# The Radius of Economic Opportunity: Evidence from Migration and Local Labor Markets

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**Abstract**

We examine the geographic incidence of local labor market growth across locations of childhood residence. We ask: when wages grow in a given US labor market, do the benefits flow to individuals growing up in nearby or distant locations? We begin by constructing new statistics on migration rates across labor markets between childhood and young adulthood. This migration matrix shows 80% of young adults migrate less than 100 miles from where they grew up. 90% migrate less than 500 miles. Migration distances are shorter for Black and Hispanic individuals and for those from low-income families. These migration patterns provide information on the first order geographic incidence of local wage growth. Next, we explore the responsiveness of location choices to economic shocks. Using geographic variation induced by the recovery from the Great Recession, we estimate the elasticity of migration with respect to increases in local labor market wage growth. We develop and implement a novel test for validating whether our identifying wage variation is driven by changes in labor market opportunities rather than changes in worker composition due to sorting. We find that higher wages lead to increased in-migration, decreased out-migration and a partial capitalization of wage increases into local prices. Our results imply that for a 2 rank point increase in annual wages (approximately $1600) in a given commuting zone (CZ), approximately 99% of wage gains flow to those who would have resided in the CZ in the absence of the wage change. The geographically concentrated nature of most migration and the small magnitude of these migration elasticities suggest that the incidence of labor market conditions across childhood residences is highly local. For many individuals, the "radius of economic opportunity" is quite narrow.

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# 1 Introduction

How much does one's location during childhood determine the labor markets that one is exposed to in young adulthood? In response to potential wage gains, do people migrate substantial distances from their childhood home? In this paper, we examine the geographic incidence of local labor market growth across locations of childhood residence.

We begin by constructing and analyzing new statistics on the migration patterns of young adults across commuting zones (CZs) in the United States. In particular, we construct a new "migration matrix" measuring the rates of movement across CZs between childhood and young adulthood. We report CZ-to-CZ migration for all CZs in the US and explore how this migration matrix varies by race and parental income. We construct the migration matrix using de-identified Census and tax data for children born between 1984 and 1992. Compared to pre-existing data, this migration matrix is unique in measuring sub-state migration patterns between childhood and young adulthood by demographic group. An interactive data tool displaying the migration matrix is available at migrationpatterns.org.

We motivate the construction of the matrix with a simple model that captures the geographic incidence of local wage growth. If real wages rise by $1 in Chicago, some of those wage gains will flow to individuals growing up in other locations. To first order, the gains are distributed in proportion to the baseline probability that individuals from other locations move to Chicago. If 1% of young adults in Chicago tend to come from Dubuque, Iowa, then children raised in Dubuque capture 1% of Chicago's real wage gains.[1] Put another way, the migration matrix allows us to quantify a child's "radius of opportunity." For children starting out in a given origin location $o$, the matrix quantifies the set of potential destinations $d$ to which the child might migrate. It therefore captures the extent to which local economic growth in a destination $d$ benefits children from that origin location.

In constructing this migration matrix we document several key migration patterns. First, we find that common destinations in young adulthood are strongly spatially concentrated around the locations in which children grew up. At age 26, 69% of individuals live in the commuting zone where they grew up. 80% of young adults have travelled less than 100 miles and 90% travelled less than 500 miles. For example, children growing up in Dubuque, IA are three times more likely to move to nearby Des Moines or Waterloo than to Chicago, just slightly further away. Similarly, those growing up in Indianapolis are twice as likely to move to nearby Terre Haute, Indiana, as opposed

[1] This example holds the value of amenities fixed; however, the migration matrix also provides guidance on the incidence of a $1 increase in the value of amenities in Chicago holding wages and prices fixed.

to Cincinnati.

Second, we document that migration patterns vary heavily across race/ethnicity and parental income. For example, Black young adults move an average of 60 miles less than White young adults – 130 vs. 190 miles. The specific destinations to which young adults move also varies by race. Among Black young adults who leave their hometown, the most common destinations is Atlanta, which draws approximately 6.7% of movers. The next most popular destinations are Houston, TX, Washington DC, and New York, NY, which each draw approximately 3% of movers. By contrast, Atlanta is just the 15th most popular destination for White young adults. White young adults are most likely to move to New York, Los Angeles, Washington DC or Denver. While Denver is the 4th most popular destination for White young adults, it is not a top 10 destination for any other race/ethnicity group.

There is also a clear relationship between average migration distances and levels of parental income. For example, young adults raised in families at the 25th percentile of income travel an average of 160 miles. By contrast, those from families at the 90th percentile travel an average of 220 miles. Average distances travelled rise rapidly at the top of the income distribution, increasing to an average of 325 miles for those born to families in the top 1%. This means that young adults from the least affluent families are more exposed to the strength of labor markets in their hometown and less exposed to the strength of more distant labor markets.

As discussed in Section 4, this migration data also provides more in-depth insights into major migration patterns within the United States. For example, over the past several decades there has been a net-inflow of Black migrants to the American South, a pattern known as the New Great Migration (Frey, 2004). By linking young adults to their parents, we can see that this migration to the South is primarily driven by individuals who grew up in affluent families. For example, Black young adults who grew up in high-income households are twice as likely to have moved to Atlanta, Dallas, and Houston than those from low-income families. Those from high income families are also ten times more likely to have moved to Washington DC.[2]

Along similar lines, there has been considerable academic interest in rates of migration to and from Appalachia (Lichter and Campbell, 2005; Ludke and Obermiller, 2014; Pollard and Jacobsen, 2020). Our data show that, despite relatively low incomes in the region, rates of out-migration from Appalachia are subdued. White young adults leave the region at lower rates than those living in

[2]These patterns can be examined further by looking at individual origin CZs. For example, Black young adults who grew up in Chicago are twice as likely to move to Gary, IN relative to Atlanta, GA. This pattern reverses for those from high-income families.

other places with similar levels of income.

These descriptive migration patterns provide information on the first-order geographic incidence of changes in wages. They do not, however, capture how migration changes in response to wage opportunities. Understanding that effect is key to capturing the full consequences of labor demand shocks. For that reason, the second half of this paper estimates the elasticity of migration with respect to changes in wage offers. Those results are then embedded within a spatial equilibrium framework to explore the welfare consequences of changes to the strength of local labor markets.

We study the elasticity of migration to wage offers using geographic variation in wages induced by the heterogeneous recovery from the Great Recession. In order to exploit that source of geographic variation in labor market recovery, we have to ensure that we are isolating wage changes due to changes in wage offers rather than changes in sorting behavior that alters the composition of workers. In other words, if we are measuring the impact of wage growth in Minneapolis on migration into the city, we need to be sure that measured wage growth there is the result of changes in wage offers, not the result of an amenity shock that attracted high income workers and resulted in a cross-sectional increase in wages.

We address this concern by developing a new method to test for whether a given measure of wage changes are due to changes in skill-specific sorting. Our test exploits an overidentification condition implied from the structure of the migration matrix. An increase in wage offers in location $d$ should affect wages for people *who grew up in location* $o$ in proportion to the probability of moving from $o$ to $d$. By contrast, a shift in the observed wages in location $d$ due solely to an amenity shock should not affect the average wages of people who grew up in location $o$. It should only change wages in the places where the former residents of location $o$ choose to settle. Hence, a demand shock has a unique "signature" when regressing changes in origin wage outcomes on the migration-weighted average of candidate destination wage changes. Variation in wages driven by demand shocks should produce a coefficient of 1. By contrast, variation in wages driven by sorting will tend to produce a coefficient less than 1.

The following example helps to illustrate the intuition underlying our test. Let us imagine that Denver becomes popular with high income individuals while Detroit becomes less popular. The compositional changes in each place will cause wages to rise in Denver and fall in Detroit. Now let us consider average wage changes for individuals born in two other locations, such as Phoenix or New Orleans. Residents of Phoenix may be more likely to go to Denver than residents of New Orleans. That said, one would not expect that wages for individuals born in Phoenix and New

Orleans would change in proportion to the probability that individuals from those locations migrate to Denver or Detroit. The wage changes in Denver and Detroit were only the result of the reshuffling of individuals, not the result of increasing wage offers for given individuals. Wages for those born in Phoenix or New Orleans should only change in proportion to baseline migration probabilities if Denver and Detroit are experiencing increases in wage offers. In section 5 of the paper, we formalize this test. We provide conditions under which the regression of origin wages on the predicted wage change quantifies the fraction of total variation in wages that is due to variation in wage offers. This means that our approach not only provides a test for demand shocks, but it also provides a quantification of the potential degree of bias due to skill-biased sorting.

We apply our approach to geographic variation in the recovery from the Great Recession. We find a coefficient of 1.030 (s.e. 0.033) when regressing changes in origin wage outcomes on the migration-weighted average of candidate destination wage changes. We also find coefficients near 1 when examining wage variation within race/ethnicity and parental income sub-groups. In short, our results suggest that the cross-CZ variation in wage changes from 2010-2017 for 26 year olds are primarily the result of labor demand shocks, not skill-biased sorting.[3]

We then use this variation in wages to provide estimates for the responsiveness of migration to changes in wage offers.[4] We begin by exploring the response to nominal wage changes. We find that young adults respond to changes in wage opportunities, and that these responses are generally larger in places they are ex-ante more likely to go. The response increases with the pre-period probability of migrating to the destination, $p$. The results are qualitatively consistent with the predictions a multinomial Logit model, which posits that migration responses should scale with the baseline migration probability. (The Logit predicts that the response should be proportional to $p\,(1-p)$.) In practice, the migration responses we observe deviate slightly from the quantitative predictions of the Logit model because they exhibit greater concavity with respect to $p$. For values of $p$ near 0, we find a semi-elasticity of migration probability with respect to wage ranks of around 0.04. That is, when wages rise by one rank point (roughly \$800, on average) in a given destination $d$, the probability of migrating there increases by $0.04p$. In contrast, for higher values of $p$ (e.g. baseline migration probabilities above 1%), the semi-elasticity falls to around $0.01p$. This pattern suggests that people are more responsive, in proportional terms, to wage offer changes in places where they

[3]Consistent with the absence of skill-biased sorting, we also use data from the American Community Survey (ACS) and show that cross-sectional wage changes across destinations from 2010-2017 are not correlated with the predicted change in incomes due to changes in education.

[4]For consistency with the literature on intergenerational mobility we measure changes in wage offers in terms of wage ranks. Our results are qualitatively very similar if log wages or wage levels are used.

were ex-ante less likely to move. Overall, most migrating individuals move to common destinations, and so the average semi-elasticity is close to 0.01. That is, when wages rise by one rank point in a given destination $d$, the probability of migrating there increases by $0.01p$.

We also examine how these elasticities vary by race/ethnicity and parental income. We show that the semi-elasticity of migration is greater for those in higher quantiles of parent income. We also show that Black young adults appear less responsive to changes in wage offers than White young adults. Hispanic young adults appear to have migratory responses of similar magnitudes to White young adults.[5]

Next, we present evidence on how prices respond to nominal wage changes. We use this, in combination with our existing estimates, to examine how migration responds to real wage changes (i.e. wages net of local price increases). In a spatial equilibrium model, prices will rise in response to labor demand shocks as long as housing supply is not infinitely elastic. This means that workers do not reap the full benefits of nominal wage changes. Part of these benefits accrue to landowners (Greenstone et al., 2010; Notowidigdo, 2011). We use information on rents from the American Community Survey (ACS) to estimate how local shocks to nominal wages translate into prices, and consequently impact real wages. On average, we find that roughly 30% of the wage increase is capitalized into the rental price of housing.[6] We examine these patterns across cities with different elasticities of housing supply, as measured in Saiz (2010), and find that capitalization of wages into prices is greater in cities with less elastic housing supply. We also return to our migration elasticities and find that the migration response to nominal wages is smaller in places with a less elastic housing supply. However, once we adjust for differential price responses, we cannot reject an identical migration response to real wages across places with high and low housing supply elasticities. As is the case for our nominal wage elasticities, we find real wage elasticities that are concave with respect to baseline migration probabilities.

Finally, we discuss the welfare implications of our results by considering the impact of a local labor market policy that aims to increase wages. While we have identified a clear migration response to changes in wage offers, the magnitude of this response is quite small and so the gains in real wages are still highly concentrated amongst inframarginal individuals who would have resided in those locations even if wages did not change. For example, we estimate that if a CZ were to experience a 2 rank wage increase (roughly \$1600 annually, or about \$0.80 per hour), it would lead to a 1%

[5]Our empirical design has insufficient power to estimate a distinct migration elasticity for Asian young adults.

[6]Under the assumption in Greenstone et al. (2010) that some portion of prices are capitalized into non-tradable goods, the total impact on prices would be closer to 50%.

inflow of residents. This means that 99% of local wage gains would flow to residents who would have lived there in the absence of the wage increase. We also estimate that amongst this 99% of inframarginal individuals, most grew up nearby. After all, more than 2/3 of young adults remain in their childhood CZ and 80% travel less than 100 miles. Of the 1% of individuals who migrated to take advantage of the wage gains, most grew up in the surrounding CZs.[7] Taken together this means that, for many individuals, particularly non-White individuals and those from low-income families, the "radius of economic opportunity" is quite narrow.

**Relation to Existing Literature** Our paper relates to a large body of work studying migration responses to economic shocks. Existing research includes analysis on migration responses to employment shocks (Blanchard and Katz, 1992; Yagan, 2014; Cadena and Kovak, 2016), the migration response to total factor productivity (TFP) shocks (Hornbeck and Moretti, 2022), the migration response to wage changes (Monras, 2020), and the migration response to specific industry shocks such as those from Chinese import competition (Autor et al., 2013, 2021; Bartik, 2018) or fracking (Bartik et al., 2019; Wilson, 2022).[8]

Relative to this literature, we work with novel data that provides estimates on migration patterns between childhood and young adulthood. That allows us to examine migration patterns in the period of life where rates of migration are highest (Bernard, 2017; Foster, 2017). This approach also allows us to explore how parental location choice shapes the labor markets to which children are exposed. In estimating our migration elasticities, we are able to examine origin by destination migration changes rather simply examining total migration flows to a destination. This allows us to empirically identify a proportional migration response – for a given shock in location $d$, the change in the probability of going from $o$ to $d$ changes in proportion to the baseline probability that individuals from location $o$ travel to location $d$.

