Accounting for Changes in Intergenerational Mobility

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Abstract: We use data from Opportunity Insights to study changes in intergenerational mobility over time in the U.S. Previous research has found no change in mobility at the national level, but we show that this hides substantial increases and decreases in mobility at the local level. These changes appear to be persistent, not simply noise. We use an R^2 decomposition to account for the changes in mobility. Changes in labor market conditions and house prices can explain two thirds of the changes in income mobility. Our results suggest caution in treating mobility as a fixed characteristic of a place.

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I. Introduction

Intergenerational mobility is widely studied and often treated as a marker of a society's level of fairness or opportunity. Recently, with access to the universe of tax records for certain birth cohorts and the ability to link parents and children based on dependent claiming, researchers have been able to study mobility in the U.S. at much finer levels — both geographically and temporally — than was previously possible. Chetty et al. (2014a) find large geographic variation in mobility. Focusing on upward mobility for children whose parents are at the 25th percentile of the national parent income distribution, they show that mobility is highest in the Mountain West and rural Midwest, and lowest in the Southeast. Chetty et al. (2014b) address the question of changes in mobility over time at the national level, and find that upward mobility was close to constant for children born 1971–1993.

We revisit the spatial and temporal variation in intergenerational mobility by examining changes in mobility across birth cohorts at the level of commuting zones (CZs), which are clusters of counties. We use statistics released by the Opportunity Insights project on income mobility for the 1980–86 birth cohorts and on college mobility for the 1984–93 birth cohorts. The changes in income mobility are mapped in Figure 1, revealing more positive changes in Texas, most of the Southeast, and some of the Midwest, and more negative changes in the West and in Florida. We find that while average income mobility did not change across these cohorts, there were large increases and decreases at the local level. Almost one third of the CZs experienced a change larger than half of the cross-CZ standard deviation in income mobility among the 1980 cohort. To assess whether some of these changes are persistent, we regress changes in mobility on lagged changes. If much of the observed changes are temporary, then mean reversion implies that earlier and later changes will be negatively correlated. We do not find this. Instead, earlier changes are only weakly predictive of later changes, suggesting persistence.

We find that places with larger black populations experienced more positive changes in both income and college mobility. Otherwise, the link between prominent CZ characteristics and changes in mobility is somewhat murky. For example, higher-income CZs experienced more negative changes in income mobility but more positive changes in college mobility. We decompose the changes in mobility for children whose parents are at the 25th percentile of the national parent income distribution into a "shift" component — an increase in children's expected income ranks across the distribution of parents' ranks — and a "pivot" component — a change in the rank-rank relationship that disproportionately benefits children of lower-income parents. We find that roughly 70–80 percent of the changes in mobility are due to shifts, and 20–30 percent of the changes are due to pivots.

We then develop an accounting exercise to better understand these changes in mobility. We explore three sets of potential explanations for changes in income mobility: changes in the demographic composition of birth cohorts, changes in labor market conditions faced by each cohort, and exposure to the decline in house prices at the end of the mid-2000s house price boom. In this exercise, we treat children born 1980–81 as the initial cohort and children born 1985–86 as the final cohort. We estimate first differences regressions of changes in mobility on changes in CZ covariates, and we use an R^2 decomposition to allocate explanatory power to each covariate.

Using birth certificate data from Vital Statistics to measure the demographic composition of birth cohorts at the CZ level, we find that changes in cohort composition can explain 22 percent of the variance in changes in income mobility. Changes in mothers' race, educational attainment, and birthplace make up the majority of this explanatory power. We next turn to the role of labor market conditions. The Opportunity Insights income mobility statistics we use are based on individuals' income at age 26, meaning that the 1980 and 1986 birth cohorts were facing very different labor market conditions at the time their incomes were observed, and especially large changes in local labor market conditions might explain some of the geographic variation in changes in mobility. We measure exposure to labor market conditions using the unemployment rate, employment-to-population ratio, and the distribution of employment across each of 21 industry codes. The data for these variables comes from the Bureau of Labor Statistics (BLS) and the Census Bureau. We find that changes in labor market conditions can explain 19 percent of the changes in income mobility, and we find an especially large role for employment in the construction industry.

Motivated by this large role for construction jobs, and by our map in Figure 1 that shows decreases in income mobility in states including California, Arizona, and Florida, we consider house prices as an explanation for changes in income mobility. Higher house prices could spur building and thereby provide employment opportunities in the construction industry. House prices could also operate less directly, as housing wealth promotes more consumption of non-tradable services (Mian and Sufi, 2014), which may boost employment and wage growth throughout the lower-skill segments of the labor market. Using the House Price Index (HPI) developed by the Federal Housing Finance Agency (FHFA), we find that changes in house prices can explain one third of the variance of changes in income mobility. When we control for cohort composition, the explanatory power of house prices increases to almost half of the variance of changes in income mobility, and the role of cohort composition becomes negligible.

We repeat this exercise for the changes in college mobility between the 1984–85 and 1992–93 birth cohorts. Changes in cohort composition can explain 14 percent of the variance of changes in college mobility, with mothers' race and education being the most important factors. Labor market conditions at age 18 are also important. In our preferred specification, changes in industry employment shares can explain 13 percent of the variance of changes in college mobility. In stark contrast to our results for income mobility, changes in housing prices explain almost none of the changes in college mobility. We also explore the potential roles of changes in tuition at public colleges and universities, and of changes in state cohort size, but we find that these factors also play at most a very minor role.

Our work complements a growing literature that uses the statistics produced by Opportunity Insights to study geographic variation in mobility. Rothstein (2019) finds that spatial variation in the link between parental income and children's human capital explains only a small share of the spatial variation in income mobility. He finds larger roles for spatial variation in earnings not mediated by human capital, and for spatial variation in marriage patterns. Lefgren, Pope, and Sims (2020) analyze variation in county-level mobility within and between states and find at most a very weak role for state-level policies in explaining spatial patterns of income mobility. Local characteristics that have been linked to income mobility include historical racial segregation (Andrews et al., 2017), the Great Migration of African Americans from the South to the North between 1940 and 1970 (Derenoncourt, 2019), school finance reforms that equalize revenues across public school districts (Biasi, 2019), low birthweight (Robertson and O'Brien, 2018), and the level of violent crime (Sharkey and Torrats-Espinosa, 2017).

We also add to the literature on changes in mobility over time. Aaronson and Mazumder (2008) and Hilger (2017) use decennial censuses and other data sources to study trends in intergenerational mobility. These papers study different types of mobility — Aaronson and Mazumder (2008) study income mobility and Hilger (2017) studies education mobility — and use different strategies to overcome the problem of matching parents and children in census data, but both find an increase in mobility for children born between roughly 1910 and 1940, followed by a decrease in mobility for children born between roughly 1940 and 1970. Lee and Solon (2009), using the Panel Study of Income Dynamics, find little change in income mobility for cohorts born between 1952 and 1975. Chetty et al. (2014a) estimate roughly constant mobility across birth cohorts 1971–1993, where mobility is measured as the slope in a linear regression of the child's income rank or college attendance on parental income rank. Chetty et al. (2017) address a different concept of mobility: the fraction of children who earn more than their parents. They estimate that, by this measure, mobility steadily declined for children born between 1940 and 1960, then declined more slowly for children born between 1960 and the early 1980s. Finally, Fletcher and Han (2018) study the transmission of education from parents to children, and find that educational mobility decreased between the 1964 and 1974 birth cohorts, then increased between the 1974 and 1986 cohorts.

Our work also contributes to a small literature that adds some qualifications to the findings produced by the Opportunity Insights project. Gallagher, Kaestner, and Persky (2019) argue that geographic differences in family characteristics can explain a large share of the spatial variation in income mobility documented by Chetty et al. (2014a). Similarly, Rothbaum (2016) finds that some spatial variation in forecasted causal effects of place in Chetty and Hendren (2018a, 2018b) can be attributed to geographic differences in resident characteristics.

