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Multidimensional Intergenerational Mobility

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Abstract

In this paper, we present novel evidence of the extent to which intergenerational mobility is generalized or specific across domains of human and health capital. That is, do children who experience greater mobility in one domain (e.g., income) also experience mobility in other domains (education, health status, health behaviors, crime). Using rich data in Add Health, we find evidence against generalized mobility—families that are more mobile in one domain are not more mobile in others. We then ask a place-based version of this question, motivated by Chetty et al. (2014)'s work showing high levels of geographically-based income mobility in the US. The school-based sampling combined with parent-child links across many outcome domains of the Add Health allows us to use a common dataset between the two analyses. Like our individual-based results, we find limited evidence of generalized mobility by place—indeed, most estimates suggest close-to-zero correlations between many of the ten domains we explore.

Keywords

Intergenerational Mobility; Spatial Heterogeneity

JEL code:

J62; R12

1 Introduction

Parents and children are similar across many characteristics. The most developed literature finds income persists across generations (e.g., Aaronson and Mazumder 2007; Chetty et al. 2014; Mazumder 2005; Solon 1992). Other research also finds intergenerational persistence in education (Fletcher and Han 2019; Hertz et al. 2007), welfare (Hartley et al. 2017), overall health (Fletcher and Jajtner 2019, 2020; Halliday et al. 2021), obesity (Classen 2010; Classen and Thompson 2016), smoking (Gilman et al. 2009; Jensen et al. 2020; Kandel et

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al. 2015), alcohol use (Anda et al. 2002; Jensen et al. 2020), criminal behavior (Besemer et al. 2017), and religion (Patacchini and Zenou 2016). However, studies suggest there is significant heterogeneity in intergenerational mobility for individuals and places (Chetty et al. 2014, 2020; Fletcher and Han 2019; Fletcher and Jajtner 2021; Halliday et al. 2021; Hertz 2005; Jajtner 2020; Mazumder 2014). Despite consistent findings of heterogeneity in intergenerational mobility across several characteristics or domains, only rarely does the literature address whether the people or places that exhibit high persistence in one domain are the same ones with persistence in other domains.

Theoretical models of intergenerational mobility (e.g., Becker and Tomes 1979; Solon 2004) suggest different groups and locations can experience different persistence patterns partly due to heterogeneous social cultures and contexts. For example, research finds there is significant heterogeneity in income mobility across the United States in time (Chetty et al. 2017; Collins and Wanamaker 2017), geography (Chetty et al. 2014; Connor and Storper 2020), and demographic characteristics (Bhattacharya and Mazumder 2011; Chetty et al. 2014, 2020; Collins and Wanamaker 2017; Mazumder 2014). Mobility may be shaped by local spending on education (Mayer and Lopoo 2008), Medicaid (O'Brien and Robertson 2018), or pollution (O'Brien et al. 2018), although evidence is mixed (Lefgren et al. 2020). An open question is whether these contexts should shape intergenerational mobility in a similar fashion across outcomes. One could expect intergenerational persistence of income to be related to intergenerational education because education partly determines one's income. Research also demonstrates that increased parent income can boost high school completion, college enrollment, and college completion for children (Bastian and Michelmore 2018; Manoli and Turner 2018). Indeed, education is sometimes used as a substitute for income mobility under the assumption that these traits are related and education mobility could exhibit fewer biases (Feigenbaum 2018). One could also expect intergenerational health and other socioeconomic measures to be related given the well-documented relationship between individual health and socioeconomic status (Chetty et al. 2016; Conti and Heckman 2010; Hurst et al. 2013; Meyer and Mok 2019) and the relationship between parent (or childhood) socioeconomic status and later-life health for children (e.g., A. Case et al. 2002; Condliffe and Link 2008; Currie 2009; Fletcher and Wolfe 2014; Hurst et al. 2013; S. Wu et al. 2018). But while these outcomes are correlated in each generation, and each outcome exhibits intergenerational persistence, little research has examined whether this persistence is itself bundled between outcomes—a *generalized* process of children emerging to appear similar to their parents across outcomes—or whether this persistence takes on different mechanisms across each outcome and is thus *specialized*.

Parents share genetic material with their biological children, which might support a generalized intergenerational mobility process. Genetic factors have been shown to shape individuals' characteristics including income (lifetime earnings heritability ~40-50%) (Hyytinen et al. 2019), education (typical heritability estimates ~40%) (Branigan et al. 2013), self-reported health status (~45%) (Romeis et al. 2000), and many health and other social behaviors (Turkheimer 2000). Since genetic material is always passed from one generation to the next, one can reasonably expect children to mimic their parents' characteristics, and intergenerational mobility could be generalizable. Environments can shape individual outcomes and are another likely component of intergenerational mobility.

For example, pollution can shape health (Liu et al. 2019; X. Wu et al. 2020); and individuals living north of the 37-degree parallel are more likely to have vitamin D deficiencies, which are linked with poor health outcomes (Holick 2004; Kim et al. 2008). All else equal, one might expect children who maintain a similar environment as they grew up in to be more similar to their parents across many characteristics relative to children who experience a new environment as adults – again supporting generalized mobility. Likewise, places that maintain a constant environment might be more likely to support similar outcomes across generations, whereas places that change (e.g., gentrification, changing social policies, or changing pollution levels) over time might support generalized diverging outcomes across generations. Maintaining a similar environment can be accomplished either by not moving or moving to a similar environment. Experiencing a new environment can happen either by change in the place itself or moving to a different environment. As a more concrete example, if social policy is effective, then states or localities with a strong social safety net may boost children from poverty, improve health, and health behaviors relative to their parents; whereas, states or localities without such measures could yield more consistent income, education, health, and behaviors across generations.

The magnitude of association between environments or genetic material and certain outcomes, however, might not be constant across various characteristics (i.e., income, education, health, and behaviors). That is to say, the effect of pollution on educational attainment is probably different than its effect on health, for example. This would support more specialized intergenerational mobility processes. Resource-constrained parents could also prioritize (im)mobility of one characteristic over another. For example, a parent who smokes may emphasize the importance of not smoking to their child, improving their health, but it may or may not affect their education, income, or obesity to the same degree. Municipalities, localities, and states also face constraints and may need to prioritize social programs targeted towards health (e.g., Medicaid expansions) over income (e.g., EITC expansions), which would support more specialized mobility.

