Dynamic Individuals, Static Neighborhoods: Migration and Earnings Changes in Poor Neighborhoods*

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Abstract

This paper uses newly-available administrative data to study the migration and earnings of residents of high-poverty neighborhoods. We find that migration rates are sizable: 36.5% of people living in a high-poverty neighborhood move to a less poor neighborhood within eight years. The growth rate of earnings is similar for individuals living in poorer and richer neighborhoods. Using a research design that isolates variation in idiosyncratic, firm-specific pay changes, we show that higher earnings generate migration to better neighborhoods. Overall, these results suggest that many individuals are not stuck in poor neighborhoods, though there is notable heterogeneity across demographic groups. Our results imply that poor neighborhoods tend to remain poor in large part because initial residents who experience earnings growth tend to move away.

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1 Introduction

Concentrated poverty is a prevalent and enduring feature of the neighborhood geography of the United States, occurring in both urban and rural areas and throughout modern history. Policymakers and researchers have focused on concentrated poverty for nearly a century, driven by concerns about public health and quality of life, as well as fears that poor neighborhoods constrain residents' upward economic and residential mobility (Riis, 1890; President's Committee on Urban Problems, 1968; Wilson, 1987; Kling et al., 2007a).

Existing research generally views individual residence in poor neighborhoods as the result of two distinct issues. The first issue is whether residents of poor neighborhoods are simply unable to afford a richer, more expensive neighborhood (Bilal and Rossi-Hansberg, 2021). The second issue is whether residents of poor neighborhoods have preferences or face non-income barriers that prevent them from moving to a different type of neighborhood (e.g., Cutler et al., 1999; Christensen and Timmins, 2022; Bergman et al., 2024).

Different approaches to these two issues have led to sharply contrasting views of *why* individuals live in poor neighborhoods. One view is that many residents of poor neighborhoods are "stuck" there, lacking both opportunities for higher income and mobility (Wilson, 1987). A distinct view, which is embodied in a large number of papers that estimate models of sorting and neighborhood demand (Epple and Sieg, 1999; Bayer et al., 2007), is that individuals consider many different types of neighborhoods and actively choose the option that maximizes their utility, subject to a budget constraint. The degree to which these contrasting views accurately describe reality is important not only for our understanding of individual migration and concentrated poverty, but also for informing a range of policies that attempt to change the trajectories of people and neighborhoods.

In this paper, we use newly available data to provide novel evidence on the earnings and migration of residents of poor neighborhoods in comparison to individuals living in less poor neighborhoods. We focus on three moments that are key to understanding why individuals live in poor neighborhoods and why neighborhoods tend to stay poor: migration rates out of poor neighborhoods, earnings growth among individuals in poor neighborhoods, and the degree to which earnings growth drives moves to richer neighborhoods.

We begin by constructing a longitudinal data set that provides a comprehensive picture of individual demographics, labor market outcomes, and location choices. The sampling frame is adult respondents to the American Community Survey (ACS) between 2005 and 2013. We then link these individuals to newly available address history data from the Census Bureau and the Longitudinal Employer-Household Dynamics (LEHD) data to construct a panel of neighborhood locations and earnings. We define high-poverty neighborhoods as census tracts with a poverty rate over 30%. This is roughly the poorest decile of tracts, and the resulting set of neighborhoods is similar to Empowerment Zones in size and demographics.

Our first set of key results are baseline rates of migration across different types of neighborhoods. Individual mobility is high generally, with 43% of all adults exiting their baseline census tract over the following ten years. People in high-poverty neighborhoods exit at a higher rate of 51%. This migration is not just between similar areas: among the people who move out of a high-poverty neighborhood, 81 percent move to a lower-poverty neighborhood.

Next, we go beyond simple transition rates and calculate longitudinal measures of exposure to high-poverty neighborhoods. Among people living in high-poverty tracts, we tabulate how many of the subsequent ten years they spend in a high-poverty tract. There is a bimodal distribution. About 54% live in a high-poverty neighborhood for all of the next ten years, while 31% spend five or fewer of those years in concentrated poverty. While these results suggest that a sizable share of individuals in poor neighborhoods are not stuck there, we find notable differences between demographic groups. About 31% of individuals under age 35 beginning in high-poverty neighborhoods spend all of the following ten years in similarly-poor neighborhoods, while the corresponding figure for individuals over age 65 experience is 71%. Renters in high-poverty neighborhoods spend less time in high-poverty neighborhoods than homeowners. We also find that young adults with children spend fewer years in a high poverty neighborhood, which is of interest because the negative effects of concentrated poverty are largest among young children (Chetty et al., 2016).

Our second set of key results are new estimates of earnings changes among individuals residing in different types of neighborhoods. While prior literature has measured earnings dynamics among poor people, there is little evidence on whether earnings growth differ for those residing in poor *neighborhoods*. People with low earnings at a point in time generally have high earnings volatility and rapid subsequent growth (Abowd et al., 2018; Guvenen et al., 2021). However, this may not be the case in very poor neighborhoods if the neighborhood environment depresses earnings growth, perhaps through poor commuting access or job referral networks (Bayer et al., 2008). We find that people with some attachment to the labor force who are living in high-poverty neighborhoods at baseline have very similar future earnings growth rates as people in less poor areas, including a long right tail of large earnings increases.

Our third set of key results quantify the relationship between changes in earnings and neighborhood choices. We first show that there is a strong correlation between these variables. Among individuals beginning in a high-poverty tract, those whose real annual earnings increase by $20,000 over an eight-year period are 13 percentage points more likely to have exited concentrated poverty by the end of this period than those who experience no earnings growth, and they end up in tracts with $7,200 higher median income.

We then proceed to estimate the causal effect of unexpected and persistent earnings changes on neighborhood choice. Isolating the causal effects of earnings changes is important for understanding the degree to which earnings is a key constraint in individuals' neighborhood choice. We use the design in Rose and Shem-Tov (2023) to examine the effects of idiosyncratic, firm-level pay shocks, which we infer using changes in coworker earnings following Koustas (2018) and Ganong et al. (2020). We find that a shock that increases annual household earnings by 1.37 log points on average over an eight-year period leads to increases in tract median incomes and housing values of 0.24 and 0.29 log points, respectively, implying elasticities of 0.175 and 0.212. These results show that individuals have a clear tendency move towards higher-income neighborhoods after positive earnings shocks, though an elasticity below 1 implies that they do not perfectly sort to neighborhoods with residents whose earnings match their own. In work that is not yet disclosed, we expand on this analysis by estimating heterogeneity across subgroups of people, including those initially in high poverty neighborhoods, and quantifying the share of migration that can be explained by typical earnings changes.

Our estimates of high out-migration rates from poor neighborhoods point to a dynamic mechanism that keeps poor neighborhoods poor: people leave them when their income rises. We quantify the importance of this mechanism by comparing the average earnings growth of the cohort of people who *start* in a high-poverty neighborhood (regardless of where they live in future years) to the set of people who *live* in the same type of neighborhood in each year. The earnings of the cohort of initial residents increases by about 25% over the subsequent ten years, which is similar to the growth of cohorts beginning in less poor neighborhoods. However, growth in the earnings of contemporaneous residents is much slower—only about 10%. This suggests that selective migration meaningfully depresses the improvement of neighborhood-level outcomes in poor neighborhoods.

This paper first contributes to prior work on the migration and labor market outcomes of individuals in high-poverty neighborhoods. A small sociology literature in the 1990s studied migration into and out of poor areas using the Panel Study of Income Dynamics (Gramlich et al., 1992; Massey et al., 1994; South and Crowder, 1997; Quillian, 2003). We improve on the migration estimates from the PSID by using a much larger sample that allows for more detail and precision. For example, we are able to show the stark heterogeneity in concentrated poverty exposure between the young and old, or between unsubsidized renters and public housing residents. We also use our nationally-representative sample to show that the high rates of mobility and neighborhood improvement observed in samples of households affected by changes or experiments in housing safety net programs (Kling et al., 2007b; Chetty et al., 2016; Chyn, 2018) are not an artifact of selection into programs like Moving to Opportunity, but instead hold more broadly. To our knowledge, our results on earnings dynamics in poor neighborhoods are new to the literature. We also provide novel evidence on how changes in labor market earnings affect the neighborhood in which individuals reside. This complements prior work by Bilal and Rossi-Hansberg (2021) on differences in cross-regional migration in response to mass layoffs between individuals with more or less liquid wealth, as well as work by Golosov et al. (2023) on residential mobility after lottery winnings.

We also add to the literature on neighborhood change (e.g., Card et al., 2008; Rosenthal, 2008; Lee and Lin, 2018; Malone and Redfearn, 2018; Couture and Handbury, 2020). Due to data limitations, these studies generally cannot observe the individual mechanisms that drive neighborhood-level trends.[1] Our results suggest that these individual-level processes are quite dynamic and not well-explained by a general poverty trap understanding.

Finally, our results have implications for the design of place-based policies and the interpretation of previous evaluations of these efforts (Neumark and Simpson, 2015). First, the high rate of resident turnover implies that directing resources to individuals living in a high-poverty neighborhood at a single point in time will do an imperfect job of targeting individuals with extended exposure to concentrated poverty (Gaubert et al., 2021). Second, the responsiveness of migration to earnings implies that small scale interventions that boost earnings of baseline residents might show up as elevated earnings in other neighborhoods. Third, our results speak to the potential of the approach described by Jacobs (1961) of "unslumming the slums, by creating conditions aimed at persuading residents to stay by choice over time." In particular, our finding that residents of high-poverty neighborhoods experience substantial earnings growth and move away from poor neighborhoods when their income rises supports the underlying premise described by Jacobs.

2 Conceptual Framework

We begin with a simple conceptual framework that highlights the quantitative relationship between individual earnings mobility and residential mobility and, in turn, helps to motivate and structure the empirical analysis that follows.