Our source of empirical variation also differs from that used by much of the previous literature, which often relies on shift-share instruments to identify the causal effect of labor demand shocks (Diamond, 2016; Dao et al., 2017).[9] We justify our approach, which is closer to OLS, using a

[7] This also means that spillover effects on the rental cost of housing in other CZs will be geographically concentrated around the initial CZ experiencing wage growth.

[8] Many of these papers examine the impact of economic shocks on outcomes other than migration. For example, Hornbeck and Moretti (2022) estimate the impact of labor demand shocks on prices. We conduct a similar analysis in Section (7).

[9] One potential drawback of using Bartik shocks to measure changes in labor demand is that the Bartik may imperfectly capture opportunities for individual wage gains if it is the case that workers are unable to costlessly shift between industries. With the Bartik approach, differences in instrumentally predicted wage changes across CZs are driven by differences in baseline industry composition. If moving across industries in costly, then most workers don't

new test that assesses whether candidate wage shocks reflect changes in labor demand or amenity changes. We show in our context that our approach leads to substantially more statistical power for identifying the response of migration to changes in wage offers.[10] We believe that our approach can provide justification for earlier and future work that uses the spatial variation in wage changes over the business cycle to identify the causal effect of labor market strength on migration decisions. We also believe our approach is generalizable to other settings where researchers seek to isolate local labor demand shocks.[11]

In interpreting our relatively small estimated migration elasticities, it is important to note that our analysis is restricted to a sample of US born children. This serves as complementary evidence to the finding of relatively high elasticities amongst non-US born individuals (Cadena and Kovak, 2016).[12]

Our approach also relates to the literature on the importance of housing markets and spatial equilibrium forces in shaping labor markets. In conducting our welfare analysis in Section 8 we rely upon estimates of the price response to labor demand shocks. We also explore the impact of housing supply elasticities on migration flows and price adjustments.[13] This is consistent with the empirical approach in (Hornbeck and Moretti, 2022) who conduct welfare analysis that examines migration and price adjustment across locations experiencing TFP shocks and also capture spillovers on other locations.

Our results capturing the migration response to real wages provide estimates that, in the spirit of the Rosen-Roback approach, can be used as a benchmark in welfare analyses of amenity changes (Diamond, 2016; Moretti, 2010). For example, it is common in this framework to compare the migratory response to the amenity change with the migratory response to a wage change to infer the monetized value of the amenity, such as environmental quality (Bartik et al., 2019).

Finally, our new set of substate migration statistics relates to a large literature in demography, sociology, and economics analyzing migration trends and understanding their determinants.[14] Our

have access to the wage gains in other CZs (Borusyak et al., 2022).

[10]Indeed, replicating our approach using traditional CZ-level industry shift-share instruments at either the 2-, 3-, or 4-digit industry level leads to estimates that are neither statistically different from zero or our baseline estimates.

[11]Our approach is also unique relative to much of the existing literature in its focus on the direct impact of wage changes. This approach is motivated by canonical location choice models in which people choose where to live in response to the spatial distribution of wage opportunities, prices, and amenities.

[12]This contrast is also consistent with the findings that non-US born individuals are more likely than US-born individuals to migrate to locations that provide strong economic opportunities for themselves and their children (Abramitzky et al., 2021; Abramitzky and Boustan, 2022).

[13]We draw upon the housing supply elasticities from (Saiz, 2010) when grouping cities by their housing supply elasticity.

[14]The two most common datasets currently used for measuring internal migration in the US are the (1) IRS county-to-county migration statistics, which does not provide information on race/ethnicity or parental income and is only

results provide a more granular picture of previously documented migration patterns. For example, our tract-level results on distance travelled from home provides additional evidence for the notion that most children do not move far from home (Bernard, 2017). Similarly, the case studies we outline in Section 4 provide more granular insights into previously-documented state-level migration patterns in the US. Previous work finds that, compared to thriving areas, depressed economies tend to be composed of residents born in nearby areas (Zabek, 2019). In the context of Appalachia, we provide evidence consistent with these findings and show that rates of out-migration by White individuals are primarily driven by the migration decisions of those from low-income families. Existing work has also documented a net-inflow of Black individuals into the American South, a pattern coined the "New Great Migration"(Frey, 2004; Hunt et al., 2008; Washington and Walker, 2022). We show the CZ-to-CZ level migration that composed these trends and document that these patterns are driven disproportionately by individuals from high income households.

The rest of this paper proceeds as follows. Section 2 outlines the data used to construct our migration matrix and conduct our estimation. Section 3 outlines our basic conceptual framework. Section 4 presents descriptive migration patterns between childhood and young adulthood. Section 5 outlines our estimation strategy and Section 6 presents our results on the migration response to changes in nominal wage. Section 7 presents results on the migration response to real wage changes while examining the impact of migration on prices along the way. Section 8 discusses the welfare implications of our findings and Section 9 concludes.

## 2 Data and Sample

We estimate the migration matrix and its elasticity with respect to changes in wage opportunities in each place using de-identified administrative and survey data from the U.S. Census Bureau. Our target sample is the universe of U.S. born children in the 1978-1992 birth cohorts.[15] Following Chetty et al. (2020), we approximate this target sample by taking all children in the Census Numerical Identification Database (Numident) of Social Security Number holders who are born in the U.S. between 1978-92.[16] We link each child to the parent who claims them as a dependent on a tax

available at 1-year migratory frequency and (2) the American Community Survey, which provides a 1% sample of the population; this has been used by much previous literature to produce state-level migration patterns. Decennial Census data has historically been used to measure medium-run migration, but there were no migration questions in the 2010 or 2020 Census as no long-form was used.

[15] As discussed below, our primary sample is the 1984-1992 cohorts, but we utilize information in earlier cohorts for the analyses of the migration response to wage changes.

[16] Our sample differs from Chetty et al. (2020) in two primary ways. First, we expand the sample to include later birth cohorts up through 1992. Second, we assign children to parents using a fixed age range across cohorts centered

form 1040 at age 16.[17] Form 1040 is available for years 1994-95 and 1998-2010. Appendix Figure A1 shows how the fraction of children matched to parents increases across cohorts, from 81% for the 1978 cohort and 88% for the 1980 cohort to roughly 94% for the 1984-1992 cohorts when we observe more complete claiming information in the form 1040 data. We therefore focus our primary analysis on cohorts 1984-1992, as indicated by the solid dots. We use the earlier cohorts to assess the robustness of our migration patterns for children of older ages. We assign childhood location using the location listed on the parents tax return at the time the child is claimed. As shown in Appendix Figure 1, we obtain geocoded location information for the address on the form 1040 for nearly all parents.

We link each parent to their tax form 1040 to measure each child's parental income. To alleviate concerns of attenuation bias, we form a 5-year average of family income when the children are aged 14-18. We average the adjusted gross income on the 1040 over this time frame, imputing zeros for non-filers. Chetty et al. (2020) show that the median reported income in the ACS for non-filers is roughly $5,000, motivating our assumption of zero income for non-filers.

We measure the locations of young adults in our sample at ages 19-35 using information from a newly constructed Residential History File (RHF). The RHF measures location using a prioritization of form 1040, information returns (W2s and 1099s), followed by information from the department of Housing and Urban Development on participants in public housing and voucher programs.[18] Using this procedure, we match over 90% of children in our sample to a location at age 26.[19] Appendix Figure A1 shows that this means that we match roughly 87% of our sample to a parent, parental location, and child location for our primary analysis sample of the 1984-92 birth cohorts.

We measure each child's race and ethnicity using information from the Decennial Census and American Community Survey (ACS). We first merge to the 2010 Decennial Census; for those without a match, we then look to the 2000 Decennial Census followed by all years of the ACS (2008-2018).

around age 16, as opposed to using the first parent to claim a child as a dependent. We make this modification in order to have a consistent age of measurement of childhood location across cohorts in our analysis.

[17] If cases where a child is not claimed by parent at age 16, we supplement this with additional claiming information between the ages of 14 and 18. We prioritize ages 15, 17, 14 and then 18 to most conduct the links as closely as possible to age 16.

[18] In cases where there are information returns with different addresses, we determine whether any information return address aligns with the next observable 1040 address. If the information return address is continuously observable in all years until it appears in the 1040, that address is prioritized. If no such match between 1040 and information return addresses exists, the de-duplication procedure prioritizes the newest address to appear in the information return. (A 3-year window is used to search for the newest address.) This allows for the prioritization of new address locations over outdated addresses that may still appear on information returns.

[19] For a small number of cases, we obtain location information that does not match to a precise geocoded location in the Census Master Address File (MAF). In these instances, we match children to CZs using the ZIP code on form 1040.

Using this procedure, Appendix Figure A1 shows we obtain race and ethnicity for 97% of the sample of children for whom we find a parent link and an adult location at age 26. This means for our analysis that conditions on the race/ethnicity of the child, we match roughly 84% of our sample to a parent, parental location, child location, and child race/ethnicity for our primary analysis sample of the 1984-92 birth cohorts. When reporting results that pool all races/ethnicity, we include those without race or ethnicity information. We report results for the following racial/ethnic categories for our main analysis: Hispanic, Non-Hispanic Asian, Non-Hispanic Black, and Non-Hispanic White. We also provide further racial/ethnic breakdowns for those not falling into one of these groups when reporting national statistics, including Non-Hispanic American Indian and Alaska Native, Some Other Race, and multiple races.

We construct two measures of children's incomes at each age in young adulthood (ages 19-35). Our first measure of income is wage income, defined as the sum of incomes across all W-2s in each year. Individuals with no W-2 receive a value of 0. This provides a measure of the formal labor market incomes earned by the young adult. Our second measure of income is family income. Following Chetty et al. (2020), we define this as the adjusted gross income on form 1040. For non-filers, we use the sum of incomes on tax form W-2. For individuals with no 1040 or W-2 in given year, we assign them a family income of zero.[20] For our primary specifications, we follow Chetty et al. (2020) and translate these income measures into ranks using the within-cohort within-age distribution of ranks computed over the full sample.[21]

When comparing our results to shift-share designs we draw upon industry information from the Longitudinal Business Database (LBD). We link workers to a 2-, 3-, or 4-digit NAICS code matching individuals at the Employer Identification Number (EIN) by county level.[22]

Finally, we measure educational outcomes and housing characteristics in adulthood for a sub-sample of individuals using the ACS. This provides information on roughly 1% of the population each year and reports the number of years of education and highest degree obtained.

[20] One concern is that our income measure omits individuals who are not filing or receiving income not captured on a W-2. As noted above, Chetty et al. (2020) show that the median reported income in the ACS for non-filers with no W-2 information is $5,000, suggesting this is not a significant concern.

[21] Individuals with 0 income are assigned the mean rank of individuals without income. In other words, if 5% of individuals have no incomes, all such individuals are assigned a rank of 0.025.

[22] Geographic information on workers is drawn from the Residential History File while EINs are drawn from W2s. Matching at the EIN by county level allows for a unique match in all cases where multi-establishment firms do not have two different NAICS codes within the same county. For all remaining NAICS code assignment we de-duplicate in a manner that matches aggregate county-level industry shares. In cases where exact matches are not found, use adjacent counties and adjacent years to identify an appropriate NAICS code.

# 3 Conceptual Framework: Partial Equilibrium

Our goal is to understand and measure the geographic incidence of local labor market growth across locations of childhood residence. To do so, we develop a general model of spatial sorting across labor markets. In this section, we use the model to study the first order partial equilibrium incidence of changes in real wage offers across place. This motivates the analysis of migration rates across commuting zones (CZs), which we discuss in the next section. We return to the model in Section 5, when we move beyond first order incidence of wage changes and study migration responses. We also use the model to derive our test for whether a proposed source of variation in wages reflects demand or amenity shocks. Finally, we utilize the model in Section 7 when we study price responses to nominal wage shocks and use the model to explore incidence of labor demand shocks in a spatial equilibrium context with housing supply and labor demand elasticities.

We set up the model as follows: There exists a set $C$ of locations. Each individual, $i$, grows up in an origin location, $o(i) \in C$, and obtains characteristics that affect their earnings potential, $\theta(i)$, which we refer to as human capital.[23] We assume $\theta$ is unobserved to the econometrician (although one might observe its correlates), and, WLOG, we assume $\theta$ is distributed uniformly over the unit interval, $[0, 1]$. After growing up in an origin location, a individual makes a choice about their adult location, $d(i) \in C$. The wage individuals obtain is a function both of their location choice and their level of human capital, $w_{\theta c}$. Each worker uses one unit of housing at a rental price $p_c$. We let $\mathbf{w}_\theta = (w_{\theta c})_c$ and $\mathbf{p} = (p_c)_c$ denote the vectors of wages and prices across places.

Individual $i$'s utility associated with each potential destination, $d$, is given by:

$$u_{id} \equiv u_{id}\left(w_{\theta(i)d} - p_d, \gamma_{id}\right).$$

The utility of living in place $d$ is given by their consumption, $w_{\theta(i)c} - p_c$, and an individual-specific term, $\gamma_{ic}$, which captures individuals' valuation of each place $c$ beyond what is captured by its wages and prices. This term captures the role of amenities and includes individuals' valuations of the local parks, coffee shops, transportation infrastructure, etc. in place $c$. We let $\Gamma_c$ denote the vector of these amenities in place $c$ so that $\gamma_{ic}$ is drawn from a distribution that depends on $\Gamma_c$. It also includes other factors that might affect their preference for each place, such as proximity to family. It is common in previous research to assume that the individual-specific component of $\gamma_{ic}$ is additive and drawn from a type 1 extreme value distribution, but we do not impose any such restriction on preferences here.

[23] One should think of $\theta$ as including all factors that affect earnings conditional on location choice.