There is very limited empirical evidence supporting either generalized or specialized mobility. Ahlberg (1998) hypothesized that “inequalities in earnings and income tend to be correlated across generations at least in part because of intergenerational correlations in education and health.” In comparing intergenerational mobility in education, income, earnings, and occupation, Feigenbaum (2018) finds that all the measures similarly suggest relatively high mobility for Iowans in the early 1900s, with higher mobility for rural sons and sons of grandparents born outside the United States. Linking across studies, non-Hispanic Black Americans experience less income (Chetty et al. 2020) and health (Fletcher and Jajtner 2020; Halliday et al. 2021) mobility. However, Halliday et al. (2018) also suggests that individuals experiencing income mobility are not the same individuals experiencing health mobility.

Therefore, it remains unclear whether intergenerational mobility ought to be generalized or specific. Yet, determining whether intergenerational mobility in various domains might be related could have important research and policy implications. For example, researchers with limited data availability might question whether available data measuring income mobility might be a reasonable proxy for other domains of mobility. Policymakers might be interested in whether a specific policy targeting breaking the intergenerational cycle of poverty might also improve health mobility. Our study makes important contributions to this literature, seeking to understand the extent to which there is a generalized or specialized transmission of characteristics across generations. We simultaneously consider the persistence of several outcomes across generations, including resources, health, and behaviors. We label this as multidimensional mobility – simultaneously considering intergenerational mobility across various domains. We first address whether children who are dissimilar to their parents in one outcome are also dissimilar in other outcomes: answering the question of whether individuals with high mobility in one domain have high mobility in other domains. We also pose a spatial version of this question motivated by previous research in several mobility domains, such as income, education, and health mobility, that suggest heterogeneous spatial patterns are present within the U.S. (Chetty et al. 2014; Fletcher and Han 2019; Fletcher and Jajtner 2019; Hertz 2008; Mayer and Lopoo 2008), and theoretical concepts laid out in Becker and Tomes (1979) and Solon (2004) regarding heterogeneous mobility by place. That is, our second exploration is to consider whether places with high mobility in one domain also have high mobility in other domains.

2 Methods

Data comes from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative panel of adolescents in grades 7 – 12 in the 1994 – 1995 academic year. Over 10,000 parent-child pairs are observed geographically clustered in around 130 schools in Wave I of the data. Add health offers a distinct sample-size advantage over other household surveys with a relatively large sample of individuals concentrated in a few birth cohorts and spatial clusters at the school-level. When examining intergenerational health mobility, Akbulut-Yuksel and Kugler (2016) and Classen (2010) rely on a sample of fewer than 5,000 mother-child pairs from the National Longitudinal Survey of Youth (NLSY) – 97. The Panel Study of Income Dynamics (PSID) is also often used in the intergenerational mobility literature. It lacks an explicit tight spatial clustering comparable to Add Health’s school design, has a wide range of birth cohorts, and has smaller samples ranging between 3,300 and 8,100 (e.g., Halliday et al. 2021; Jajtner 2020; Willson and Shuey 2019).

We examine intergenerational mobility for parent-child pairs across ten domains. These domains were selected primarily based on data availability and the previous literature. For inclusion, each domain has existing studies documenting an intergenerational link with available data from each generation in Add Health. The one exception is intergenerational earnings, which was excluded in lieu of intergenerational income since income is comprised of earnings. Many domains have a rich tradition in the literature seeking to understand the relationship between parents and children for researchers and policymakers. For example, understanding the persistence of income, education, or incarceration can lend insights into economic opportunities for children. Documenting the intergenerational relationship of health illustrates how such inequities can perpetuate across generations while knowing how parent and child health behaviors are related may help understand the broader intergenerational health relationship. The domains we examine are grouped into three categories. *Resource* domains comprise intergenerational relationships in income, education, or public assistance (Aaronson and Mazumder 2007; Chetty et al. 2014; Fletcher and Han 2019; Hartley et al. 2017; Hertz et al. 2007; Mazumder 2005; Solon 1992). *Health* domains include overall health, obesity, smoking, binge drinking, and alcoholism (Anda et al. 2002; Classen 2010; Classen and Thompson 2016; Fletcher and Jajtner 2021, 2020; Gilman et al. 2009; Halliday et al. 2021; Jensen et al. 2020; Kandel et al. 2015). Incarceration and religion are grouped as *other* mobility domains (Besemer et al. 2017; Patacchini and Zenou 2016). Survey questions, construction of the measure, and the wave that data were gathered are in Appendix Table A1.

Half of the domains are continuous traits, which are ranked within each generation of Add Health. This not only follows standard practice in the income and health mobility literature (e.g., Chetty et al. 2014; Halliday et al. 2021), but it also helps address lifecycle biases that are likely present in the data structure. For example, parents are typically older than children at observation in our sample. Yet, income, health, and drinking behaviors all change over the lifecourse. Ranking these characteristics among one's generation then helps assuage, but not eliminate, lifecycle biases as parent and children's observed characteristics are relative to their peers. Continuous outcomes are coded such that higher values correspond to higher levels of the resource, health, or other outcomes.

Parent variables are typically measured in the parent instrument or wave I (1994 – 1995). For continuous variables, they are the average measure for two-parent households. For binary variables, parent measures represent whether either parent exhibited the outcome. Single-parent households do not incorporate any averaging. Child variables are observed in wave IV (2008) and wave V (2016-2018) when available (see Appendix Table A1). Some variables lend themselves to time-averaging (e.g., income or health) while others (e.g., education or ever smoking) are stock variables where wave V reports typically dominate. When time-averaging is appropriate, it can reduce measurement error from a single observation (Halliday et al. 2021; Solon 1992). In the case of stock variables, there are reporting errors where individuals indicate in wave IV that they were previously a regular smoker and subsequently, in wave V, indicate they never smoked. In these cases, the wave IV report is used, and the individual is classified as a smoker.

The analysis is split into an individual- and place-based version of our question. For the individual-level analysis, we ask whether children who are more mobile in one outcome are also more mobile in other outcomes. Following Halliday et al. (2018) individual mobility is calculated in each domain as the difference between parent and child outcomes:

$$\Delta y = y_c - y_p \qquad (1)$$

y_c and y_p represent child and parent outcomes, respectively. In the case of binary outcomes, Δy captures the directionality of mobility, while in the case of continuous traits it additionally captures the magnitude. Pairwise individual mobility correlations are then examined across all ten mobility domains to identify whether children who are highly mobile in one domain have similar mobility experiences in other domains.