II. Data

a. Opportunity Insights data on income and college mobility

Our data on intergenerational mobility comes from the Opportunity Insights project.[1] The process of measuring mobility is described in detail in Chetty et al. (2014a), so we will only provide a summary here. Opportunity Insights begins with tax records for individuals born 1980–91 who are U.S. citizens as of 2013. Parents of these individuals are identified based on dependent claiming. Income, for both parents and children, is defined as household pretax income. Parent family income is averaged over 1996–2000, and child family income is measured at age 26. The earliest cohort in the

[1] We use the file "Trends in Mobility: Commuting Zone Intergenerational Mobility Estimates by Birth Cohort."

income mobility data is children born in 1980 and observed in 2006. The final cohort for which we have income mobility data is children born in 1986 and observed in 2012.

Opportunity Insights ranks parents in the national distribution of parent income, and children in the national distribution of child income among the appropriate cohort. Income mobility is then defined as the expected rank achieved by children whose parents are at the 25th percentile of the national parent income distribution. This is computed using simple regressions, specific to each CZ and cohort, of children's ranks on parents' ranks, and taking the fitted value for children with parents at the 25th percentile. That is, if the child's rank is r and the parents' rank is p, then the expected outcome for children in CZ c and cohort t, conditional on parental income, is

$$\bar{r}_{pct} = \alpha_{ct} + \beta_{ct} p \ . \tag{1}$$

Chetty et al. (2014a) focus on the 1980–82 cohort and define $\bar{r}_{25,c}$ as absolute mobility (AM). We adopt that definition in this paper.

College mobility is based on the relationship between parents' income and children's college attendance at age 19. The measurement is the same as for income mobility in equation (1), but replacing the child's income rank with an indicator of the child's college attendance as the outcome of interest. Opportunity Insights defines college attendance as the existence of a 1098-T form filed on the child's behalf by a college or university. These forms are filed directly by the college or university, so college attendance is well measured regardless of whether the child files a tax return. The first birth cohort for which Opportunity Insights provides college mobility data is 1984, and the final cohort is 1993. College attendance is measured at age 19 in the data set we use, which therefore spans 2003 to 2012 for this group of cohorts.

The Opportunity Insights data reports α_{ct} and β_{ct} for CZ-cohort cells with at least 250 children. For simplicity, Opportunity Insights assigns each child permanently to the first CZ in which they are observed. For most children, geographic location is assigned using 1996 tax returns, which is the first available year of parent tax return data.

b. Limitations

Because there are just a few hundred observations in some CZ-cohort cells, statistical noise in the mobility estimates complicates our goal of learning about changes in mobility. This noise is smaller in larger CZs, so all of our results are weighted by cohort size, and in our descriptive analysis, we present some results both for all CZs and for the largest half of CZs. In our regressions, the dependent variable is the change in mobility over time, and the noise in the underlying mobility data may reduce the precision of our estimates. For example, if the noise in the CZ-cohort mobility estimates is classical, this would increase the variance of our dependent variable, and our standard errors would be too large.

There are a couple of measurement concerns specific to our analysis of income mobility. One is related to the distinction between the permanent and transitory components of income. As is well known in the literature on intergenerational mobility, single-year measures of parents' income may reflect large transitory shocks, and this can attenuate the estimated intergenerational transmission (Solon, 1992; Zimmerman, 1992). Opportunity Insights handles this in the usual way, averaging parents' income across 1996–2000 to obtain a better estimate of parents' permanent income, before assigning parent income ranks. The resulting mobility estimates should no longer be biased downward, but will still be somewhat noisy because children's income is measured using a single year. This is another reason we expect our standard errors to be overstated, as discussed in the previous paragraph.

A second concern about the measurement of income mobility is that children's income is observed relatively early in their careers, at age 26. Yearly earnings is a downwardly biased measure of permanent earnings earlier in life, and upwardly biased later in life (Grawe, 2006). Because this measurement error is non-classical, it can bias estimates of intergenerational persistence when it affects the dependent variable, as it does in equation (1). Opportunity Insights measured parents' income closer to mid-career, as recommended in the literature (Haider and Solon, 2006), but this was not possible for children. Using a smaller sample drawn from earlier birth cohorts, Chetty et al. (2014a) find that estimated intergenerational persistence is similar when children's income is measured at ages 26 and 40. Also, the presence of any life cycle bias in the estimated *level* of mobility would not necessarily affect the estimated *changes* in mobility over time, the outcome of interest in this paper, as long as the degree of life cycle bias is stable across birth cohorts.

c. Sources of CZ-level correlates of mobility

Our data on CZ-level correlates of mobility comes from a wide variety of sources. In the next section, we correlate changes in mobility with some basic CZ characteristics, such as income per capita and percent black. These characteristics were published with the mobility statistics by Opportunity Insights, and originally come from the 2000 census.

When seeking to explain changes in mobility through changes in CZ characteristics, we use data on demographic characteristics of birth cohorts, labor market conditions, house prices, in-state tuition, and state cohort size. The data on cohort size and on demographic characteristics of birth cohorts, such mother's race and educational attainment, is computed using birth certificate data from Vital Statistics. Local unemployment rates are from the Local Area Unemployment Statistics program of the Bureau of Labor Statistics. We obtain employment estimates from the same source, and combine these with estimates of the adult population from the Surveillance, Epidemiology and End Results (SEER) program to compute employment-population ratios. Industry employment shares are from the Census Bureau's County Business Patterns data. House Price Index data is from the Federal Housing Finance Agency. Finally, we obtain data on in-state tuition and fees at public colleges and universities from The Integrated Postsecondary Education Data System (IPEDS).

III. Changes in mobility

This section presents a description of changes over time in mobility. Together, the results on income mobility (1980–86) and college mobility (1984–93) cover 14 birth cohorts. We begin by characterizing the distribution of the changes in mobility, and the geographic variation in these changes. We then use a handful of CZ characteristics to study the correlates of the changes in mobility. By studying successive changes in mobility for one-year or two-year cohorts, we show that the changes in mobility appear to be persistent, not merely noise or transitory fluctuations. Finally, we separate the mobility changes into "shifts" and "pivots" of the rank-rank relationship between children's income and parents' income, and find that 70–80 percent of the mobility changes are due to shifts in the rank-rank relationship.

a. The geographic distribution of changes in mobility

Table 1 summarizes the distribution of changes in mobility at the CZ level. The mean change in income mobility between the 1980 and 1986 cohorts, weighted by cohort size, is less than 0.2 percentiles, echoing the absence of change in mobility at the national level documented by Chetty et al. (2014b). But there are large changes in income mobility at the local level: 202 of the 631 CZs had a change in mobility that was greater in magnitude than 2.4 percentiles, which is half of the 1980 cross-CZ standard deviation in mobility. College mobility increased by 3.1 percentiles on average between the 1984 and 1993 birth cohorts, and there is again a wide distribution of changes across CZs.

Table 2 lists the places with the most positive and negative changes in mobility. We show these for all CZs and for the largest half of CZs, recognizing that some of the largest changes among all CZs could be due to noisy estimates from smaller places. The most positive changes in income mobility are heavily concentrated in North Dakota and Texas, likely reflecting resource booms in those areas between 2006 and 2012, when income at age 26 was measured for these cohorts. As we examine larger CZs, Texas remains quite overrepresented. The most negative changes in income mobility are more geographically dispersed, but as we focus on larger CZs, places in California and Florida make up half of the list. The bottom half of Table 2 lists the most positive and negative changes in college mobility. The large changes are more geographically scattered than for the changes in income mobility. One notable exception is that Texas and North Dakota are overrepresented among the most negative changes, likely reflecting the higher incomes available to non-college workers because of regional resource booms.

Figure 1 maps the changes in income mobility at the CZ level. For this map, we show the change between the 1980–81 and 1985–86 cohorts; this smoothes out some of the noise in the single-cohort estimates and matches our accounting exercise in the following section. The most positive changes are in Texas, the Upper Midwest, and the Southeast. The most negative changes are in the West, but moderately negative changes are also visible in Florida, the Middle Atlantic, and New England. Most parts of the Rust Belt experienced little change in income mobility. Appendix Figure A1 maps the changes in college mobility between the 1984–85 and 1992–93 birth cohorts.

b. Descriptive analysis of changes in mobility

In Table 3, we use some CZ characteristics (from Opportunity Insights data, and based on the 2000 census) to describe which types of places had more positive or negative changes in mobility. In selecting which characteristics to use, we were heavily guided by the discussion in the original Chetty et al. (2014a) study of geographic variation in income mobility. In each regression, we include the initial level of mobility, for two reasons. First, Chetty et al. (2014a) found that the level of mobility was correlated with a number of CZ characteristics. Second, we expect some mean reversion in the changes in mobility, and including the initial level therefore improves the precision of our estimates. Each regression is weighted by average cohort size.

