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Geographic Effects on Intergenerational Income Mobility

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Abstract

The notion that where one grows up affects future living standards is increasingly well established in social science. Yet research on intergenerational economic mobility often ignores the regional and neighborhood context of childhood, especially local purchasing power. We hypothesize that unexplained variation in intergenerational mobility is partly attributable to regional and neighborhood conditions—most notably access to high quality schools. Using the Panel Study of Income Dynamics and other data, we find that neighborhood income has roughly half the effect on future earnings as parental income and roughly the same effect as shared sibling characteristics. Growing up in an economically segregated metropolitan area also has a large negative effect on future earnings, though somewhat smaller than the neighborhood effect. We estimate that lifetime household income would be $500,000 dollars higher if people born into a bottom quartile neighborhood would have been raised in a top quartile neighborhood. These results are robust to considerations of regional purchasing power and migration between metro areas. Finally, we replicate the results for economic segregation at the metropolitan level using aggregated metropolitan level statistics of intergenerational income elasticities based on millions of IRS records.

INTRODUCTION

A large literature has focused on how to measure intergenerational income mobility properly, how to compare it across countries, and how to document changes over time. Recently, studies have also begun to explore the causes of intergenerational mobility and generally have concluded that there is much left to explain after individual and family characteristics are controlled (see Black and Devereux 2010 for a review). Surprisingly few prior studies have considered neighborhood and other geographic influences on mobility, including the fact that living costs differ substantially across areas.

Of those studies reviewed by Black and Devereux, that of Raaum, Salvanes, and Sorenson (2006) found significant but small and declining neighborhood effects on intergenerational income and educational mobility in Norway, which they attribute to its egalitarian schooling policies. Solon, Page, and Duncan (2000) find significant but small correlations between neighborhood characteristics and future earnings in the United States (though larger than in Norway) and Page and Solon (2003) attribute the correlation to the propensity of people growing up in the same neighborhood to share urban as opposed to rural adult earnings environments. They reach these conclusions by using the Panel Study of Income Dynamics (PSID) to compare correlations of boys who grew up in the same neighborhood with those who did not.

Page and Solon (2003) confronted a number of methodological challenges: they defined neighborhood as living in a shared cluster sample in the PSID (which they argue is similar to a neighborhood) rather than a common census tract; they measured neighborhoods only once (in 1968 for people born between 1952 and 1962; they assessed earnings using just five years of data (from 1987 to 1991); and they had a sample size of just 443 individuals from 287 families across 120 clusters. As a result, the average neighborhood had only two families to compare. In our analysis we also use the PSID to study neighborhoods effects; but we develop an alternative methodological approach that allows us to identify neighborhood effects more accurately. Instead of using a dummy variable to indicate a shared neighborhood, we control for average income in the subject's census tract as obtained from the U.S. decennial census.

This approach allows us to consider the degree to which individuals living in different neighborhoods with similar incomes are alike, while also enabling us to measure the neighborhood environment across the first 16 years of life (yielding 6.4 observations on average, instead of using just one). Also, because we are conducting our analysis many years after Page and Solon, we have a larger sample size to work with: 1,793 individuals matched to parents, 1,288 matches with neighborhood income data, 899 sibling matches with neighborhood data (instead of 443) and more years to observe future adult earnings (15 instead of 5). We also incorporate metropolitan area variables to control for the regional context and housing prices, which has been missing from prior studies of intergenerational mobility.

HOW GEOGRAPHIC CONTEXT AFFECTS EARNINGS

The most obvious channel through which neighborhoods affect future earnings is through school quality. There is a large and rich literature analyzing the consequences of randomly assigning children to schools (through lotteries) of varying quality. While not quite unanimous across different cities and populations (Berry Cullen, Jacob, and Levitt, 2006), the overwhelming majority of these studies show a very large causal effect on academic performance from attending higher quality schools (Chetty et al. 2011; Chetty, Friedman, and Rockoff 2011; Dobbie and Fryer 2011; Hoxby and Rockoff 2005; Peterson and Howell 2006; Peterson et al 2003; Rockoff 2004; Heckman et al 2010; Hastings and Weinstein 2008; Schwartz 2010; Massey et al. 2013). Some of these studies also examine long-term effects on educational outcomes. For example, Chingos and Peterson (2012) find that the offer of a voucher to black elementary school children in New York City increased future college enrollment by over 7 percentage points (or 24%) relative to a control group. Chetty et al (2011) find significant effects on earnings at age 27 from experiment-caused enrollment in higher quality kindergarten.

While the weight of evidence supports the notion that poor children would do better socioeconomically if they attended better schools, there is also a strong and well-documented relationship between residential segregation and access to such schools (Rivkin 1994; Logan, 2011; Rothwell, 2012; Hastings and Weinstein 2008). Putting these two literatures together, it follows that the integration of income groups across neighborhoods will have large positive effects on the future wellbeing of poor children because of improved school quality.

This conclusion, which rests considerably on randomized control trials, holds even if school quality is the only meaningful neighborhood-level determinant of future wellbeing. Indeed, two studies used the random assignment of refugees to neighborhoods to estimate later educational performance, both finding that exogenous assignment to higher quality neighborhoods (measured in terms of better schools or better educated neighbors) significantly raised school performance and educational attainment; and the positive effect was particularly large for those who spent the earliest years of life in high quality areas (Aslund et al. 2011; Gould et al 2004).

Of course, many other determinants of future socioeconomic status vary widely across neighborhoods beside school quality, including exposure to crime and violence (Billings et al 2012), employment and internship opportunities (Stoll 2005; Kain 1992), access to financing for housing or business formation (Rugh and Massey 2010), role model and peer effects on occupational choice, reproduction, healthy dietary and exercise habits (Diez Roux 2001), religious adherence (Gruber 2005), and investment in learning (Aslund et al 2011). It is likely, of course, that these traits are correlated with one another and with school quality such that overall neighborhood quality has an even larger effect than variation in school quality alone (Sampson 2013).

One explanation for why neighborhood quality varies so much is that the demand to live in better neighborhoods pushes housing costs higher in high quality zones. There is clearly a strong correlation between school quality and housing costs across attendance zones (Black, 1999; Rothwell 2012). Chetty and Friedman (2011) find that each additional $1,000 in parental income increases school quality by almost one standard deviation. At the same time, however, housing prices are distorted by local government regulations (Freund 2007; Fischel 1985; Fischel 1990; Glaeser and Gyourko 2003; Glaeser, Gyourko, and Saks 2005; Glaeser and Ward 2009; Rothwell 2011; Massey, Rothwell, and Domina 2009; Pendall, Puentes, and Martin 2006). Rothwell (2012) finds that actual and relative differences in housing costs near high and low quality schools are much lower—between 40 and 60 percent lower—in metropolitan housing markets with few restrictions on high density housing compared to the most regulated. It may well be the case that the market-based barriers to living near a high quality school are fairly small and greatly enlarged through the local politics and historic legacy of zoning.

