schools. *Sociol. Educ.* **85**, 287–301 (2012).
40. Logan, J. R., Zhang, W. & Oakley, D. Court orders, white flight and school district segregation, 1970–2010. *Social Forces* **95**, 1049–1075 (2017).

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Author contributions

All authors contributed equally.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	The sample was generated using SQL in BigQuery and Python version 3.9.
Data analysis	Analyses were conducted using Python version 3.9 and R version 4.3.0. The GPS pings were transformed into "stays" using a propriety algorithm from the data provider that is similar to ST-DBSCAN (Birant and Kut, 2007).

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The primary data that supports the findings is provided by Replica, an urban data platform, and is provided under a restricted agreement for the current study. Therefore, it is not publicly available. Other data in the study comes for the Census and is accessed via IPUMS (https://usa.ipums.org/usa/) as well as from Opportunity Insights (https://opportunityinsights.org/data/).

Human research participants

Reporting on sex and gender	NA
Population characteristics	Based on imputed characteristics, the sample population lives in areas that have slightly lower median income, slightly lower levels of education, and a slightly smaller share of the population that is white, than the national population.
Recruitment	NA
Ethics oversight	IRB

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Behavioural & social sciences study design

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Study description	The study is a quantitative analysis of non-experimental data. We use GPS data to estimate a number of measures of urban mobility and isolation. We compare these results between youth and adults, and across both race and economic lines.
Research sample	The data is a panel of GPS locations for a sample of cellphones across the US provided by Replica, an urban data platform. We use all data available from Replica for 2019. The final sample consists of 9.4 million units observed over time. Because our data is over-sampled from lower-income, less white, less educated, and more dense areas, we re-weight home locations to match the distribution of the 2019 5-year ACS. Our final panel is representative in the sense that it matches the national distribution. We also demonstrate that it matches time use patterns for students in the American Time Use Survey (see Section 3.3 of the paper) and that it matches travel patterns for youth in the National Household Transportation Survey (see Section 3.4).
Sampling strategy	The data-provider collects GPS data from mobile devices. The full dataset from the data-provider is used, so there is no sampling procedure.
Data collection	The data was received from the data-provider in the form of administrative records; there was no experiment run nor collection procedure.
Timing	January 1, 2019 through December 31, 2019
Data exclusions	We remove data for devices not in one of the top one hundred most populous metropolitan Core-Based Statistical Areas. We also exclude devices for which we observe insufficient data to identify a home or work location.
Non-participation	No participants were involved in this study.
Randomization	No randomization occurred in this study as no experiments were run.

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Methods

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