We consider the reduced-form causal relationship between a particular neighborhood charac-

[1] Recent work showing that gentrification primarily occurs through changes in in-migration rather than out-migration is a notable exception (McKinnish et al., 2010; Ellen and O'Regan, 2011; Brummet and Reed, 2021).

teristic experienced by individual i at time t, $\ln q_{i,t}$, and the log income of the person, $\ln y_{i,t}$:

$$\ln q_{i,t} = \beta_i \ln y_{i,t} + \xi_{i,t}, \tag{1}$$

where β_i captures the effect of income on neighborhood characteristics for person i, and $\xi_{i,t}$ captures all other determinants besides income. The basic relationship between neighborhood characteristics and income in equation (1) emerges from many different types of models of neighborhood choice and sorting in which higher-income individuals have higher willingness to pay for a given neighborhood feature. For example, in a discrete choice model similar to Bayer et al. (2007), if higher-income individuals have a higher valuation of characteristic $\ln q_{i,t}$, then they will sort into neighborhoods that offer this characteristic. The causal relationship between income and neighborhood choice may vary across individuals and contexts. Variation in β_i can arise as a result of differences in preferences, constraints, or choice sets of neighborhoods accessible at different costs.[2]

This simple framework facilitates an accounting of the contribution of earnings mobility to neighborhood mobility. In particular, the change in a neighborhood characteristic over a given time interval is:

$$\Delta \ln q_i = \beta_i \Delta \ln y_i + \Delta \xi_i, \tag{2}$$

where $\Delta \ln q_i \equiv \ln q_{i,1} - \ln q_{i,0}$ is the change between periods 0 and 1 in the neighborhood characteristic, and $\Delta \ln y_i$ is the change in income.

Equation (2) highlights three distinct factors that contribute to residential mobility, which correspond to the empirical quantities we estimate below. First, residential mobility depends on the rate of earnings growth, $\Delta \ln y_i$. Second is the extent to which higher earnings growth leads individuals to move to different types of neighborhoods, β_i. Third is the baseline propensity to move

[2]The parameter β_i depends on the neighborhood characteristic being considered, though we suppress that notation for simplicity. Though β_i is expressed as an elasticity with respect to income, it is not simply a preference parameter, since the magnitude of β_i will generally depend on the equilibrium distribution of prices across neighborhoods.

to different types of neighborhoods *irrespective* of earnings growth, $\Delta\xi_i$, due to life-cycle patterns, idiosyncratic preference changes, or other non-income shocks. For example, treating $\ln q_{i,t}$ as the log median income or poverty rate of a neighborhood, equation (2) implies that individuals will be "stuck" in a poor neighborhood ($\Delta \ln q_i = 0$) if they experience no income growth ($\Delta \ln y_i = 0$) or income growth does not translate into higher neighborhood quality ($\beta_i = 0$) and they do not experience non-earnings changes that move them to a better neighborhood ($\Delta\xi_i = 0$). This framework also applies more generally to the residential mobility of individuals who start out in all types of neighborhoods, and our empirical analysis will consider these individuals as well.

Our analysis focuses on measuring and estimating the empirical objects identified in this framework to highlight the relative importance of each determinant of residential mobility. We do this overall and by subgroup in order to evaluate what drives differences in residential mobility across demographic groups.

3 Data and Sample Construction

3.1 Data Sources

We draw longitudinal address location information from the Census Bureau's Master Address File-Auxiliary Reference File (MAFARF). The MAFARF includes the geolocated housing unit of residence for the near-universe of adults in the U.S. in each year from 2000 to 2021, which is derived from federal tax, health, and housing records.[3] We use these data to identify each individual's (2010 vintage) census tract in each year, which we use as our definition of neighborhood throughout the paper.

We use earnings data the from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) database. Our LEHD extract contains 25 states and at least the 2000 to 2021 time period for all states. The data includes quarterly employment and earnings for individuals whose employers participate in unemployment insurance, as well as employer information, such as in-

[3] Graham et al. (2017) and Voorheis et al. (2023) discuss the administrative data sources used to construct the MAFARF, and Sullivan and Genadek (2024) describe how the data can be used for research on migration.

dustry NAICS code.[4] The included states are representative of the country in terms of population, region, and demographic composition.[5] We adjust earnings (and all other dollar-valued variables used in the analysis) to 2019 dollars using the Consumer Price Index.

Individual and household demographics are drawn from the American Community Survey (ACS), which is an annual survey spanning roughly three percent of households in the U.S. For each individual, we observe demographics including age, sex, education, and race/ethnicity. At the household level, we observe whether a household rents or owns their primary residence, their estimated house value or monthly rent, and total household income. In addition, the ACS contains self-reported measures of earnings, wages, and hours worked that supplement the LEHD data.

Finally, we construct neighborhood characteristics by aggregating ACS responses to the tract level. We calculate poverty rates, median household incomes, and median home values using the 2005 to 2009 waves of ACS, which coincides with the start of our sample period. We use time-invariant measures of neighborhood characteristics to ensure that these variables are not influenced themselves by the migration that we study.[6]

3.2 Sample Construction

We combine these data sources to create a large and representative panel of individuals containing information on demographics, residential location, and labor market outcomes. We then use that overarching panel to construct a migration sample, which we use for exercises that do not require earnings information, and an earnings sample.

The initial sampling frame consists of respondents to the 2005 to 2013 waves of the ACS. We restrict to individuals who, at the time they were sampled in the ACS, were at least 25 years old, not full-time students or in the armed forces, not the child of the household head, and not living in group quarters or a census tract in which more than 20 percent of the population is between the

[4] Abowd et al. (2018) provide a useful summary of the LEHD's construction and coverage rate.

[5] Our LEHD extract consists of Arizona, California, Colorado, Connecticut, Delaware, Indiana, Iowa, Maine, Maryland, Massachusetts, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Utah, Virginia, Washington, Wisconsin, and Wyoming.

[6] We have conducted supplemental analyses to ensure that our results are robust to using time-varying neighborhood characteristics.

ages of 18 and 25. The last restriction, which affects about one percent of census tracts, is intended to remove neighborhoods with high amounts of college student housing from the sample.

We define the baseline year for each individual as the year that they were sampled in the ACS.[7] We then merge in longitudinal address information from the MAFARF for the three years prior to and ten years following the baseline. For people living in a state included in our LEHD extract in the baseline year, we then add information on employment and earnings.

Throughout the paper, we group tracts into broad categories based on their poverty rate. The categories are 0 to 10 (roughly the bottom half of tract poverty rates), 10 to 20 (percentiles 50 to 75), 20 to 30 (percentiles 75 to 90), and 30 to 100 percent (the highest decile). The highest poverty category has similar characteristics to the distressed tracts targeted in neighborhood revitalization policies such as Empowerment Zones. For robustness, we also use population-weighted quintiles of median household income (defined nationally) to define neighborhood categories in some exercises.

Depending on the exercise, we use different subsamples of this overarching panel. Defining these samples separately highlights that we measure migration with no requirements on labor market attachment, while our earnings dynamics results require some restrictions on earnings and age that are common to the literature.

Migration sample: For results on migration that do not incorporate any earnings or employment information, we use the matched ACS-MAFARF data for the full U.S. In order to include ten years of neighborhood locations following the baseline ACS survey, we include only respondents to the 2005 to 2011 ACS waves. The migration sample consists of 13.2 million unique individuals, including 670,000 who live in the high-poverty neighborhood category in the baseline year.

Earnings sample: For results on earnings dynamics or the relationship between earnings and migration, we use the matched ACS-MAFARF-LEHD data. We include the 2005 to 2013 ACS waves and use an eight-year follow-up window. (We make this slight change from the selection

[7] In the event that an individual was sampled twice, we use their first response.

criteria of the migration sample to reduce the share of observations that begin during the peak of the Great Recession.) In addition to reducing the number of states included, we further restrict the sample to include only people with at least moderate labor force attachment. We drop individuals who were over age 55 or reported working fewer than 1042 hours in the ACS. The resulting sample contains 1.7 million unique individuals, including 60,000 in high-poverty tracts at baseline. Finally, to prevent outliers from driving our estimates, we also treat person-years in which an individual was observed to earn less than $4,000 or over $300,000 in the LEHD as missing. Similar sample restriction are common in the literature on earnings dynamics (e.g. Abowd et al. 2018).[8]

4 Migration Across Neighborhoods

4.1 Migration Rates

We first document high rates of migration across neighborhoods, with higher rates among individuals living in poorer neighborhoods. Among all individuals in our migration sample, 43 percent of people move to a different tract over a ten-year period. Figure 1 plots the probability that an individual lives in their baseline tract in each of the ten subsequent years, separately for individuals beginning in different types of neighborhoods. Panel A shows that rates of out-migration are elevated for higher-poverty neighborhoods: in tracts where the poverty rate exceeds 30 percent, over 10 percent of individuals move out of the tract every year and 51 percent of individuals live in a different neighborhood ten years later. Even in low poverty neighborhoods, over 40 percent of residents move out of the tract within 10 years. Panel B shows a similar pattern of higher migration rates out of poorer neighborhoods when classifying tracts based on their median income.[9]

This initial analysis examines *all* transitions out of one's initial tract; thus, it is possible that

[8] The next version of this paper will include some results for individuals without this degree of moderate attachment to the labor market.

[9] Brummet and Reed (2021) find that about half of the residents of initially low-income, central city tracts in 2000 had moved by the time they were observed in 2010–2014. Despite the difference in sample and data sources, this is quite close to our estimate for low-income or high-poverty neighborhoods. Because we focus on a broader set of geographies and a later and expanded set of years, the similarity of these two estimates suggests a fair degree of recent stability in out-migration rates from poor neighborhoods.

some of these moves are across quite short distances or within areas that are in practice viewed as the same neighborhood. In soon-to-be-disclosed exercises, we measure the exit rate from the "district" neighborhood units developed in Mast (2025), which consist of 10 tracts on average. This will quantify how often moves across tracts reflect a change in this broader neighborhood measure.

The economic significance of these moves depends on the types of neighborhoods people are moving to. If individuals from poor neighborhoods simply move to other poor neighborhoods, there may be little improvement in the conditions or opportunities they face. We report the full matrix of transitions across neighborhood types in Table 1, using an eight-year period to align with some exercises later in the paper. There is a large amount of mass off the diagonal, especially among people originating in poorer neighborhoods. For example, 36.5 percent of people who begin in the highest poverty category transition to a tract with a poverty rate below 30 percent eight years later.[10] This implies that 81 percent of tract movers move to lower-poverty neighborhoods (= 36.5/45). The small relative size of the highest-poverty category (roughly 10 percent of tracts and 5 percent of individuals in the sample) mechanically increases its out-migration rate relative to the other tract categories, but in Panel B we similarly see that 17.8 percent of the bottom tract income quintile transitions to the third quintile or above by year 8.[11] Individuals also move from richer to poorer neighborhoods, although these types of moves are somewhat less common. This asymmetry is consistent with both net population declines in poor neighborhoods and individuals migrating to less poor neighborhoods as they age. To illustrate this, we will add the number of people who "age in" to the sample in each neighborhood poverty category in a future disclosure.