The foregoing research provides compelling evidence that neighborhoods have important causal effects on life chances. However, another literature assessing housing mobility programs targeted to very poor families found few effects from lower exposure to neighborhood poverty. In his analysis of a municipal program in Toronto, for example, Oreopoulos (2003) exploited random variation in the average income of neighborhoods where public housing was located and found few effects on economic outcomes. He acknowledged, however, that even the best public housing locations were in moderately low income and not affluent neighborhoods.

In a multi-city evaluation in the United States known as the Moving to Opportunity Demonstration Project (MTO), public housing residents were randomly allocated vouchers that required them to move into a low-poverty neighborhood and compared with residents who received vouchers with no restrictions or residents who received no voucher at all (Ludwig et al. 2008). The results found few improvements on educational or economic outcomes, but fewer than half of those who received the experimental voucher used it to move (Sanbonmatsu et al 2011). This may reflect the difficulty of finding housing in better neighborhoods and the fact that many landlords in such neighborhoods in refuse to rent to voucher recipients (Beck 1996). Indeed, the compliance rate for MTO was quite low compared with other mobility programs (for example, see Chingos and Peterson 2012).

Even more problematic was the fact that those MTO participants who did use the voucher to move to low poverty neighborhoods still lived in racially segregated neighborhoods and sent their children to very disadvantaged schools and over time even the movers tended to gravitate back to high poverty neighborhoods (Clampet-Lundquist and Massey 2008).[1] Youth in the experimental group attended schools with an average ranking in the bottom quartile (at the 22nd percentile or 25th percentile of compliers) on state exams with a black student population share of 86% (or 82% for compliers—see Sanbonmatsu et al 2011).[2] In contrast, other studies find large positive effects of neighborhood on the success of children raised in those environments, using quasi-experimental methods (Rosenbaum, 2005; Massey et al. 2013; Schwartz (2010). The differences in neighborhood quality are likely considerably larger in these studies.

Our main goal here is to estimate how variation in neighborhood quality and metropolitan characteristics affect the transmission of intergenerational income. No published study that we are aware of has done this directly using the PSID or another longitudinal data source, but as suggested above and as we discuss below, several studies that suggest that such an analysis might well bear fruit. Bowles and Gintis (2002), for example, find that intelligence and easy-to-measure environmental factors like race, wealth, and education explain only one-third of the intergenerational association between the incomes of parents and offspring, with wealth, education, and race being far more important than IQ.

One explanation for the small share of variance explained is provided by Olivetti and Passerman (2013), who argue that much of the intergenerational association of income stems from unmeasured regional characteristics. Indeed the economic geography literature contains a number of studies showing geographic effects on migration and income growth:

1After 10–15 years, the average neighborhood poverty rate for the experimental group was 31% overall and 20% for compliers, compared to 40% for the control group. The minority population share was an astonishing 82% for the experimental group (75.5% for compliers), compared to 88% for the control group.

2To put this in perspective, the average black public school student nationally attends a school at the 37th percentile, compared to the 60th percentile for the average white public school student (Rothwell 2012).

Housing price appreciation affects the decision and ability to migrate (Ermisch and Wasbrook 2012); labor demand and income growth—which manifest themselves in housing prices—affect the attractiveness of a place to migrants (Rothenberg Pack 1973); And dense expensive cities often “select” for high-skilled workers by concentrating high-skilled industries (Combes, Duranton, and Gobillon, 2008; Détang-Dessendre, Drapier, and Jayet 2004).

Unfortunately, the literature often ignores how intra-metropolitan geography affects the quality of education and hence upward mobility. Important evidence for this comes from an analysis of the PSID from Wodtke, Harding, and Elwert (2011). They show that growing up in the most disadvantaged neighborhood lowers the high school graduation rate by 20 percentage points (from 96% to 76%). There is also strong experimental evidence linking school quality to future and lifetime earnings. Chetty and Friedman (2011) link random-assignment driven educational outcomes to tax records of parents and children at age 27 and find that 40% of the correlation between parental earnings and the future earnings of their children was attributable to differences in school quality.

An important omission from the literature on mobility is the failure to account for differences in regional purchasing power. To illustrate how regional purchasing power translate into real material advantage, consider data from a Brookings Institution report on housing costs near high scoring public schools (Rothwell 2012). In both Los Angeles and Cleveland, annual housing costs are roughly three times higher in the estimated school attendance zone near the average top-quintile elementary school compared to the average bottom quintile elementary school. Yet, in Los Angeles, the absolute cost difference to buy a home near a top school is $337,000 dollars ($733,000 vs. $396,000), whereas it is only $127,000 in Cleveland ($216,000 versus $88,000).[3] The affect of regional purchasing power on income inequality has been documented (Azzoni and Servo 2002).

Here we use the PSID to predict intergenerational income elasticities while accounting for these geographic effects. We also show results for intergenerational educational outcomes. To supplement our analysis, we draw on metropolitan-level measures of intergenerational income mobility developed by Chetty et al (2013) from individual tax returns obtained from the Internal Revenue Service.

In the next section we describe the data and methods used in our analysis and then use our model to estimate individual and contextual influences on intergenerational income elasiticities. Specifically, we estimate the effect of average income within childhood neighborhoods on future adult earnings and compare it to the effects of parental income and sibling income, where the latter represents a proxy for both the family environment and genetic endowments. We then investigate the robustness of our results to potential confounding effects, explore the effects on educational outcomes, and conclude by using data from Chetty et al (2013) to analyze measures of intergenerational elasticity at the

[3]The population-weighted correlation between the absolute cost difference and median home prices is 0.82, and a standard deviation increase in median home values is associated with a $72,000 increase in the difference between home values in top and bottom quintile attendance zones, compared to an average difference of $162,000. Access to good schools is a highly valued good, and higher relative home prices require higher incomes to obtain it. Rental prices show similar though less dramatic differences.

metropolitan scale to see if our small-sample micro level analysis holds up using a different database from a larger sample of records. Like Chetty et al (2013), our results show that metropolitan level economic and racial segregation—which jointly act to lower neighborhood quality for low income, black residents—is highly correlated to lower metropolitan income mobility, as predicted from our analysis of microdata.

DATA AND METHODS

Source of Data

Our primary dataset is the Panel Study of Income Dynamics, one of the largest and longest-running longitudinal studies ever done. The PSID follows individuals and families over time beginning in 1968 using a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Almost every year since, data has been collected for these individuals and their descendants by researchers at the Institute for Social Research at the University of Michigan. Here we make use of a restricted use file that pairs individual records with census tract information. To create a database of paired parent-child incomes, we start with the cohort born between 1965 and 1975. Total family incomes were averaged over the first 16 years in the lives of cohort members. These early family incomes were then compared with the later average family incomes of adult cohort members beginning at age 30 up through 2009 when interviewees were as old as 44 years.

To identify sibling incomes, we take advantage of the difference between two family ID variables. One is the unique family ID for the original family unit in the 1968 sample and the other is the ID for the present household in any given year. These data were likewise restricted to the 1965 to 1975 cohort to yield siblings similar in age and only income starting at age 30 was counted. For each year, sibling income equals total household income for the 1968 family unit (born in the same 10-year cohort) minus present household income, making sure that household income is measured only once for each member. Mean sibling income is total sibling income divided by the number of siblings. Since we are measuring family income—which we believe more accurately captures advantage than other measures—we also adjust for the number of potential income earners in the individual's adult household. We limit such adults to those 30 and older from the perspective of our 1965–1975 birth cohort. In PSID, this is the number of individuals that share the same family-interview identifier for a given year. Our final variable—number of adults in household—calculates the average number of qualifying adults for each year in which income is observed.