We assume individuals choose their destination, $d$, to maximize $u_{id}$:

$$d(i) = argmax_d \, u_{id}$$

leading to experienced utility $u_{id(i)}$.

Suppose wages in place $d$ increase from $w_{\theta d}$ to $w_{\theta d} + \nu_d$ for all people who reside in destination $d$. Suppose for now that this increase in wages, $\nu_d$, is a "real" wage increase so that prices, $p_d$, and amenities, $\Gamma_d$, are not changing. Our first question is: what is the impact of this real wage increase on the economic well-being of individuals growing up in each origin, $o$?

In order to assess this, let $U_o(\nu_d)$ denote the aggregate willingness to pay by people in origin $o$ for the wage increase in destination $d$. The envelope theorem implies that if real wages increase by a small amount, $d\nu_d$, any individuals who already intended to live in location $d$ have a marginal willingness to pay of $d\nu_d$. Any individual who did not intend to live in location $d$ has a willingness to pay of zero. Therefore, the aggregate willingness to pay for those growing up in origin $o$ is given by the probability that those individuals move to destination $d$ as adults:

$$\frac{dU_o}{d\nu_d}|_{\nu_d=0} = \Pr\{d(i) = d|o(i) = o\} \equiv M_{d|o} \tag{1}$$

Equation (1) shows that $M_{d|o}$ characterizes the first order partial equilibrium incidence of labor market shocks to real wages. We refer to $M_{d|o}$ as the "migration matrix". This matrix is endogenous to the level of real wages, $w_{\theta d} - p_c$, and amenities, $\Gamma_c$, offered by each place, although we suppress this notation for simplicity.

As written, the matrix pools across all types $\theta$. We also provide estimates of the migration matrix for different observable individual characteristics, namely parental incomes and race/ethnicity. We also provide some national statistics by education, which is observed for the subset of the sample that has participated in the American Community Survey.

# 4 Migration Matrix: Results

The first contribution of this paper is to provide a new public dataset reporting the number of people who move from each origin CZ during childhood (measured at age 16) to each destination CZ during young adulthood (measured at age 26). This "migration matrix" is reported for the full sample along with results de-aggregated by parental income quintile and four categories of race

and ethnicity: Hispanic, Non-Hispanic Asian, Non-Hispanic Black, Non-Hispanic White.[24,25] We infuse a small amount of doubly-symmetric geometrically distributed noise to each cell to ensure our estimates satisfy the differential privacy requirements of sub-state releases of Census Bureau data. In practice, this adds or subtracts a couple of people from each demographic-by-origin-by-destination migration count cell. The resulting migration matrix and an associated interactive data tool is publicly available at www.migrationpatterns.org. This section describes several lessons learned from the data.

Most young adults do not move far from their childhood home.[26] Figure 1 presents results on individuals growing up in each of six childhood CZs: Indianapolis IN, Dubuque IA, Atlanta GA, Los Angeles CA, Minneapolis MN, and New York NY. The figure reports the fraction of individuals from each origin CZs residing in each destination CZ. On average, roughly 2/3 of young adults reside in their childhood CZ. For those who leave, the most common destinations are frequently nearby and quite often within the same state. For example, more children growing up in Indianapolis move to Terre Haute, Indiana (0.78%) than to New York City (0.58%). Similarly, those growing up in Dubuque, Iowa are almost twice as likely to move to Waterloo (3.59%) or Des Moines (4.12%) than move to Chicago (2.30%), which is only slightly further away. Similar patterns of locally concentrated migration can be seen in each of the example CZs in Figure 1.

Figure 2 presents a birds eye view of these patterns by plotting the population cumulative distribution function (CDF) of the distance moved for each young adult in our sample. Distances are plotted between origin and destination Census tracts. At age 26, 30% of individuals are living in the same tract where they resided at age 16. 58% have moved less than 10 miles. 80% have moved less than 100 miles. There is, however, a thick upper tail in the distribution: 10% of children move more than 500 miles.[27]

[24]The racial/ethnic groups are not exhaustive. For completeness we also include migration patterns for those who report another race/ethnicity not in these categories, those who report multiple races/ethnicities, or those who cannot be linked to a 2000 or 2010 Decennial Census or the 2005-2018 ACS. To limit bias from noise infusion in our aggregate migration counts, we pool these groups into a single 'other' category.

[25]We choose to release migration statistics separately by parent income and race/ethnicity because it explains more heterogeneity in migration patterns relative to other potential subgroup divisions. Appendix Table 1 reports the correlation of migration patterns by child gender, parent income, child race/ethnicity, and child birth cohort. We find correlations that are below 90% for both race/ethnicity and parent income; but for gender we find a correlation of 0.994, and for cohorts we find correlations exceeding 0.97. This motivates our approach of pooling gender and cohorts in order to increase the precision of the data release (which requires each demographic cell to be infused with independent noise).

[26]This insight is well-documented in existing literature (e.g. Frey et al. (2005); Molloy et al. (2011)). Our core contribution relative to this existing work is the ability to document sub-state migration patterns, focus on migration patterns between childhood and young adults (the period in life where migration rates are highest), and analyze the heterogeneity in migration based on parental background characteristics.

[27]Our baseline results focus on moves at age 26. The time period from age 16-26 contains the highest migration

These results have direct implications for the geographic incidence of local labor market growth. To first order, when a CZ experiences wage growth the overwhelming majority of those wage gains will flow to individuals who grew up within 100 miles of that CZ. Individuals who grow up more than a few hundred miles away are unlikely to see the benefits of that real wage growth.

**Variation Across Demographic Groups** While average migration distances are relatively short, there is important variation in migration patterns by race/ethnicity and parental income. Figure 3A presents the average distance moved by child race/ethnicity for Hispanic and non-Hispanic Asian, Black, and White young adults.[28] For example, Black young adults move an average of 133 miles from home by age 26 while White young adults move an average of 194 miles.[29] This pattern occurs both because Black individuals are more likely to remain in their childhood CZ and because, conditional on migrating, they move shorter distances. (Appendix Figure A4 decomposes the relative contribution of those two factors.)[30]

There is also variation across race/ethnicity in the specific destinations to which individuals travel. Figure 4 focuses in on the city of St Louis, Missouri to show these patterns in detail. Panel A maps the destination probabilities for White young adults and Panel B presents those patterns for Black young adults. 81% of Black young adults who grew up in St. Louis stay there at age 26 compared to 73% of White young adults. Among those that leave, Black young adults are more than four times as likely to move to Atlanta, and roughly twice as likely to move to Houston and Dallas. By contrast, White young adults are more than four times as likely to move to Denver, more than twice as likely to move to Seattle, and twice as likely to move to New York City. Table 1 repeats this basic exercise, aggregating across all origin CZs and reporting results for all four race/ethnicity

rates over the life cycle. Rates of migration decline with age in adulthood Bernard (2017). Appendix Figure A2 presents the same CDF as Figure 1, this time measuring outcomes at age 35. Broadly, it produces similar results: 74% of 35-year-olds continue to reside within 100 miles and 13% move more than 500 miles.

[28] Appendix Table 3 presents further race/ethnicity breakdowns.

[29] Appendix Figure A3 repeats Figure 3 using distances measured at age 35. We find that, compared to migration measured at age 26, average migration distances increase by approximately 40 miles for all race/ethnicity groups. So, by age 35, White young adults on average live 234 miles from their childhood location, whereas Black young adults live an average of 165 miles away.

[30] The figure also shows that Hispanic young adults have shorter average migration distances than White young adults (144 versus 190 miles). This is primarily because a greater share of Hispanic young adults remain their childhood CZ. 78% of Hispanic young adults reside in their childhood CZ, in contrast to 67% for White young adults. Conditional on moving, Hispanic young adults move to destinations that are further away than the destinations chosen by White young adults (655 vs 562 miles on average). This pattern is consistent with state-level findings of Frey et al. (2005) who finds that, conditional on out-of-state migration, Hispanic migration patterns are more dispersed than other race/ethnicity groups. The figure also shows that, on average, Asian young adults move greater distances than Black, White, or Hispanic young adults. The panels on the right of the figure reveal that Asian children continue to travel farther than children of other races/ethnicities even when re-weighting the origin locations of children to match the spatial distribution of origin locations of White children. In this sense, the greater distances traveled for Asian young adults is not explained by the differences in where they grew up.

groups in the data. It displays a top 10 list of the most common destinations for individuals of each race/ethnicity group. It shows, for example, that Denver is the 4th most popular destination for White young adults, but it is not a top 10 destination for Black, Hispanic, or Asian young adults. Similarly, San Antonio is the 3rd most common destination for Hispanic young adults, but it isn't in the top 10 for any other race/ethnicity group.

Migration patterns are also related to the racial/ethnic composition of one's origin CZ. For each race/ethnicity group, Appendix Figure A5 presents the fraction of young adults who reside in their childhood CZ plotted against the share of same-race/ethnicity individuals in that origin CZ. Consistent with the state-level findings in Frey et al. (2005), we find that Hispanic, Black and Asian individuals are less likely to leave the place they grew up in if that CZ has a higher fraction of same-race/ethnicity inhabitants. By contrast, the stay rates of White young adults are not correlated with the fraction of White children in their origin CZ.

Just as migration distances vary across race/ethnicity groups, they also vary across levels of parental income. Young adults raised in high-income households move much farther on average than young adults raised in low-income families. Figure 3B reports these patterns, showing average distance traveled by percentile of parental income. For example, it shows young adults raised in families at the 25th percentile of income travel an average of 160 miles while those from families at the 90th percentile travel an average of 220 miles.[31] Average distances travelled rise rapidly at the top of the income distribution, increasing to an average of 325 miles for those born to families in the top 1%. Figure 3C reports these patterns separately by race/ethnicity. Black young adults whose parents are at the 20th percentile of the income distribution move 110 miles on average, in contrast to 155 miles for White young adults with similar parental incomes. At high levels of parental incomes, these differences in move distances across race disappear: Black young adults with parents in the top 1% move 357 miles on average, slightly more than the 323 miles moved by White young adults with similar levels of family income.[32] Broadly, these patterns show that individuals from least affluent families are more exposed to the strength of labor markets in their hometown and less exposed to the strength of more distant labor markets. Similarly, compared to White and

[31]The pattern is slightly nonlinear. Appendix Figure A6 shows that the pattern is monotonic in parental income when conditioning on parent marital status. For the combined graphs the flattening in the middle of the distribution occurs because in middle-income single parent households have higher move distances than children in middle-income households with married parents.

[32]Education is an additional potential channel that can generate differences in distances moved. Appendix Figure A7 uses the 1% sample of the ACS to study distance moved by education category and race/ethnicity. As expected, distances moved are higher for those with more years of education. We continue to find similar differences across race/ethnic groups conditional on years of education.

Asian young adults, Black and Hispanic young adults are more exposed to the strength of the labor market in which they grew up.

**Migration Case Studies** These migration patterns across demographic groups can help provide a more detailed picture of major migration patterns within the United States. Here, we highlight two such patterns: the New Great Migration and the lack of out-migration of White individuals from Appalachia.

The evidence presented in Figure 4 and Table 1 on out-migration patterns across races/ethnicities is consistent with a recent literature documenting net-inflows of Black individuals into the American South. This trajectory has been called a "New Great Migration" (Frey, 2004). By linking young adults to their parents, we are able to examine how these migration patterns differ across levels of parental income. We can see that this migration is disproportionately driven by individuals who grew up in affluent families. For example, in Appendix Figure A8, we show migration destinations for Black individuals raised in St Louis. We examine rates of migration for those whose parents were in the top 20% of the income distribution and compare them to the migration rates of those whose parents were in the bottom 20%. We find that those with high income parents were twice as likely to move to Atlanta (1.92% vs 0.88%), Houston (1.22% vs 0.65%) and Dallas (1.48% vs. 0.60%). They are more than ten times more likely to move to Washington, DC (1.48% vs. 0.13%). By contrast, Black individuals who grew up in high income households are no more likely than their low-income counterparts to migrate to other CZs within 250 miles of St Louis. In Appendix Figure A9, we show similar patterns for those growing up in Chicago; Black young adults from low-income families are twice as likely to move to nearby Gary, IN than to Atlanta, GA; the reverse is true for Black young adults from high-income families.[33]

Along similar lines, there has been considerable academic interest in rates of migration to and from Appalachia (Lichter and Campbell, 2005; Ludke and Obermiller, 2014; Pollard and Jacobsen, 2020). Our results show that, despite relatively low incomes in the region, rates of out-migration by White individuals from Appalachia are subdued. This pattern appears to be driven by individuals born into low-income families. Those young adults leave the region at lower rates than those living in other places with similar levels of income.

Appendix Figure A10 illustrates this pattern by plotting the fraction of White children from

[33]Despite differences rates of migration across levels of parental income, it is important to note that the the vast majority of Black young adults stay close to home. This is consistent with the evidence in Sharkey (2015), who notes that the migration flows that make up the New Great Migration are much smaller than those seen during the Great Migration.

low-income families who remain in their origin CZ. That CZ stay rate is plotted as a function of the mean income of the CZ. While more affluent CZs have higher stay rates on average, the commuting zones that compose Appalachia have above average stay rates at all levels of income. Panel B shows that this pattern is strongest amongst young adults raised in low-income households. CZ stay rates in Appalachia consistently exceed the stay rates of other CZs with similar levels of income. By contrast, the pattern dissipates when considering young adults from high income families. Within that group, rates of out-migration from Appalachia are similar to the rates of migration from other CZs with comparable levels of mean income.

These demographic trends and broad migration patterns once again have direct implications for the welfare consequences of local wage growth. They suggest that, across different races/ethnicities and across different locations of childhood origin, individuals are differentially exposed to local labor market growth. Put another way, the fact that likely migration destinations differ across demographic groups means that those groups would differentially benefit from growth in specific US labor markets. Differences in average migration distances across demographic groups also suggest that the radius of opportunity differs across those groups. The radius of opportunity for Black and Hispanic individuals may be smaller than the radius for White and Asian individuals. The same is true for individuals born into low-income households.