The top half of Table 3 studies correlates of changes in income mobility, treating 1980–81 as the initial cohort and 1985–86 as the final cohort. The coefficient on the initial level of mobility is always negative and statistically significant, consistent with our expectation of some mean reversion in the mobility estimates. We include other correlates first one at a time in columns (2)–(6), then jointly in column (7). There is some evidence of more positive changes in income mobility in more disadvantaged areas: lower income per capita and a higher fraction black are associated with more positive changes. But in the final column, a higher social capital index and a lower fraction of single-mom households are also associated with more positive changes. The Gini index among the bottom 99 percent is statistically insignificant in all regressions. The bottom half of Table 3 repeats this exercise for changes in college mobility between the 1984–85 cohort and the 1992–93 cohort. We again find that places with a larger black population experienced more positive changes, but CZs with higher income per capita also experienced more positive changes in college mobility. The coefficients on the other three CZ characteristics are statistically insignificant.

c. Persistence of changes in mobility

The question of whether these changes in mobility are transitory or persistent is crucial for the interpretation of our findings above, and for the usefulness of our decomposition exercise below. If the changes are transitory — for example, caused by short-lived local economic shocks, or the result of year-to-year variation in the composition of parents in smaller areas — then mobility may well be a fixed characteristic of a place, but it may be important to use many years of data in estimating the amount of mobility. On the other hand, if the changes in mobility are persistent, then we should be wary of treating mobility as a fixed characteristic of a place.

To address this question of persistence, we regress changes in mobility on lagged changes and cohort fixed effects. That is, for CZ c and cohort t, we estimate

$$\Delta \mathrm{AM}_{ct} = \alpha + \beta \, \Delta \mathrm{AM}_{c,t-1} + \gamma_t + \varepsilon_{ct} \,. \tag{2}$$

If mobility in each CZ were on a linear trend with no transitory disturbances, then $\beta = 1$. If mobility follows a random walk, so that previous changes persist indefinitely, then $\beta = 0$. And if changes in mobility are purely transitory disturbances, then a positive change would be expected to be followed by a negative change, such that

$\beta = -0.5$.[2] We cluster standard errors at the state level to account for spatial correlation across CZs.

Table 4 shows the results of this exercise. In panel A, we use all available data, which includes CZ-cohort cells with at least 250 births. If we use one-year birth cohorts, the coefficient on the lagged change is negative and statistically significant, consistent with an important role for transitory fluctuations. But if we use two-year birth cohorts, the estimates are close to zero, suggesting persistence in the changes. For college mobility, we have a long enough panel to use three-year cohorts — that is, we regress the change between the 1987–89 and 1990–92 cohorts on the change between the 1984–86 and 1987–89 cohorts. Here, we find the coefficient on the lagged change is positive, which suggests not just persistence but the presence of some underlying trend.

We take these results as strong evidence that many of the changes in mobility do not fade out within a few years. The college mobility series covers a full decade, but we would certainly be interested in the longer-term persistence of these changes if further data was available. We can use the data on income and college mobility to construct a consolidated series that covers 14 birth cohorts from 1980 to 1993; this is similar to the exercise in Chetty et al. (2014b). To do this, we take advantage of the fact that both income and college mobility are observed for the 1984–86 cohorts. For each CZ, we compute the ratio of income mobility to college mobility, then multiply college mobility for the 1987–93 cohorts by this ratio to put it on the same scale as income mobility.[3] When we repeat our persistence analysis using this consolidated series, we again find that changes appear persistent if using cohorts that are two years or longer. The consolidated panel is long enough that we can study four-year cohorts, and interestingly, we find a very large and statistically significant coefficient on the lagged change, consistent with underlying trends in mobility. We do not use this consolidated series in our decomposition exercise below, because it would be hard to interpret the results.

We expect that, to the extent that some changes in mobility reflect year-to-year fluctuations in the composition of birth cohorts, the transitory component of estimated

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[2] For details, see Wooldridge (2016), pp. 420–421. The coefficients we estimate are identical to those described in his two-step procedure.

[3] The results are similar if we construct the consolidated series by using the college mobility data for the 1984–93 cohorts and rescaling the income mobility data for the 1980–83 cohorts. The results are also robust to using the 1984, 1985, or 1986 cohorts to scale the data, instead of using an average of the three cohorts.

mobility may be more important in smaller areas. Therefore, in Panel B of Table 4, we repeat the entire persistence exercise for the largest half of CZs. We find that the coefficient on the lagged change is generally more positive among the larger CZs than among all CZs, consistent with the hypothesis that changes in mobility have a smaller transitory component in larger areas.

d. Decomposition of changes into "shifts" and "pivots"

Mobility for children whose parents are at the 25th percentile of the national parent income distribution can increase when outcomes improve for all children across the parent income distribution or when outcomes for children from low-income families improve relative to outcomes for children from high-income families, holding constant the outcome for children born to the median parents. We call these two explanations "shifts" and "pivots" in the rank-rank relationship between children's outcomes and parents' income.

Figure 2 illustrates our concepts of shifts and pivots. The red line is the rank-rank relationship between children's income and parents' income in some initial year. The solid blue line is the rank-rank relationship in some later year. The average income rank for children whose parents are at the 25th percentile of the national parent income distribution has improved from roughly the 38th percentile to the 48th percentile in this example. The improvement for children of lower-income parents occurs both because the entire rank-rank relationship for year 2 lies above the line for year 1 and because the rank-rank relationship in year 2 is flatter than in year 1.

We define the shift component of mobility as the expected outcome for children whose parents are at the median of the national parent income distribution. With reference to the notation in the income rank-rank relationship in equation (1), the shift component is $\bar{r}_{50,ct} = \alpha_{ct} + 50\,\beta_{ct}$. Then, taking as given the expected outcome for children of the median parents, the pivot component is the expected penalty to children whose parents are at the 25th percentile relative to those whose parents are at the median; this is $\bar{r}_{25,ct} - \bar{r}_{50,ct} = -\,25\,\beta_{ct}$.

In our hypothetical example in Figure 2, the dotted blue line helps illustrate our definitions. The change due to a shift is the roughly 8 percentile increase in outcomes for children whose parents are at the median of the national parent income distribution. Pivoting this blue line at the median of the parent income distribution to achieve the actual year 2 rank-rank relationship produces a further benefit of roughly 2 percentiles for children whose parents are at the 25th percentile of the national parent income distribution.

Shifts matter more than pivots in explaining changes in mobility for children of low-income parents. When we consider all one-year changes in income mobility and weight the changes by cohort size, shifts account for 69 percent of changes in mobility, and pivots account for the remaining 31 percent of changes. When we focus on the changes in income mobility between the 1980–81 and 1985–86 cohorts, shifts account for 83 percent of the changes in mobility, and pivots account for just 17 percent of the changes. The results are similar for college mobility. If using all one-year changes in college mobility, shifts account for 82 percent of the changes in mobility. If we focus on changes between the 1984–85 and 1992–93 birth cohorts, shifts account for 72 percent of the changes in mobility.

IV. Accounting for changes in upward mobility

a. Empirical strategy

We focus on explaining changes in mobility between initial and final two year cohorts — the change between 1980–81 and 1985–86 for income mobility, and between 1984–85 and 1992–93 for college mobility. To better understand the sources of these changes, we regression mobility on CZ covariates such as the demographic composition of the cohort or the labor market conditions faced by the cohort when their incomes are measured. Our persistence analysis in the previous section suggests estimating these regressions using first differences instead of fixed effects. Therefore, denoting CZs by c, we estimate

$$\Delta \mathrm{AM}_c = \alpha + \mathbf{\Delta x}_c' \beta + \varepsilon_c \, . \tag{3}$$

All regressions are weighted by cohort size, and we cluster standard errors at the state level to account for spatial correlation across CZs.