Geographic clusters of parent-child pairs in approximately 130 Wave I Add Health middle and high schools are used to estimate place-specific mobility. We include schools with at least 20 respondents from the core sample (i.e., the random sample of students within each school participating in the panel survey) to estimate place mobility in each of the ten mobility domains. For each place (i.e., school) in the sample we estimate equation (2) below: regressing parent outcomes on child outcomes controlling only for age in each generation:

$$y_c = \beta_0 + \beta_1 y_p + \sum \beta_j X_j + \varepsilon_c \tag{2}$$

β_1 is the coefficient of interest, and estimates the persistence of outcomes across generations for each place in the sample. y_c and y_p continue to represent child and parent outcomes, respectively, and X_j is a vector of quadratic age controls in each generation. Pairwise correlations of place-specific intergenerational persistence are calculated across all ten domains to determine whether places with high mobility (i.e., low persistence) in one domain tend to have similar mobility across other domains. Previous literature has found associations between specific place characteristics and local mobility (Chetty et al. 2014; Fletcher and Jajtner 2021). Therefore, we additionally regress various Census tract and school characteristics on persistence estimates to explore whether there are characteristics that consistently predict mobility patterns regardless of domain.

3 Results

3.1 Individual Mobility

Table 1 describes the individual sample. On average parents are around 41 – 42 years old while children are between 29 and 38 years old when they are observed in the sample. The large age range for children is due to different domains being observed in different waves. For example, public assistance and alcohol domains are only available in wave IV, when the average child is around 29 years old. Income is typically observed as an average of wave IV and wave V reports, leading to an average age at observation of 34 years. Education is the highest reported attainment, which is typically reported in wave V – when children are on average 38 years old. Reflecting lifecycle variations associated with our sample, parents on average have lower alcohol consumption. The children's generation tends to have higher educational attainment, more obesity, and less smoking relative to parents reflecting temporal trends in these characteristics.

Figure 1 is the individual mobility correlation matrix across domains and highlights heterogeneity in individual mobility across domains. Most correlations are positive, meaning mobility in one domain is linked with mobility in other domains. However, the link is not strong. The visualization in Figure 1 is based on an overall low level of cross-domain correlations, which ranges from −0.06 to 0.28. As a reference point, this sample's observed intragenerational correlation of parent income and parent education is near 0.5. Although correlations are typically positive, the fact that the strongest across-domain correlations are less than 0.3 suggests that, ultimately, there is modest evidence of generalized mobility in the data.

We hypothesized that one source of generalized mobility could be environmental persistence across generations, leading to higher correlations with other mobility domains. In other words, if children maintain a similar environment in adulthood as they had growing up, they might be more likely to mimic their parents' characteristics. The final three rows of the correlation matrix in Figure 1 demonstrate that again there is a modest positive link between most mobility domains and environment mobility. Environment mobility is calculated in the same way as individual mobility. It is the difference in Census tract income, poverty, or unemployment between parents and children – equation 1. The correlations remain low, again pointing to specialized mobility rather than generalized mobility.

Further supporting the concept that individual intergenerational persistence may be more specific, rather than generalized, is Figure 2. It plots the number of domains where children are better off and the number of domains where children are worse off. "Better off" is defined as parent-child pairs where the child is either a) strictly better off or b) has the same characteristic as their parent that is desirable (e.g., not smoking). "Worse off" includes parent-child pairs where the child is either a) strictly worse off or b) has the same characteristic that is undesirable (e.g., smoking). The size of the marker at each combination represents the number of parent-child pairs exhibiting the specific combination of domains where children are better or worse off than their parents. If mobility is generalized, we would expect large clusters of individuals along the x- and y-axis of the figure: representing a large number of children who are either (a) always worse off or (b) always better off than their parents. If generalized mobility holds, we would also expect there to be relatively small markers in the interior of the figure or along the diagonal as these combinations would indicate children are better off than their parents in some domains, while they are worse off in other domains. In contrast, one of the largest cluster combinations in Figure 2 is along the diagonal where children are better off than their parents in only four to seven (out of ten domains) and worse off in the remaining domains. This would be more suggestive of specialized mobility. Therefore, it is likely that children who experience high income mobility, for example, are not necessarily the same ones that experience high overall health mobility.

3.2 Place Mobility

There are approximately 130 geographic clusters (i.e., schools) in our sample that are used to gauge the heterogeneity of intergenerational mobility across the US in multiple domains. Table 2 shows that there are differences in average place-specific mobility across domains (β_1), and that ample variation exists across places within each domain ($\sigma(\beta_1)$ – the standard deviation of persistence estimates in the sample). Our sample finds persistence can range from zero to more than 0.5 within each domain. This mirrors the stark heterogeneity in income mobility across the US documented by Chetty et al. (2014) and suggests that different places tend to observe different mobility patterns across all domains. There are 4 schools that estimate statistically negative persistence – 2 in the "alcohol" domain, 1 in the "overall health" domain, and 1 in the "incarceration" domain. Estimates from the upper limit of the 95% confidence interval are however relatively close to zero and the schools are retained in the sample.

Figure 3 is the analogous correlation matrix for place mobility across domains. As with individual cross-domain mobility correlations, place mobility correlations across domains remain low – never rising above 0.25 in absolute value. Environmental mobility also does not exhibit clear patterns with other mobility domains. Often the correlation is negative (last three rows of the correlation matrix in Figure 3), but still with very small magnitudes (except obesity mobility and environmental mobility in terms of average Census tract poverty). In contrast to individual cross-domain mobility, place cross-domain mobility (Figure 2) also exhibits more negative correlations. Public assistance is negatively correlated with overall health mobility – exhibiting the strongest negative correlation in the matrix (excluding correlations with environment mobility.) – and overall health is also negatively correlated with obesity mobility. Most notably, a place's income mobility is negatively correlated with several health behavior mobilities (Obesity, Alcohol, Binge Drinking). This would suggest that places where kids have more economic opportunity (i.e., income mobility) are places where some health behaviors could be more persistent. Recall that persistence measures are silent on the direction of mobility. Thus, perhaps places with high economic opportunity are places where parents consistently pass on good health behaviors to their children (i.e., low income persistence and high persistence in health behaviors). Although, heterogeneity in estimation biases could also contribute to that observation (discussed in the next section). Overall, these findings suggest that places that are characterized by high income mobility are often not the same ones with high health mobility, or that mobility is more specialized than generalized geographically.