Thus far, our discussion of the radius of opportunity has focused on the first order incidence of wage growth, holding migration patterns constant. In the material that follows, we examine how migration changes in response to wage opportunities. Measuring these effects, and embedding them within a spatial equilibrium model, allows us to more fully explore the welfare consequences of changes to local labor markets.

# 5 Exogenous Wage Variation

Do individual migration decisions change in response to varying labor market conditions? In this section, we estimate how the rate of migration from an origin CZ, $o$, to a destination CZ, $d$, changes in response to variation in wage offers.

Identifying these migration responses is valuable because they have a direct impact on the welfare consequences of changes in wage offers. Section 3 showed that, to first order, the migration matrix provides guidance on the partial equilibrium incidence of real wage shocks. Individuals from origin $o$ have a willingness to pay for a real wage gain in destination $d$ equal to $M_{d|o}$, the counter-factual probability of going to that location. That said, migration changes reduce individual willingness-

to-pay for wage gains. The logic of the envelope theorem suggests that individuals who migrate in response to the potential wage gain don't experience the same increase in welfare. As a result, the welfare gain of a wage subsidy in location $d$ will fall in proportion to the number of subsidy recipients who received the subsidy as the result of a behavioral response (migrating). In order to assess the full welfare gains of a labor demand shock it is therefore crucial to estimate $dM_{d|o}$, the migration response to the changes in real wages.

Our estimand of interest is most easily described as the impact of a one unit increase in wage offers for all types $\theta$ in location $c$ on the probability of migrating from origin $o$ to destination $d$. Here, location $c$ can represent, $o$, $d$, or some alternate location $d'$. (Our estimation strategy works for any location $c$. In presenting our results, we explore how migration varies in response to origin, destination, and outside option shocks.)

In order to estimate the migration response to wage offers we need a source of variation in wage offers that is orthogonal to preferences. In particular, the variation must be orthogonal to skill-biased amenity sorting. For example, if we are utilizing wage increases in the city of Minneapolis, we need to be sure that the city underwent changes in wage offers, not simply a compositional change in the type of people who live in Minneapolis. If the increase in wages in Minneapolis was due to the city's new popularity with high wage individuals, that would interfere with our ability to measure the causal relationship between wage offers and migration.

In this section, we develop and implement a new test of exogeneity for a given source of wage variation. We use this approach to validate our use of the geographic variation in wage changes during the 2010-2017 the recovery from the Great Recession. That said, our approach can be applied more broadly to other settings of interest.

## 5.1 A Test of Exogenous Wage Variation

Recall that $w_{\theta c}$ is the wage paid to a type $\theta$ individual in location $c$. For simplicity, we assume wage offers are the sum of a location premium, $w_d$, and a wage paid to each type, $\theta$. We write the wage offers for type $\theta$ in location $d$ as the sum of their type and a location premium:

$$w_{\theta d} = w_d + \theta$$

where $\theta$ is the wage received by an individual of type $\theta$ in an average place and $w_d$ is the location-specific premium. (It is straightforward to show that our empirical test extends to the case of nonseparability between $d$ and $\theta$.)

We let $X_{od}$ denote the average wages at age 26 of people who choose to move from $o$ to $d$:

$$\begin{aligned} X_{od} &= E\left[w_{\theta c} | o\left(i\right) = o, d\left(i\right) = d\right] \\ &= w_d + s_{od} \end{aligned}$$

so that the observed wages of individuals who move from $o$ to $d$ are equal to the location premium, $w_d$, plus the average type among those going from $o$ to $d$, $s_{od} = E\left[\theta | o\left(i\right) = o, d\left(i\right) = d\right]$.

Next, let $dX_{od}$ denote the observed change in these average wages at age 26. In our empirical implementation, this will correspond to the changes in average wages in a place between 2010 and 2017. The 2010 measure captures individuals in their mid-20s during the depth of the recession, whereas the 2017 measure captures individuals in their mid-20s after several years of strong economic growth.

The key concern is that variation across places in $dX_{od}$ reflects not just changes in wage offers to a given set of people, but also reflects changes in the composition of the types of residents who move between these places. We can see this mathematically by decomposing the observed change in wages for those moving between $o$ and $d$, $dX_{od}$, into two key parts:

$$dX_{od} = dw_d + ds_{od} \tag{2}$$

The first term is the average change in *wage offers* for a given type $\theta$ for individuals that reside in $d$ as young adults. This is the variation we want to isolate when examining how wages impact migration. The second term is the change in average wages due to changes in the *composition* of the types, $\theta$, of individuals who move from $o$ to $d$. If a city like Minneapolis saw average wages rise because it became popular with high $\theta$ individuals from the origin, that would be captured in this second term.

The goal of our test is to identify a source of variation in wages that isolates changes in wage offers, $dw_d$. We do so by examining a candidate source of variation in wages, $dZ_{od}$.We assume $dZ_{od}$ has been scaled so that on average a one unit increase in $dZ_{od}$ corresponds to a one unit increase in $dX_{od}$. In other words, one should think of $dZ_{od}$ as the predicted values from the first stage regression of $dX_{od}$ on an instrument of interest. In our implementation below, $dZ_{od}$ will be the first stage prediction of $dX_{od}$ from a regression of $dX_{od}$ on a leave-out measure of wage changes for those in destination $d$.[34] In other words, our instrument for $dX_{od}$ is composed merely of destination-level

[34]When $o \neq d$ we instrument with the wage changes of individuals in the two cohorts immediately preceding our cohort of interest. This use of older cohort instruments allow us to remove any concerns about a finite sample mechanical relationship between average wage changes and outcomes, while also ensuring that our wage variation is concentrated on individuals with a similar skill type, $\theta$.

cross-sectional variation in wages. If we have identified an appropriate instrument the correlation between $dZ_{od}$ and $dX_{od}$ will be due to its correlation with wage offers (i.e. a good source of variation) rather than skill-specific sorting (a bad source of variation for our purposes).

With this in mind, we use the migration matrix to develop a new test for whether $dZ_{od}$ is driven by variation in wage offers as opposed to changes in skill-specific sorting. Our test rests on the following logic: If wages rise in location $d$ due to shocks that are orthogonal to amenity-based sorting, then wages for individuals from origin $o$ should increase in proportion to the probability these individuals migrate from origin $o$ to location $d$. The key here is tracing the effects of wage changes in various destinations back onto individuals at their location of origin. For example, if wage offers go up in Chicago by \$1, we would expect wages for those growing up in Dubuque, IA to go up by roughly the probability that those individuals reside in Chicago as adults – i.e. by $M_{d|o}$. By contrast, if the wage variation is driven by the effect of amenity shocks that caused higher-earning individuals to migrate to Chicago (e.g. instead of other locations such as NYC), one would not expect a systematic relationship between the wage increases in Chicago and the change in incomes for those growing up in Dubuque. This motivates a test that compares *observed* changes in the outcomes of children who grew up in each origin to *predicted* changes in their outcomes based on the instrumental variation. The prediction is constructed from weighted average of the proposed wage variation where the weights are given by the pre-period probability of migrating to a given destination from each origin.[35]

To formalize this, let $Y_o$ denote the average incomes of children who grew up in each origin,

$$Y_o = E\left[\theta|o\right] + \sum_d M_{d|o} w_d \tag{3}$$

Here, $E\left[\theta|o\right]$ is the average level of human capital for those from the origin, and $\sum_d M_{d|o} w_d$ is the migration-weighted average of the location-specific wage offers,

We now suppose that we have a change in $Y_o$ (e.g. 2010 vs 2017 incomes), which we denote $dY_o$. We can take a total derivative of equation (3) to understand the underlying forces that might cause

[35] Comparing between two different origin cities helps to illustrate this intuition. Let us imagine that Denver becomes popular with high income individuals while Detroit becomes less popular. The compositional changes in each place will cause wages to rise in Denver and fall in Detroit. Now let us consider average wage changes for individuals born in two other locations, such as Phoenix or New Orleans. Residents of Phoenix may be more likely to go to Denver than residents of New Orleans. That said, there is no reason that wages for individuals born in Phoenix and New Orleans should change in proportion to the probability that individuals from those locations migrate to Denver or Detroit. The wage changes in Denver and Detroit were merely the result of the reshuffling of individuals, not the result of increasing wage offers for given individuals. Wages for those born in Phoenix or New Orleans should only change in proportion to baseline migration probabilities if those locations are experiencing labor demand shocks.

a change in $Y_o$:

$$dY_o = \underbrace{\sum_d M_{d|o} dw_d}_{\text{Wage Offers}} + \underbrace{\sum_d dM_{d|o} w_d}_{\text{Location}} + \underbrace{dE\left[\theta|o\right]}_{\text{Human Capital}} \tag{4}$$

There are three reasons that one might see an increase in $Y_o$. First, wage offers may increase in the destinations that are common among people from origin $o$. Second, migration patterns might shift so that people tend to go to labor markets that pay higher wages, $w_d$. Third, there might be an increase in the human capital origin $o$ that, even holding fixed where people go, causes an increase in wages.

The key insight of our test is that the wage offer component is unique in how it enters both equations (2) and (4). A one unit increase in $dw_d$ should increase $dY_o$ by $M_{d|o}$. This means that if $dZ_{od}$ reflects wage offer changes, then a one unit higher $dZ_{od}$ should predict changes in $dY_o$ in proportion to the migration probability $M_{d|o}$. Building on this intuition, for each origin we can predict the change in $dY_o$ using the migration-weighted average of the proposed wage variation, $\sum_d M_{d|o} dZ_{od}$. We then regress changes in incomes in the origin, $dY_o$, on these changes in predicted incomes:

$$dY_o = \alpha + \kappa \sum_d M_{d|o} dZ_{od} + \eta_o$$

The regression coefficient, $\kappa$, is given by the standard formula:

$$\kappa = \frac{cov\left(dY_o, \sum_d M_{d|o} dZ_{od}\right)}{var\left(\sum_d M_{d|o} dZ_{od}\right)} \tag{5}$$

Suppose for the moment that the instrumented variation is not correlated with the location premia or human capital terms in equation (4) (we will return to this issue later). If $dZ_{od}$ is correlated with $dX_{od}$ only through changes in $dw_d$, we would expect that $\kappa = 1$. By contrast, suppose $dZ_{od}$ is only correlated with the sorting components of the place. In this case, we would expect no covariance between $dY_o$ and the weighted average of $dZ_{od}$.[36] More generally, $\kappa$ would reveal the impact of a 1 unit increase in an origin's exposure to the instrumental variation, $\sum_d M_{d|o} dw_d$, on the origin's exposure to the true causal effect of place:

$$\kappa = \frac{cov\left(\sum_d M_{d|o} dw_d, \sum_d M_{d|o} dZ_{od}\right)}{var\left(\sum_d M_{d|o} dZ_{od}\right)} \tag{6}$$

[36] The denominator would still be positive in this case as it would measure the heterogeneity across origins in exposure to places that are positively vs negatively selected.

In this sense, as $\kappa$ ranges from 0 to 1, it captures the extent to which variation in $dZ_{od}$ reflects variation in true wage offers as opposed to selection.

Equation (4) shows that there are two threats to interpreting $\kappa$ as the fraction of the variation in the instrument that reflects true wage offers. First, $\sum_d M_{d|o} dZ_{od}$ might be correlated with the change in human capital in the origin. Second, $\sum_d M_{d|o} dZ_{od}$ might be correlated with the change in whether people from the origin move to high versus low location premia locations, $\sum_d dM_{d|o} w_d$. One can test for these potential biases by assessing the correlation between $\sum_d M_{d|o} dZ_{od}$ and proxies for these terms. We find that in our particular case, these two conditions are likely to be met.[37]

## 5.2 Our Application: Heterogeneous Recovery from the Great Recession

Our empirical analysis uses geographic variation in wages induced from the heterogeneous recovery from the Great Recession as a source of exogenous variation in wages. Recall from above that $X_{od}$ is the average wages at age 26 of people who choose to move from $o$ to $d$. Here, $dX_{od}$ denotes the observed change in these average wages at age 26 between 2010 and 2017. The 2010 measure captures individuals in their mid-20s during the depth of the recession, whereas the 2017 measure captures individuals in their mid-20s after several years of strong economic growth.

We instrument for the observed wage change, $dX_{od}$, using the wage changes of individuals who migrate to location $d$ from all origin locations other than $o$. For $o \neq d$, let $W_{odc}$ denote the leave out average age 26 wages for individuals in cohort $c$ who migrate to $d$ from all other origins $o \neq d$:

$$W_{odc} = E\left[w_{\theta,c} | o(i) \notin \{d, o\}, d(i) = d, c(i) = c\right].$$

This means, for example, that the wage change for migrants from Phoenix to Boston is instrumented with the wage change of Boston in-migrants who grew up in all locations other than Phoenix. In order to capture wage variation for stayers who do not leave their origin CZ (i.e. $d(i) = o(i)$), we take a different approach, motivated by the fact that those who remain in their origin CZ have lower average wages than those who leave. We construct $dZ_{oo}$ using wage changes amongst individuals in the cohorts immediately preceeding our cohort of interest (i.e. their wages are measured in the same year but at age 27-28 instead of age 26). Within those older cohorts, we construct wage changes among the subset of individuals who choose to stay in their origin location. This instrument allows us to remove any concerns about a finite sample mechanical relationship between average wage

[37] As discussed in the next section, we assess the correlation between $\sum_d M_{d|o} dZ_{od}$ and measures of human capital using changes in years of education. We assess the correlation with location premia using migration changes weighted by mean wages in the destinations.

changes and our outcome of interest, while also ensuring that our wage variation is concentrated on individuals with a similar skill type, $\theta$.

Given these definitions of $W_{odc}$, we obtain our variation in wages from a regression of the change in $X_{od}$ on the change in $W_{od}$:

$$dX_{od} = a + bdW_{od} + \epsilon_{od} \tag{7}$$

We obtain a first stage coefficient of $b = 0.66$ and use this to form the predicted values, $dZ_{od}$.