We assess the role of three sets of covariates in explaining changes in income mobility. The first group of covariates are intended to reflect changes in the demographic composition of birth cohorts. For example, if there is an increase in the share of a cohort that is born to mothers who have not completed high school, we might expect that income mobility will decrease as a result. These cohort composition variables are measured using Vital Statistics birth certificate data. For each CZ-cohort cell, we include the following mothers' characteristics: percent black, percent other race (that is, neither white nor black), percent high school dropouts, percent with a college degree, percent born in Mexico, percent foreign-born (other than Mexico), percent single (that is, never married), and median age. We also include the percent of births that are low birthweight (below 2,500 grams). When we study college mobility, we add the log state cohort size, also measured from Vital Statistics data.

The second group of covariates we include are measures of labor market conditions. In the income mobility regressions, these are measured in the year in which the cohort is age 26, which is when income is observed for the purposes of the Opportunity Insights data. In the college mobility regressions, we use labor market conditions at age 18. Labor market conditions may be especially important given the timing of this study. For our initial 1980–81 cohort, income is observed in 2006–07, near the peak of a business cycle, and for our final 1985–86 cohort, income is observed in 2011–12, during a very weak recovery from the Great Recession. Using the local employment statistics from the BLS and the Census Bureau's County Business Patterns data, we measure, for each CZ-year cell, the unemployment rate, employment-population ratio, and the shares of employment in each of 21 industry codes. In the college mobility regressions, we also include in-state tuition at public colleges and universities at age 18, which we obtain from IPEDS.

In the map of changes in income mobility in Figure 1, many of the largest negative changes are in Florida and in Western states that were most affected by the collapse of the mid-2000s housing boom. A severe decline in house prices might affect both employment and wages at the lower end of the local labor market in ways that are only imperfectly captured by our labor market indicators. For example, if homeowners respond to lower housing wealth by cutting spending on non-tradable services, any resulting decline in, say, retail employment would be picked up by our labor market indicators, but slower wage growth in that industry would not be. Therefore, we aggregate county-by-year House Price Index estimates from the FHFA to the CZ-year level to measure each CZ's exposure to the decline in house prices. As with the labor market indicators, we time the HPI to the relevant year: age 26 for the income mobility regressions, and age 18 for the college mobility regressions.

We include the initial level of mobility in all regressions. Although Chetty et al. (2014a) found that the level of mobility is correlated with CZ characteristics, we have no reason to expect the initial level of mobility to be correlated with *changes* in those characteristics, which are the explanatory variables in our analysis. Indeed, we find that the coefficients on changes in CZ characteristics are not much affected by controlling for the initial level of mobility. However, initial mobility is still predictive of successive changes through mean reversion, and including it therefore improves the precision of our estimates.

We seek to explain the geographic variation in changes in mobility, so we use an R^2 decomposition proposed by Farooqui (2016) to measure the share of the changes in mobility that can be explained by each CZ covariate. Let $\widetilde{\beta}$ be the coefficient vector from a version of the first differences regression (3) in which ΔAM and each explanatory variable, Δx_k, has been standardized. Then the proportion of the variance in ΔAM explained by Δx_k is

$$R^2_{x_k} = \widetilde{\beta}_k \operatorname{corr}(\Delta \mathrm{AM}, \Delta x_k)\ . \tag{4}$$

Intuitively, $R^2_{x_k}$ is higher when Δx_k has a larger "effect" on changes in mobility, holding other covariates constant, and when the linear fit between ΔAM and Δx_k is tighter, holding constant the slope of this fit. Note that $R^2_{x_k}$ can be negative if the conditional and unconditional correlations between ΔAM and Δx_k have different signs.

b. Results for changes in mobility

Table 5 shows our regression estimates and the results of our R^2 decomposition for changes in income mobility. In the first column, we include only the cohort composition measures. These alone can explain 22 percent of the changes in income mobility. Changes in racial composition account for 9 percent, changes in mothers' place of birth account for 7 percent, and the other indicators make more modest contributions.

In the second column, we remove the cohort composition variables and include the labor market indicators and housing prices. These variables can explain 53 percent of the changes in income mobility. Unsurprisingly, decreases in the unemployment rate and increases in the employment-population ratio are both associated with greater income mobility, but their explanatory power is modest in the presence of the other variables. Industry employment shares account for 12 percent of the changes in income mobility, and housing prices account for 34 percent of the changes. In unreported results, we have estimated a version of column (2) that omits the Housing Price Index, and we find that this omission increases the estimated role of the 21 industry employment shares, led by construction.

In the final column of Table 5, we include all of our CZ covariates. Together, they can explain 77 percent of the changes: the initial level of mobility accounts for 18 percent of the changes, changes in house prices alone can explain 48 percent of the changes, industry employment shares continue to be important, and the other variables play smaller roles.

In Table 6, we apply our decomposition exercise to changes in college mobility between the 1984–85 cohort and the 1992–93 cohort. In column (1), cohort composition can explain 14 percent of the changes, led by mothers' race and mothers' education. In column (2), industry employment shares account for 15 percent of the changes in college mobility; in the unreported detailed results for the 21 industries, the largest coefficients are on construction and on mining and resource extraction. In the final column, our explanatory variables can account for about one third of the changes in college mobility. Cohort composition can explain 12 percent of the changes and industry employment shares can explain 13 percent of the changes. Notably, the Housing Price Index plays a negligible role. Two additional predictors of college attendance, in-state tuition and state cohort size, also have very little explanatory power.

c. Separate results for changes in mobility due to "shifts" and "pivots"

In section III, we described our approach to decomposing changes in mobility into "shifts," which are changes that affect children across the distribution of parent income, and "pivots," which are changes in the slope of the rank-rank relationship between children's outcomes and parents' incomes that disproportionately help or hurt the outcomes of children of low-income parents. Here, we repeat our accounting exercise separately on the shift and pivot components of changes in mobility, in order to learn more about how the mechanisms we study are affecting mobility.

Our results for income mobility are shown in Table 7. The first column, labeled "Total change," simply repeats the final column of Table 5, in which we include all of our CZ covariates in the accounting exercise. In the next column, we use the shifts in income mobility as the dependent variable, then repeat our first differences regression and R^2 decomposition. The final column uses the pivots in income mobility as the dependent variable. Note that the regression coefficients in the second and third columns sum to the coefficient in the first column.

Changes in labor market conditions and house prices explain the vast majority of the "shifts" in mobility. House prices account for 54 percent of the variance of the shifts, the unemployment rate and employment-population ratio account for another 14 percent, and the industry employment shares can explain a further 13 percent. Cohort composition measures play a larger role in accounting for pivots. Racial composition explains about 6 percent of the variance in pivots, and mothers' birthplace explains another 7 percent. Altogether, the cohort composition measures account for 16 percent of the variance in the pivot component. The unemployment rate explains about 5 percent of the variance, and house prices play almost no role in accounting for pivots.

In Table 8, we repeat this exercise for college mobility. The results for the "shift" component of college mobility are remarkably similar to the overall results in the first column: industry employment shares explain 13 percent of the shifts, and mothers' race, mothers' education, and the employment-population ratio all explain small shares of the "shifts." In the final column, the explanatory variables together can explain just a little over a quarter of the "pivots" in college mobility. Mothers' birthplace is the most important factor, accounting for 10 percent of the "pivots," and industry employment shares are the next most important, explaining 7 percent of the "pivot" component.

In Appendix Table A1, we explore whether our results are sensitive to our use of two-year initial and final cohorts. We repeat our decompositions of income and college mobility in the final columns of Tables 5 and 6 using three-year cohorts — 1980–82 to 1984–86 for income mobility and 1984–86 to 1991–93 for college mobility. The results are very similar to our findings in Tables 5 and 6 using two-year cohorts.

V. Discussion

We document substantial increases and decreases in intergenerational mobility across the 1980–93 birth cohorts at the local level in the U.S. We show that these changes appear to be persistent, not simply the result of noise or transitory fluctuations that disappear within a few years. In accounting for these changes, we find that a relatively narrow set of CZ characteristics — demographic characteristics of cohorts, labor market conditions, and house prices — can explain well over half of changes in income mobility and about a third of changes in college mobility. House prices alone can explain one third to one half of the changes in income mobility, providing a very parsimonious explanation for the geographically concentrated decreases in mobility that we show in Figure 1. This finding is consistent with other research emphasizing the exposure of local labor markets to consumption shocks driven by housing wealth. Labor market conditions not reflected by changes in house prices are also important in explaining changes in mobility, and changes in the demographic characteristics of birth cohorts play a relatively minor role.