Comparable statistics on transition rates between neighborhood types appear in a number of papers that take advantage of the PSID's addition of respondents' tract location in the 1990s (Gram-

[10]For comparison, the one-year out-migration rate out of the highest-poverty category is 8.8 percent (Appendix Table A.1). Extrapolating this one-year out-migration rate forward as a Markovian transition probability would imply an eight-year out-migration rate of 47.9 percent ($= 1 - (1 - 0.088)^8$), which is much higher than what we estimate directly. This is consistent with heterogeneous migration propensities leading to dynamic self-selection (Bayer and Juessen, 2012).

[11]Both sets of results show that while a substantial share of individuals who start in low income neighborhoods move to richer neighborhoods, they nonetheless are more likely to live in poor neighborhoods than the overall population.

lich et al., 1992; Massey et al., 1994; South and Crowder, 1997). This work similarly finds high migration rates across high- and low-poverty areas, but the small size of the PSID limits them to one-year transitions and coarser neighborhood categories. When the estimated quantities coincide, we find similar results to these papers, which suggests that across-neighborhood migration rates have not changed much over time.

4.2 Longitudinal Exposure to Concentrated Poverty

These initial results indicate that many residents of high-poverty neighborhoods at a given point in time will exit over the subsequent decade. We quantify *longitudinal* exposure to high-poverty neighborhoods in Table 2, separately for a number of demographic groups. For this analysis, we take the set of people living in tracts with poverty rates over 30 percent in their baseline year and calculate the share of the following ten years that they spend in tracts above this threshold. We freeze tract poverty rates at their 2005–2009 ACS levels and consider the role of neighborhood change separately.[12]

The first row of Table 2 shows that the overall distribution of exposure to high-poverty neighborhoods is bimodal. Thirty-one percent of individuals living in a high-poverty tract at baseline spend no more than 5 out of the next 10 years in concentrated poverty, while 54 percent experience a full 10 years of exposure. Column 5 shows that exits from concentrated poverty typically entail moves to significantly lower-poverty neighborhoods—the average person who has exited concentrated poverty by year 5 lives in a tract with poverty rate 24 percentage points lower than their baseline tract.

The lower rows of the table show that the persistence of exposure to high-poverty neighborhoods varies widely across demographic subgroups. The starkest differences are across age groups. The share of residents with 10 years of subsequent exposure increases from 31 percent among people who were 25–35 at baseline to 71 percent among those over 65. Renters spend fewer of the next 10 years in high-poverty neighborhoods compared to homeowners: the share of people with

[12] We include only individuals who appear in the MAFARF in at least 8 follow-up years. For those appearing in only 8 or 9 years, we scale exposure to 10 years using the fraction of observed years spent in concentrated poverty.

10 years of exposure to high poverty is 41 percent for renters and 66 percent for homeowners. Exposure is generally more persistent for Black and Hispanic individuals than for White individuals, though the racial difference is less than a third of the difference between renters and homeowners.

Households with children are a particularly interesting subgroup, as prior literature has generally found that concentrated poverty has larger negative effects on young children (Chetty et al., 2016). We find that adults in households with children have lower exposure to concentrated poverty than other individuals. The share of individuals spending all 10 years in a high-poverty neighborhood is 10 percent lower for adults in households with children, and 30 percent lower for adults under age 40 in households with children (who are most likely to have young children), compared to the overall sample.

Notably, column 5 shows that, conditional on exiting concentrated poverty, the resulting decline in poverty rate is similar across different groups. In soon-to-be-disclosed results, we will report concentrated poverty exposure among several additional subgroups: low- and high-income households, large and small metro areas, households using rental vouchers, and households living in public housing.

Finally, we consider people who exit concentrated poverty without moving through neighborhood change. Column 6 shows the share of people who stayed in their baseline tract for ten years and saw the tract's poverty rate fall below 25 percent in the 2015–2019 ACS. These are "stayers" whose neighborhood poverty rate fell by at least 5 percentage points during the sample period. These stayers represent 12.7 percent of all individuals who start in a high-poverty neighborhood and nearly 25 percent ($= 0.127/0.538$) of all stayers. The average person in this group sees their tract poverty rate fall by 15 percentage points, as shown in column 7. We will examine the effects of neighborhood change more completely in a future disclosure.

This exercise is closely related to Quillian (2003), who uses the PSID to consider exposure to concentrated poverty. Our findings are consistent with their PSID results—for example, we both find that out-migrants reduce their tract poverty by about 20 percentage points. However, the administrative data allows us to expand the analysis significantly. We report results for finer subgroups, identifying the sharp age gradient and differences between households with and without children, which are important features for connecting to the neighborhood effects literature. We also have a large enough sample to define a higher tract poverty threshold (30 versus 20 percent), which is more similar to the neighborhoods typically targeted by revitalization policies.[13] Although it is focused on a different outcome, prior work on poverty spells (i.e. the amount of time that an individual is poor) also has a similar flavor. Bane and Ellwood (1986) and Stevens (1999) find a bimodal distribution in which many people experience only short spells in poverty, but a large mass is also persistently poor.

5 Earnings Dynamics Across Neighborhoods

Little is known about earnings dynamics in poor neighborhoods or, more generally, how earnings growth varies across people living in different neighborhoods. The combination of the LEHD and MAFARF data allows us to fill this hole in the literature. However, it is important to note that this data only includes earnings from formal wage and salary employment. In addition, these exercises use our earnings sample, which includes only 25 states and requires that individuals in the baseline year are under age 56, report working at least half-time (1042 hours per year) in the ACS, and can be matched to the LEHD. These restrictions shrink the earnings sample to about 13 percent of the migration sample, with the decrease being particularly pronounced in poor areas.[14]

To begin, Figure 2 shows the distributions of eight-year earnings changes among people living in different types of neighborhoods in the baseline year. The distributions are surprisingly similar, although the lowest poverty category has a higher share of large changes, likely due to higher baseline earnings and a higher share of labor force exits. Notably, a large number of people in the poorest neighborhoods see significant labor market improvements, with 17 percent experiencing

[13] Some related work considers how the probability of exiting high-poverty areas varies with household characteristics and years spent in high-poverty areas (South and Crowder, 1997; Frenette et al., 2004). Similarly, Lee et al. (2017) and Sampson and Sharkey (2008) study specific sequences of neighborhood locations.

[14] In a future disclosure we will report earnings results for a broader set of individuals with less attachment to the labor force.

real earnings growth over \$20,000.[15] In a future disclosure, we will report the rate of large earnings improvements among the subgroups in Table 2.

We more formally examine differences in mean earnings growth across individuals living in different types of neighborhoods in Table 3. Column 1 shows results from regressing eight-year individual earnings changes (in levels in Panel A and arc percent in Panel B) on indicator variables for individuals' baseline neighborhood poverty category, with neighborhoods where the poverty rate exceeds 30 percent being the omitted reference group.[16] Mean earnings increases in levels are significantly higher in less poor neighborhoods, ranging from \$4,100 higher in the lowest poverty category to \$850 in the 20–30 percent category. Adding CBSA and year fixed effects in column 2 shrinks the differences only slightly. However, these differences vanish when we examine mean earnings growth *rates* in Panel B. The average arc percent change is quite similar across neighborhoods, even in the specification with no location controls.

Are the differences across neighborhoods largely explained by individual characteristics, or do they reflect either unobservable individual characteristics or the effect of neighborhoods on individual outcomes? Column 3 of Table 3 suggests they can mostly be explained by differences in the observable characteristics of people living in different neighborhoods. The difference between the highest and lowest poverty neighborhoods shrinks to \$1,100, and the coefficients on the intermediate poverty categories fall to below \$500. Adding individual characteristics has little effect on the arc percent change differences, which remain small. While these are not causal estimates, the results are consistent with past work that found that neighborhoods do not have a large effect on adult labor market outcomes (Kling et al., 2007b).

On the whole, our results on earnings dynamics illustrate that there is significant individual earnings growth at all neighborhood poverty levels. The observed patterns could be generated by the combination of individual earnings dynamics documented in prior literature (e.g. high volatility, rapid growth among individuals who start with low earnings) and small effects of neigh-

[15] Massey et al. (1994) used the PSID to compute the probability that individuals living in different types of neighborhoods transition into or out of poverty in the subsequent year.

[16] The arc percent change is the percent change using the start and end point average as the denominator: $\frac{(y_1 - y_0)}{(y_1 + y_0)/2}$.

borhoods on individual earnings. As with migration, these results are not consistent with a pure poverty trap story of concentrated poverty. Individuals in poor neighborhoods experience substantial earnings and residential mobility.

6 Earnings Changes and Migration

We next examine the relationship between earnings growth and residential mobility. We begin with descriptive evidence illustrating that individuals tend to move to higher-income neighborhoods when their income rises. We then use a research design based on idiosyncratic, firm-specific changes in pay to estimate a positive, causal effect of earnings growth on migration to richer neighborhoods. Overall, this evidence shows that earnings growth is a quantitatively important channel of individual migration across neighborhoods.

6.1 Descriptive Evidence

Figure 3 shows how neighborhood choices vary with long-term earnings changes. In Panel A, we bin individuals along the x-axis by their change in real annual earnings over an eight-year horizon and plot the average change in the 2005–2009 median income of their endline census tract relative to that of their initial tract on the y-axis.[17] Because the relationship may differ for individuals beginning in different types of neighborhoods, we stratify individuals based on their baseline tract poverty rate.

People with larger increases in earnings systematically move to higher-income tracts, with a stronger relationship among individuals who begin in higher-poverty neighborhoods. In the highest poverty category, a $10,000 increase in annual earnings over an eight-year period is associated with a $4,000 larger increase in tract income. In contrast, among individuals beginning in the lowest-poverty neighborhoods, a $10,000 increase in earnings is associated with only a $600 increase in tract income. The y-axis intercepts vary significantly across neighborhoods as well. The average

[17] For individuals who do not move, the change in tract median income is equal to 0. Thus, the average eight-year change in tract income reflects both the extent and direction of migration.

person with no earnings change who began in the highest poverty category improves their tract income by $10,000, while the same earnings change is associated with a slight decrease in tract income among people beginning in low-poverty tracts. This points to differences in the trajectory of people in different neighborhoods that are unrelated to earnings, potentially driven by life-cycle factors or mean reversion.