Finally, we find little evidence of place characteristics consistently predicting mobility across domains (Appendix Table A2), again supporting more specialized mobility. We select place characteristics based on availability in Add Health and use in previous literature. For example, Chetty et al. (2014) investigate local correlates of income mobility including local racial composition, portion of single parents, household income, and the Gini coefficient (a measure of the dispersion of household income). Fletcher and Jajtner (2021) also investigate the correlates of health mobility including region, urbanicity, hospital beds, whether there is a school PTA, the presence of a health education requirement, and the portion of smokers. To this list we add health expenditures as an alternative to hospital beds per capita, and the portion of movers. The latter is important since simply moving away from a childhood environment may yield generalized mobility. Results suggest that while income is more persistent in the South, mobility is statistically similar across regions for most domains. Rural areas tend to have lower alcohol persistence relative to urban areas, but this pattern is also not consistent across other domains. Income and education are perhaps more persistent in areas with higher socioeconomic status (as measured by median income), but lower in areas with high income inequality (i.e., the standard deviation of income) or areas with more single parents. Schools with a higher portion of non-Hispanic Black or Hispanic students tend to have lower education, and religion persistence while schools where a higher portion of students' parents are married tend to have more education, smoking, alcohol, and religion persistence. While these magnitudes are of modest consequence (e.g., a 10%-point increase in the portion of married parents can increase education persistence by 0.03 relative to average education mobility of 0.36), the portion of married parents is correlated with only four of the ten domains and even a regression with all covariates included can explain relatively little of the total persistence variation in any domain.

4 Discussion

The correlation of intergenerational mobility across several domains is generally positive, but small in magnitude. This would suggest that while there may be some elements of generalized intergenerational mobility, mobility is more specialized than it is generalized. This conclusion appears to apply to both individuals and places. Our results suggest that researchers should proceed with caution if they seek to understand overall intergenerational mobility patterns from one or two domains, as the patterns they uncover may not be applicable to other domains. For policymakers, our results suggest that expectations of positive externalities, although they exist (e.g., O'Brien and Robertson 2018), need to be tempered with the knowledge that intergenerational mobility is mostly specialized.

There are, however, several data limitations to bear in mind. About half of the domains use continuous outcomes while the other half rely on binary outcomes. To investigate the sensitivity of our results to this feature, we collapse all continuous variables into binary measures. Income is replaced with an indicator for poverty (Federal Poverty Threshold). Education is split into individuals with a high school degree (or GED) or less versus those who have attended at least some college. Self-reported health is collapsed to a binary indicating either very good or excellent health versus poor, fair, or good health. Binge drinking is reduced to an indicator for any binge drinking versus none, and religious attendance is replaced with a binary for attending services more than once per month versus less. The direction of correlations across domains is preserved by ones corresponding to higher ranks of the continuous outcome formulation while zeros correspond to lower ranks. Figures A1 and A2 in the appendix demonstrate that this exercise reveals little change in the main results for individual or school mobility, respectively. We conclude that this data limitation is not likely to alter conclusions. Additionally, there are many intergenerational mobility metrics available. We have focused on just one for individuals and one for places. Since various mobility metrics are not always consistent (Deutscher and Mazumder 2021), future research should investigate whether other mobility measures concur with our conclusions.

There are also several estimation biases that could affect our estimates. Tables 2 and 3 demonstrate that mobility estimates may be attenuated based on previous literature (e.g., Chetty et al. 2014; Classen 2010; Fletcher and Jajtner 2019; Halliday et al. 2021; Mazumder 2005). This may stem from observing each generation's outcome only once or twice (Halliday et al. 2021; Solon 1992) or lifecycle bias (Haider and Solon 2006). However, when we examine results using child data observed only in Wave IV or V alone to assess these biases to the degree possible, we find similar individual results. School mobility correlations however exhibit some sensitivity. For example, the correlation between overall health and smoking persistence using wave IV data only is −0.11, while using wave V data only the correlation is 0.3. The correlation of incarceration and religion persistence flips from negative 0.07 in Wave IV to positive 0.07 in Wave V. While both attrition and lifecycle biases could produce these patterns, correlation magnitudes remain small. With future waves of Add Health data, portions of these data limitations could be addressed.

Another key limitation is that estimation biases (attenuation, attrition, and lifecycle) may not be equally present across all domains. Importantly, this would likely support specialized mobility over generalized mobility. Tables 2 and 3 highlight that estimates of education mobility, where lifecycle and attenuation bias may be minimal, seems to be closer to the previous literature (Feigenbaum 2018; Fletcher and Han 2019; Hertz et al. 2007; Sacerdote 2007) relative to other domains. However, specialized mobility is consistent with the hypothesis that genes and environments could have different effects on different characteristics. Some literature suggests relatively little cross-domain mobility (A. C. Case and Katz 1991; Halliday et al. 2018); although, there could be more consistency in earnings, education, and occupation mobility (Feigenbaum 2018).

Overall, while continued research is warranted, the low cross-domain correlations we find in our data, point toward more specialized mobility than generalized mobility. That is to say that people and places with high mobility in one domain are not necessarily highly mobile in other domains. Income and education mobility are the most highly correlated mobility domains, although the cross-domain correlation never rises above 0.3. While individual cross-domain mobility correlations in income and health behaviors are generally slightly positive, the same correlations can be negative for places. This could be because individual mobility statistics can account for the direction of mobility whereas place mobility statistics do not. Intergenerational transmission of genetic material or environment stationarity across generations likely counteracts our observed specialized mobility. Despite these influences, our results lend more support to the notion that genetic influences can differ or that the effect of certain environments is of different magnitudes across domains. Alternatively, or in addition, parents or policymakers could prioritize (im)mobility in one domain over another, leading to more specialized mobility. Our data is not able to disentangle these different mechanisms, but perhaps future data collection could.

We conclude that processes of intergenerational mobility appear specialized—domain-specific—rather than generalized, and thus contexts and policies that interrupt persistence in one area may not in other areas. As intergenerational mobility research continues to investigate impacts of policies and environments on income mobility (e.g., Mayer and Lopoo 2008; O’Brien et al. 2018; O’Brien and Robertson 2018), expanding to investigate their relationship with other mobility domains should be encouraged. Finally, pending further research, our results should offer caution to policymakers hoping for strong positive externalities to health or education mobility based solely on income mobility literature. (Harris et al. n.d.)