Given these estimates of $dZ_{od}$, we then form the migration-weighted average for each origin, $\sum_d M_{d|o} dZ_{od}$. Here, we construct the migration probabilities based on the pre-period migration matrix, individuals in the 1982 and 1983 cohorts.[38]

We then regress the change in incomes in the origin, $dY_o$, on this migration-weighted average of $dZ_{od}$. Figure 5 presents a binned scatter plot of this relationship. We find that a one unit increase in $\sum_d M_{d|o} dZ_{od}$ corresponds on average to an 1.030 unit increase in $dY_o$ (s.e. 0.033). This means that if individuals from a given origin have a 1% chance of going to a given destination, then a 1 rank increase in wages in that destination should produce an average wage increase in the origin of .0103 ranks. The fact that this point estimate is near 1 suggests that nearly all of this leave-out geographic variation in wages, $dZ_{od}$, reflects changes in the wage offers among destination locations, rather than changes in the skill composition of those destination.

Equation (4) shows that there are two alternative rationales for why one might find a correlation between the changes in incomes in the origin, $dY_o$, and the predicted change in wages from the migration-weighted average of $dZ_{od}$, $\sum_d M_{d|o} dZ_{od}$. First, the predicted change in wages may be correlated with human capital shocks in each origin, $dE[\theta|o]$. Second, the predicted change in wages may be correlated with changes in location premia do to migration, $E\left[dM_{d|o} w_{\theta d}\right]$. It is straightforward to show that wage offer changes have a unique prediction of a coefficient of $\kappa = 1$.[39] One might still worry, however, that a range of offsetting forces happen to align to generate coefficients of $\kappa = 1$.

With that concern in mind, we explore whether $\sum_d M_{d|o} dZ_{od}$ is correlated with proxies for the

[38] This helps prevent potential attenuation due to any sampling variation in the estimation of the migration rate, while also ensuring that there is no mechanical relationship between our instrumental variation and our outcome of interest $dY_o$.

[39] Human capital shocks to an origin would cause increases in wages in the migratory destinations that are only a small fraction of the wage change in the origin. For example, suppose there is a human capital shock in Dubuque, IA that increases everyone's wages by \$100 regardless of where they reside as young adults. Suppose 1% of residents in Chicago are from Dubuque. In that case, we would observe wages go up in Chicago by \$1. Hence, when regressing the wage change in Chicago on the wage change in Dubuque it would generate a coefficient of 100. This intuition is borne out by simulations that show that regressing observed wage changes on the predicted changes based on wages in the destinations would lead to coefficients that tend to differ dramatically from 1.

human capital or location terms in equation (4). We begin by using measures of education as a proxy for human capital. Figure 6 Panel A replaces $dY_o$ in equation (5) with the change in predicted incomes conditional on years of education using the sub-sample linked to the American Community Survey.[40] We find no significant positive relationship between these measures of wage changes. In fact, we find a slightly negative relationship of -0.133 (s.e. 0.076). This suggests our test for exogeneity of $dZ_{od}$ is not biased from the presence of human capital sorting. This, of course, does not mean that measures of education don't predict incomes. In Appendix Figure A11, we show that, in the cross section, income levels predicted based on education are highly correlated across place with $Z_{od}$. The same pattern does not hold, however, when examining changes in wages. Panel B shows that the change in 2010-2017 average wages among 26 year-olds in each CZ is not correlated with the change in predicted incomes based on years of education.

A second potential concern is that between 2010 and 2017, our instrumental variation may be correlated with the location term in Equation (4). This would occur if changes in predicted origin wage growth were correlated with (potentially unrelated) changes in migration that led individuals to sort into locations that had higher average location wage premia. We do not observe the causal effect of locations on wage outcomes, but we can proxy for this by measuring each origin's change in exposure to high income labor markets. More precisely, we can take the 2010 incomes of people in each destination, $Y_d$, and construct the sum of the change in migration probabilities multiplied by this average income, $\sum_d dM_{d|o}Y_d$.[41] We can then regress this on our instrumental variation for the strength of labor markets, $\sum_d M_{d|o}dZ_{od}$. Panel B shows that this yields a coefficient of -0.0078. (s.e. 0.0120), which is both small in magnitude and not statistically different from zero. On net, these results show that the wage variation is not strongly correlated with changes in human capital or the location premiums for those growing up in each origin. This provides justification for interpreting $\kappa$ as the fraction of variation in $dZ_{od}$ that reflects changes in wage offers, as in equation (6). It suggests that virtually all of this variation reflects changes in wage offers as opposed to skill-biased sorting.

While our initial results show that the geographic variation in the recovery from the Great Recession is not driven by skill-biased sorting, we can reinforce these patterns by examining wage changes within demographic groups. In other words, rather than calculating a single $\kappa$, we can

[40] We also include controls for parental income quintile and child race in forming this prediction, although the results are similar with or without those controls.

[41] We rely upon the intuition from Card et al. (2022) that cross-sectional changes in wages are correlated with the causal effect of places on wages. They find that the true causal effects are just 1/3 of the total variation in cross-sectional wage differences. We adopt a conservative approach and construct our measure based on average location wages. If assuming that 100% of cross-sectional wage variation in causal doesn't produce a bias in our results, then estimating the effects with a lower variance estimate of $\sum_d M_{d|o}dZ_{od}$ should have no impact either.

examine sub-group specific wage changes and examine whether they predict origin wage changes. We can examine whether that sub-group specific wage variation is driven by amenity base sorting.

In order to do this, we construct the variation $dZ_{od}$ conditional on parental income quintile and our 4 categories of child race and ethnicity (Asian, Black, Hispanic, White). The results are presented in the coefficient plot in Figure 7. The first row repeats the estimate of $\kappa$ for the pooled coefficient reported in Figure 5. The second row reports the coefficient from an estimate of $\kappa$ when measuring demographic-specific wage changes, $dZ_{od}$, and including intercepts in (5) that vary by demographic subgroup. This yields a coefficient of 1.08 (s.e. 0.03). The subsequent five rows restrict this regression to each of the five parental income quintiles. The subsequent four rows report the coefficient $\kappa$ when restricting to each race/ethnicity category. In each parental quintile and race/ethnicity category, we find coefficients close to 1, with the exception of a less precise estimate when analyzing wage changes among Asian individuals. Across all subgroups, the analysis suggests that nearly all of the wage variation in $dZ_{od}$ reflects variation in wage offers.

The remaining rows of Figure 7 present the corresponding placebo tests using the predicted incomes conditional on education. Here, we generally find coefficients close to zero, suggesting that changes in the human capital shocks at the origin are not generating a bias in our test. Taken together, these test provide strong evidence our proposed variation in wages, $dZ_{od}$, derived from the 2010-2017 recovery to the Great Recession reflects changes in wage offers, as opposed to changes in the skill composition of the local labor market.

# 6 Migration Responses to Nominal Wages

Having identified a source of exogenous variation in wage offers, we now seek to estimate how migration responds to those changes in wage offers. The basic model outlined in Section 3 suggests that real wages (wages adjusted for differences in cost of living) determine the decision to migrate. Our estimation strategy therefore proceeds in two steps. First, we estimate the migration response to nominal wage changes and, second, we estimate the impact of nominal wage changes on prices. We then combine these two figures to produce an estimate for the migration response to real wage changes. We take this two-step approach, rather than controlling directly for prices, because controlling for prices can introduce bias if there is there are aggregate amenity shocks that are correlated with migration flows.[42] We present estimates for the elasticity of nominal wages in this section and

[42]The intuition for this concern is as follows. Our coefficient of 1s test has demonstrated that we have exogenous variation in nominal wage offers that are not driven by skill-based amenity sorting. If we regress migration changes on real wage changes, we have to incorporate a price adjustment in each location. If certain locations have become

calculate the price responses in the section that follows.

With infinite data variation, the estimand of interest would be the response of migration from $o$ to $d$ of a change in wages in location $c$:

$$dM_{d|o} = \alpha_{od} + \sum_{c} \beta_{odc} dX_{oc} + \epsilon_{od}$$

where $dX_{oc}$ is the change in wages in location $c$ for those coming from origin $o$. Unfortunately, estimating $\beta_{odc}$ separately for every $odc$ tuple would be over 400 million coefficients. We therefore begin our exploration with a lower dimensional specification that focuses on two core variables that are likely to determine $M_{d|o}$ : the wage changes in the destination, $dX_{od}$, and the wage changes in the origin, $dX_{oo}$. Motivated by a broad class of models that measure proportional changes in individuals choices, we split our regression separately by quantiles of the distribution of $M_{d|o}$ from the pre-period migration matrix. The intuition here is that changes in migration from $o$ to $d$ in response to wage changes in $d$ will vary with the baseline probability that individuals migrate from $o$ to $d$. Let $g(o,d)$ denote bins of the pre-period, $M_{d|o}$, estimated for the 1982-83 cohorts. For our baseline approach, we pool very small values of $M_{d|o}$ into one bin that includes all below-median values of $M_{d|o}$ as well as bins locations where $M_{d|o} = 0$.[43] We then pool the origin-destination pairs with above-median values of $M_{d|o}$ into 20 equally-sized bins. We then run a regression of the 2010-2017 change in $M_{d|o}$ on the destination and origin wage changes, separately for each bin:

$$dM_{d|o} = \alpha_{g(o,d)} + \beta^{dest}_{g(o,d)} dX_{od} + \beta^{orig}_{g(o,d)} dX_{oo} + \epsilon_{od} \tag{8}$$

We estimate equation (8) for all $(o,d)$ pairs such that $o \neq d$. In other words, we start by estimating the impact of wage shocks on migration to potential destination locations. We instrument for $dX_{oo}$ and $dX_{od}$ using the leave-out variation in wages discussed in the previous subsection.[44]

Figure 8 presents the coefficients for $\beta^{dest}_{g}$ for each bin of $M_{d|o}$, $g(o,d)$. The x-axis reports the mean value of $M_{d|o}$ within each bin, and the vertical axis reports the estimated $\beta^{dest}_{g}$ coefficient for each bin. Panel A presents all bins. Panel B zooms in on smaller values of $M_{d|o}$ by excluding the top bin. Broadly, we find that increases in wage offers in a destination cause greater in-migration to that destination, $\beta^{dest}_{g} > 0$. For the top bin of $M_{d|o}$, where the average value of $M_{d|o}$is 2.9%, we

more desirable to individuals of all types $\theta$, that would drive up prices and bias our estimates of the causal effect on real wages on migration. In particular, this would result in an attenuated elasticity of real wages as places with larger price adjustments would see more in-migration due to amenity shocks and lower real wage changes.

[43]The distribution of the migration probabilities is such that, for most of the 740 potential destinations from each origins, $M_{d|o}$ is quite small. Pooling the bottom half of $M_{d|o}$values into a single bin has no meaningfully impact on our results.

[44]Formally, we run an IV regression of equation (8) using $dW_{oo}$ and $dW_{od}$ as instruments. Appendix Figure A12 presents the first stage relationships between $dW_{oo}$ and $dW_{od}$ and $dX_{od}$ and $dX_{oo}$.

find that a 1 rank increase in wages leads to an increase in $dM_{d|o}$ of around 0.0284pp (s.e. 0.008pp). We find proportionally smaller migration responses to wage changes in destinations with a lower baseline likelihood of migration, $M_{d|o}$. There is only a minimal detectable effect of wage increases on migration for places where individuals are highly unlikely to go.

While the migration responses vary in proportion to baseline migration probabilities, we find that the response is non-linear. For destinations with small baseline probabilities, we find a response that is roughly $0.04M_{d|o}$ (a semi-elasticity of 0.04 with respect to wage ranks), whereas for destinations with higher baseline probabilities we estimate a response of approximately $0.01M_{d|o}$.[45] Most migration occurs between origins and high probability destinations, and, consequently, the aggregate semi-elasticity is close to the value observed in the top bin. The results suggest that a 1 rank increase in a destination's wages (i.e. roughly \$800) causes a 1% increase in the number of 26 year old migrants who move to that area.[46]

The shape of Figure 8 is qualitatively consistent with the prediction of canonical common coefficients multinomial Logit models. Both in these models and in our results, migration responses in a given location vary with the baseline probability of going there. That said, the patterns we observe deviate slightly from the quantitative predictions of the multinomial logit model. The logit would predict that the migration response in each destination is proportional to $M_{d|o}\left(1 - M_{d|o}\right)$. This means that for small values of $M_{d|o}$, a Logit parameterization would yield a fairly linear relationship in $M_{d|o}$. Our results indicate that the migration response diminishes fairly rapidly as $M_{d|o}$ rises. Figure 9 (Panel A) shows that the multinomial pattern is formally rejected in the data. The figure presents the predicted values from fitting the dots to a curve that scales with $M_{d|o}\left(1 - M_{d|o}\right)$. The figure also shows the estimated migration response if the bins of $M_{d|o}$ were replaced with a cubic function. The observed results follow the cubic pattern much more closely, as young adults are proportionally more responsive to wages in places that they are less likely to move. In other words, wage changes in unlikely destinations result in disproportionately larger inflows of young residents.

We can learn more about the migration response to potential wage changes by examining the other coefficients reported in Equation (8). Figures 9B and 9C reports the coefficients for the origin wage changes, $\beta_g^{orig}$, alongside the estimates of $\beta_g^{dest}$ that were reported in Figures 8A and 8B. Consistent with what one would expect, the coefficient on origin wage changes is negative. A positive

[45] Using the confidence interval in the top bin we can calculating that the associated elasticities range from 0.4% to 1.5%.

[46] These baseline results focus on the migratory response to changes in individual income. Appendix Figure A13 shows that the estimated patterns are quite similar when considering family income instead of individual income.

wage change in an individual's origin makes them less likely to move to some new destination $d$. The coefficients are roughly the mirror image of the destination coefficients, but the magnitudes themselves are slightly smaller. This is not unsurprising, as individuals who move to a new destination may be substituting away from alternative destination locations, rather than simply substituting away from their origin (Borusyak et al., 2022).