Panel B of Figure 3 restricts to individuals originating in high-poverty neighborhoods and plots the probability that they move to a lower-poverty category. The baseline probability of exit is about 44 percent for individuals with no earnings growth.[18] Consistent with results on tract income, the exit probability increases rapidly as earnings grow: 57 percent of individuals with earnings growth of $20,000 to $30,000 exit a high-poverty neighborhood.[19]

In future work, we will expand these estimates by reporting results separately by subgroup, considering entry to high-poverty neighborhoods, and reporting neighborhood change among people who are not in the earnings sample.

6.2 Quasi-Experimental Methodology

While these correlations are suggestive, they do not necessarily capture the *causal* relationship between earnings growth and residential mobility, For instance, the relationships documented above may reflect life-cycle trends in both earnings growth and neighborhood choice without there being a direct causal relationship between the two. Unanticipated changes in earnings are particularly interesting to study in this context, as forward-looking individuals might make migration choices based on expected earnings in the future. We obtain this type of variation by exploiting idiosyncratic changes in pay at specific employers as in Koustas (2018) and Ganong et al. (2020). Isolating the role of earnings changes is valuable for distinguishing among the mechanisms that determine migration and for considering place-based policies.

[18] This is slightly higher than the exit rate of 38 percent in Table 1 because we use the earnings sample for this exercise.

[19] Some related work has studied the correlation between changes in individual poverty status and migration. Using Canadian administrative data, Frenette et al. (2004) find that less than half of migration into or out of concentrated poverty coincides with a large earnings change or change in household composition. Using the PSID, Massey et al. (1994) do not find that people who moved in a year are more likely to have entered or exited poverty in the same year.

Our research design seeks to compare observationally similar individuals who are employed at observationally similar firms at baseline, but whose firms' payroll grows at different rates. Using idiosyncratic changes in pay at particular firms allows us to hold broader changes in neighborhood conditions constant. Following Rose and Shem-Tov (2023), we focus on individuals who are observed in the ACS in some year between 2005 and 2013 and can be matched to the LEHD. For this analysis we further restrict our earnings sample to individuals for whom we can identify at least 25 coworkers in the LEHD data. For each individual, we construct the "pay shock" as the average percent change in earnings among a holdout sample of coworkers who are observed in the LEHD but not sampled in the ACS between 2005 and 2013. We measure this earnings change between the baseline quarter (when individuals were sampled in the ACS) and four quarters later.[20,21] Using year-over-year changes in earnings limits the impact of seasonality, and our restriction to individuals with at least 25 LEHD coworkers limits the noise in the pay shock variable.

To compare observably similar individuals at similar firms, we include both individual-level and firm-level controls in our primary specification. The individual controls include: initial hourly wage (constructed from information in the ACS), 2005–2009 median income of the tract of residence in the ACS, age, sex, race, ethnicity, and education. Firm-level controls (computed using the holdout sample) include: the log of firm employment, mean pay, median pay, average separation rates, average new worker accession rates, and average separations into non-employment.[22] Finally, we also include fixed effects to control for differential trends across 2-digit NAICS industries and local labor markets (at the CBSA level).

The resulting regression regression specification is:

$$Y_{i,t,k} = \mu_i + \sum_{k=-5,k\neq-1}^{8} \beta_k \text{PayShock}_{i,t} + \theta_{k\times t_q} + \omega_{n(i)\times s(i)\times t_y\times k} + \lambda_{c(i)\times t_y\times k} + X_i'\alpha_{t,k} + \epsilon_{i,t,k}, \quad (3)$$

[20] We restrict the coworker sample to those who earn more than $2,600 at baseline (roughly half-time employment at minimum wage) and are employed at the same firm from the quarter before baseline (i.e., the quarter when a person is observed in the ACS) until the fifth quarter after baseline. Thus, these are coworkers who do not separate from their firm. Since our main sample is drawn from ACS respondents, this holdout sample and the main sample do not overlap.

[21] To limit the influence of outliers, we successively winsorize individual earnings, the percent change in individual earnings, and the pay shock at the 99th percentile.

[22] These firm-level controls are all averaged over the four quarters prior to the baseline quarter.

where $Y_{i,t,k}$ is the outcome of interest, such as log earnings or log tract income, for individual i in year k relative to initial ACS response time t. The pay shock for person i, which is defined as of time t, is $\text{PayShock}_{i,t}$. We allow the coefficients on this variable to vary with relative time, k, and scale it so that coefficients can be interpreted as the effects of a 10 percent year-over-year increase in coworker earnings. We control for common changes over time using the fixed effects $\theta_{t_q \times k}$, which capture the interaction between the ACS quarter of observation (t_q) and relative year of observation (k). The fixed effects $\omega_{n(i)\times s(i)\times t_y \times k}$ allow trends in outcomes to vary arbitrarily based on individuals' baseline 2-digit NAICS industry codes ($n(i)$), baseline state of residence ($s(i)$), and ACS year of observation (t_y). The fixed effects $\lambda_{c(i)\times t_y \times k}$ additionally absorb variation in changes over time by baseline CBSA of residence ($c(i)$) and ACS year of observation. X_i is the vector of individual and firm-level controls, which are interacted with relative time and time of ACS response.[23] We cluster our standard errors at the firm level.

6.3 Causal Effects of Earnings Changes on Migration

We plot the dynamic effects of the coworker pay shocks on individual earnings in Panel A of Figure 4. An increase in coworker earnings of 10 percent is associated with an immediate increase in individual annual earnings of about 2.5 percent. Although the shocks are only defined based on changes in coworker earnings in a single year, their effect on annual earnings reverts only gradually, remaining elevated by 1 percent in year 8. Accordingly, *cumulative* earnings effects grow over time.

The changes at firms captured by the coworker pay shock can affect workers through multiple margins. We find that a positive coworker pay shock increases the probability of remaining at one's initial firm, which, all else equal, might lower the incentive to migrate.[24] Since households can smooth income in response to shocks through adjustments to partners' labor supply, and total

[23]To allow for flexible functional forms, we use indicator variables for quintiles of control variables that are continuous (including hourly wage, 2005–2009 median income of the tract of residence in the ACS, age, the log of firm employment, mean pay, median pay, average separation rates, average new worker accession rates, and average separations into non-employment).

[24]In our data, coworker shocks can be either positive or negative. Thus, analogously, a negative coworker pay shock decreases the probability that individuals remain at their initial firm, which could increase the incentive to migrate.

household income is most relevant for relocation decisions, we also display effects on *household* earnings, defined as combined LEHD earnings of individuals and their partners (as reported in their ACS response).[25] The combined effect on household earnings is slightly smaller than the effect on individual earnings.

Turning to the effects on migration, Panel B of Figure 4 shows that individuals with more positive earnings shocks are more likely to move, with a cumulative effect size reaching 0.4 percentage points eight years after the initial shock. Our earlier results indicate that the baseline probability of moving over an eight-year period is roughly 40 percentage points, implying a 1 percent increase in the probability of moving in response to a persistent 1–2 percent increase in annual earnings. Interestingly, the effect on the probability of moving to a higher-income tract than one's baseline, shown in the green markers, is nearly the exact same magnitude. This suggests that almost all induced relocation is in the same direction as the earnings change: positive coworker pay shocks shift individuals towards higher-income neighborhoods, while negative coworker pay shocks shift individuals to poorer neighborhoods.[26]

Figure 5 considers the relationship between the earnings shock and measures of neighborhood quality. More positive shocks are correlated with moves towards tracts with higher 2005–2009 median income and median housing values. In contrast to the effects on earnings, which fade over time, the effects on neighborhood quality *increase* over time, reaching roughly 0.25 percent at their peak.[27] One useful approach to assessing the magnitude of these responses is to benchmark the end-year effect on tract income (0.24 log points) or home values (0.29 log points) relative to the average effect on household earnings over the post-period (1.37 log points), which reflects the persistent change in earnings. This yields elasticities of 0.175 and 0.212, respectively.[28] Thus,

[25]For individuals who do not report a partner in the ACS, individual and household income are the same.

[26]While the increase in short-run mobility after earnings shocks is consistent with the increase in move rates among lottery winners documented by Golosov et al. (2023), we find that moves after persistent earning shocks are more directed to higher-income neighborhoods than moves after one-off lottery winnings.

[27]One potential explanation of these dynamics is that lumpy relocation decisions are irreversible, and are therefore made based on expectations of long-run income rather than contemporaneous income, such that mobility increases as the persistence of income shocks becomes evident. Relocation decisions may also be sensitive to *accumulated* earnings gains or losses, particularly for credit-constrained individuals buying homes.

[28]In related work, Hilger (2016) estimates the impact of a layoff on zip code median house value using a sample of fathers observed in tax data. The implied elasticity of zip code median house value to earnings is 0.07 (reflecting a

while individuals do not perfectly re-sort after income shocks, they do systematically move to better neighborhoods.[29]

While we will explore this issue more fully in soon-to-be-disclosed results, it is useful to combine the estimates in Figure 5 with typical variation in earnings changes to quantify the degree to which earnings affects migration and neighborhood upgrading. The estimates in Table 3 imply that average eight-year individual earnings growth is around 10 percent. Combined with the estimates shown in Figures 4 and 5, this suggests that typical earnings growth generates an approximately 7 percent (2.7 percentage point) increase in out-migration rates and a 1.6 percent increase in tract median household income.

In soon-to-be-disclosed results, we will expand on this analysis in several ways. First, we will focus on exit from high poverty neighborhoods as an additional outcome variable of interest. Second, we will report heterogeneity in the effects of coworker pay shocks on income and migration. Finally, we will describe robustness checks of the specification in equation (3), which imposes symmetric effects of positive and negative coworker pay shocks.

7 Implications for Neighborhood Change and Place-Based Policy

So far, we have focused on estimating individual-level changes in migration and earnings. We next illustrate how these individual dynamics come together to create a powerful mechanism that keeps poor neighborhoods poor. We then discuss how this general dynamic of poor neighborhoods can inform the design and evaluation of place-based policies.