To measure the quality of the neighborhood environment, we use 1970 census tract income data, which are reported as a range relative to poverty levels. Poverty rates adjust (slightly) for the number of children and the number of adults in the household but not local prices. The mid-points of each income-to-poverty line range were used to calculate a household average income for each tract (where this ratio is adjusted by the number of adults and children in the household). The 1970 census income data were then assigned to each year of childhood for the first 16 years of life. Average childhood neighborhood income is the average tract income of the various neighborhoods that children inhabited through that age.

In regressions examining educational outcomes, we also use census data from the same year to measure exposure to college educated adults and high school dropouts. This is our proxy for neighborhood education quality. Our analysis of data from Brookings Institution suggests that the percentage of students scoring at proficiency on state exams increases by 3 points for every 10 percentage point increase in the census tract share of adults with a college degree.[4]

Measuring Regional Purchasing Power

We also consider that purchasing power varies widely across different areas of the United States. As a result, income may be more accurately measured in local prices. Indeed, failing to measure income in local prices could result in significant measurement error and even bias, given that price differences between one's adult environment and one's childhood environment are likely related to parental affluence.

Local prices other aforementioned census data were obtained from the National Historical Geographic Information System (Minnesota Population Center, 2011). To maintain constant geographic boundaries for metropolitan areas, census tracts and other geographic identifiers were matched to the most recent Office of Management and Budget metropolitan statistical area definitions using a county to metropolitan area crosswalk developed and maintained by Moody's Analytics.

To control for interregional differences in purchasing power, we constructed a local price index using rental prices.[5] The baseline U.S. average is the housing unit-weighted metropolitan average rental price. This is the average national price of a housing unit in a metropolitan or micropolitan area. The metropolitan price index is the regional average rental price divided by this national rental price value. Individual family income is adjusted each year from 1995 to 2009 using the 2000 price index for the metropolitan area resided in. The final value is the average of each purchasing-power adjusted income across all years (with mean year of 2003.8). Parental and sibling incomes are adjusted using the 1970 price index (for the cohort born between and including 1965 and 1975) and also take the average adjusted income across multiple years. Likewise, neighborhood income levels were divided by the 1970 metropolitan area housing price index to arrive at a measure of purchasing power adjusted neighborhood income and these too were averaged across yearly observations.

The local price index, as described above, relies entirely on housing prices. This is the consequence of limited data on the prices of other products, but there are reasons to believe that housing prices constitute an accurate proxy for local prices. Indeed, the 2011 Consumer Expenditure Survey shows that housing is the single largest category of expenditure for

[4]These data are discussed in Rothwell (2012), and they made available for this analysis. The data are 2009–2010 test scores for all public schools. The standard deviation for tract college attainment is .16. This regression predicts student proficiency rates (adjusted for state, grade level and subject) as a function of census tract educational attainment, weighing results by the size of the student population in the school. Controlling for metropolitan fixed effects raises the t-statistics but has little effect on the coefficient. Likewise, test scores go up by 5 percentage points for every $20,000 change in neighborhood median household income, which is a standard deviation.

[5]A previous draft of this paper used housing prices and obtained similar results. We were persuaded by a reviewer that rental prices more accurately captured cost-of-living differences.

American families—representing just over one third of all spending. Food and local services (like transportation, entertainment, childcare, education, and health services—though not insurance or drugs, necessarily) are also largely determined by local prices and wages. These categories combined represent at least half of total expenditure. Expensive and durable national market products like automobiles and electronics comprise just 7.4 percent of total expenditures. Moreover, all retail purchases are affected by both national and local prices, since business rent and employee salaries are largely locally determined.[6]

We are aware of two more comprehensive measures of regional prices but neither would work in this study. One is the ACCRA Cost-of-living index produced by the Council for Community and Economic Research. Unfortunately, these data are only available starting in 1990, whereas we need data from 1970 and 2000. Rental prices, however, capture most of this variation. We obtained data from the Census Bureau for 73 urban areas. The correlation between the ACCRA index and rental prices was 0.89.[7] The other source is the U.S. Bureau of Economic Analysis's regional price parities for metropolitan areas (Aten, Figueroa, and Martin, 2012). This method combines data on housing expenditures with data on expenditures for other items where available. They adjust for quality using a hedonic model. In practice, these regional price parities are highly correlated with average rent and average housing value of a metropolitan area (the correlation is 0.87 and 0.82, respectively, using 2010 data for all metropolitan areas).

Aggregate Mobility Data

As noted earlier, we supplement our analysis of data he PSID with data from the Harvard-U.C. Berkeley Equality of Opportunity Project (Chetty et al. 2013). That research team gained special access to individual records from the Internal Revenue Service and matched the income tax filings of 6.2 million young adults in 2011 to the income of their parents from 1996 through 2001—when they were roughly 16 to 21 years old. The team has published intergenerational income elasticities by commuting zones, which roughly correspond to metropolitan areas. We take a similar empirical approach with these data—running OLS regressions, though work only the aggregated metropolitan level.

Empirical Model

Our empirical analysis starts with a simple OLS regression of adult family income on log family income during the first 16 years of life. This is the basic intergenerational elasticity coefficient or IGE. The analysis then attempts to explain more and more of the observed association by adding successive blocks of variables to capture geographic aspects of mobility. The final estimating equation looks like this:

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[6]The range in local service prices across regions can be seen in data from the U.S. General Services Administration, which is responsible for setting transparent standards for government contractor and employee compensation for travel expenses. To do this, they rely on computations of revenue per room for hotels in each zip code of the country. The federal government will compensate employees for $295 per night if they stay in Manhattan. The per diem rate in Tucson, Arizona, however, is just one quarter the Manhattan rate, or $77. Even the per diem rate for "meals and incidental expenses" is 50 percent higher in Manhattan.

[7]The correlation with average housing value is 0.91 and 0.91 with the BEA index described next. Data are published in "Table 728. Cost of Living Index—Selected Urban Areas," U.S. Census Bureau, Statistical Abstract of the United States: 2012

$$P_{m,t+1}I_{i,t+1}=P_{h,t}\beta_1 F_{i,t}+\beta_2 S_{i,t+1}+\beta_3 L_{i,t}+\beta_4 X_{i,t}+\beta_5 R_{h,t}+e_{i,h,t} \quad 1$$

where I is the log of household income in adulthood (the later period), F is the log of family income in childhood, S is the log of sibling income presently, L is the log of childhood neighborhood income, X is a vector of individual characteristics exogenously correlated with income, R is a vector of regional variables, and e is an exogenous error term with conditional mean zero and homoscedastic variance. The subscript m refers to adulthood metropolitan area, while h refers to hometown metropolitan area and i subscripts the individual. P represents a local rental price index.