Our results suggest that it may not be appropriate to treat mobility as a fixed characteristic of a place. Because children's income was measured at age 26 for the purposes of producing the mobility statistics we study, the 1980–86 cohorts are observed over the period 2006–12, which spans the largest U.S. recession since the Great Depression. We expect that mobility changed more during this period than it typically would over the course of six years, but our findings highlight how risky it could be to measure a place's mobility using a small number of birth cohorts. A longer panel of income mobility data would be quite valuable in understanding the dynamics and sources of changes in mobility, which would complement recent work by Derenoncourt (2019) and Tan (2019) on some long-run determinants of intergenerational mobility at the local level. We would also be very interested in studying changes in mobility by sex or race. However, while Opportunity Insights has released detailed estimates of the geographic distribution of mobility for particular demographic groups, they have not published estimates about how mobility for these groups has changed over time at the local level.

Finally, our results contain a note of optimism. There is a growing literature studying the determinants of intergenerational mobility, summarized at the end of our introduction above. The existence of apparently persistent changes in mobility, very little of which seems to be driven by changes in population characteristics, makes it more plausible that public policy can be used improve upward mobility for children of low-income parents.

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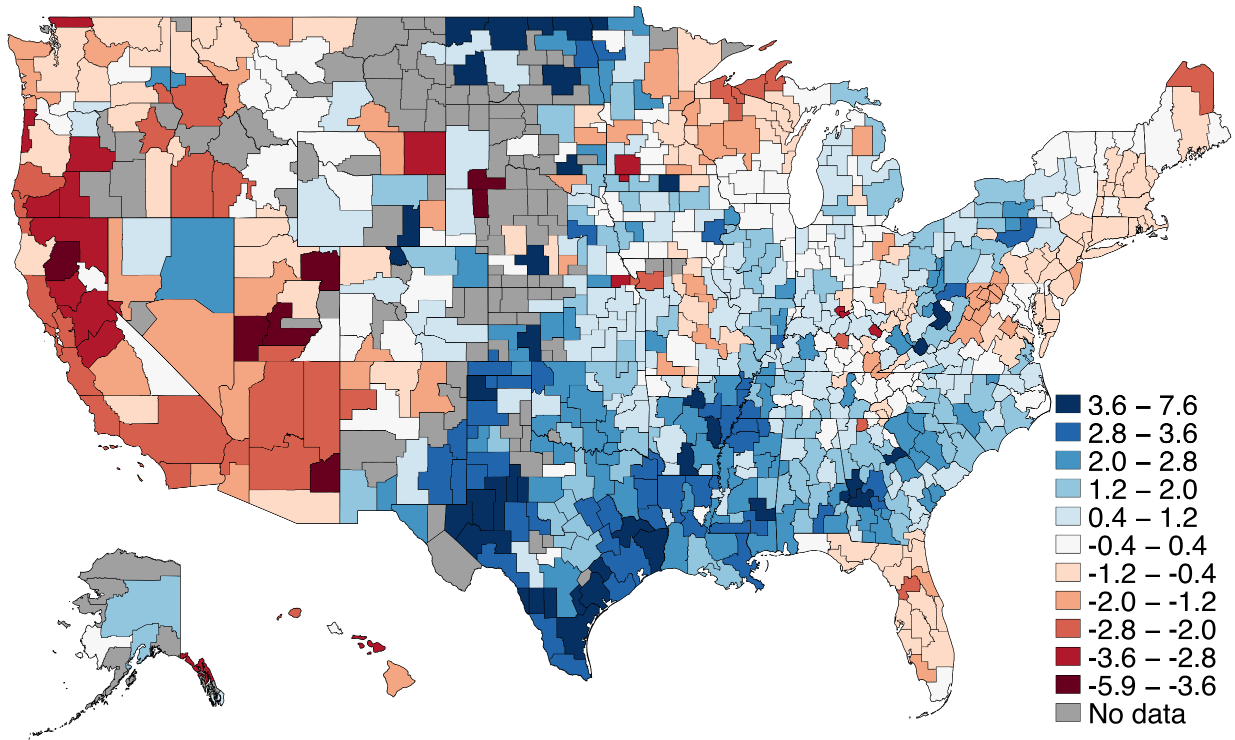
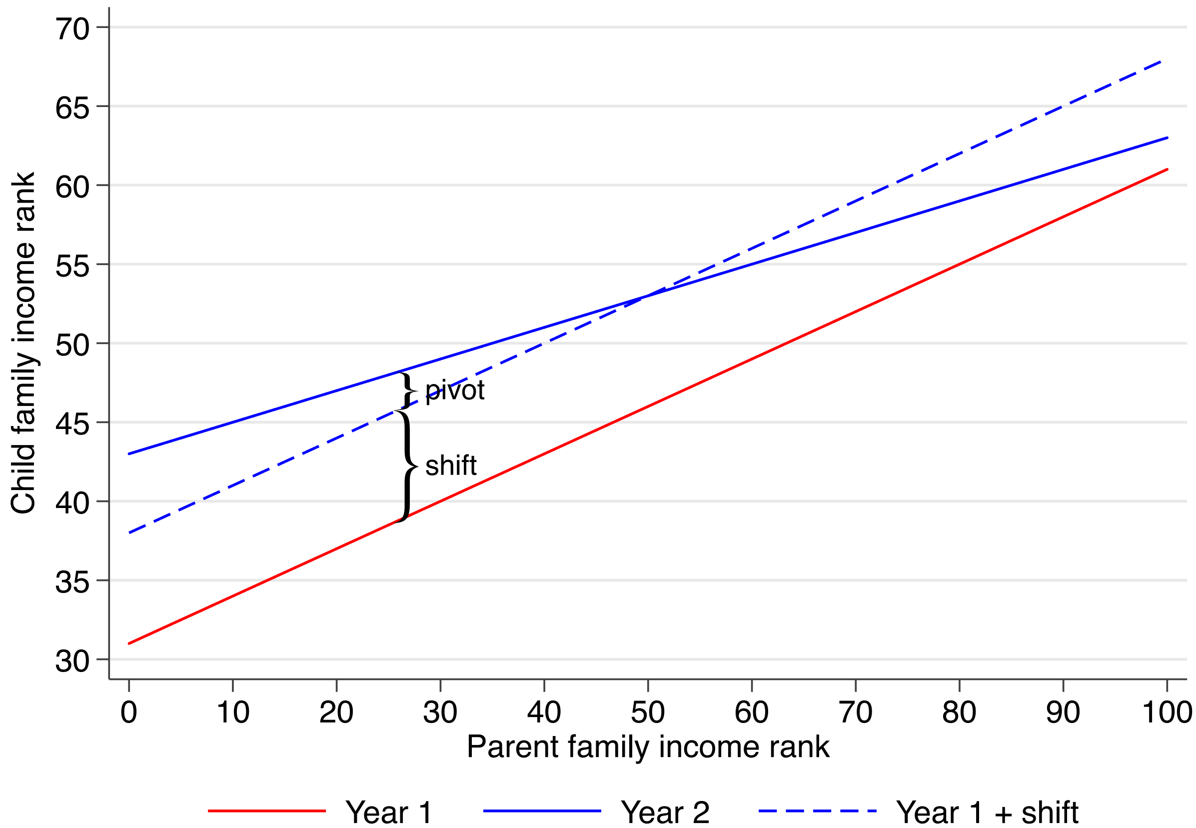
Figure 1: Changes in income mobility between the 1980–81 and 1985–86 birth cohorts



Notes: Mobility statistics for each commuting zone and birth cohort are from Opportunity Insights. Mobility is defined as the expected income percentile, measured nationally among the birth cohort at age 26, achieved by children whose parents are at the 25th percentile of the national parent income distribution.

Figure 2: Decomposing changes in mobility into shifts and pivots



Notes: This graph shows a hypothetical change in absolute mobility. Opportunity Insights mobility statistics include the intercept and slope to describe the parent-child income rank-rank relationship for each CZ and cohort. This example shows that an increase in mobility can occur because of a "shift" in the rank-rank relationship that benefits children across the parent income distribution (we define this as the increase in mobility for a child whose parents are at the median of the national parent income distribution) and because of a "pivot" in the rank-rank relationship at the median of the parent income distribution that flattens the rank-rank profile and improves outcomes for children of lower-income parents.