1.2 percent decrease in zip code median house value and a 17.7 percent decrease in earnings five years after layoff). By comparison, we get an elasticity of 0.14 (reflecting a 0.22 log point increase in tract median house value and a 1.56 log point increase in individual earnings five years after the earnings change). Our approach differs in the sample composition, use of a range of coworker pay shocks (not layoffs) to study intensive-margin earnings changes, and focus on tracts instead of zip codes.

[29] The perfect re-sorting benchmark here considers a situation where individuals always move to neighborhoods where median earnings equals their own earnings conditional on deciding to move. In that case, a 1 percent increase in household earnings would lead households to move to a neighborhood where median income was 1 percent higher, which would lead to an elasticity of 1.

7.1 Individual Dynamics and the Persistence of Concentrated Poverty

In *The Death and Life of Great American Cities*, Jane Jacobs described a process through which individual migration and earnings dynamics can lead to neighborhood stagnation:

> "Once a slum has formed, the pattern of immigration that made it is apt to continue... Successful people, including those who achieve very modest gains indeed, keep moving out... they are quickly replaced by others who currently have little economic choice."

Our individual-level results have shown that each element of this mechanism exists, but they do not demonstrate their importance for neighborhood-level outcomes.

Our linked earnings and migration data provide us with a unique opportunity to transparently assess the story described by Jacobs. In particular, we compare the earnings growth among the *initial cohort* of residents in high-poverty neighborhoods to the earnings of the same neighborhoods' *contemporaneous residents* in subsequent years. The initial cohort's earnings growth reveals how much individual economic improvement a neighborhood could conceivably capture, and the wedge between this and contemporaneous resident earnings reveals the net effect of selective in- and out-migration.

We first compute growth in mean earnings among the cohort of people who lived in each tract poverty category in the 2005 ACS, regardless of where they lived in later years (restricting to the 1965 to 1980 birth cohorts to minimize the roles of retirement and labor force entry.) As shown in Figure 6, earnings growth is quite large over the subsequent ten years for every category, between 24 and 26 percent in real terms. This is consistent with our earnings dynamics results, again illustrating the point that individual earnings growth exists in all types of neighborhoods.

We next compute the mean earnings in each year for the contemporaneous residents of each tract type (restricting to ACS respondents in the same birth cohorts). In low-poverty tracts, resident earnings grow at about the same speed as the earnings of the initial cohort. That is, the mean earnings of low-poverty tract residents in 2015 is similar to the 2015 mean earnings of people who lived in low-poverty tracts in 2005. This is not true in either the 20–30 or 30+ percent poverty neighborhoods, where contemporaneous earnings grow by only 11 percent over the ten-year period. This wedge appears because of another fact that we documented at the individual level: people whose earnings increase tend to move to better neighborhoods, and they are replaced by lower-earning in-migrants. Because migration rates are high, this selectivity significantly depresses neighborhood earnings growth, to less than half of its baseline cohort. (In future work, we will add the earnings of new in-migrants to this figure.)

This dynamic helps explain why concentrated poverty tends to persist through macroeconomic fluctuations and local economic shocks—those forces affect individual outcomes, but selective migration limits their pass-through to neighborhood-level outcomes. The result is quite different from a pure poverty trap story, in which poor neighborhoods would feature depressed earnings growth and low migration rates. Of course, the two stories are by no means mutually exclusive; negative neighborhood effects and the selective out-migration of people with good income realizations can coexist and reinforce each other, and our descriptive statistics suggest that some people really may be stuck. But the exercise illustrates that the dynamic mechanism is strong enough to meaningfully affect neighborhood outcomes.

To our knowledge, we are the first to illustrate and quantify this mechanism. Several recent papers have taken a similar, flow-based perspective to gentrification and shown that changes in in-migration patterns, rather than involuntary out-migration of incumbent residents, is the primary mechanism through which this type of neighborhood change occurs (McKinnish et al., 2010; Ellen and O'Regan, 2011; Brummet and Reed, 2021; French et al., 2023). Sampson and Sharkey (2008) and Quillian (1999) also connect individual changes to neighborhood outcomes using a flow approach.

7.2 Implications for Place-Based Policy

There is enormous demand for successful neighborhood revitalization policies. Unfortunately, existing evaluations of these policies have found mixed results at best. We do not evaluate a specific policy, but our results help develop the "theory of the problem" of poor neighborhoods, which could improve the design of policies that target them (Rossi et al., 2003).

First, high migration rates in poor neighborhoods will affect the success of revitalization policies. The typical program targets a relatively small set of neighborhoods in a metro area. For example, metropolitan areas that were part of the Empowerment Zone program saw about 10 percent of their tracts be included in the zone. This combination of small target areas and high migration rates means that (a) directing resources to individuals living in a high-poverty neighborhood at a single point in time will do an imperfect job of targeting individuals with extended exposure to concentrated poverty and (b) the set of people who have been exposed to the policy will dissipate widely across the city, as individuals continually move into and out of the treatment area. Thus, the targeted area will not capture all the effects a policy has on individuals. This also implies that evaluations that use untreated areas in the same city as a control group may see spatial spillovers that attenuate treatment effect estimates. Paradoxically, our estimates of the causal effect of earnings growth on migration suggest that this problem only gets worse when a policy is effective at increasing resident incomes (as many neighborhood revitalization efforts aim to do).

Second, our results inform the potential of the policy approach suggested in Jacobs (1961) of revitalizing high-poverty neighborhoods by retaining the initial residents who have good income realizations.[30] This policy approach is out of step with current thinking on concentrated poverty, which often focuses on helping people move out of poor neighborhoods. Evaluating the full welfare effects of these opposing approaches is well beyond the scope of this paper, but our results suggest that earnings growth in these areas is strong enough that a policy that successfully increases retention could significantly boost outcomes like average neighborhood incomes.

[30] Jacobs (1961) wrote:

> "Unslumming hinges, paradoxically, on the retention of a very considerable part of a slum population within a slum. It hinges on whether a considerable number of the residents and businessmen of a slum find it both desirable and practical to make and carry out their own plans right there, or whether they must virtually all move elsewhere."

8 Conclusion

This paper uses recently available data to present three key sets of results on individual migration and earnings dynamics. First, we provide evidence of high migration rates across individual neighborhoods and types of neighborhoods classified by income and poverty rates. Migration rates are higher in poor neighborhoods. Second, we show that earnings growth rates are similar across richer and poor neighborhoods. Third, we use both descriptive and quasi-experimental approaches to estimate a positive relationship between earnings growth and migration to richer neighborhoods.

Taken together, these results suggest that most residents of poor neighborhoods are not simply "stuck" there. Instead, many residents of poor neighborhoods experience sizable earnings gains and move to richer neighborhoods. At the same time, we document substantial heterogeneity in these patterns, and the next version of this paper will provide a more complete description of this heterogeneity in terms of both earnings and migration dynamics. The dynamic process of individuals moving to richer neighborhoods when their own income rises is an important mechanism in keeping poor neighborhoods poor.

This paper also lays the groundwork for future research that addresses neighborhood questions using longitudinal individual data. These data are becoming more easily accessible in both the United States and other countries, and there is potential to learn a lot more about neighborhoods. The labor literature boomed after better longitudinal data sources allowed researchers to observe worker flows, leading to new insights on search and matching models, the evolution of firm productivity, compensating differentials, and the role of firms in the worker's life cycle earnings. In the neighborhoods literature, there is room for similar advancement on topics like the effects of neighborhood revitalization policies, measuring neighborhood quality, the passthrough of larger-geography shocks to neighborhoods, measuring racial or income segregation, and the dynamics of particular types of neighborhood change.

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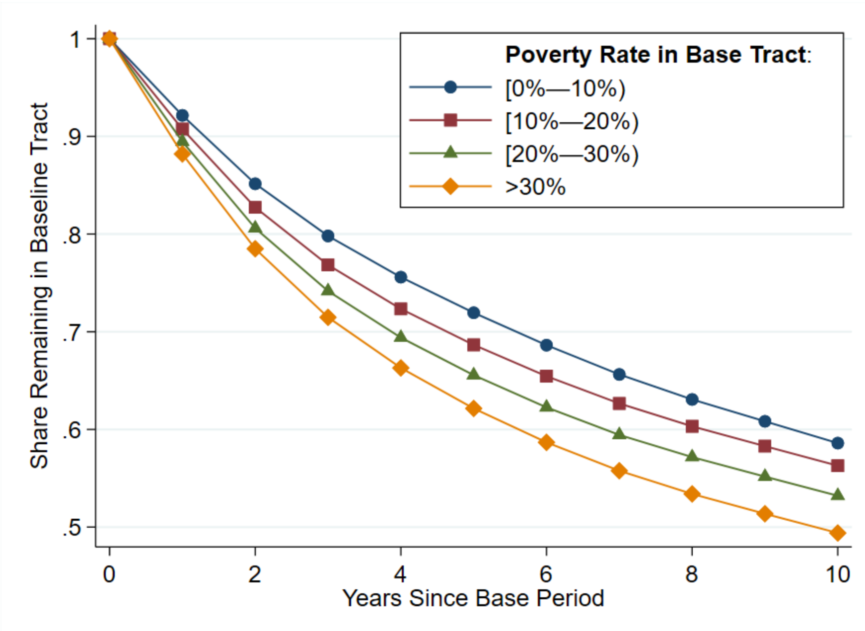
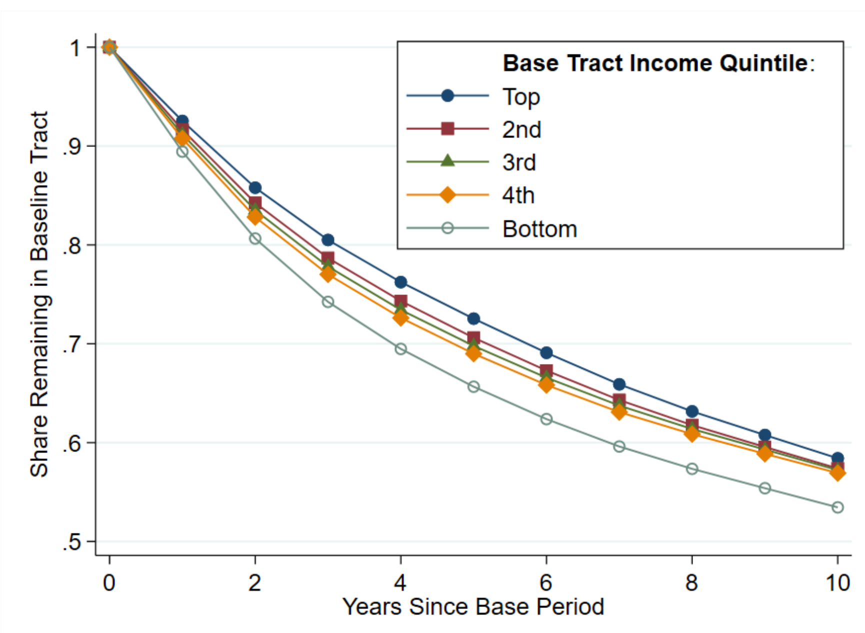
Figure 1: Share of Individuals Remaining in Baseline Tract Over 10 Years