When $P_{m,t+1} = P_{h,t}$, the standard IGE regression is valid with no consideration of P, but that is a strong assumption. Even for those who do not leave their hometown metropolitan areas (the case where m=h), national price growth is likely to be higher or lower than hometown price growth. Consider than in the metropolitan area of Cleveland, nominal home price increased by 218% from 1980 to 2010, whereas in the New York City metropolitan area home prices increased by 367% over the same period. That means someone raised and living in New York City would have to see much higher income growth than someone raised and living in Cleveland in order to maintain the same relative purchasing power. As it happens, many people do move from their hometown metropolitan area, and the price differences across regions are often enormous. In areas like Pine Bluff, Arizona and Steubenville, Ohio a dollar of earnings is worth 7 to 8 times more than a dollar of earning in San Jose, if home prices are used to adjust incomes and 2.4 to 2.6 times as much if rental prices are used.

The most significant threat to the validity of our analysis is that neighborhood quality is not randomly distributed. For adults, however, childhood neighborhood is an exogenous variable, since they have no practical control over where they grow up. Our concern thus moves from selection to omitted variable bias, since parents with low incomes may be otherwise relatively advantaged in non-observable ways if they live in a middle- to high-income neighborhood. This is why we control for sibling income. Our main assumption is that any unmeasured advantage that could translate into future earnings conferred to offspring is absorbed more or less equally by siblings. Suggestive evidence for this assumption comes from recent research on parental investment in education. Differences between siblings in whether or not their parents send them to pre-school are not related to birth-weight (Datar, Kilbum, and Loughran 2010).

As the analysis proceeds, we control first for average sibling income to proxy the family environment and exogenous individual variables (sex, age, and race) and the number of potential household earners to see how the IGE changes. Next we add geographic measures at the neighborhood level and then metropolitan-level indicators, including area size (natural log of average MSA population during childhood), class segregation (average Gini index for inequality in home values during childhood), average home values (mean MSA home value during childhood), housing market conditions (growth in MSA home values 1980–2010), and geographic location (latitude and longitude of childhood MSA). The geographic coordinates are meant to capture unobserved differences across regions—such as access to coasts, weather (which may affect migration and industry orientation, as with tourism, agriculture, and fishing), proximity to the Mexican border, a history of slavery, or the fact that western states have much newer populations, with a larger percentage of migrants. We then perform a number of robustness checks, including adding controls for individual and parental education.

In the introduction, we argued that neighborhood effects operate through schools and access to quality education, even if through no other channels. Thus, we also model an "intergenerational educational elasticity" equation. Here, using a probit function we predict the probability of post-secondary attainment (ie 13 or more years of education), as a function of parental educational attainment variables and neighborhood bachelor's attainment rate and high school drop-out rates, as well as the other controls from above. Another robustness check relaxes our assumption that the error term is exogenous. Instead we assume that childhood neighborhood is endogenous because of correlation with omitted parental characteristics. Instead we assume that the parent's metropolitan area is exogenous. We instrument for childhood neighborhood with metropolitan level measures for economic segregation and the college educational attainment rate.

To put our results in perspective, we take advantage of the full PSID panel to estimate lifetime for children growing up in different neighborhoods based on our regression results. Specifically, we regress inflation-adjusted wages on age for various age bands (16–24, 25–34, 35–44, 45–54, 55 and older), while controlling for individual fixed effects. This gives us the slope of the experience-earnings curve. Taking the coefficient from our neighborhood effects regression and multiplying it by the difference in neighborhood income for top and bottom quintiles, gives us an estimate of the average income gains at age 34 (the average age of second-generation adults in our sample). Using the age coefficients, we apply a logarithmic growth formula to simulate past and future earnings using age 34 as the base year. Our method starts earnings at age 16 such that expected growth during that period and subsequent periods would be enough to reach the base year by age 34 and subsequent earnings are projected out to match the age-income slope. We show the results using national prices, local prices, and both, adjusted for the net present value of earnings at age 34.

Finally, to overcome concerns about the small sample size in the PSID, we also take advantage of newly created database of metropolitan level income mobility. In the final analysis, we analyze only aggregate metropolitan level data using the Harvard-U.C. Berkeley database developed by Chetty et al. (2013) with a focus on the factors that are most likely to predict higher neighborhood level quality (and school quality) for lower income children—economic and racial segregation.

Table 1 summarizes the data from the PSID. For our cohort, the mean birth year is just under 1970 and the mean age in adulthood is 34 with average income centered in 2004. Parental income, observed during the first 16 years of life, has an average of 10.85 in log terms or $61,027 when measured in 2010 consumer-price-index-adjusted dollars. Mean family income in adulthood is $78,086, implying that the average person in this cohort experienced an annualized real growth rate of roughly 0.7% in family income relative to parental family income. When converted to local prices, parental income is somewhat lower and family income somewhat higher, suggesting that people tended to move to higher cost metropolitan areas.

In terms of background characteristics, the sample was 47% male, with household head's being 39% black and 3% Hispanic. The high percentage of blacks can be explained by the PSID's oversampling of poor families (Hill 1991) and our use of the mostly metropolitan area interviewees for which we have geographic data. The average respondent had 1.28 siblings whose average age was 35 years. The average Gini index for MSA home values in childhood was 0.19, with an observed range of 0.11 to 0.32 and the average monthly rent value during this time was \$100 with a range from \$50 to \$150. The average rate of growth in home values was around 4% per year. The average neighborhood income was 2.3 times the poverty rate (ln of 0.8), using both national and local prices, but the range is much wider after adjusting for local prices.

CONTEXTUAL EFFECTS ON INTERGENERATIONAL INCOME MOBILITY

Starting with the most basic analysis, in the first column of Table 2 we estimate an IGE of 0.65 for the cohort born from 1965 to 1975. This figure is on the high end of estimates for the United States. We suspect the reason is that we use more observations than most studies, which allows means to smooth out annual fluctuations in earnings during both childhood and adulthood. The next column shows what happens to the IGE when we control for sibling income, race, sex, and the presence of another adult (typically a spouse) from the same cohort. Sibling incomes are correlated with adult family income, as expected, and blacks and women earn significantly less than expected, given parental and sibling income. The IGE falls to 0.43 after adding these covariates.

Childhood geography also has important effects on future earnings. The third column introduces the log of neighborhood income (measured as the ratio to the poverty line) to reveal that a one percent increase in neighborhood income raises adult income by 0.42%, a highly significant effect ($p<0.01$). The fourth column adds in the metropolitan-level controls, three of which prove to be significant statistically. In terms of housing conditions, a standard deviation increase in the Gini coefficient for childhood housing inequality reduces adult income by 5%, while a standard deviation increase in the rate of housing appreciation raises income it by 7%. Latitude is also highly correlated with mobility. A one standard deviation increase in latitude (i.e. moving northward) lowers adult income by 9%.

The addition of metropolitan-level variables increases the effect of neighborhood income in childhood, raising the coefficient from 0.42 to 0.58, implying an 11% increase in adult income for each standard deviation increase in neighborhood income or an increase of 28% moving from the bottom to the top quintile. Together, the variables included in the model explain just over a third of the intergenerational income elasticity, reducing it from 0.65 in the first column to 0.42 in the fourth column, with the adjusted R-squared value increasing by more than half from 0.25 to 0.39. Overall, these results are consistent with standard neighborhood effects models.