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Appendix

Table A1:

Survey questions across domains

Domain	Trait Construction	Parent Question	Child Question (wave IV)	Child Question (wave V)
Resources				
Income	Real $ amount ranked within generations	About how much total income, before taxes did your family receive in 1994? Include your own income, the income of everyone else in your household, and income from welfare benefits, dividends, and all other sources. [PA55]	Thinking about your income and the income of everyone who lives in your household and contributes to the household budget, what was the total household income before taxes and deductions in {2006/2007/2008}? Include all sources of income, including non-legal sources. [H4EC1]	What was the total household income before taxes and deductions in the last calendar year for all household members who contribute to household expenses? [h5ec2]
Education	Years of education ranked within generations	How far did you [your current spouse/ partner] go in school? [PA12 & PB8]	What is the highest level of education that you have achieved to date? [H4ED2]	What is the highest level of education that you have achieved to date? [h5od11]
Public Assistance	Binary Any Assistance = 0	Are you receiving public assistance, such as welfare? [PA21]	Between {1995/2002} and {2006/2007/2008}, did you or others in your household receive any public assistance, welfare payments, or food stamps? [H4EC18]	N/A
Health				
Overall Health	HALex adjusted health ranked within generations	How is your general physical health? [PA58] How is your current (spouse/partner)s general health? [PB21]	In general, how is your health? [H4GH1]	In general, how is your health? [h5id1]
Obesity	Binary BMI > 30 = 0 "Obesity" = 0	Does {NAME}'s biological father/ mother currently have the following health problem (check all that apply): Obesity [PC49A_2 & PC49A_3]	Body Mass Index [H4BMI]	How tall are you in feet and inches? What is your current weight in pounds? [h5id3, h5id2f, h5id2i]
Smoking	Binary Ever Smoked = 0	Has he [resident mother/father] ever smoked cigarettes? [H1RM14 & H1RF14]	Have you ever smoked cigarettes regularly--that is, at least one cigarette every day for 30 days? [H4TO3] Daily smoker at Wave IV (constructed variable) [C4VAR035]	Have you ever smoked cigarettes regularly--that is, at least one cigarette every day for 30 days? [h5to1]
Binge Drinking	Days / month ranked within generations	How often in the last month have you had five or more drinks on one occasion? [PA62]	During the past 12 months, on how many days did you drink {5 or more/4 or more} drinks in a row? [H4TO37]	During the past 12 months, on how many days did you drink [female: 4/ male: 5] or more

Domain	Trait Construction	Parent Question	Child Question (wave IV)	Child Question (wave V)
				drinks in a row? [h5to15]
Alcoholism	Binary "Alcoholism" or Abuse/ dependence = 0	Does {NAME]'s biological mother/ father currently have the following health problem (check all that apply): Alcoholism [PC49E_2 & PC49E_3]	Lifetime diagnosis of alcohol abuse or dependence (constructed variable) [C4VAR023]	N/A
Other				
Incarceration		(Has/did) your biological mother/ father ever (spent/ spend) time in jail or prison? [H4WP3 & H4WP9]	Have you ever spent time in a jail, prison, juvenile detention center or other correctional facility? [H4CJ17]	Have you ever served time in a jail, prison, juvenile detention center, or other correctional facility? [h5cj5]
Religiosity		How often have you gone to religious services in the past year? [PA23]	How often have you attended church, synagogue, temple, mosque, or religious services in the past 12 months? [H4RE7]	How often have you attended church, synagogue, temple, mosque, or religious services in the past 12 months? [h5re2]

Notes: Trait construction indicates whether the domain is continuous (i.e., ranked within generations) or binary. Raw variable names from Add Health's online codebook are in square brackets and identify the wave from which data is gathered. All raw variables beginning with "P" are from the parent interview in wave I, while all variables beginning with "1", "H4", or "h5" are from waves I, IV, or V, respectively. The Public Assistance and Alcohol domains do not have comparable questions in Wave V. Smoking data in wave V does not have a comparable constructed variable for "Daily Smoker".

Table A2:

Place characteristics associated with intergenerational mobility

	Resources			Health					Other	
	Income	Education	Public Assistance	Overall Health	Obesity	Smoking	Alcohol	Binge Drinking	Incarceration	Religion
Location Characteristics										
West (ref. South)	−0.168*** (0.041)	−0.059 (0.039)	−0.085 (0.075)	−0.036 (0.036)	0.041 (0.037)	0.012 (0.033)	0.052 (0.044)	0.048 (0.060)	−0.067 (0.043)	0.147*** (0.039)
Midwest (ref. South)	−0.121** (0.039)	−0.018 (0.039)	0.050 (0.072)	−0.030 (0.035)	−0.032 (0.036)	−0.029 (0.033)	0.050 (0.043)	0.094 (0.058)	−0.002 (0.041)	0.044 (0.038)
Northeast (ref. South)	−0.068 (0.045)	−0.016 (0.045)	−0.146+ (0.083)	0.003 (0.041)	−0.024 (0.042)	−0.047 (0.038)	0.063 (0.049)	0.021 (0.067)	−0.063 (0.048)	−0.011 (0.044)
Rural (ref. Urban)	−0.067 (0.048)	0.002 (0.047)	0.095 (0.090)	−0.005 (0.044)	0.051 (0.044)	−0.048 (0.040)	−0.152** (0.053)	0.003 (0.072)	−0.039 (0.051)	−0.063 (0.047)
Suburban (ref. Urban)	−0.051 (0.034)	−0.005 (0.033)	0.052 (0.063)	−0.007 (0.031)	0.017 (0.031)	−0.037 (0.028)	−0.043 (0.037)	0.004 (0.050)	−0.081* (0.036)	−0.017 (0.033)
Census Tract Characteristics										
Tract Median Income (1990)	0.001 (0.002)	−0.001 (0.002)	0.002 (0.003)	−0.001 (0.001)	0.000 (0.002)	−0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.003+ (0.002)	0.002 (0.002)
Tract σ(Income) (1990)	−0.002 (0.005)	0.008 (0.005)	−0.000 (0.010)	0.004 (0.005)	−0.001 (0.005)	0.004 (0.004)	−0.002 (0.006)	−0.005 (0.008)	−0.011* (0.005)	−0.005 (0.005)