Table 1: Summary statistics for absolute mobility

	Income mobility 1980–1986		College mobility 1984–1993	
	Unweighted	Weighted	Unweighted	Weighted
Initial level of mobility				
Mean	45.28	43.42	32.47	32.96
Standard deviation	4.87	3.37	8.45	6.13
Number of CZs	635		641	
Change in mobility				
Mean	0.74	0.16	1.08	3.12
Standard deviation	2.33	1.95	6.74	5.03
Percentiles				
5th	– 3.07	– 2.65	– 11.17	– 5.41
25th	– 0.86	– 1.30	– 2.50	–0.19
50th	0.75	0.06	1.75	3.36
75th	2.26	1.51	5.20	6.27
95th	4.32	3.48	11.09	11.00
Number of CZs	631		625	

Notes: Mobility statistics for each commuting zone and birth cohort are from Opportunity Insights. Mobility is defined as the expected income percentile, measured nationally among the birth cohort at age 26, achieved by children whose parents are at the 25th percentile of the national parent income distribution. We show the cross-CZ distribution of mobility among the 1980 cohort and the cross-CZ distribution of changes in mobility between the 1980 and 1986 cohorts. The final column weights CZs by the average cohort size over the period 1980–86.

Table 2: Commuting zones with largest positive and negative changes in mobility

Income mobility, 1980–1986 birth cohorts

All CZs				Largest half of CZs			
Most positive changes		Most negative changes		Most positive changes		Most negative changes	
Williston, ND	9.67	St. George, UT	– 7.15	Midland, TX	8.43	St. George, UT	– 7.15
Minot, ND	8.90	Safford, AZ	– 5.34	Victoria, TX	6.27	Ocala, FL	– 4.65
Midland, TX	8.43	Richfield, UT	– 5.36	Corpus Christi, TX	5.27	Fredericksburg, VA	– 4.17
Dickinson, ND	8.17	Rolla, MO	– 4.88	Columbus, GA	4.88	Cape Coral, FL	– 3.57
Pearsall, TX	7.74	Gordon, SD	– 4.68	Clarksdale, MS	4.44	Klamath Falls, CA	– 3.57
Beeville, TX	7.50	Ocala, FL	– 4.65	Laredo, TX	4.06	Modesto, CA	– 3.54
Dumas, TX	7.28	Juneau, AK	– 4.47	Lubbock, TX	3.97	Bellingham, WA	– 3.49
Pecos, TX	6.91	Worthington, MN	– 4.36	New Orleans, LA	3.81	Medford, OR	– 3.36
Sweetwater, TX	6.90	Gillette, WY	– 4.22	Huntsville, TX	3.78	Sacramento, CA	– 3.36
El Dorado, AR	6.68	Pine City, MN	– 4.20	Houston, TX	3.70	Bend, OR	– 3.33

College mobility, 1984–1993 birth cohorts

All CZs				Largest half of CZs			
Most positive changes		Most negative changes		Most positive changes		Most negative changes	
Kosciusko, MS	21.43	Willison, ND	– 28.10	Talladega, AL	20.64	Santa Barbara, CA	– 17.89
Talladega, AL	20.64	Olney, IL	– 25.68	Santa Fe, NM	15.34	Victoria, TX	– 16.48
Beeville, TX	17.11	Vincennes, IN	– 25.42	Columbia, TN	14.71	La Crosse, WI	– 12.01
Mount Sterling, KY	17.01	Crystal City, TX	– 21.77	Lorain, OH	13.70	Wheeling, WV	–11.88
Dyersburg, TN	15.91	Vernon, TX	– 19.98	Boise City, ID	13.01	Green Bay, WI	–9.80
Santa Fe, NM	15.34	Harrison, AR	– 19.69	Columbus, OH	12.96	Sarasota, FL	– 9.38
Greenwood, MS	15.23	Uvalde, TX	– 19.31	Fresno, CA	12.90	Bluefield, VA	– 9.20
Columbia, TN	14.71	Santa Barbara, CA	– 17.89	Albuquerque, NM	12.64	Tyler, TX	– 9.17
Twin Falls, ID	14.30	Minot, ND	– 17.19	St. Louis, MO	12.45	Longview, TX	– 8.93
Lorain, OH	13.70	Sidney, ND	– 16.73	Decatur, IL	12.28	Miami, FL	– 8.73

Notes: Mobility statistics for each commuting zone and birth cohort are from Opportunity Insights. Mobility is defined as the expected income percentile, measured nationally among the birth cohort at age 26, achieved by children whose parents are at the 25th percentile of the national parent income distribution. We show the most positive and negative changes between the 1980 and 1986 birth cohorts. Median and mean births are with reference to the average cohort size during the period 1980–86. The median cohort size is 1,766 and the mean cohort size is 5,258.

Table 3: Changes in mobility and commuting zone characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in income mobility, 1980–81 to 1985–86							
Initial income mobility	– 0.222***	– 0.220***	– 0.242**	– 0.250***	– 0.293***	– 0.179***	– 0.255***
	(0.055)	(0.049)	(0.092)	(0.065)	(0.073)	(0.061)	(0.053)
Income per capita ($1000s)		– 0.081***					– 0.106***
		(0.016)					(0.017)
Gini among bottom 99%			– 0.024				0.048
			(0.063)				(0.056)
Social capital index				0.314			0.628***
				(0.328)			(0.141)
Percent single moms					– 0.083		– 0.230***
					(0.051)		(0.079)
Percent black						0.019	0.076***
						(0.018)	(0.019)
N	630	630	630	621	630	630	621
R^2	0.197	0.313	0.201	0.229	0.212	0.203	0.467
Change in college mobility, 1984–85 to 1992–93							
Initial college mobility	– 0.137***	– 0.238***	– 0.148***	– 0.152***	– 0.128***	– 0.130***	– 0.224***
	(0.047)	(0.056)	(0.047)	(0.047)	(0.046)	(0.044)	(0.047)
Income per capita ($1000s)		0.193***					0.148**
		(0.048)					(0.055)
Gini among bottom 99%			– 0.115				– 0.132
			(0.073)				(0.082)
Social capital index				0.737			0.423
				(0.353)			(0.419)
Percent single moms					0.084		0.024
					(0.096)		(0.121)
Percent black						0.069**	0.099*
						(0.034)	(0.057)
N	622	622	622	613	622	622	613
R^2	0.038	0.124	0.060	0.065	0.043	0.067	0.189

Notes: Results are from regressions of the change in mobility on the indicated CZ characteristics. Except for initial income mobility, CZ characteristics were measured using the 2000 census, and were included in the Opportunity Insights mobility dataset. Regressions are weighted by average cohort size during the period 1980–86. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Persistence of changes in mobility

	One-year cohorts	Two-year cohorts	Three-year cohorts	Four-year cohorts
Panel A: All CZs				
Income mobility, 1980–1986				
Lag change in mobility	– 0.174***	0.145		
	(0.051)	(0.124)		
Obs. [unique CZs]	3,185 [640]	633 [633]		
College mobility, 1984–1993				
Lag change in mobility	– 0.317***	– 0.085*	0.231***	
	(0.041)	(0.047)	(0.085)	
Obs. [unique CZs]	5,029 [637]	1,874 [628]	623 [623]	
Consolidated series, 1980–1993				
Lag change in mobility	– 0.294***	– 0.109	0.382***	0.670***
	(0.043)	(0.109)	(0.109)	(0.202)
Obs. [unique CZs]	7,579 [642]	3,139 [637]	1,252 [630]	622 [622]
Panel B: Largest half of CZs				
Income mobility, 1980–1986				
Lag change in mobility	– 0.044	0.235		
	(0.061)	(0.143)		
Obs. [unique CZs]	1,620 [324]	324 [324]		
College mobility, 1984–1993				
Lag change in mobility	– 0.316***	– 0.053	0.252**	
	(0.053)	(0.061)	(0.098)	
Obs. [unique CZs]	2,576 [322]	966 [322]	322 [322]	
Consolidated series, 1980–1993				
Lag change in mobility	– 0.278***	– 0.102	0.449***	0.751***
	(0.054)	(0.135)	(0.121)	(0.223)
Obs. [unique CZs]	3,888 [324]	1,620 [324]	648 [324]	324 [324]