In order to capture the role of wage changes in other potential destinations, we modify the specification above to include controls for the average change in wages in places other than the origin and destination. For each origin-destination cell, we construct the average wage change in other destinations, $\frac{1}{1-M_{d|o}-M_{o|o}}\sum_{c\neq o,d} M_{c|o}dX_{oc}$ and we construct an instrument using $dZ_{oc}$ in place of $dX_{oc}$. This leads to a regression of the form

$$dM_{d|o} = \alpha_{g(o,d)} + \beta^{dest}_{g(o,d)}dZ_{oo} + \beta^{orig}_{g(o,d)}dZ_{od} + \beta^{out}_{g(o,d)}\frac{1}{1-M_{d|o}-M_{o|o}}\sum_{c\neq o,d} M_{c|o}dZ_{oc} + \epsilon_{od} \tag{9}$$

We estimate this regression separately for each $M_{d|o}$ bin, $g$. Figure 9D presents the resulting coefficients for $\beta^{dest}_g$, $\beta^{orig}_g$, and $\beta^{out}_g$ in equation (9). We again find similar increasing patterns for $\beta^{dest}_g$. Our estimates of $\beta^{dest}_g$ are statistically indistinguishable from the coefficients estimated in the initial specification, which did not include an outside option wage change. When analyzing the origin and outside option coefficients, $\beta^{orig}_g$ and $\beta^{out}_g$, we find relatively imprecise estimates. The point estimates suggest that, compared to a change in origin wages, wage changes in other destinations have a slightly larger negative effect on migration. That said, the high correlation between these two terms make it difficult to precisely separate these effects. The point estimates here are loosely consistent with a model where wage shocks have a larger impact on *where* someone goes, rather than *whether* they go. In other words, wage shocks have a small impact on whether someone leaves their origin but, conditional on the choice to leave, wage shocks impact destination choice. In the next section we explore that pattern in more detail.

**The Likelihood of Leaving Home** Another way to assess the role of wage changes on location choice is to examine how origin wage changes impact rates of out-migration from one's origin CZ. We explore these patterns with a specification analogous to the one established in equation (8), but now consider the case when $o = d$.[47] Figure 10 presents a binned scatter plot presenting the relationship between changes in the stay probability and the change in the predicted wages in the origin. We

[47]Note that now we cannot separately estimate a destination and origin wage change, and the outside option shock is now capturing the weighted average wage shock in all potential destinations.

find a coefficient of 0.0023 (s.e. 0.0006). The sign of the coefficient suggests that young adults are more likely to stay in their origin CZ when the CZ experiences higher wage growth. That said, the magnitude of this response is proportionally much smaller than the response to wage changes in destinations locations. For an average stay rate of 0.69 (or 69%), the slope of 0.002 implies that a 1 rank increase leads to a 0.3pp increase in the likelihood of staying in the origin. This is less than one third the magnitude of the semi-elasticity response to destination wages. This result is consistent with the idea that the choice *whether* to migrate is less responsive to wage changes than the choice *where* to migrate.[48,49]

**Demographic Heterogeneity in Migration Responses** The analysis in Section 5 demonstrated that our identifying wage variation captures exogenous changes in wage offers within demographic subgroups. As a result, we can extend our elasticity analysis to those subgroups as well. We begin by specifying a version of equation (9) by demographic subgroup, $s$. We consider a regression of changes in the migration probability from $o$ to $d$ for subgroup $s$ :

$$dM_{d|os} = \alpha_{g(o,d,s)} + \beta^{dest}_{g(o,d,s)} dX_{oos} + \beta^{orig}_{g(o,d,s)} dX_{ods} + \beta^{out}_{g(o,d,s)} \frac{1}{1 - M_{d|os} - M_{o|os}} \sum_{c=o,d} M_{c|os} dX_{ocs} + \epsilon_{ods} \tag{10}$$

where we re-define the quantiles of $M_{d|os}$ to correspond to the distribution of the subgroup-specific migration probabilities. We begin by pooling together all the sub-group variation to estimate a single set of coefficients. This approach leads to a wider support due to the additional subgroup variation. Appendix Figure A14 presents these results for the $\beta^{dest}_g$ coefficients, plotted alongside the estimates from the pooled results. These results trace out a very similar pattern to our previous demographic-pooled coefficients in equation (9).

Next, we can explore how the estimates in equation (10) vary across demographic subgroups. Recall that the results in Section 4 showed that Black and Hispanic young adults move shorter distances than White young adults, and those from low-income families move shorter distances than those from high-income families. We can now ask whether migration elasticities vary across these subgroups.

[48] This result is also consistent with the findings in Monras (2020), who looks at migration patterns across the full population and finds that negative economic shocks reduce in-migration but have little impact on out-migration.

[49] One potential concern with this specification is that we are not controlling for the change in wages in nearby locations. It could be that origin wage changes are correlated with destination wage changes. Appendix Table 2 includes controls for the outside option, as in equation (9), but we do not find the expected negative coefficient on the outside option. This could be due to spatially correlated labor market shocks that are not perfectly captured in our specification.

Figure 11 Panel A presents the estimates of $\beta_g^{dest}$ in equation (10) separately for Black, Hispanic, and White young adults.[50] In order to increase power, we estimate the results for quintiles of the distribution of $M_{d|os}$. The results suggest, compared to White young adults, Black young adults have lower rates of migration change in response to wage changes. Those effects are calculated conditional on baseline migration rates, which means that the effect is driven by a differential response to underlying wage changes rather than a different baseline migration matrix. By contrast, the migration elasticity for Hispanic young adults looks similar to the migration elasticity for White young adults.[51] In interpreting these results it is important to be note that our analysis here is restricted to individuals born in the United States. In complementary work, Cadena and Kovak (2016) argue that the location choices of Mexican-born immigrants living in the US are highly responsive to labor market opportunities.

Figure 11 Panel B presents results on migration elasticities across individuals with different levels of parental income. In particular, it shows the migration elasticity by quintile of baseline migration separately for those with Q1 and Q2 parental income versus those with Q4 and Q5 parental income. We find that individuals from affluent families are much more responsive to wage changes, even conditional on the pre-period likelihood of migration.[52] In other words, not only do individuals from affluent families have a higher baseline likelihood of leaving their childhood CZ, they are also more responsive to changes in wage opportunities in other CZs.[53]

Putting these results together, we find that there is a clear migration response to changes in wage opportunities. We find that the decision whether to stay in one's origin CZ is less responsive to wage changes than the decision of where to go. We find that the migration response to wage changes is smaller for Black young adults and those from low-income families. Those sets of individuals have

[50] Unfortunately, we have insufficient statistical power to provide informative elasticities for Asian young adults.

[51] These results have implications for welfare analysis that seeks to place monetized value on a local amenity, such as environmental quality. A common approach in existing literature relies on the use of a spatial equilibrium model to infer the value of a localized amenity from the migratory and price responses to amenity changes (Bartik et al. (2019)). The intuition of the approach is as follows: Suppose that population increases 1% from a $1000 wage increase (roughly consistent with our estimates). Suppose for simplicity that housing is in infinite supply, and so there are no price effects. Now suppose there is an exogenous change in local amenities that cause the population to rise by 2%. In a broad class of models, dividing the migratory response to the amenity by the migratory response to a wage change yields the monetized value of the amenity. In this case, this implies that the amenity is valued at $2000 in yearly wages. These estimates suggest caution in applying a single migration elasticity uniformly across the population. A lack of a migratory response among particular demograhic subgroups may not be indicative of low valuations for amenity changes.

[52] These results are broadly consistent with the findings in Bound and Holzer (2000) who found that the migration response to labor demand shocks is smaller for Black workers and for lower-income workers.

[53] Appendix Figure A15 repeats these patterns focusing on the likelihood of staying in one's origin CZ. Consistent with the patterns above, we find that Black young adults and those from low-income (Q1+Q2) families are less responsive to changes in wages than White and Hispanic young adults and those from affluent families.

both shorter average migration distances and lower average migration elasticities with respect to wage changes.

**Robustness: Timing of Wage Changes and Delayed Migratory Responses** Our primary specification measures location response to contemporaneous changes in wages at a 7 year interval, which might best be thought of as a "medium run" or "business cycle" frequency response of migration. This raises the question of whether these migration responses would be smaller if they were analyzed at different time horizons. (It could be the case that migration changes operate with a significant lag. It could also be that migration decisions will also depend on the anticipation of future wages, as is the case in dynamic location choice model with moving costs (Kennan and Walker, 2011)). This motivates an analysis of whether future wages also affect migration decisions.

While we are limited in the time window over which we can link children to their parents and thus childhood location, we can readily explore how our results differ if we consider a shorter time window. To that aim, Appendix Figure A16 Panels A and B reproduce the estimates of equation (9) using wage changes with less than a 7-year time horizon. Panel A consider the impact of 2-year wage changes (2010-2012) and Panel B considers the impact of 4-year wage changes (2010-2014). For comparison we continue to report the estimates from our 7-year baseline results. The results show that we find attenuated migration patterns when wages are measured at the 2 year interval. Once we expand the time horizon to 4 years, however, the results are quite similar to our baseline results.

The presence of a clear effect within a 4-year time intervals means we can use the longer time window to explore whether migration patterns are differentially responsive to future wages. In order to assess this, Appendix Figure A16 Panel C considers a regression of migration changes at the 4 year interval (2010-2014) on wage changes between 2010-2018. Here we find the migration elasticities on the 2010-2018 wage changes are slightly smaller than the elasticities on the 2010-2014 wage changes. The fact that the future wage changes are less predictive of migration is largely consistent with a static model of location choice. We caution, however, against interpreting this too strongly. The ideal regression would include both 2010-2014 and 2010-2018 wage changes. We, unfortunately, lack enough statistical power to rule out meaningful effect sizes in such a specification. Our results suggest that the migration elasticity responses we identify are quite stable when measuring wage changes with time intervals of at least 4 years and that future wages do not serve as a better predictor of migration than current wages.

**Robustness: Alternative Shift-Share Variation in Wages** The use of a shift-share design is a common empirical strategy to generate variation in labor demand across local labor markets (Bartik (1991); Goldsmith-Pinkham et al. (2020); Borusyak et al. (2022)). Such an approach generates wage variation by first estimating the share, $s_{id}$, of workers in each location, $d$ and each industry, $i$. (This is calculated using pre-period employment shares.) The instrument is constructed for each location as those employment shares are then multiplied by the national change in employment demand in each industry, $\Delta D_i$.[54]

Drawing upon the Census Longituduinal Business Database (LBD) we link individuals in our sample to the NAICS code of the industry in which they work. We then form the share of 26 year olds that are in each 2-, 3-, or 4- digit industry in each location in 2010. We measure $\Delta D_i$ the national-level change in average wages ranks among 26 year-old workers in each industry. We use these inputs to form an instrument for the change in labor market strength in location $d$ between 2010 and 2017:

$$b_d = \sum_i s_{id} \Delta D_i$$

We then repeat our analysis from Sections 5 and 6 to examine the migration response to wage changes using $b_d$ as our instrumental variation in wage changes. We begin by using our test in Section 5 to evaluate whether the instrumentally predicted wage change is orthogonal to changes in skill-biased sorting. The test asks whether origin locations that are exposed to locations with higher values of $b_d$ (i.e. places whose industrial composition saw favorable demand changes between 2010-2017) saw wages rise in proportion to their exposure to those locations. Analogous to the baseline approach, we regress $dX_{od}$ on $b_d$ for each o-d pair and form the predicted values for the shift-share instrument, $dZ^{ss}_{od}$. We then regress $dY_o$ on the migration weighted average, $\sum_d M_{d|o} dZ^{ss}_{od}$, forming our estimate of $\kappa$ as in equation (5).

Appendix Figure A17 Panels A-C presents the results for 2-, 3-, and 4-digit industries, respectively. For the 2-digit industry specification, we find a coefficient of -4.34 (s.e. 1.6); for the 3-digit industry specification we find a coefficient of -0.699 (s.e. 1.566); and for the 4-digit industry specification we find a coefficient of -1.498 (s.e. 1.608). We can reject a coefficient of 1 for the 2-digit specification (we can even reject a coefficient of 0). For the 3- and 4-digit specifications, the estimates are not statistically distinguishable from 1 but are also not distinguishable from 0. This means that we unable to validate that Bartik-induced wage variation is orthogonal to wage changes from

[54] $\Delta D_i$can be captured using changes in wages or changes in employment. For the analysis that follows we use change in rank wages.

skill-biased sorting. The scale of the x-axis on the binned scatter plot also highlights the dramatic difference in magnitude of the variation for the shift-share versus our baseline specification in Figure 5: the interquartile range for the shift-share instrument is about 3% of the range for our baseline instrument (0.1 versus 3 ranks).

Next, we evaluate the migratory response to changes in predicted demand using the shift-share variation. We estimate equation (9) using $b_d$ as instruments for $dX_{od}$ (and $b_o$ for $dX_{oo}$). Appendix Figure A18 Panels A-C present the results for the 2-, 3, and 4-digit industry specifications. We present the estimates using the same binning method as our baseline approach. For each specification, we find very imprecise estimates. The results are not statistically distinguishable from our baseline estimates but they are also not distinguishable from zero. This suggests that the industry-based shift-share design does not contain sufficient power to examine how the migratory response to demand shocks varies with baseline migration probabilities.

**Summary** This section documents four main results. First, we show that higher nominal wage offers lead to in-migration. We estimate with an average semi-elasticity of $M_{d|o}$ with respect to wage ranks of 0.01. Second, we find that while the rate of migration to a destination rises in proportion to the baseline probability of migrating there, the effect is concave in $M_{d|o}$. This means that, compared to the prediction of the multinomial Logit, the effect diminishes more rapidly in $M_{d|o}$. It suggests that individuals are proportionally more responsive to wage offers in low-likelihood destinations. Third, we find suggestive evidence that the migration response to destination wage changes is greater than the migration response to origin wage changes. This is consistent with a model where wage changes impact the decision of where to move, rather than whether to move. Fourth, we find significant demographic heterogeneity in migration responses to wage offers: among the sub-groups we analyze, Black individuals and those from low-income families have the smallest responses to changes in wage offers.