Neighborhood advantage, as well as regional economic integration and growing home wealth appear to drive up future income beyond what parental and sibling incomes would predict. Socially and economically, the neighborhood effect is a large effect. Using a standard deviation as the standard, the neighborhood effect is just under half of the parental effect (25%) and 72% of the sibling effect (11%) in the final model. Even these comparisons somewhat downplay the neighborhood effect. Statistically, the coefficient of variation is four times higher for neighborhood income than for parental income, implying it is "easier" to change the former than the latter. Intuitively, one can imagine a fairly low cost apartment building or attached single family units existing within a block or two of expensive detached single-family homes on mid-sized to large lots (Massey et al. 2013). Different zoning arrangements can bring huge changes in neighborhood quality and overall metropolitan level segregation without redistributing incomes (Rothwell and Massey 2009, 2010).

We now analyze the importance of these effects on actual incomes. For those born into the bottom quartile of neighborhood income, eventual family income was $55,000 in 2010 prices. This compares to $78,000 for those raised in top quartile neighborhoods. The regression results imply that if that individual had grown up in a top quartile neighborhood instead, eventual earnings would have been 26% higher, or $70,000, all else being equal. The foregoing results do not adjust for local purchasing power, but given the strong link between school quality and neighborhood housing prices and the wide variation in housing prices, there is reason to believe that local purchasing power is particularly important when it comes to assessing neighborhood quality. We investigate this by converting our measures of earnings into local prices for the following variables: future family income, parental income at childhood, future sibling income, and childhood neighborhood income. All use the 1970 price deflator except for future family income, which uses a 2000 price index. We then replicate the regressions shown in Table 2 and present them in Table 3.

Overall, this approach yields similar results, with a slight increase in the adjusted R-squared in the final model (to 0.39). Yet, the geographic variables become more important and the IGE falls to 0.38 in the model corresponding to column 4 in Table 2 (versus .42 using national prices). The effect from the metropolitan measure of segregation becomes somewhat larger in magnitude and still negative and significant statistically, and most importantly for this paper, the neighborhood income variable becomes larger when analyzes with local prices.

In this local-purchasing power-adjusted model, a one-standard deviation change in childhood neighborhood income measured in local prices corresponds to a 15% change in eventual adult earnings ($.63 \times .24$), compared to an 11% effect using national prices. This is now two-thirds of the parental income effect using local prices (22%) and larger than the sibling effect (11%). The change from moving from a bottom to top quartile neighborhood is now 38% (instead of 26%). In this model, latitude remains significant and longitude (Western orientation) is also associated with significantly higher earnings. Using national prices appears to have obscured some of the local and metropolitan effects.

Neighborhood effects on lifetime earnings

To illustrate the importance of neighborhoods to lifetime earnings, we use the coefficients of neighborhood effects in column 4 of Tables 2 and 3 to estimate differences in lifetime earnings between those who grow up in bottom quartile neighborhoods compared to those who grow up in top quartile neighborhoods. The results of this exercise are summarized in Table 4. Starting with national prices, this exercise suggests predicted lifetime household income is $635,000 higher for those growing up in top quartile neighborhoods compared to those coming of age in bottom quartile neighborhoods, holding all else equal. Since average household income is measured at age 34, we also use this to calculate the net present value difference at age 34. We applied a 3% discount rate, which inflated past earnings (when income was lower) and deflated future earnings. This yields a $508,000 difference in lifetime earnings at age 34.

The neighborhood effect from lifetime earnings is considerably higher when measured in local prices than when measured in national prices. This is predictable given that real neighborhood advantage and disadvantage depend on local rather than national prices, especially for access to high quality schools. As the right hand side of Table 4 shows, the difference in lifetime earnings is $911,000 for those growing up in a top quartile neighborhood compared to those coming of age in a bottom quartile neighborhood. In net present value terms, at age 34, the difference is $729,000. To provide a sense of this magnitude, the average difference in lifetime earnings between someone with a high school diploma and someone with a bachelor's degree is $1.1 million (not expressed in present value terms), according to a Census Bureau report (Julian 2012). In other words, the effect of growing up in an affluent neighborhood compared to a poor neighborhood is almost as large (83% as large) as the effect of completing a bachelor's degree compared to ending educational attainment with just a high school diploma.

Robustness of Results to Omitted Variables

We believe the biggest threat to the validity of our results come from omitted variables. Since we are using childhood environment—which is exogenous to individuals—we believe there is little chance of reverse causation from future income to childhood neighborhood context. Indeed, our results are robust to using the metropolitan area gini coefficient as an instrumental variable for neighborhood income. The two are strongly negatively correlated and the analysis passes standard tests for instrumental validity.[8]

More importantly, the models shown thus far focus only on income, but other parental characteristics—such as education—are also likely to be important sources of intergenerational advantage and may be correlated with neighborhood income, biasing the results. In results available upon request, we include dummy variables for the highest level of parental education during any point in childhood (less than high school, some college, and

[8]Specifically, we replicated columns 4 from Tables 2–3 but moved the Gini coefficient to an instrument on the assumption that one's metropolitan area is often exogenous (since most people don't move). We also included metropolitan bachelor's degree attainment as another instrument so we could generate Sargan statistics for over-identification. The Anderson and Sargan tests (using IVREG2 in STATA) suggest that the instruments are highly correlated with neighborhood income and valid. The coefficient on local-price adjusted neighborhood income becomes 4.3 in this analysis, which is implausibly large.

bachelor's degree or higher, with high school diploma being the omitted category). The only significant difference from high school educated parents were parents with at least 16 years of education, which adds 20% to future income, using both national or local prices. Including these variables lowers the neighborhood effect using national and local prices only slightly to 51% and 58% respectively (from 58% and 63%). These variables and the metropolitan level variables remain highly significant.

Like Chetty et al (2013), we consider educational attainment to be an outcome largely determined by childhood experience and family circumstances. Yet, one might also wonder what a neighborhood effect might look like even for those with the same level of education. This could be interpreted as the value of skills acquired through education, which will differ based on secondary and post-secondary quality and the field of study (eg engineering and computer science pay higher than liberal arts majors). When we include individual educational attainment dummies, the coefficients on the parental dummies become insignificant, the IGE falls to 30% and 26% (for national and local prices, respectively), but the neighborhood effect increases back to the levels shown in Tables 2 and 3. In other words, the neighborhood effect seems to operate through skill acquisition and not only years of education attained. In any case, the effect does not depend highly on parental education.

We also consider other ways to measure neighborhood disadvantage and how this intersects with race. Using our baseline models as the foundation, we first analyze two alternatives measures of neighborhood quality: The share of childhood census tract population that is black—which is likely correlated with under-investment and lower quality schools as a result of Jim Crow policies—and the share that has a bachelor's degree—which likely predicts higher quality schools. When entered separately, both variables are significant in predicting lower or higher levels of adult earnings, but when all three are entered together, it is clear that neighborhood income has the most explanatory power. Since they are highly correlated, we show models with only the income measure.