Notes: Results are from regressions of changes in mobility on lagged changes in mobility. All regressions include cohort fixed effects. Regressions are weighted by average cohort size during the period 1980–93. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Decomposition of changes in income mobility, 1980–81 to 1985–86 birth cohorts

	(1)		(2)		(3)	
	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2
Initial income mobility	– 0.157***	0.139	– 0.121***	0.181	– 0.200***	0.179
	(0.032)		(0.012)		(0.017)	
Cohort composition						
Δ % mothers black	– 0.052	0.002			– 0.070	0.003
	(0.112)				(0.047)	
Δ % mothers other race	– 0.370**	0.087			– 0.376***	0.088
	(0.158)				(0.071)	
Δ % mothers dropout	– 0.061	0.037			0.040	– 0.024
	(0.083)				(0.036)	
Δ % mothers college	– 0.061	0.001			– 0.015	0.0003
	(0.037)				(0.042)	
Δ % mothers Mexican	0.570**	0.019			0.008	0.0003
	(0.266)				(0.086)	
Δ % mothers foreign	– 0.139	0.046			0.345***	– 0.115
	(0.088)				(0.049)	
Δ % mothers single	0.028	0.0002			– 0.043	– 0.0003
	(0.077)				(0.034)	
Δ median mother's age	– 0.350	0.015			– 0.001	0.0001
	(0.234)				(0.174)	
Δ % low birthweight	– 0.251	0.008			0.161*	– 0.005
	(0.182)				(0.095)	
Labor market and housing prices						
Δ unemployment rate			– 0.116**	0.051	– 0.106*	0.047
			(0.051)		(0.060)	
Δ employment-population ratio			0.032	0.019	0.032*	0.019
			(0.025)		(0.019)	
Δ employment shares			✓	0.121	✓	0.094
Δ Housing Price Index			0.539***	0.335	0.773***	0.481
			(0.089)		(0.096)	
R^2	0.354		0.707		0.766	
N	630		622		622	

Notes: Results are from regressions of changes in mobility between the 1980–81 and 1985–86 cohorts on changes in the indicated CZ characteristics. Regressions are weighted by average cohort size during the period 1980–86. Demographic data on cohort composition is from Vital Statistics; labor market data is from BLS, Census Bureau, and SEER; and housing price index data is from FHFA. Values of R_x^2 are computed using the decomposition proposed by Farooqui (2016); see text for details. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Decomposition of changes in college mobility, 1984–85 to 1992–93 birth cohorts

	(1)		(2)		(3)	
	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2
Initial college mobility	– 0.192***	0.053	– 0.130***	0.036	– 0.156***	0.043
	(0.057)		(0.045)		(0.054)	
Cohort composition						
Δ % mothers black	0.493**	0.063			0.529***	0.067
	(0.205)				(0.189)	
Δ % mothers other race	0.066*	– 0.002			0.083**	– 0.003
	(0.037)				(0.041)	
Δ % mothers dropout	– 0.197**	0.034			– 0.232**	0.040
	(0.096)				(0.098)	
Δ % mothers college	0.229	0.032			0.227	0.031
	(0.273)				(0.234)	
Δ % mothers Mexican	0.241***	– 0.040			0.328***	– 0.056
	(0.080)				(0.114)	
Δ % mothers foreign	– 0.065	0.002			– 0.022	0.001
	(0.228)				(0.212)	
Δ % mothers single	– 0.048	0.004			– 0.061	0.005
	(0.079)				(0.077)	
Δ median mother's age	0.805	0.015			0.463	0.008
	(0.744)				(0.665)	
Δ % low birthweight	1.201***	0.033			1.130***	0.030
	(0.386)				(0.291)	
Conditions at age 18						
Δ unemployment rate			– 0.479*	– 0.001	– 0.267	– 0.0003
			(0.258)		(0.251)	
Δ employment-population ratio			– 0.318**	0.030	– 0.369***	0.035
			(0.136)		(0.132)	
Δ employment shares			✓	0.145	✓	0.127
Δ Housing Price Index			0.002	0.0001	0.597	– 0.006
			(0.606)		(0.611)	
Δ average in-state tuition			0.075	0.001	0.068	0.001
			(0.191)		(0.190)	
Δ log state cohort size			– 4.052	0.011	– 3.674	0.010
			(2.842)		(3.980)	
R^2	0.191		0.222		0.334	
N	622		614		614	

Notes: Results are from regressions of changes in mobility between the 1980–81 and 1985–86 cohorts on changes in the indicated CZ characteristics. Regressions are weighted by average cohort size during the period 1980–86. Demographic data on cohort composition is from Vital Statistics; labor market data is from BLS, Census Bureau, and SEER; and housing price index data is from FHFA. Values of R_x^2 are computed using the decomposition proposed by Farooqui (2016); see text for details. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Decomposition of changes in income mobility due to shifts and pivots

	Total change		Change due to shift		Change due to pivot	
	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2
Initial income mobility	− 0.200***	0.179	− 0.090***	0.044	− 0.110***	0.307
	(0.017)		(0.014)		(0.010)	
Cohort composition						
Δ % mothers black	− 0.070	0.003	− 0.027	− 0.002	− 0.043*	0.026
	(0.047)		(0.051)		(0.023)	
Δ % mothers other race	− 0.376***	0.088	− 0.205**	0.048	− 0.172***	0.033
	(0.071)		(0.076)		(0.035)	
Δ % mothers dropout	0.040	− 0.024	0.048	− 0.027	− 0.009	0.007
	(0.036)		(0.031)		(0.017)	
Δ % mothers college	− 0.015	0.0003	− 0.015	0.001	0.0001	0.0001
	(0.042)		(0.041)		(0.0176)	
Δ % mothers Mexican	0.008	0.0003	− 0.125	− 0.003	0.133**	0.009
	(0.086)		(0.094)		(0.058)	
Δ % mothers foreign	0.345***	− 0.115	0.180***	− 0.083	0.165***	0.061
	(0.049)		(0.041)		(0.023)	
Δ % mothers single	− 0.043	− 0.0003	0.012	0.001	− 0.055***	0.024
	(0.034)		(0.034)		(0.017)	
Δ median mother's age	− 0.001	0.0001	− 0.006	0.0003	0.005	0.0001
	(0.174)		(0.163)		(0.057)	
Δ % low birthweight	0.161*	− 0.005	0.069	− 0.002	0.092*	− 0.002
	(0.095)		(0.069)		(0.053)	
Labor market and housing prices						
Δ unemployment rate	− 0.106*	0.047	− 0.201***	0.125	0.095***	0.053
	(0.060)		(0.055)		(0.028)	
Δ employment-population ratio	0.032*	0.019	0.023	0.016	0.008	0.001
	(0.019)		(0.015)		(0.008)	
Δ employment shares	✓	0.094	✓	0.127	✓	0.028
Δ Housing Price Index	0.773***	0.481	0.714***	0.536	0.059	− 0.008
	(0.096)		(0.083)		(0.037)	
R^2	0.766		0.782		0.538	
N	622		622		622	