# 7 Price Impacts and Migration Responses to Real Wages

The previous section outlines migration response to exogenous variation in nominal wages. Economic theory suggests, however, that an increase in nominal wages will increase migration, drive up prices and, consequently, stem the flow of in-migration. In other words, migration decisions should depend on real, rather than nominal wages. In order to capture how migration changes in response to real wages, we need to measure how nominal wage changes translate into real wage changes.

Capturing price changes in response to migration also allows us to more fully assess the incidence of demand shocks. To see this, consider a change to labor demand, such as the change during recovery from the Great Recession. Let $dw_d$ denote the impact of the shock in location $d$ on nominal wages, and let $dp_d$ denote the impact of the shock on the rental price of housing in each location. The aggregate marginal willingness to pay for this shock by those growing up in $o$ is now given by[55]:

$$dU_o = \sum_d M_{d|o} \left( dw_d - dp_d \right) \tag{11}$$

In contrast to the formula in equation (1), a general equilibrium welfare analysis needs to account for how prices change in response to economic shocks.

In order to explore these dynamics, we begin by nesting our model in Section 3 into a spatial equilibrium structure that clarifies how nominal and real wages are related in such an equilibrium. The model shows the relationship between the rental price of housing and nominal wage changes. It shows that this relationship is impacted both by the elasticity of housing supply and the elasticity of migration with respect to real wages. With this in mind, we then directly estimate the extent to which our exogenous wage offer increases cause changes in prices. This allows us to estimate the elasticity of migration with respect to real wage shocks and ultimately assess how these migration responses impact the welfare consequences of local wage shocks.

## 7.1 Wages and Prices in Spatial Equilibrium

Before turning to the empirical specifications, it is helpful to clarify how prices and wages should be related across local labor markets. To do so, we return to the model in Section 3 and add three spatial components. We assume (1) there are firms in each CZ with a demand for labor, (2) workers growing up in each origin decide where to live, and (3) housing in each CZ is supplied as an increasing function of the local price of housing.

On the labor demand side, we posit a labor demand function $L_c^D(w)$ that measures the number of workers that are demanded in place $c$ at wage $w$. For simplicity, we suppress the dependence of wages on human capital, $\theta$.[56] We can therefore express labor demand as a vector, $L^D(\mathbf{w}) = \left( L_c^D(w_c) \right)_c$,

[55] Equation (11) assumes the wage changes are constant for all types $\theta$ moving into the destination, $d$. If the changes in wages vary by type $\theta$, let $dw_{c\theta}$ denote the change in wage offers to type $\theta$ in location $c$ and let $f(\theta|o,d)$ denote the p.d.f./p.m.f. types $\theta$ that choose to move between origin $o$ and destination $d$ in the status quo world absent the shock. Define $dw_{od} = \int dw_{\theta d} f(\theta|o,d)\, d\theta$. Then, the correct formula for incidence replaces $dw_d$ with $dw_{od}$ so that $dU_o = \sum_d M_{d|o} \left( dw_{od} - dp_d \right)$.

[56] Our core expressions below extend to the more general case as long as labor supply responses do not vary with $\theta$. With heterogeneity across $\theta$, price responses to the shock depend on the full vector of supply responses to real wages across $\theta$.

of labor demands in each place when wages are $\mathbf{w} = (w_c)_c$. The labor supply in each location, $c$, is given by the sum of the migration from each origin, $o$,

$$L_c^S(\mathbf{w} - \mathbf{p}) = \sum_o M_{c|o}(\mathbf{w} - \mathbf{p}) \Pr\{o\}$$

We can express labor supply as a vector $L^S(\mathbf{w} - \mathbf{p})$ where each row corresponds to the labor supply in location $c$, $L^S(\mathbf{w} - \mathbf{p}) = \left(L^S(\mathbf{w} - \mathbf{p})\right)_c$.

Labor market clearing requires that wages and prices are such that the total number of workers who want to live in each place $c$ equal the labor demanded at those wages:

$$L^S(\mathbf{w} - \mathbf{p}) = L^D(\mathbf{w}) \tag{12}$$

For the housing market, we assume that workers must rent a unit of housing in the location in which they work. We let $H_c(p_c)$ denote the supply of housing in place $c$ at price $p_c$. In vector form, we let $H(\mathbf{p}) = (H_c(p_c))_c$ denote the vector of housing supply in each place when prices are $\mathbf{p} = (p_c)_c$. Housing market clearing requires that the total amount of housing available equals the number of people who wish to live in the place at the prevailing prices:

$$H(\mathbf{p}) = L^S(\mathbf{w} - \mathbf{p}) \tag{13}$$

A spatial equilibrium is a vector of wages $\mathbf{w} = (w_c)$ and housing prices $\mathbf{p} = (p_c)$ such that (i) the labor market clears (equation (12)) and the housing market clears (equation (13)).

**Incidence of a Labor Demand Shock** We can utilize this simple model to explore the incidence of labor demand shocks. Suppose there are a set of demand shocks that shift the labor demand curve outward. For example, imagine that labor becomes more productive in each location. If each place $c$ sees productivity rise by $d\eta_c$, labor demand moves from from $L^D(\mathbf{w})$ to $L^D(\mathbf{w} - \mathbf{d}\eta_\mathbf{c})$.

Let $dp_c$ and $dw_c$ denote the impact of this change in demand on prices and wages in each place. We write the demand shock, wage changes, and price changes in vector notation as $\mathbf{d}\eta = (d\eta_c)_c$, $\mathbf{dw} = (dw_c)_c$ and $\mathbf{dp} = (dp_c)_c$. We can totally differentiate the labor market and housing market equilibrium conditions to assess how the demand shock influences prices and wages in each place. For the labor market equilibrium, we have:

$$\Delta L^S(\mathbf{dw} - \mathbf{dp}) \quad = \quad \Delta L^D(\mathbf{dw} - \mathbf{d}\eta) \tag{14}$$

and, for the housing market equilibrium we have:

$$\Delta H \mathbf{dp} = \Delta L^s(\mathbf{dw} - \mathbf{dp}) \tag{15}$$

where $\Delta L^S$, $\Delta L^D$, and $\Delta H$ denote the Jacobian of labor supply (w.r.t. real wages), labor demand (w.r.t. nominal wages), and housing supply (w.r.t. housing prices).[57]

Equation (15) shows how prices and nominal wages vary in response to demand shocks. Solving for **dp**, we have an equation that characterizes how equilibrium wage offers are related to equilibrium prices:

$$\mathbf{dp} = \left(\Delta H + \Delta L^S\right)^{-1} \Delta L^S * \mathbf{dw} \tag{16}$$

Equation (16) motivates a regression to assess how wage changes in each location translate into price changes. The matrix structure of equation (16) highlights the importance of considering the impact of nominal wage shocks not just on the own CZ but also neighboring CZs. For this reason, we consider a regression akin to how we estimated the migration response to nominal wages. We regress changes in prices on the change in wages in the destination, origin, and other potential destinations by replacing $dM_{d|o}$ in equation (9) with $dp_d$.

Given these figures we can then construct an estimate of the migratory response to real wages using the following equation[58]:

$$\frac{\partial M_{d|o}}{\partial \left(w_{od} - p_d\right)} = \frac{\frac{dM_{d|o}}{dw_d}}{1 - \frac{dp_d}{dw_{od}}} \tag{17}$$

## 7.2 Empirical Results

In order to measure the relationship between nominal wages and prices, we construct a measure of rental price of housing using the American Community Survey in 2010 and 2017. Following previous literature (Bergman et al. (2019)), we focus on the average yearly rent for renters of 2-3 bedroom units in each CZ. We then re-estimate equation (9) by placing the rental cost of housing on the left hand side of the regression instead of our traditional migration term.

Figure 12 Panel A presents the coefficients of $\beta_g^{dest}$. The figure shows clearly that nominal wage increases cause increases in the rental price of housing. A one rank increase in wages (roughly $800

[57] If wage changes are different for different levels of $\theta$, the correct term is

$$\begin{aligned} \Delta H \mathbf{dp} &= E_\theta \left[\Delta L_\theta^s \left(\mathbf{dw}_\theta - \mathbf{dp}\right)\right] \\ &= E_\theta \left[\Delta L_\theta^s\right] E_\theta \left[\mathbf{dw}_\theta - \mathbf{dp}\right] + cov\left(\Delta L_\theta^s, \mathbf{dw}_\theta\right) \end{aligned}$$

[58] To see this note that

$$\begin{aligned} \frac{dM_{d|o}}{dw_{od}} &= \frac{\partial M_{d|o}}{\partial \left(w_{od} - p_d\right)} \frac{d\left(w_{od} - p_d\right)}{dw_{od}} \\ &= \frac{\partial M_{d|o}}{\partial \left(w_{od} - p_d\right)} \left(1 - \frac{dp_d}{dw_{od}}\right) \end{aligned}$$

in age 26 wage earnings) leads to an increase in the rental cost of housing of \$200-300. This implies that roughly 25-35% of the changes in nominal wages are capitalized into housing prices.[59][60]

We use this result on changing prices to produce an estimate of the semi-elasticity of migration with respect to real wage changes. The nominal wage response of $0.01M_{d|o}$ found in Section 6 corresponds to real wage responses varying from $0.01M_{d|o}$ to $0.025M_{d|o}$ depending on the local housing supply elasticity. For each 1 rank increase in wages in destination $d$, the probability of migrating from origin $o$ to destination $d$ rises by $0.01M_{d|o}$ to $0.025M_{d|o}$ .

**Elastic versus Inelastic Housing Supply** In developing a more complete picture of these price adjustment patterns, we also explore how the observed price changes differ across different destination locations. An influential body of academic work documents heterogeneity in the elasticity of housing supply across areas of the United States (Saiz, 2010). An implication of that work is that housing supply elasticities may impact the extent to which wage increases are capitalized into prices. Figure 12 Panel A presents some suggestive evidence of this pattern by showing the capitalization of prices into wages based on pre-period migration probabilities, $M_{d|o}$. There is more capitalization in locations with higher values of $M_{d|o}$. This is consistent with what one might expect because these locations tend to be larger cities with less elastic housing supply. Figure 12 Panel B presents more direct evidence of these patterns by drawing upon housing supply elasticities from Saiz (2010). We estimate impact of wage shocks on rental prices separately for the 30 most inelastic CZs as compared to the other CZs for which housing supply elasticity information is available. We find clear evidence that a larger fraction of wage increases are capitalized into house prices in places where housing supply is inelastic.

Having explored the impact of housing supply elasticities on price changes, we then explore how housing supply constraints affect migration decisions. We begin by showing how the migration response to nominal wage shocks differs across places with high versus low housing supply elasticities. Figure 12 Panel C shows that, as expected, there are slightly larger inflows into more elastic housing

[59] Appendix Figure A19 considers a more traditional regression of log rental costs on log individual income. This yields a coefficient of around 0.5. Accounting for the fact that housing is roughly 35% of total expenditures, it suggests a pass-through of roughly 20%.

[60] Moretti (2013) also finds evidence that increases in house prices also lead to increases in the price of non-tradables. Accounting for this additional changes in prices, increases individual living costs by \$175. With that adjustment included approximately 50% of nominal wages are capitalized into housing prices. We arrive at that result in the following manner: Moretti (2013) finds that a 1% increase in house prices leads to a 0.35% increase in the price of other goods. In our data, a 1% increase in the rental cost of housing corresponds to \$140. Our estimates suggest that the rental price of housing increases by roughly 2%. The associated impact on non-tradeables should lead to an additional 0.7% increase in prices. Non-housing income is roughly \$25K, and so a 0.7% increase in prices leads to a reduction in purchasing power of \$175.

markets.[61] Figure 12 Panel D combines the results from Panel C with the change in prices across locations in order to estimate the migration response to real wage shocks. While the migration response to nominal wages may differ across locations with different housing supply elasticities, the migration responses to real wages are relatively similar. This adjustment from nominal to real migration elasticities moves the two sub-group coefficients closer together. This is consistent with a model where, conditional on baseline migration probabilities, the response of migration to real wage changes is constant across destinations.

# 8 Welfare Implications in Spatial Equilibrium

We conclude with a brief discussion of the welfare implications of our results. To do so, we consider the impact of a 2 rank (roughly $1600) increase in the wage offers in a given destination – or, roughly a $0.80 per hour wage increase for a full time worker.[62] This increase could, for example, be driven by a place-based subsidy. For an average CZ, our price adjustment results suggest that 70% of these wage increases flow to workers and 30% flow to landowners in this destination. Our point estimates for the migration response imply that the impacted destination should see its population rise by roughly 0.9pp. This is the result of a 0.6pp increase in in-migration and a 0.3pp reduction in out-migration.[63] In tracing out the incidence of the wage increase, these migration flows mean that approximately 99% of the direct beneficiaries are inframarginal – they would have lived in the CZ regardless of the wage increase. Moreover, most of those inframarginal individuals grew up in or nearby the CZ. (Recall more than 2/3 of individuals remain in their origin CZ and 80% travel less than 100 miles.) That said, our results also suggest that the wage increase may have some spillovers on other locations. When the population increases by 1% in location $d$, those individuals move away from other places. The increased outmigration will cause the rental cost of housing to fall in other locations. In particular, if the housing supply elasticity is similar in those other locations, the magnitude of that decline should be equal to the price increase in location. Hence, the 30% incidence on landowners in location $d$ will be a transfer from landlords in other destinations. This also means that the cost of living will decline in those areas, providing a transfer to the residents who remain. Interestingly, while these effects can produce real wage gains outside of location $d$,

[61] These estimates are a bit imprecise, so while the point estimates clearly diverge, there are overlapping confidence intervals within certain quantile bins.

[62] Appendix Table A4 presents the results from a regression of average individual incomes in the CZ on average individual income rank, yielding a coefficient of $808.8 in the baseline (2010) period.