	Resources			Health					Other	
	Income	Education	Public Assistance	Overall Health	Obesity	Smoking	Alcohol	Binge Drinking	Incarceration	Religion
Tract % Single Parent (1990)	−0.005^{+} (0.003)	−0.006* (0.003)	−0.002 (0.005)	0.000 (0.003)	−0.000 (0.003)	−0.003 (0.002)	−0.005 (0.003)	0.002 (0.004)	−0.001 (0.003)	−0.006* (0.003)
State % teen smoking	0.004 (0.008)	−0.002 (0.008)	−0.027^{+} (0.014)	−0.000 (0.007)	0.017* (0.007)	0.010 (0.006)	−0.008 (0.008)	−0.005 (0.012)	−0.000 (0.008)	0.008 (0.008)
County Hospital Beds (100s / 100,000)	−0.012^{+} (0.006)	0.003 (0.006)	−0.013 (0.011)	−0.002 (0.006)	−0.005 (0.006)	0.001 (0.005)	0.011^{+} (0.007)	−0.004 (0.009)	0.001 (0.006)	−0.004 (0.006)
Health Expenditures (per 100)	−0.006 (0.009)	−0.013 (0.009)	−0.008 (0.018)	−0.002 (0.009)	−0.001 (0.009)	0.002 (0.008)	−0.005 (0.010)	0.007 (0.014)	0.002 (0.010)	−0.008 (0.009)
School Characteristics										
%nH Black	−0.000 (0.001)	−0.001* (0.001)	0.000 (0.001)	0.000 (0.001)	−0.000 (0.001)	−0.001 (0.000)	−0.001 (0.001)	0.001 (0.001)	−0.001 (0.001)	−0.002*** (0.001)
% Hispanic	0.001 (0.001)	−0.003** (0.001)	0.002 (0.002)	0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.002^{+} (0.002)	−0.001 (0.001)	−0.000 (0.001)
% Married	0.001 (0.001)	0.003* (0.001)	−0.001 (0.002)	0.000 (0.001)	−0.001 (0.001)	0.002^{+} (0.001)	0.003* (0.001)	0.000 (0.002)	−0.000 (0.001)	0.003* (0.001)
School PTA	−0.022 (0.054)	−0.076 (0.054)	0.051 (0.100)	−0.047 (0.049)	0.047 (0.051)	−0.011 (0.045)	−0.024 (0.060)	0.045 (0.082)	0.051 (0.058)	−0.029 (0.054)
Health Education										
Requirement	−0.058 (0.053)	0.039 (0.053)	0.108 (0.099)	0.041 (0.048)	−0.075 (0.049)	0.041 (0.044)	0.063 (0.059)	−0.097 (0.079)	0.047 (0.057)	−0.114* (0.051)
% Movers	−0.057 (0.111)	0.235* (0.106)	0.049 (0.205)	0.075 (0.097)	−0.079 (0.101)	0.005 (0.093)	0.164 (0.120)	0.008 (0.164)	0.004 (0.119)	0.131 (0.105)
N (min -- max)	122 -- 125	127 -- 130	124 -- 127	126 -- 129	127 -- 130	127 -- 130	124 -- 127	125 -- 128	126 -- 129	127 -- 130
R^2 (all covariates included)	0.258	0.143	0.173	0.081	0.155	0.100	0.149	0.128	0.156	0.280

Source: Authors' calculations using Add Health

Notes: All regressions control for location characteristics. Coefficients in rows under "Location Characteristics" come from a single regression for each column. Coefficients under Census Tract Characteristics and School Characteristics are all from independent regressions controlling for location characteristics. That is to say that each cell represents a separate regression. The only exception is Median Income and σ(Income), which are from a single regression. Standard errors are in parentheses. The final row with a reported R^2 is from a regression including all covariates simultaneously.

***p<0.001

**p<0.01

*p<0.05

$^{+}$p<0.1.

	Income†	Education†	Public Assistance	Overall Health†	Obesity	Smoking	Alcoholism	Binge Drinking†	Incarceration	Religion†
Resources										
Income (Non-poverty = 1)		0.258***	0.221***	0.150***	-0.009	0.064***	0.052***	0.022*	0.071***	0.041***
Education (Some College + = 1)	0.141***		0.098***	0.115***	-0.028**	0.163***	0.011	0.062***	0.098***	0.079***
Public Assistance	0.249***	0.044***		0.075***	0.019*	0.048***	-0.011	-0.034***	0.031***	-0.022*
Health										
Overall Health (V. Good + = 1)	0.073***	0.048***	0.059***		0.166***	0.107***	0.066***	0.034***	0.037***	0.049***
Obesity	-0.021*	-0.064***	0.019*	0.150***		-0.046***	-0.008	-0.061***	-0.032***	-0.016+
Smoking	0.058***	0.081***	0.048***	0.090***	-0.046***		0.096***	0.137***	0.111***	0.092***
Alcoholism	0.054***	0.018*	-0.011	0.053***	-0.008	0.096***		0.281***	0.167***	0.072***
Binge Drinking (None = 1)	0.031***	0.042***	-0.036***	0.016+	-0.065***	0.108***	0.226***		0.118***	0.172***
Other										
Incarceration	0.055***	0.081***	0.031***	0.029**	-0.032***	0.111***	0.167***	0.088***		0.071***
Religion (> 1/month = 1)	0.013	0.025**	-0.023**	0.028**	-0.008	0.075***	0.065***	0.145***	0.058***	

Figure A1: Replacing continuous outcomes with binary indicators (Individual-level results)
Source: Authors' calculations using Add Health.
Notes: Correlations are pairwise. Continuous traits are marked with a dagger (†). Lower triangle collapses continuous measures to binary formulations. Upper triangle repeats main results from Figure 1.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. $p = 2 \times ttail(df, t)$;
$ttail = reverse\ cumulative\ t\ distribution$ with; $df = n - 2$, $t = \mid \hat{\rho} \mid \frac{\sqrt{n-2}}{1-\hat{\rho}^2}$, and
$\hat{\rho} = estimated\ correlation.$

	Income†	Education†	Public Assistance	Overall Health†	Obesity	Smoking	Alcoholism	Binge Drinking†	Incarceration	Religion†
Resources										
Income (Non-poverty = 1)		0.221*	0.080	0.099	-0.045	0.044	-0.073	-0.110	0.008	-0.076
Education (Some College + = 1)	0.092		0.144	0.086	0.185*	0.061	-0.031	0.053	0.042	0.142
Public Assistance	0.111	0.059		-0.212*	0.142	0.077	-0.130	-0.001	0.094	-0.063
Health										
Overall Health (V. Good + = 1)	0.212*	0.023	-0.098		-0.103	0.020	0.162+	-0.129	0.064	0.045
Obesity	0.050	0.136	0.142	-0.072		0.018	-0.118	0.057	0.135	0.172+
Smoking	-0.069	0.121	0.077	0.033	0.018		0.019	-0.022	0.098	0.106
Alcoholism	0.062	-0.070	-0.130	0.026	-0.118	0.019		-0.057	-0.041	0.106
Binge Drinking (None = 1)	-0.091	-0.006	0.034	-0.140	0.020	-0.039	-0.038		-0.069	0.150+
Other										
Incarceration	0.023	0.120	0.094	0.068	0.135	0.098	-0.041	-0.063		0.020
Religion (> 1/month = 1)	0.132	0.046	-0.091	0.061	0.143	-0.078	-0.042	0.144	-0.041	

Figure A2: Replacing continuous outcomes with binary indicators (School-level results)
Source: Authors' calculations using Add Health.
Notes: Correlations are pairwise. Continuous traits are marked with a dagger (†). Lower triangle collapses continuous measures to binary formulations. Upper triangle repeats main results from Figure 1.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. $p = 2 \times ttail(df, t)$;
$ttail = reverse\ cumulative\ t\ distribution$ with; $df = n - 2$, $t = \mid \hat{\rho} \mid \frac{\sqrt{n-2}}{1-\hat{\rho}^2}$, and
$\hat{\rho} = estimated\ correlation.$