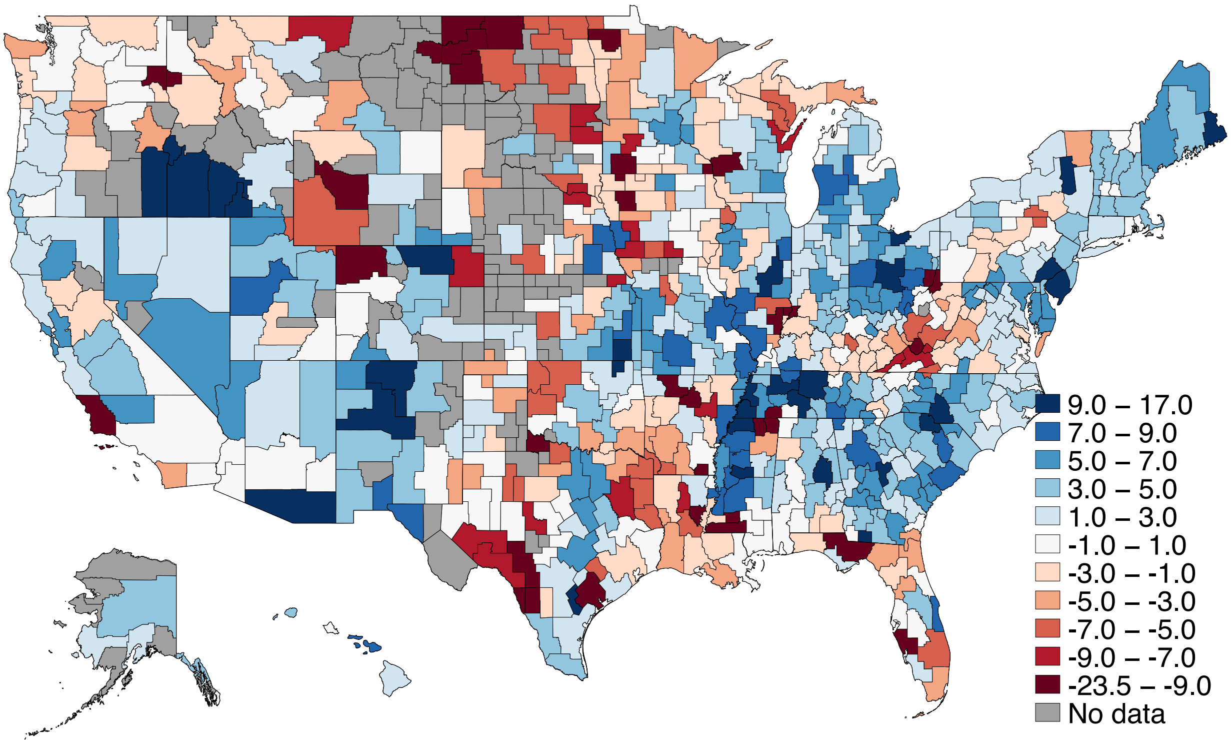
Notes: Results are from regressions of changes in mobility between the 1980–81 and 1985–86 cohorts on changes in the indicated CZ characteristics. In the first column, the dependent variable is the change in mobility. In the second column, the dependent variable is the change due to shifts in the parent-child income rank-rank relationship, and in the third column, the dependent variable is the change due to pivots in the parent-child income rank-rank relationship; see text for precise definitions of these terms. Regressions are weighted by average cohort size during the period 1980–86. For data sources, see notes to Table 5. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Decomposition of changes in college mobility due to shifts and pivots

	Total change		Change due to shift		Change due to pivot	
	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2
Initial college mobility	– 0.156***	0.043	– 0.157***	0.043	0.001	– 0.0004
	(0.054)		(0.052)		(0.013)	
Cohort composition						
Δ % mothers black	0.529***	0.067	0.322**	0.048	0.207***	0.014
	(0.189)		(0.147)		(0.068)	
Δ % mothers other race	0.083**	– 0.003	0.040	– 0.002	0.042*	0.006
	(0.041)		(0.028)		(0.025)	
Δ % mothers dropout	– 0.232**	0.040	– 0.123	0.026	– 0.108***	0.006
	(0.098)		(0.087)		(0.034)	
Δ % mothers college	0.227	0.031	0.235	0.052	– 0.008	0.003
	(0.234)		(0.197)		(0.048)	
Δ % mothers Mexican	0.328***	– 0.056	0.168*	– 0.045	0.160***	0.061
	(0.114)		(0.096)		(0.043)	
Δ % mothers foreign	– 0.022	0.001	0.125	– 0.0001	– 0.147*	0.043
	(0.212)		(0.153)		(0.086)	
Δ % mothers single	– 0.061	0.005	– 0.036	0.004	– 0.025	– 0.001
	(0.077)		(0.067)		(0.021)	
Δ median mother's age	0.463	0.008	0.833	0.032	– 0.370*	0.042
	(0.665)		(0.532)		(0.199)	
Δ % low birthweight	1.130***	0.030	0.858***	0.023	0.272**	0.014
	(0.291)		(0.294)		(0.134)	
Conditions at age 18						
Δ unemployment rate	– 0.267	– 0.0003	– 0.249	– 0.0001	– 0.019	– 0.0001
	(0.251)		(0.208)		(0.100)	
Δ employment-population ratio	– 0.369***	0.035	– 0.370***	0.044	0.001	– 0.0001
	(0.132)		(0.122)		(0.047)	
Δ employment shares	✓	0.127	✓	0.126	✓	0.071
Δ Housing Price Index	0.597	– 0.006	0.232	– 0.003	0.364	0.006
	(0.611)		(0.540)		(0.254)	
Δ average in-state tuition	0.068	0.001	0.092	0.003	– 0.024	0.003
	(0.190)		(0.180)		(0.071)	
Δ log state cohort size	– 3.674	0.010	– 6.097*	0.023	2.423*	0.007
	(3.980)		(3.436)		(1.251)	
R^2	0.334		0.378		0.274	
N	614		614		614	

Notes: Results are from regressions of changes in mobility between the 1980–81 and 1985–86 cohorts on changes in the indicated CZ characteristics. In the first column, the dependent variable is the change in mobility. In the second column, the dependent variable is the change due to shifts in the parent-child income rank-rank relationship, and in the third column, the dependent variable is the change due to pivots in the parent-child income rank-rank relationship; see text for precise definitions of these terms. Regressions are weighted by average cohort size during the period 1980–86. For data sources, see notes to Table 5. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figure A1: Changes in college mobility
between the 1984–85 and 1992–93 birth cohorts



Notes: Mobility statistics for each commuting zone and birth cohort are from Opportunity Insights. Mobility is defined as the expected income percentile, measured nationally among the birth cohort at age 26, achieved by children whose parents are at the 25th percentile of the national parent income distribution.

Appendix Table A1: Decomposition of changes in income and college mobility due to shifts and pivots, using three-year cohorts

	Income mobility 1980–82 to 1984–86		College mobility 1984–86 to 1991–93	
	$\widehat{\beta}$	R_x^2	$\widehat{\beta}$	R_x^2
Initial mobility	– 0.154***	0.170	– 0.107***	0.023
	(0.015)		(0.043)	
Cohort composition				
Δ % mothers black	– 0.086*	0.005	0.469**	0.050
	(0.047)		(0.213)	
Δ % mothers other race	– 0.377***	0.087	0.102*	0.001
	(0.074)		(0.055)	
Δ % mothers dropout	– 0.0004	0.0003	– 0.255***	0.041
	(0.0398)		(0.073)	
Δ % mothers college	– 0.024	0.0007	0.245	0.033
	(0.047)		(0.245)	
Δ % mothers Mexican	0.052	0.002	0.410***	– 0.056
	(0.108)		(0.146)	
Δ % mothers foreign	0.305***	– 0.106	– 0.091	0.002
	(0.055)		(0.243)	
Δ % mothers single	– 0.029	0.001	– 0.073	0.007
	(0.041)		(0.071)	
Δ median mother's age	– 0.058	0.004	0.271	0.005
	(0.156)		(0.849)	
Δ % low birthweight	0.203**	– 0.007	1.278***	0.038
	(0.091)		(0.387)	
Other explanatory variables				
Δ unemployment rate	– 0.065	0.028	– 0.311	– 0.003
	(0.056)		(0.295)	
Δ employment-population ratio	0.180	0.010	– 0.512***	0.059
	(0.020)		(0.159)	
Δ employment shares	✓	0.082	✓	0.116
Δ Housing Price Index	0.744***	0.468	1.080**	0.010
	(0.092)		(0.451)	
Δ average in-state tuition			0.360*	0.008
			(0.188)	
Δ log state cohort size			0.092	– 0.0001
			(4.370)	
R^2	0.744		0.378	
N	622		614	

Notes: Results are from regressions of changes in mobility between the 1980–81 and 1985–86 cohorts on changes in the indicated CZ characteristics. In the first column, the dependent variable is the change in mobility. In the second column, the dependent variable is the change due to shifts in the parent-child income rank-rank relationship, and in the third column, the dependent variable is the change due to pivots in the parent-child income rank-rank relationship; see text for precise definitions of these terms. Regressions are weighted by average cohort size during the period 1980–86. For data sources, see notes to Table 5. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$