(a) By Baseline Tract Poverty Rate Category



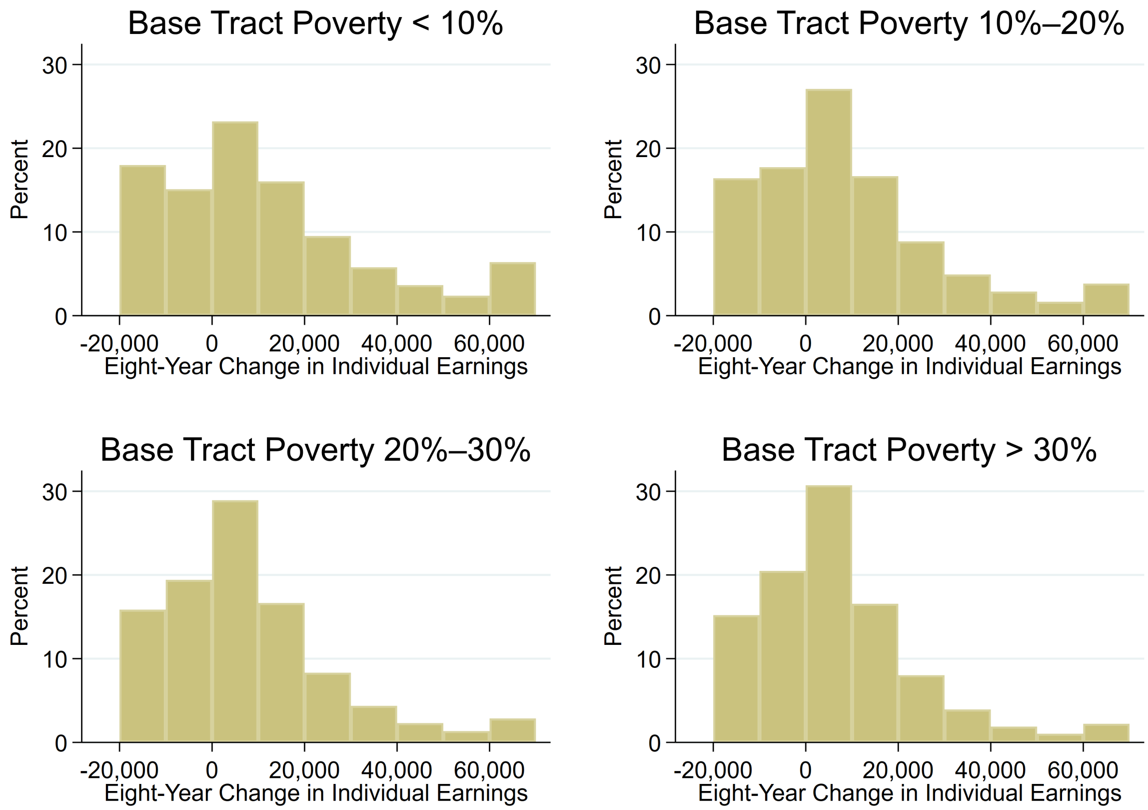
(b) By Baseline Tract Income Quintile



Notes: This figure shows the share of individuals who live in their baseline census tract for each of the 10 years after the baseline year (the year an individual is sampled in the ACS). Individuals are stratified based on the baseline tract's poverty rate (Panel A) or quintile of median household income (Panel B). This figure uses the migration sample, as described in Section 3.2.

Source: Authors' calculations using data from the ACS and MAFARF.

Figure 2: Distribution of Eight-Year Earnings Changes, By Baseline Tract Poverty Rate

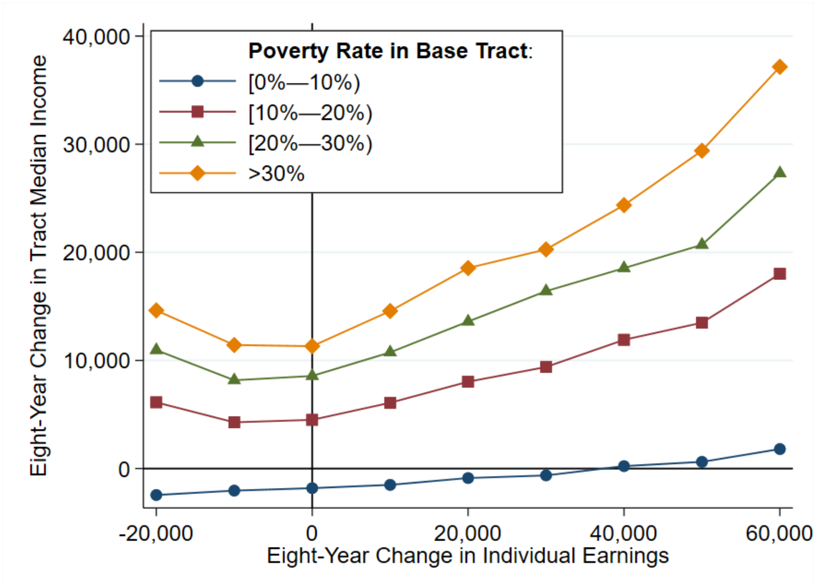


Notes: This figure shows the distribution of earnings changes over an eight-year period that starts when an individual is sampled in the ACS. Individuals are stratified based on the baseline tract's poverty rate. The left- and right-most bins are open-ended. The figure uses the earnings sample, as described in Section 3.2.

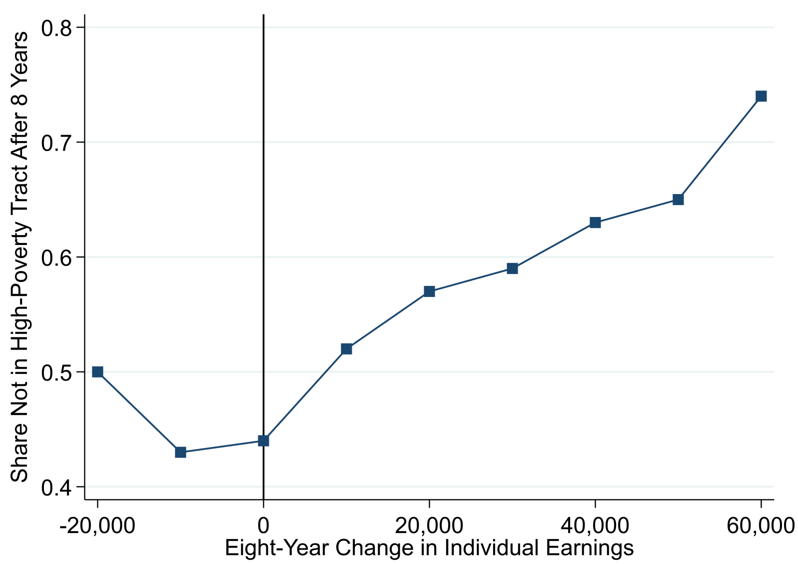
Source: Authors' calculations using data from the ACS, MAFARF, and LEHD.

Figure 3: Tract Mobility and Earnings Mobility Over Eight Years

(a) Movement to Higher-Income Tracts, by Baseline Tract Poverty



(b) Exit From High-Poverty Tracts

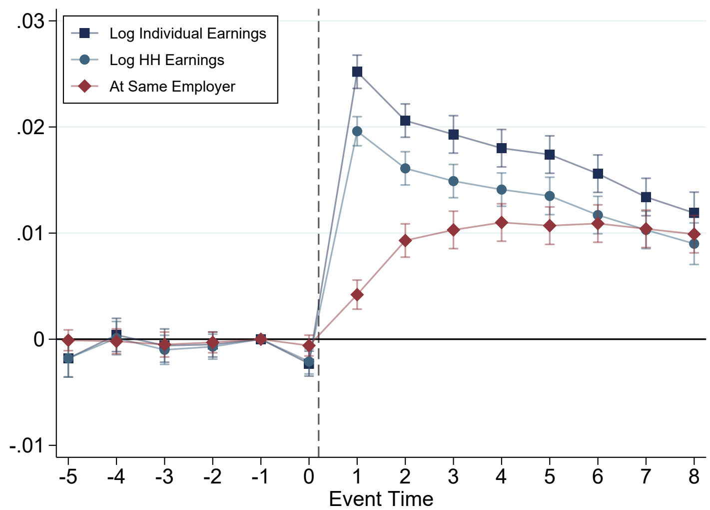


Notes: Panel A is a binned scatter plot that shows the average difference in tract median household income between the individual's baseline tract and the tract they live in eight years later for different levels of earnings changes over an eight-year period that starts when an individual is sampled in the ACS. Individuals in Panel A are stratified based on the poverty rate of their baseline tract. Panel B shows the average probability of transitioning out of a high-poverty tract (baseline poverty rate over 30 percent) for those beginning in a high-poverty tract. The left- and right-most bins are open-ended. The figure uses the earnings sample, as described in Section 3.2.