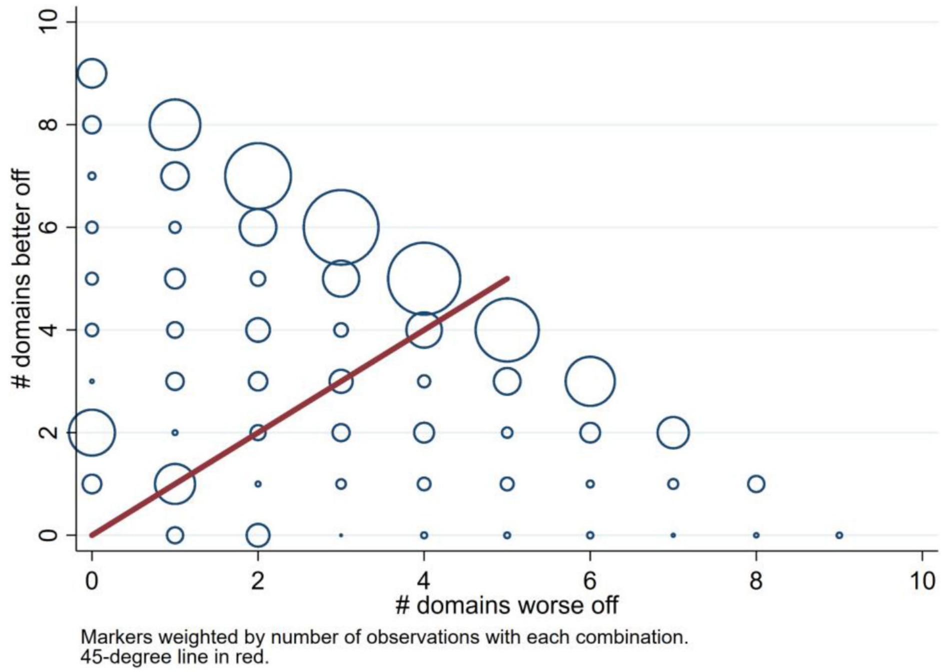

Figure 3A: Number of domains where children are better and worse off than their parents – religion domain excluded

Source: Authors' calculations using Add Health

Notes: Notes from Figure 2 apply. Religion domain is excluded because it does not exhibit a natural ordering of "better" versus "worse", inclusion of this domain or swapping the ordering of better/worse does not materially change results (see Figure 2). The forty-five degree line (in red) highlights combinations where children are better off in half of the domains and worse off in the other half of observed domains. Not all parent-child pairs observe all domains.

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- Theoretically, intergenerational mobility could be generalized or specific
- Empirically, we find more evidence of specific mobility
- People and places with high income mobility may not have high health mobility

Correlation: -0.2 0 0.3

	Income†	Education†	Public Assistance	Overall Health†	Obesity	Smoking	Alcoholism	Binge Drinking†	Incarceration	Religion†
Resources										
Income†										
Education†	0.258***									
Public Assistance	0.221***	0.098***								
Health										
Overall Health†	0.150***	0.115***	0.075***							
Obesity	-0.009	-0.028**	0.019*	0.166***						
Smoking	0.064***	0.163***	0.048***	0.107***	-0.046***					
Alcoholism	0.052***	0.011	-0.011	0.066***	-0.008	0.096***				
Binge Drinking†	0.022*	0.062***	-0.034***	0.034***	-0.061***	0.137***	0.281***			
Other										
Incarceration	0.071***	0.098***	0.031***	0.037***	-0.032***	0.111***	0.167***	0.118***		
Religion†	0.041***	0.079***	-0.022*	0.049***	-0.016+	0.092***	0.072***	0.172***	0.071***	
Environment										
Tract Median Income†	0.231***	0.115***	0.076***	0.076***	-0.004	0.048***	0.005	0.027**	0.032**	0.019+
Tract Poverty†	0.198***	0.106***	0.068***	0.068***	-0.027*	0.046***	0.025*	0.041***	0.034**	0.025*
Tract Unemployment†	0.124***	0.104***	0.042***	0.070***	-0.037***	0.029**	0.019+	0.047***	0.007	-0.004

Figure 1: Cross-domain matrix of Individual mobility

Source: Authors' calculations using Add Health.

Notes: Correlations are pairwise – using all available observations from the pair of domains. Sample sizes range from 10,381 (Alcoholism & Income) to 15,111 (Smoking & Education). Continuous traits are marked with a dagger (†). All Census Tract data is from wave I (parents) and wave V (children). *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

$p = 2 \times ttail(df, t); ttail = reverse\ cumulative\ t\ distribution$ with; $df = n - 2$, $t = |\hat{\rho}| \frac{\sqrt{n-2}}{1-\hat{\rho}^2}$, and

$\hat{\rho} = estimated\ correlation.$

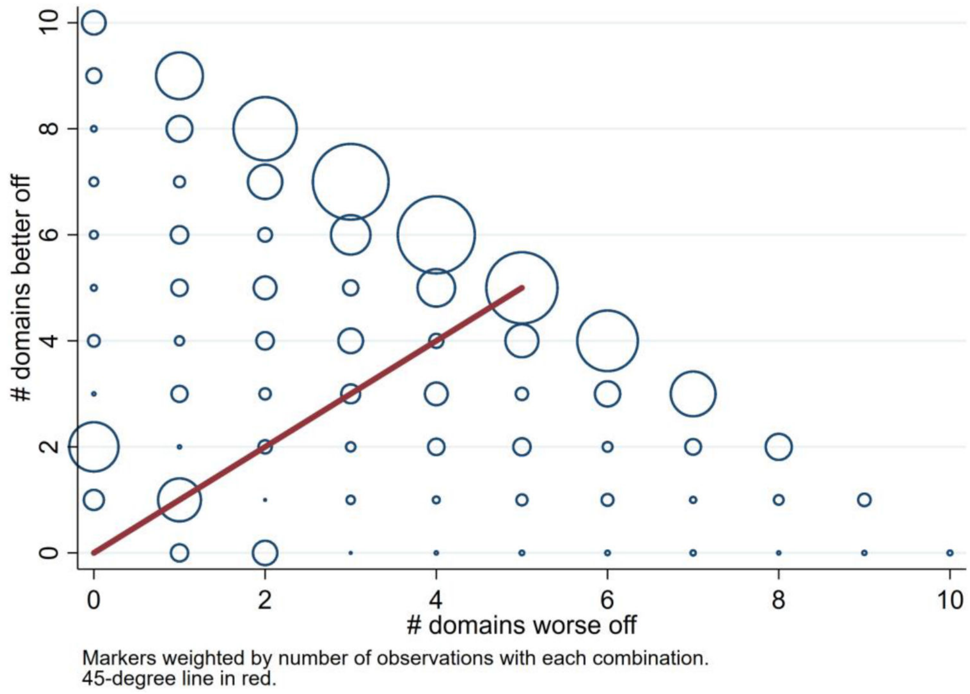

Figure 2: Number of domains where children are better and worse off than their parents