Analyzing these alternative neighborhood variables offers an important with respect to race. The previous results (from Tables 2 and 3), show that blacks are significantly less upwardly mobile. For a given level of black parental income, future income is 16% to 18% lower. Because of Jim Crow, predominantly black and white neighborhoods differ by more than just income. Indeed, if the black population neighborhood share is included, the coefficient on the black dummy variable becomes insignificant. It thus appears that the lower intergenerational income mobility of African Americans can be explained by their disproportionate segregation in poor, disadvantaged neighborhoods, consistent with Sharkey (2013), as well as Massey and Denton (1993).

Migration and Earnings

Next, we consider yet another threat to the validity of our findings: the potential endogeneity between migration and income. In other words, high cost areas may "select" high-earning workers. Migration patterns might bias these results if two conditions are met: migrants tend to move to higher cost areas, and childhood endowments predict relative price changes between adult and childhood economies. We find that one third of individuals in our sample (with full data on neighborhoods and location) moved metropolitan areas since childhood.

For who moved, they were slightly more likely to move to higher cost metropolitan areas. The average rental price index increased by 3 percent from 1970 to 2000 for movers. For those that did not move, relative prices between 2000 and 1970 were almost the same on average, but there was still wide variation, with some facing rental prices two-thirds as low as their parents, while others experienced prices 2.5 times higher. Without attempting to introduce a complex model of domestic migration, we also simply note that family income has a small but statistically significant positive correlation with the ratio of adult prices to childhood prices.

To analyze geographic migration in the context of our model, we ran three alternative model specifications for both national and local prices. We first compare what happens when one simply controls for whether or not someone has a new hometown—that is whether or not their most frequently resided in metropolitan area as an adult matches the one most frequently resided in as a child. Then we restrict the model first to movers and then non-movers. The results are available upon request. We find no evidence that migrant selectivity accounts for the neighborhood effect. The neighborhood income coefficient remains significant and of roughly the same magnitude in all six specifications. Using national prices, we find that the neighborhood effect swells to .87 for movers but is .53 for non-movers. In local prices, the effect is of the same magnitude for movers and non-movers (.62), which itself provides evidence that measuring incomes in local prices captures important differences in inter-regional prices brought upon through migration.

Intergenerational Educational Elasticity

As we described above, one theory of mobility is that neighborhoods affect the acquisition of human capital and hence income through the quality of elementary and secondary education. Thus, one should see evidence that neighborhoods also affect the quantity of education received over the course of one’s lifetime. We test that hypothesis by using a probit regression model that predicts post-secondary attainment (more than 12 years of education) based on observable familial characteristics and neighborhood educational attainment.

We find support for the theory. As Table 5 shows, the bachelor’s degree attainment rate of the childhood neighborhood has a significant effect on the probability of eventually obtaining a level of education beyond high school. A one-standard deviation increase in the neighborhood attainment rates raises the probability of attainment by 8 percent. This is roughly 40% of the parental effect, if one combines the coefficients from parental bachelor’s degree attainment with income and adjusts the effect sizes by a standard deviation. While this is a sizeable effect, none of our regional variables are significant, and we also tried entering the metropolitan level bachelor’s degree attainment rate but found that insignificant as well. Overall, neighborhoods and regions seem to predict eventual education less well than eventual incomes.

Robustness of Individual Analysis to Larger Aggregated Analysis

While somewhat unique in ambition and data specificity, the PSID offers just a small sample of the US population and smaller still when matched to geographic data and restricted to a single cohort—albeit a large one, in this case. To check the robustness or our main findings we analyze a much larger sample (based on 6.2 million individual IRS records) from the Harvard-Berkeley Economic Opportunity Project. Unfortunately, we cannot replicate our analysis exactly because we do not have access to the individual records. Instead, we have access to metropolitan specific IGE measures. For each metropolitan area, we have the coefficient of log parental income on log adult child income at age 30. There are other important differences. The Harvard-Berkeley cohort was born in 1980 or 1981 instead of 1965–1975; parental income was observed at aged 16 to 21, instead of 0–16; adult income was observed in 2010 and 2011 at age 30 instead of repeated observations from age 30 to 44.

With those caveats aside, it is straightforward to interpret a lower metropolitan area IGE as indicative of higher than expected incomes for those born into low income families, though it also implies lower than expected incomes for those born into affluence. More directly still, the Harvard-Berkeley team explicitly provides a measure of upward mobility for each metropolitan area: the coefficient on a regression of future income rank on parental incomes for those at the 25th percentile. In this context, metropolitan area characteristics can be used to explain why incomes for this population are higher-than-expected (or higher than average) in some areas and lower in others. This is more or less equivalent to trying to tease out which metropolitan characteristics predict higher-than-expected incomes in individual regressions, controlling for parental income.

As with the individual analysis, the aggregated metropolitan metrics of mobility are highly correlated with economic segregation. The implication is that the future earnings of adults born into low income households is higher than expected in more economically integrated metropolitan areas. This can be seen across three measures of mobility shown in Table 6. Two measures of economic segregation are used, which are meant to capture slightly different aspects of segregation at different time periods. One is the segregation of the poor from the Harvard-Berkeley team and measured in 2000. It is a Thiel index where the population is divided at the 25th percentile. The other measure of segregation is the one used earlier—the neighborhood home value Gini coefficient, measured in 1980.

In the first column, the metro-specific IGE is regressed on the same metropolitan characteristics used in the individual PSID analysis, except that individual race variables are replaced by aggregate metropolitan population shares. Column 2, replaces the dependent variable with an IGE measure that adjusts for local prices, and column 3 uses a measure of upward mobility: The expected income rank of people born at the 25th percentile. At least one of the segregation measures is significant in the excepted direction in all three regressions, but the regression with local prices (column 2) is the only one in which both measures of segregation predict lower mobility.[9]

[9]These results are robust to including many other control variables such as teen pregnancy rate, other measures of income, and population density, education shares, state policy variables (e.g. minimum wage, union laws), and black-white residential segregation instead of economic segregation.

CONCLUSION

By matching longitudinal data from the PSID with geographic data on neighborhood and metropolitan level data, we find that economic segregation significantly depresses economic mobility across the generations. After controlling for parental and sibling incomes and using childhood measures of neighborhood and metropolitan environment, we predict future income based on exogenous measures of household advantage/disadvantage. We also consider how geographic migration and regional purchasing power affect nominal measures of intergenerational mobility. Finally, we supplement our analysis with metropolitan measures of mobility based on an extremely large sample of 6.2 million individuals.

Across these different models and measures of intergenerational mobility, results consistently show that growing up in a poor neighborhood in an economically segregated metropolitan area has a strong negative effect on future earnings. The neighborhood effect is almost equal to half of the parental income effect, which is large enough to have major sociological and economic implications. We estimate a difference of roughly half a million dollars in lifetime income for those growing up in top quartile neighborhoods compared to bottom quartile neighborhoods.