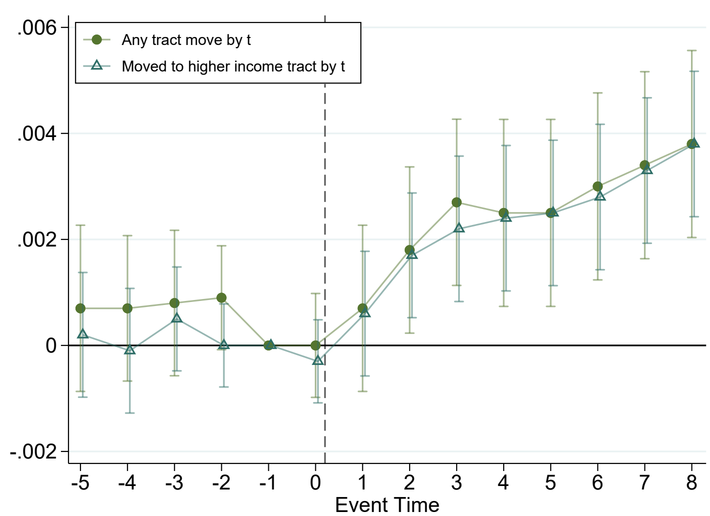
Source: Authors' calculations using data from the ACS, MAFARF, and LEHD.

Figure 4: Effects of a Coworker Earnings Shock on Labor Market and Migration Outcomes

(a) Effects on Labor Market Outcomes



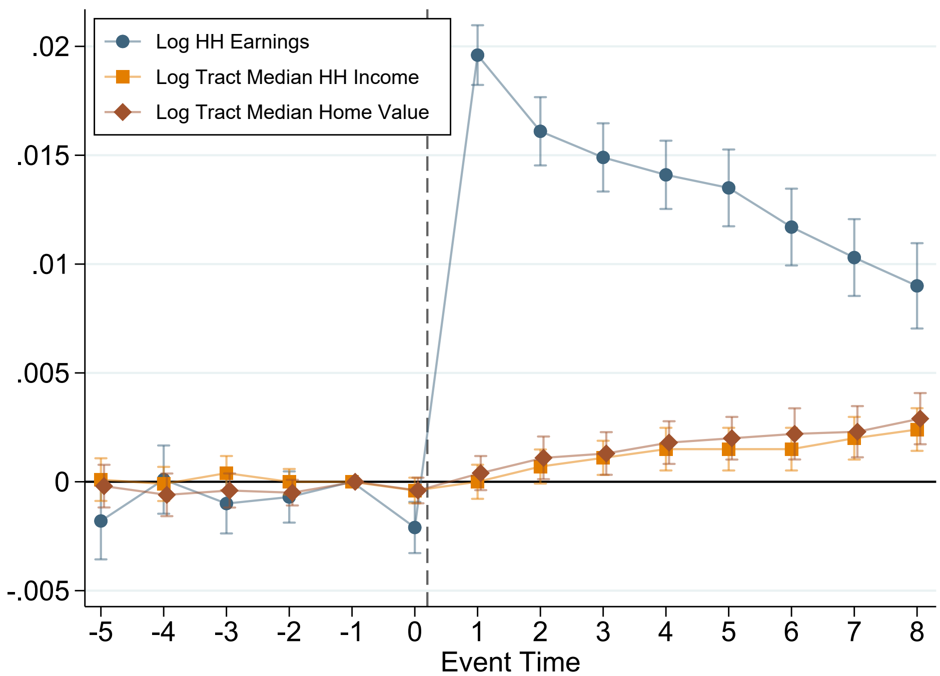
(b) Effects on Migration Outcomes



Notes: This figure displays OLS estimates of equation (3) with 95 percent confidence intervals. The figure uses a subset of the earnings sample consisting of individuals working at firms with at least 25 employees in the holdout sample, as described in Section 6.2. Effects are scaled so that coefficients can be interpreted as the effect of a 10 percent increase in coworker quarterly earnings over a four-quarter period that begins when an individual is sampled in the ACS. Panel A displays effects on the log of individual LEHD annual earnings, the log of household LEHD earnings (defined as the sum of one's own earnings and the earnings of any other individual who was a spouse or partner in the base year in the ACS), and an indicator for remaining at the baseline firm. Panel B displays effects on the cumulative probability of having moved from one's baseline tract and the cumulative probability of moving to a tract with higher median household income than one's baseline tract. Standard errors are clustered at the firm level.

Source: Authors' calculations using data from the ACS, MAFARF, and LEHD.

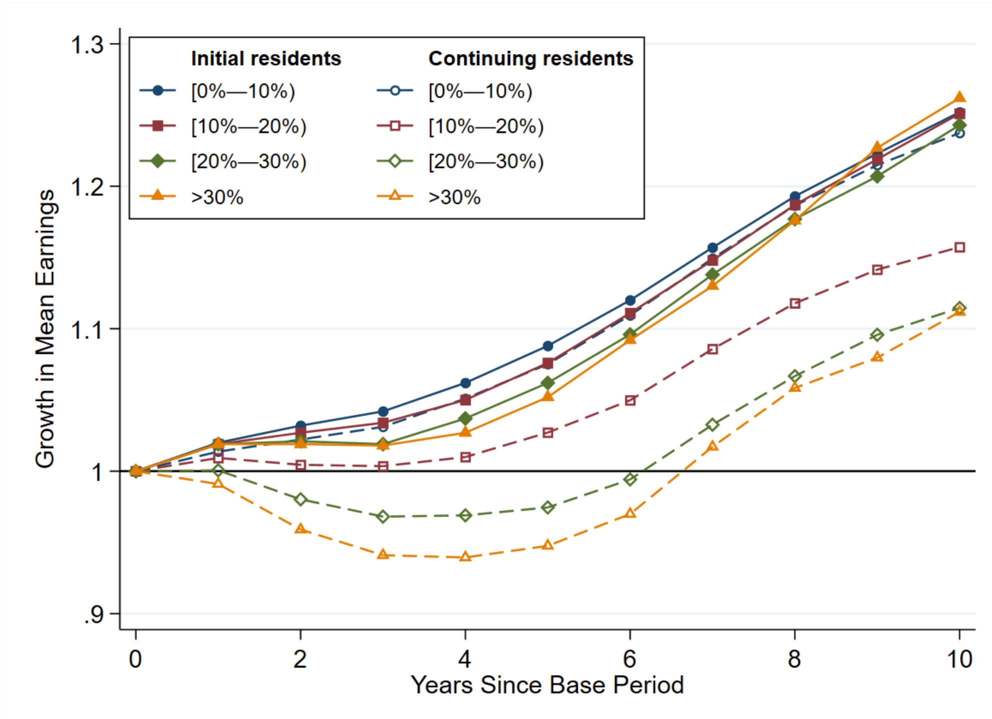
Figure 5: Effect of a Coworker Earnings Shock on Neighborhood Choice



Notes: This figure displays OLS estimates of equation (3) with 95 percent confidence intervals. The figure uses a subset of the earnings sample consisting of individuals working at firms with at least 25 employees in the holdout sample, as described in Section 6.2. Effects are scaled so that coefficients can be interpreted as the effect of a 10 percent increase in coworker quarterly earnings over a four-quarter period that begins when an individual is sampled in the ACS.. The outcomes are the log of household LEHD earnings (reproduced from Panel A of Figure 4 for comparison), along with the log median household income and log median house value (calculated from 2005–2009) of the tract where individuals reside in each year. Standard errors are clustered at the firm level.

Source: Authors' calculations using data from the ACS, MAFARF, and LEHD.

Figure 6: Growth in Average Tract Earnings Versus Earnings Growth of Baseline Residents



Notes: This figure compares the evolution of average earnings in neighborhoods at different poverty levels among individuals who reside in these neighborhood types in each year ("continuing residents") and among individuals who initially resided in each neighborhood type in the baseline year. Average earnings for initial residents appear in solid lines, and earnings for continuing residents are in dashed lines. The exercise uses the earnings sample, as described in Section 3.2, and further restricts to the 1965 to 1980 birth cohorts to minimize the role of retirement and labor force entry. Mean earnings in each year are normalized by the value in the baseline year, and baseline years from 2005 to 2009 are included.

Source: Authors' calculations using data from the ACS, MAFARF, and LEHD.

Table 1: Eight-Year Transition Rates Across Neighborhood Types

Panel A: Neighborhood poverty rate

	Year $t+8$				
Year t	0–10	10–20	20–30	30+	Individuals
0–10	88.4	8.7	2.2	0.8	7,370,000
10–20	19.8	73.6	4.6	2	3,890,000
20–30	16.1	14.9	64.6	4.5	1,300,000
30+	12.7	13.9	9.8	63.5	672,000

Panel B: Quintile of neighborhood median income

	Year $t+8$					
Year t	1	2	3	4	5	Individuals
1	71.8	10.4	8.2	6.1	3.5	2,070,000
2	7.8	70.3	9.2	7.7	5	2,610,000
3	5.1	7.5	70.6	9.5	7.3	2,780,000
4	3.2	5.3	7.8	72.5	11.2	2,820,000
5	1.8	3.1	5.2	9.1	80.9	2,950,000

Notes: This table reports the share of people who start in each type of neighborhood in year t (the year they are sampled in the ACS) that end up in each type of neighborhood in year $t+8$. We classify census tracts based on 2005–2009 poverty rates in Panel A and population-weighted quintiles of the 2005–2009 median household income distribution in Panel B. This exercise uses the migration sample, as described in Section 3.2. The last column reports the rounded number of individuals in the sample who start in each type of neighborhood.

Source: Authors' calculations using data from the ACS and MAF.