Source: Authors' calculations using Add Health

Notes: "Better off" is defined as parent-child pairs where the child is either a) strictly better off or b) has the same characteristic that is desirable (e.g., not smoking). "Worse off" includes parent-child pairs where the child is either a) strictly worse off or b) has the same characteristic that is undesirable (e.g., smoking). Marker size indicates the number of parent-child pairs exhibiting the specific numerical combination of better- and worse-off domains. Although religion does not exhibit a natural ordering of "better" versus "worse", inclusion of this domain or swapping the ordering of better/worse does not materially change results (see Appendix Figure A3). The forty-five degree line (in red) highlights combinations where children are better off in half of the domains and worse off in the other

	Income†	Education†	Public Assistance	Overall Health†	Obesity	Smoking	Alcoholism	Binge Drinking†	Incarceration	Religion†
Resources										
Income†										
Education†	0.221*									
Public Assistance	0.080	0.144								
Health										
Overall Health†	0.099	0.086	-0.212*							
Obesity	-0.045	0.185*	0.142	-0.103						
Smoking	0.044	0.061	0.077	0.020	0.018					
Alcoholism	-0.073	-0.031	-0.130	0.162+	-0.118	0.019				
Binge Drinking†	-0.110	0.053	-0.001	-0.129	0.057	-0.022	-0.057			
Other										
Incarceration	0.008	0.042	0.094	0.064	0.135	0.098	-0.041	-0.069		
Religion†	-0.076	0.142	-0.063	0.045	0.172+	0.106	0.106	0.150+	0.020	
Environment										
Tract Median Income†	-0.055	-0.085	0.030	-0.084	-0.074	-0.075	-0.074	-0.007	0.117	-0.067
Tract Poverty†	0.088	0.044	0.082	0.013	-0.304***	-0.069	0.092	-0.091	0.027	0.090
Tract Unemployment†	0.049	-0.030	0.119	-0.002	-0.077	-0.091	0.079	-0.136	0.087	-0.053

Correlation: -0.2 0 0.3

Figure 3: Cross-domain matrix of Place Mobility

Source: Authors' calculations using Add Health core sample.

Notes: Correlations are pairwise. Continuous traits are marked with a dagger (†). All Census Tract data is from wave I (parents) and wave V (children). *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. $p = 2 \times ttail(df, t)$; $ttail = reverse\ cumulative\ t\ distribution$ with; $df = n - 2$, $t = |\hat{\rho}| \frac{\sqrt{n-2}}{1-\hat{\rho}^2}$, and $\hat{\rho} = estimated\ correlation$.

Table 1:

Descriptive Statistics for Individual Mobility Sample

Domain	N	Child	Parent	Child Age	Parent Age	β_1	Δy
Resources							
Income	11,250	$90,232 (1,731)	$81,391 (2,987)	34.003 (0.125)	41.670 (0.178)	0.361 (0.017)	1.639 (0.786)
Education	13,398	14.773 (0.093)	13.825 (0.099)	37.739 (0.120)	41.873 (0.178)	0.461 (0.020)	0.339 (0.680)
Public Assistance	12,034	20.767 (0.988)	8.080 (0.850)	28.923 (0.110)	42.171 (0.174)	0.276 (0.027)	−0.127 (0.009)
Health							
Overall Health	12,857	82.159 (0.314)	81.050 (0.446)	33.882 (0.126)	41.867 (0.177)	0.188 (0.014)	−1.691 (0.618)
Obesity	13,169	38.624 (0.980)	23.347 (0.632)	33.938 (0.126)	41.796 (0.173)	0.211 (0.014)	−0.153 (0.010)
Smoking	15,367	48.347 (1.153)	66.540 (0.850)	37.804 (0.119)	41.869 (0.180)	0.172 (0.014)	0.182 (0.009)
Alcohol	11,923	26.566 (1.163)	15.231 (0.672)	28.918 (0.111)	42.109 (0.178)	0.050 (0.018)	−0.113 (0.012)
Binge Drinking	13,148	0.947 (0.029)	0.268 (0.017)	33.836 (0.129)	41.837 (0.188)	0.119 (0.020)	−3.506 (0.710)
Other							
Incarceration	13,921	14.916 (0.777)	14.996 (0.809)	37.718 (0.120)	41.838 (0.172)	0.174 (0.022)	0.001 (0.007)
Religion	13,390	13.215 (0.418)	24.451 (0.614)	33.885 (0.125)	41.808 (0.176)	0.341 (0.015)	−0.446 (0.587)

Source: Authors' calculations using Add Health Waves I, IV, & V.

Notes: Standard errors in parentheses. Parents are on average 41-42 years old. β_1 is the full sample persistence estimate from equation (2) and Δy is the average individual mobility from equation (1). While average values of income, education, health, binge drinking days, and religious attendance are reported in "Child" and "Parent" columns, average mobility reported in the final two columns is based on ranked characteristics within each generation.

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Table 2:

Descriptive Statistics for Place Mobility Sample

	N	Students per school	Mean Students per school	β_1	$\sigma(\beta_1)$
Resources					
Income	125	22 -- 140	57.4	0.256	0.178
Education	130	20 -- 150	66.3	0.359	0.166
Public Assistance	110	21 -- 142	61.5	0.169	0.314
Health					
Overall Health	129	20 -- 144	64.2	0.139	0.151
Obesity	130	20 -- 148	65.9	0.206	0.157
Smoking	130	21 -- 167	74.4	0.129	0.141
Alcohol	126	22 -- 142	61.7	0.052	0.189
Binge Drinking	126	21 -- 150	65.7	0.093	0.248
Other					
Incarceration	129	20 -- 150	68.0	0.130	0.181
Religion	130	20 -- 149	66.0	0.275	0.174

Source: Authors' calculations using Add Health core sample.

Notes: Persistence estimates (β_1) represent the average over all Wave I Add Health schools. $\sigma(\beta_1)$ is the standard deviation of the persistence estimate and captures the variation of persistence across place.