The neighborhood effect is even larger when measured using local purchasing power instead of national prices. Using home prices to build a local price index, we re-estimate the intergenerational mobility models and find that the neighborhood effect is roughly two-thirds of the parental income effect. Moreover, when measured in local purchasing power terms, growing-up in an affluent neighborhood adds $729,000 in estimated lifetime earnings (expressed as net present value at age 34) relative to growing up in a poor neighborhood.

These conclusions could be strengthened if we had a larger sample size. To overcome this limitation at least partially we show that the results are consistent with aggregate estimates from millions of IRS records, though we lacked access to the individual data necessary to replicate our individual-level analysis. Our study is also limited by the fact that families are not randomly assigned to neighborhoods, meaning that unmeasured parental characteristics could explain these results. Yet, we believe any such bias is likely to be small, since we also control for sibling income. So long as siblings absorb roughly the same levels of parent advantage and disadvantage, then their future incomes should be highly correlated with the unmeasured parental characteristics that affect offspring income. We believe that is a fairly realistic assumption but bears further investigation.

Additionally, our analysis suggests methodological insights into intergenerational mobility studies that may have broader implications for social science work. Failing to adjust for regional purchasing power can lead to Type 2 error, which may have important implications for other studies not finding evidence of neighborhood effects when measuring neighborhood disadvantage in terms of national prices. We believe future studies of income mobility need to more thoroughly consider local and regional economic context. Moreover, we believe that future research projects could substantially illuminate the connection between parental advantage and children’s educational advantage by directly matching parental incomes with childhood educational quality and local economic circumstances.

Finally, we believe there are important policy considerations that follow from this analysis. Leaders of both U.S. political parties often state the need to boost the equality of opportunity, and yet anti-segregation policies—such as deregulating anti-density building restrictions, boosting the value of housing vouchers, or fostering broader access to high quality schools—are never mentioned. Our analysis suggests that these interventions could be very effective in reducing long-run inequality.

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Table 1

Summary Statistics of PSID Database

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln mean family income, 2010 prices	1175	10.96	0.84	5.28	13.79
Ln mean family income in local prices, 2010 prices	1175	11.02	0.84	5.26	14.03
Ln Parents' income when child, 2010 prices	1287	10.85	0.60	8.45	13.00
Ln Parents' income when child in local prices, 2010 prices	1287	10.92	0.59	8.68	12.98
Mean sibling family income (if 30 and older), 2010 prices	899	11.02	0.72	5.78	13.79
Mean sibling family income (if 30 and older) in local prices, 2010 prices	899	11.09	0.72	6.16	13.47
Male	1288	0.47	0.50	0.00	1.00
Black	1288	0.39	0.49	0.00	1.00
Hispanic	1288	0.03	0.18	0.00	1.00
Number of same cohort adults in household	1288	1.19	0.26	1.00	2.50
Average income childhood neighborhood, 2010 prices	1288	0.81	0.19	0.03	1.07
Average income childhood neighborhood in local prices, 2010 prices	1288	0.83	0.24	−0.09	1.60
Childhood neighborhood share of adult population with at least a bachelor's degree	1288	0.10	0.09	0.00	0.69
Childhood neighborhood share of adult population with no high school	1288	0.48	0.19	0.08	0.93
MSA Population when child	1199	2.88	4.10	0.01	16.70
Neighborhood housing inequality of MSA when child	1199	0.19	0.03	0.11	0.32
Average home value in MSA when child	1216	4.61	0.20	3.92	5.01
Growth of home values in home MSA, 1980–2010	1216	4.04	1.37	2.03	7.22
Latitude of childhood MSA	1216	38.01	4.46	26.10	48.84
Longitude of childhood MSA	1216	−89.24	14.82	−122.90	−70.42
Individual has less than high school diploma	1224	0.11	0.31	0.00	1.00
Individual has attended 13 to 15 years of school	1224	0.29	0.45	0.00	1.00
Individual has attended at least 16 years of school	1224	0.23	0.42	0.00	1.00
Most educated parent has less than high school diploma	1288	0.27	0.44	0.00	1.00
Most educated parent has attended 13 to 15 years of school	1288	0.20	0.40	0.00	1.00
Most educated parent has attended at least 16 years of school	1288	0.18	0.38	0.00	1.00
Mean age during adulthood period	1288	33.99	2.01	30.00	44.00
Mean Year born	1288	1969.77	3.36	1965.00	1975.00
Mean Year Observed During Adulthood Period	1288	2003.76	3.24	1995.00	2009.00

Variable	Obs	Mean	Std. Dev.	Min	Max
Have lived in different MSA as adult compared to childhood	1288	0.34	0.47	0.00	1.00
Number of siblings	1288	1.28	1.42	0.00	8.00
Sibling age	937	35.01	2.41	26.00	44.00

Table 2

Intergenerational Income Elasticities Conditional on Sibling Neighborhood and Metropolitan Area Characteristics Using National Prices

	Ln of total family income			
	1	2	3	4
Ln of parental income	0.645***	0.428***	0.454***	0.422***
	(0.0263)	(0.0350)	(0.0492)	(0.0521)
Ln of average sibling's family income		0.190***	0.182***	0.164***
		(0.0301)	(0.0375)	(0.0392)
Male		0.0837**	0.104**	0.103**
		(0.0352)	(0.0448)	(0.0471)
Black		−0.184***	−0.116*	−0.155**
		(0.0433)	(0.0611)	(0.0675)
Hispanic		0.0361	0.0374	−0.0200
		(0.117)	(0.132)	(0.143)
Adults in Household		0.606***	0.594***	0.642***
		(0.0672)	(0.0864)	(0.0908)
Ln Average income of neighborhood during childhood			0.422***	0.580***
			(0.159)	(0.179)
MSA Population when child				0.00244
				(0.00766)
Neighborhood housing inequality of MSA when child				−1.630**
				(0.787)
Ln Average rent value in MSA when child				−0.0540
				(0.146)
Growth of home values in home MSA, 1980–2010				0.0476**
				(0.0222)
Latitude of childhood MSA				−0.0207***
				(0.00604)
Longitude of childhood MSA				0.00323*
				(0.00194)
Constant	3.972***	3.514***	2.963***	4.779***
	(0.284)	(0.412)	(0.539)	(0.856)
Unique Individuals in Sample	1,793	1,395	899	832
Adjusted Rˆ2	0.251	0.339	0.365	0.386

Standard errors in parentheses,

*** p<0.01,

** p<0.05,

* p<0.1.