Table 2: Exposure to High Poverty Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Share by years in high poverty tract			Mean 5-year change in poverty rate,	Share spending 10 years in tract and poverty rate falls	Mean 2009–19 change in tract poverty rate, column 6
	Individuals	≤5	6–9	10	movers	below 25%	sample
Overall	530,000	0.309	0.153	0.538	-0.237	0.127	-0.148
Age 25–35	92,000	0.502	0.19	0.309	-0.239	0.07	-0.14
Age 35–45	100,000	0.364	0.165	0.471	-0.235	0.117	-0.147
Age 45–55	120,000	0.264	0.145	0.59	-0.233	0.142	-0.148
Age 55–65	110,000	0.207	0.123	0.67	-0.238	0.163	-0.15
Over age 65	100,000	0.156	0.133	0.711	-0.246	0.153	-0.151
Black	180,000	0.29	0.173	0.537	-0.238	0.093	-0.144
Hispanic	130,000	0.27	0.141	0.589	-0.225	0.145	-0.151
White	190,000	0.353	0.138	0.509	-0.243	0.149	-0.148
Other	28,000	0.383	0.164	0.453	-0.247	0.134	-0.153
Owner-occupant	300,000	0.217	0.124	0.659	-0.245	0.173	-0.151
Renter	220,000	0.405	0.184	0.412	-0.233	0.079	-0.139
No kids	320,000	0.275	0.143	0.582	-0.241	0.137	-0.149
Has kids	210,000	0.352	0.166	0.482	-0.234	0.114	-0.146
No kids, under 40	42,000	0.537	0.175	0.288	-0.247	0.071	-0.147
No kids, over 40	280,000	0.223	0.137	0.641	-0.238	0.15	-0.149
Has kids, under 40	100,000	0.437	0.187	0.376	-0.235	0.088	-0.141
Has kids, over 40	110,000	0.262	0.143	0.595	-0.231	0.142	-0.149

Notes: This table provides summary statistics among individuals in the migration sample who are observed living in a high poverty neighborhood (where the 2005–2009 poverty rate exceeds 30 percent) in the year they are sampled in the ACS. Column 1 reports the number of observations. Columns 2–4 report the share of individuals who spend less than or equal to 5, 6 to 9, or 10 of the subsequent 10 years in a high-poverty neighborhood. Column 5 reports the mean 5-year change in the poverty rate among individuals who move out of a high-poverty neighborhood by year 5. Column 6 reports the share of individuals who spend 10 years in a tract that initially has a poverty rate above 30 percent but falls below 25 percent in the 2015-2019 ACS. Column 7 reports the mean 2009–2019 change in the poverty rate among the sample of stayers in column 6. We restrict to individuals who were observed in the MAFARF in at least 8 of the 10 years following their ACS year, proportionally adjusting exposure of those observed in fewer than 10 years.
Source: Authors' calculations using data from the ACS and MAF.

Table 3: Initial Residential Neighborhood and Subsequent Earnings Dynamics

	(1)	(2)	(3)
Panel A: Eight-year change in earnings, dollars			
Poverty rate 0–10	4143	3425	1147
	(136.3)	(132.3)	(129.5)
Poverty rate 10–20	2203	2015	473
	(144.2)	(138.8)	(130.4)
Poverty rate 20–30	851.5	694.1	-68.83
	(160.9)	(154)	(142.3)
Intercept	5726	6234	8110
	(125.1)	(123.5)	(121.8)
Individuals	1,674,000	1,674,000	1,674,000
R-squared	0.0015	0.0185	0.059
CBSA and year FE		X	X
Individual controls			X
Panel B: Eight-year change in earnings, arc percent			
Poverty rate 0–10	-0.0025	-0.0061	-0.006
	(0.0028)	(0.0028)	(0.0029)
Poverty rate 10–20	-0.0014	-0.0034	-0.0059
	(0.003)	(0.0029)	(0.0029)
Poverty rate 20–30	-0.0038	-0.0048	-0.0065
	(0.0034)	(0.0033)	(0.0032)
Intercept	0.104	0.1069	0.1076
	(0.0028)	(0.0028)	(0.0028)
Individuals	1,674,000	1,674,000	1,674,000
R-squared	0	0.0135	0.0401
CBSA and year FE		X	X
Individual controls			X

Notes: This table reports regressions in which the dependent variable is the change in individual earnings over the eight-year period that starts when an individual is sampled in the ACS, measured in dollars (Panel A) or the arc percent (Panel B). The key explanatory variables of interest are indicators for the poverty rate of the neighborhood where an individual is observed at the start of the eight-year period; the omitted indicator is for the poverty rate above 30 percent. Columns 2 and 3 include CBSA and year fixed effects. Column 3 includes fixed effects for individual race, age, and baseline education. The exercise uses the earnings sample, as described in Section 3.2. Standard errors, clustered at the level of the baseline tract, are reported in parentheses.

Source: Authors' calculations using data from the ACS, LEHD, and MAF.

Online Appendix

A Life Cycle Patterns

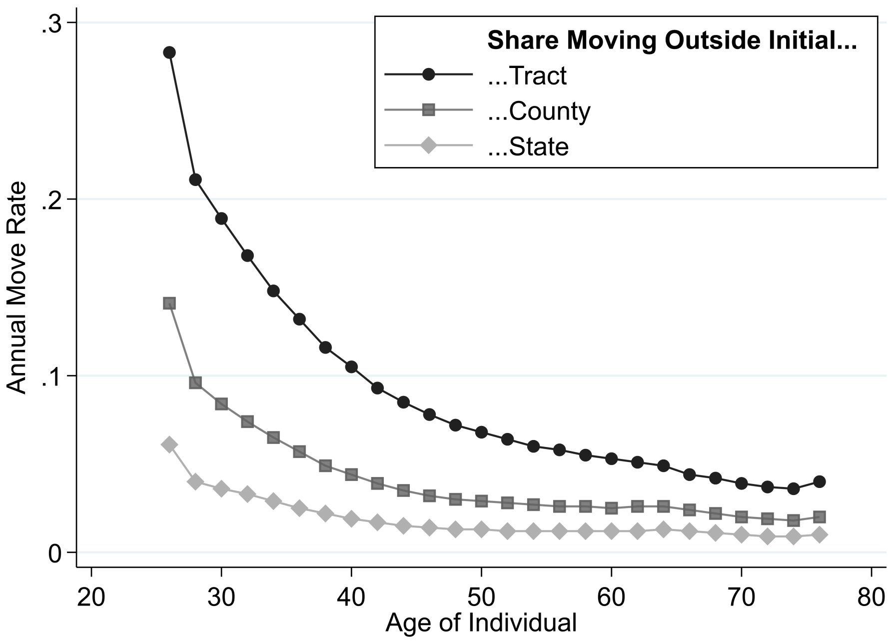
The top panel of Figure A.1 shows that migration rates vary greatly by age. Nearly 30 percent of 25 and 26 year-olds move in a given year, versus 15 percent of 35 year-olds and only 6 percent of 55 year-olds. For all age groups, between 50 and 60 percent of moves are across tracts within a county. This steep gradient in overall migration rates likely reflects a number of ways that moving costs increase with age, including increasing homeownership rates and growing household sizes. It may also occur because people gradually discover and move to their desired location. Regardless of the reason, it is clear that a disproportionate share of migration across neighborhoods is driven by young people.

The bottom panel of Figure A.1 shows how individuals' experienced neighborhood characteristics tend to improve over the course of the life cycle.[31] The share of individuals who reside in a high poverty neighborhood falls from 11 percent at age 25 to 7 percent at age 64. This represents a 36 percent decrease in the share of people living in a high poverty neighborhood over four decades; by comparison, the results in Table 1, Panel B show a comparable movement out of high poverty neighborhoods over just an eight-year period. We view this evidence as suggesting that life cycle forces can explain some, but likely not all, of the cross-neighborhood migration patterns, which leads us to focus on the role of changes in earnings next.

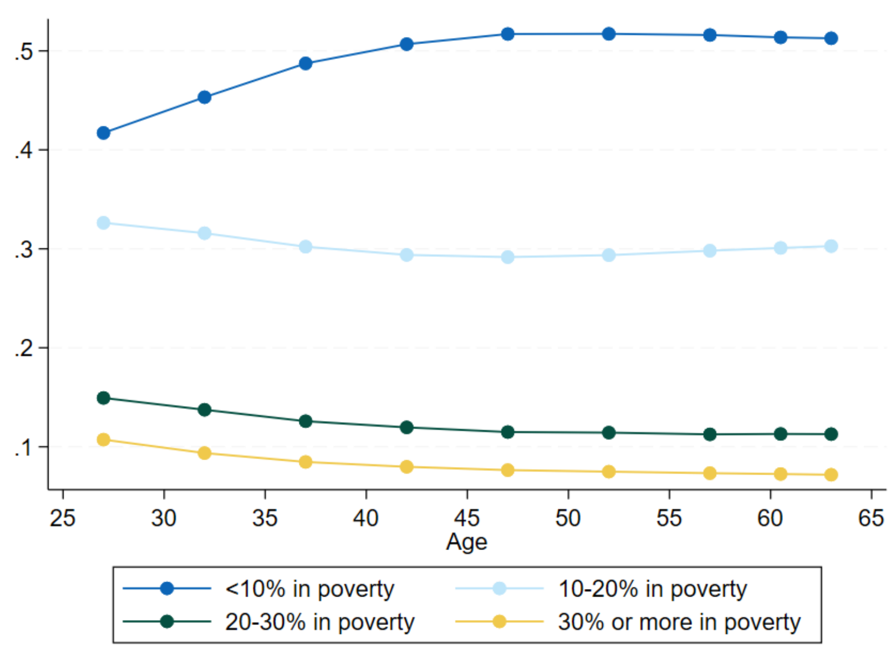
[31]As in our main analysis, we measure neighborhood conditions at a single point in time to isolate the role of migration.

Figure A.1: Annual Neighborhood Mobility, By Age

(a) Migration Rate



(b) Share Living in Tracts With Different Poverty Rates



Notes: Panel A displays the share of individuals in each two-year age bin who move across census tract, county, or state lines in a year. This figure uses the migration sample, as described in Section 3.2, and migration is measured over the year after an individual is sampled in the ACS. Panel B displays the average of the log median household income level from 2005–2009 that is experienced by individuals of each age. This comes from publicly available ACS data for all U.S. residents.

Source: Authors' calculations using data from the ACS and MAFARF.

Table A.1: One-Year Transition Rates Across Neighborhood Types

Panel A: Neighborhood poverty rate

	Year $t+1$			
Year t	0–10	10–20	20–30	30+
0–10	97.2	2	0.5	0.2
10–20	4.2	94	1.2	0.6
20–30	3.5	3.7	91.5	1.3
30+	2.7	3.4	2.7	91.2

Panel B: Quintile of neighborhood median income

	Year $t+1$				
Year t	1	2	3	4	5
1	93.5	2.6	1.9	1.3	0.7
2	2.1	93.1	2.1	1.7	1
3	1.3	1.8	93.3	2.1	1.4
4	0.8	1.2	1.8	94	2.2
5	0.4	0.7	1.1	1.9	96

Notes: Table reports the share of people who start in each type of neighborhood in year t (the year they are sampled in the ACS) that end up in each type of neighborhood in year $t+1$. We classify census tracts based on 2005–2009 poverty rates in Panel A and population-weighted quintiles of the 2005–2009 median household income distribution in Panel B. This exercise uses the migration sample, as described in Section 3.2.

Source: Authors' calculations using data from the ACS and MAF.