Table 3

Intergenerational Income Elasticities Conditional on Sibling Neighborhood and Metropolitan Area Characteristics Using Regional Price Parity Adjusted Incomes

	Ln of total family income in local prices			
	1	**2**	**3**	**4**
Ln of parental income in local prices	0.629***	0.396***	0.428***	0.383***
	(0.0263)	(0.0351)	(0.0494)	(0.0519)
Ln mean siblings' family income in local prices		0.196***	0.188***	0.160***
		(0.0300)	(0.0370)	(0.0385)
Male		0.0903***	0.106**	0.117**
		(0.0347)	(0.0447)	(0.0466)
Black		−0.190***	−0.149**	−0.183***
		(0.0429)	(0.0587)	(0.0663)
Hispanic		−0.00690	0.0505	0.00315
		(0.116)	(0.132)	(0.141)
Adults in Household		0.588***	0.596***	0.644***
		(0.0663)	(0.0861)	(0.0897)
Ln mean income of childhood neighborhood in local prices			0.365***	0.632***
			(0.108)	(0.159)
MSA Population when child				0.00184
				(0.00756)
Neighborhood housing inequality of MSA when child				−1.855**
				(0.779)
Ln Average rent value in MSA when child				0.257
				(0.183)
Growth of home values in home MSA, 1980–2010				0.0524**
				(0.0220)
Latitude of childhood MSA				−0.0229***
				(0.00595)
Longitude of childhood MSA				0.00393**
				(0.00192)
Constant	4.176***	3.864***	3.254***	3.972***
	(0.289)	(0.422)	(0.557)	(1.087)
Unique Individuals in Sample	1,793	1,395	899	832
Adjusted R^2	0.241	0.325	0.361	0.389

Standard errors in parentheses,

*** p<0.01,

** p<0.05,

* p<0.1.

Table 4

Estimated Lifetime Earnings Effect of Moving Child from Bottom to Top Quartile Neighborhood

	National Prices	**Local Prices**
In 2010 Prices		
Lifetime income if raised in bottom quartile	$2,442,612	$2,396,837
Lifetime income if raised in top quartile	$3,077,692	$3,307,635
Difference	$635,079	$910,798
Net Present Value at age 34 in 2010 Prices		
Lifetime income if raised in bottom quartile	$1,954,818	$1,918,184
Lifetime income if raised in top quartile	$2,463,071	$2,647,094
Difference	$508,253	$728,910

Analysis starts at age 34 with mean observed earnings for adults who grew up in bottom quartile neighborhoods. That sum is multiplied by the neighborhood effect (the coefficients from column 4 Tables 2–3 multiplied by the average difference in neighborhood income top and bottom across quartiles) to calculate the top quartile incomes at age 34. Incomes for others years were adjusted using slope of an age-income regression. The age premium was estimated to be 7% from age 16–24, 2.6% from 35–34, .8% from 35–44, .01% from 45–54, and -1.1% from 55–65. Net present value is based on 3 percent discount rate–roughly equal to average long-term treasury bond yields.

Table 5

Probit Estimation of Probability of post-secondary educational attainment conditional on childhood parental and geographic conditions

	Probability of post-secondary educational attainment					
	1	**2**	**3**	**4**	**5**	**6**
Ln of parental income				0.152***	0.127***	0.127***
				(0.0311)	(0.0408)	(0.0427)
Ln mean siblings' family income				0.0787***	0.0701**	0.0776**
				(0.0258)	(0.0309)	(0.0322)
Ln of parental income in local prices	0.152***	0.134***	0.134***			
	(0.0307)	(0.0406)	(0.0431)			
Ln mean siblings' family income in local prices	0.0559**	0.0474	0.0561*			
	(0.0257)	(0.0303)	(0.0317)			
Parent has less than high school education	−0.160***	−0.144***	−0.122**	−0.142***	−0.131***	−0.115**
	(0.0345)	(0.0456)	(0.0487)	(0.0350)	(0.0460)	(0.0488)
Parent has some college or associate's degree education	0.136***	0.155***	0.145***	0.115***	0.144***	0.142***
	(0.0384)	(0.0450)	(0.0475)	(0.0393)	(0.0456)	(0.0477)
Parents has bachelor's degree	0.372***	0.354***	0.343***	0.353***	0.343***	0.339***
	(0.0364)	(0.0452)	(0.0482)	(0.0385)	(0.0467)	(0.0488)
Male	−0.118***	−0.126***	−0.122***	−0.116***	−0.123***	−0.122***
	(0.0290)	(0.0356)	(0.0373)	(0.0291)	(0.0356)	(0.0373)
Black	0.0247	−0.0141	−0.0496	0.0229	−0.0250	−0.0477
	(0.0358)	(0.0483)	(0.0519)	(0.0352)	(0.0471)	(0.0516)
Hispanic	0.0694	0.0705	0.0301	0.0362	0.0536	0.0277
	(0.0962)	(0.102)	(0.112)	(0.0978)	(0.103)	(0.112)
Adults in Household	0.171***	0.144**	0.164**	0.170***	0.140**	0.157**
	(0.0558)	(0.0696)	(0.0725)	(0.0558)	(0.0697)	(0.0726)
Neighborhood college attainment rate		0.904**	0.900**		0.911**	0.882**
		(0.370)	(0.391)		(0.372)	(0.391)
Neighborhood less than high school completion rate		0.243	0.338		0.276	0.332
		(0.192)	(0.216)		(0.194)	(0.216)

	Probability of post-secondary educational attainment					
	1	2	3	4	5	6
MSA Population when child			0.00589			0.00620
			(0.00642)			(0.00644)
Neighborhood housing inequality of MSA when child			−0.203			−0.250
			(0.635)			(0.636)
Ln Average rent value in MSA when child			0.000634			−0.156
			(0.115)			(0.111)
Growth of home values in home MSA, 1980–2010			0.00456			0.00335
			(0.0180)			(0.0180)
Latitude of childhood MSA			−0.00234			−0.00253
			(0.00436)			(0.00436)
Longitude of childhood MSA			−0.000503			−0.000396
			(0.00148)			(0.00148)
Pseudo-R-sq.	0.165	0.178	0.180	0.167	0.180	0.179
Observations	1,395	928	855	1,395	928	855

Standard errors in parentheses,

*** p<0.01,

** p<0.05,

* p<0.1

Table 6

Regression of metropolitan level IGE and upward mobility on regional characteristics

	IGE	IGE in local prices	Expected Income for 25th percentile parents
	1	2	3
Black population share, 1980	15.63***	18.41***	−15.08***
	(2.269)	(2.166)	(1.860)
Hispanic population share, 1980	−0.129***	−0.116***	0.00801
	(0.0175)	(0.0167)	(0.0144)
Segregation of poor index, 2000	6.153	23.99***	−26.91***
	(8.010)	(7.647)	(6.567)
Neighborhood home value gini index, 1980	17.48***	15.71***	1.571
	(4.015)	(3.832)	(3.291)
MSA Population, 1980	−1.52e-07	−1.29e-07	1.33e-07
	(1.47e-07)	(1.40e-07)	(1.21e-07)
Average home value, 1980	−9.84e-05***	−6.39e-05***	2.96e-05**
	(1.66e-05)	(1.58e-05)	(1.36e-05)
Growth of home values in home MSA, 1980–2010	−0.526***	−0.430***	−0.390***
	(0.170)	(0.162)	(0.139)
Latitude	0.102**	0.0660*	0.0644*
	(0.0411)	(0.0393)	(0.0337)
Longitude	0.0892***	0.116***	−0.00800
	(0.0152)	(0.0145)	(0.0125)
Constant	36.55***	38.30***	42.53***
	(2.322)	(2.217)	(1.904)
Observations	328	328	328
Adjusted R-squared	0.694	0.729	0.467

Standard errors in parentheses,

*** p<0.01,

** p<0.05,

* p<0.1.