[63] We arrive at this 1pp by assuming a stay rate of 70%. With a semi-elasticity of 0.01 for those who leave their origin, the migration response to a 2 rank change for those leaving the origin is $2 * 0.3 * 0.01 = 0.006$. For those who stay in their origin, the migration response to a 2 rank change is 2*.0023*0.7=0.003.

the spillovers will still be concentrated in nearby locations. The spatial concentration of migration flows and the proportional nature of migration responses means that spillover real wage gains will be highly localized.

# 9 Conclusion

In this paper, we provide new estimates on the migration patterns of young adults in the United States.[64] The majority of young adults stay close to home. Average migration distances are shorter for Black and Hispanic young adults than for White and Asian young adults. Average migration distances are also shorter for those with lower levels of parental income. Next, we examine how the migration decisions of young adults respond to labor market conditions. Our approach uses geographic variation in labor demand shocks induced by the heterogeneous recovery from the Great Recession. In order to exploit this identifying variation, we develop and implement a new test for whether wage variation across places reflects demand shocks as opposed to amenity-driven sorting. Given the difficulty of identifying exogenous sources of labor market shocks, we hope our method can be useful in future applications. Having verified that our identifying geographic variation in wages is primarily driven by demand shocks, we then find a causal effect of wage opportunities on migration. We find that the migration response to wage changes increases with the baseline probability of migrating to a given destination. Along the way we demonstrate the migratory response to wage changes are large, and the price responses are smaller, in destinations with more elastic housing supply. We examine the responsiveness of migration to wages with demographic sub-groups and find higher elasticities for White and Hispanic young adults as compared to Black young adults. We also find higher elasticities for individuals born into higher income households.

We use our results to think about the welfare consequences of local wage growth. While there is a clear and detectable impact of real wages on migration, the magnitude of those changes is small. Nearly all of the beneficiaries of local wage growth are inframarginal individuals, those who did not migrate to receive the benefits of the shock. The majority of those individuals grew up in locations nearby. From a policy perspective, our results suggest that improvements in local labor markets can have significant positive, yet geographically concentrated, benefits. Put another way, for many individuals the "radius of economic opportunity" appears to be quite narrow.

[64] An interactive data tool displaying those migration patterns can be found at migrationpatterns.org.

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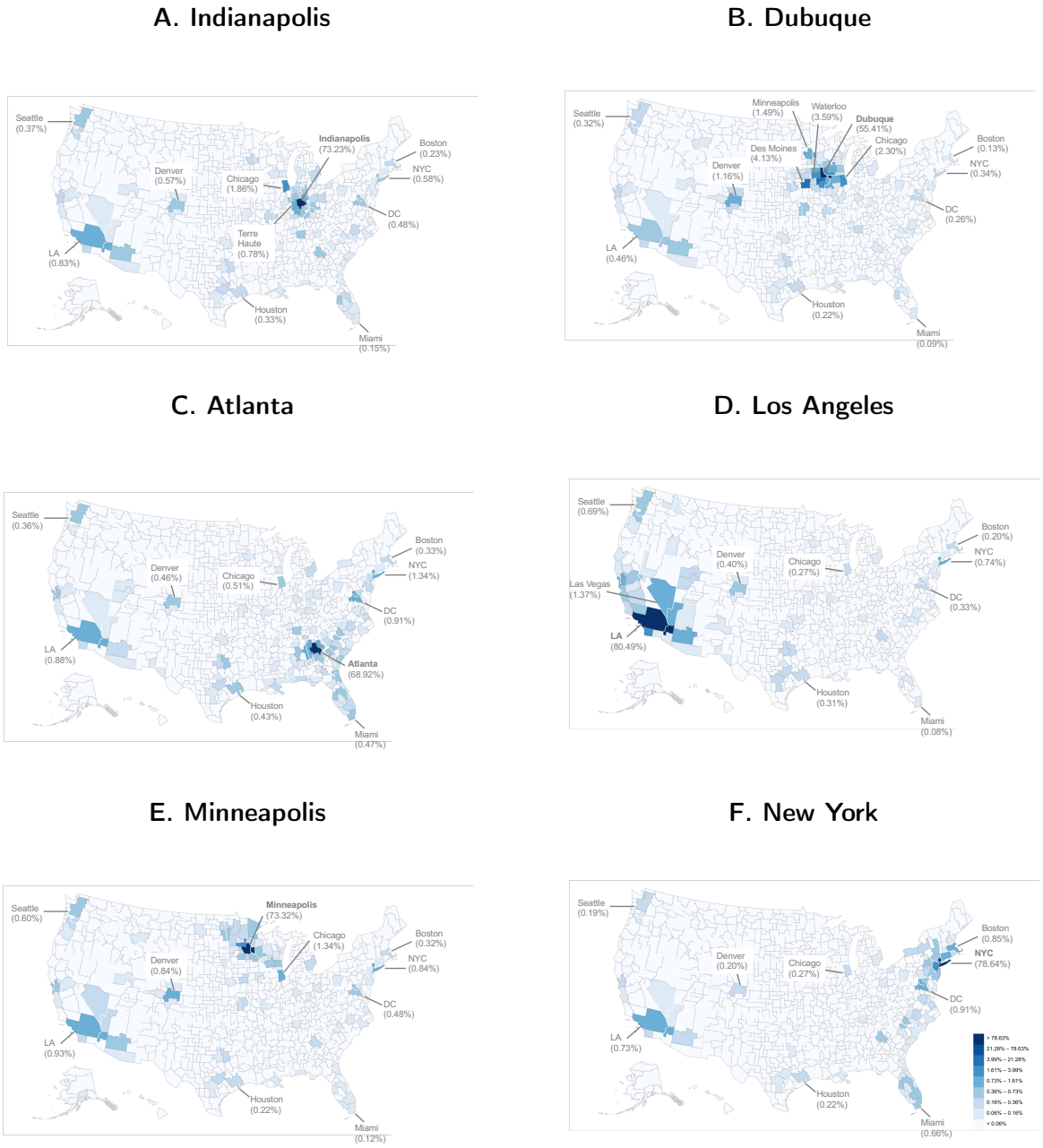
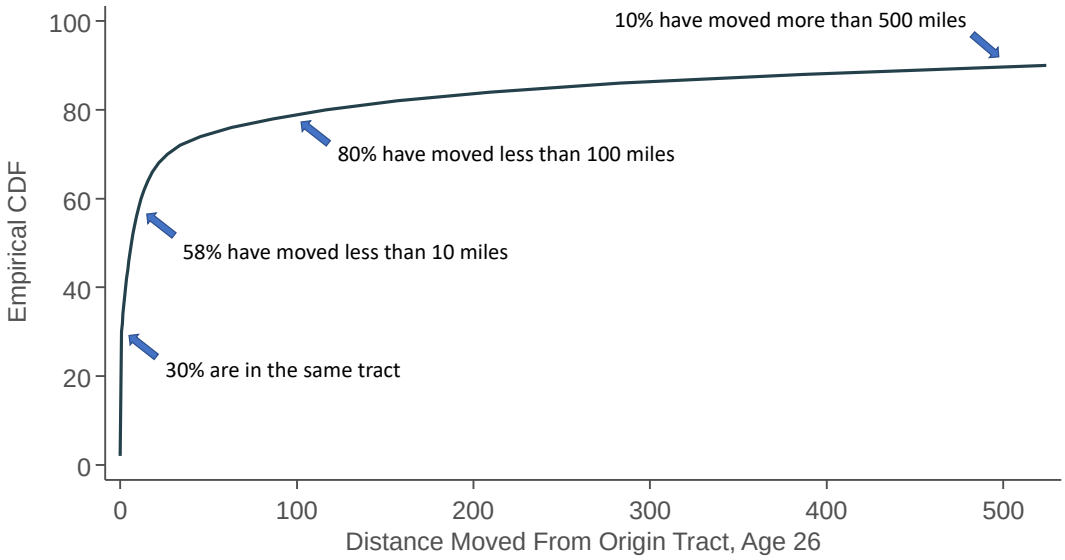
FIGURE 1: Migration Destinations For Select Origin CZs




*Notes:* This figure presents the fraction of young adults that reside in each destination CZ conditional on growing up in various origin CZs in the US. Darker colors correspond to a greater fraction of residents moving to the CZ. We report each origin's stay rate, defined as the share of young adults who live in their childhood CZ and report the fraction of migrants to each destination for select destinations. Panels A-F show the results for children who grew up in Indianapolis, IN; Dubuque, IA; Atlanta, GA; Los Angeles, CA; Minneapolis, MN; and New York, NY. Panel F reports the legend. The darkest color always corresponds to the origin CZ; the remaining thresholds are constant across all panels.

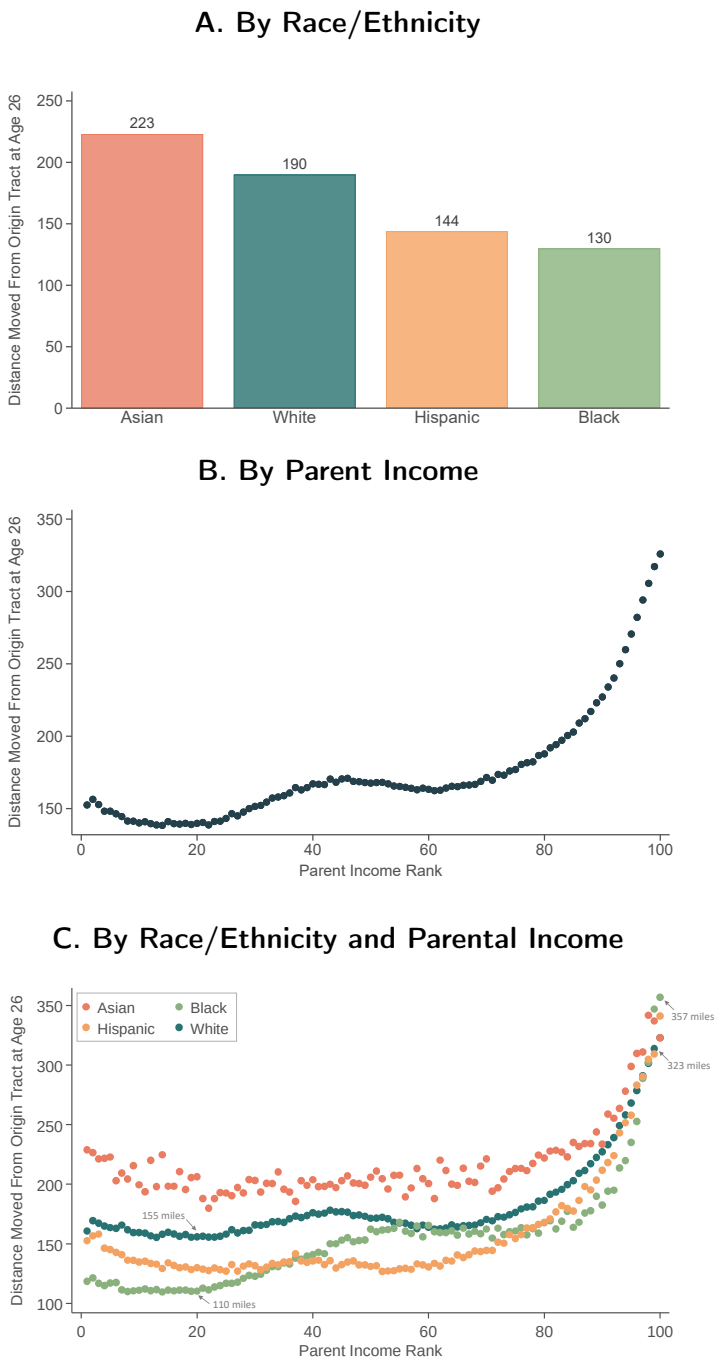
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 2: Cumulative Distribution of Distance Traveled at Age 26




*Notes:* This figure presents the cumulative distribution of distances moved for each young adult in our sample. We measure distance as the distance between the centroid of the childhood Census Tract (at age 16) and the Census Tract in which the child resides at age 26.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 3: Average Distance Traveled by Parent Income and Child Race

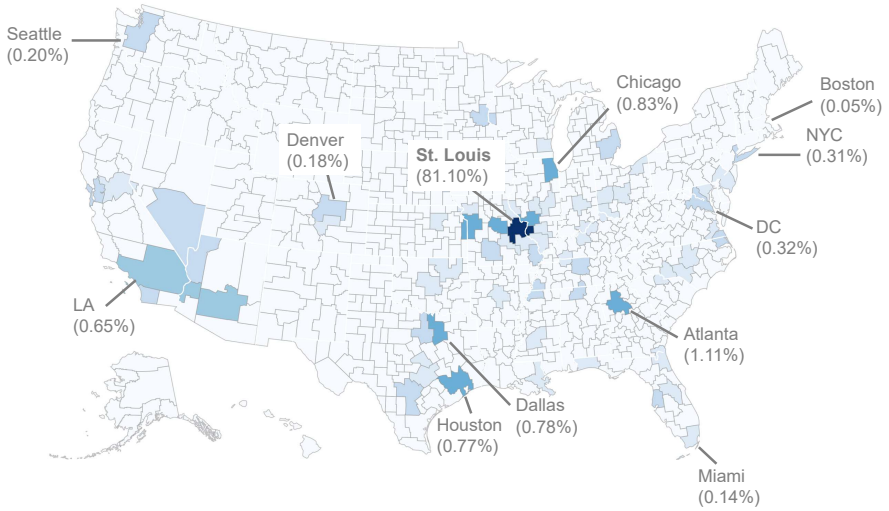



*Notes:* This figure presents the average distance moved between childhood (measured at age 16) and young adulthood (measured at age 26) separately by parental income and the child's race/ethnicity. Panel A reports the mean distance traveled by child race/ethnicity for our four child race/ethnicity categories: Hispanic, Non-Hispanic Black, Non-Hispanic White, and Non-Hispanic Asian. Panel B reports the mean distance traveled by parental income quantile. Panel C reports the mean distance traveled by parental income quantile separately for the four child race/ethnicity categories.

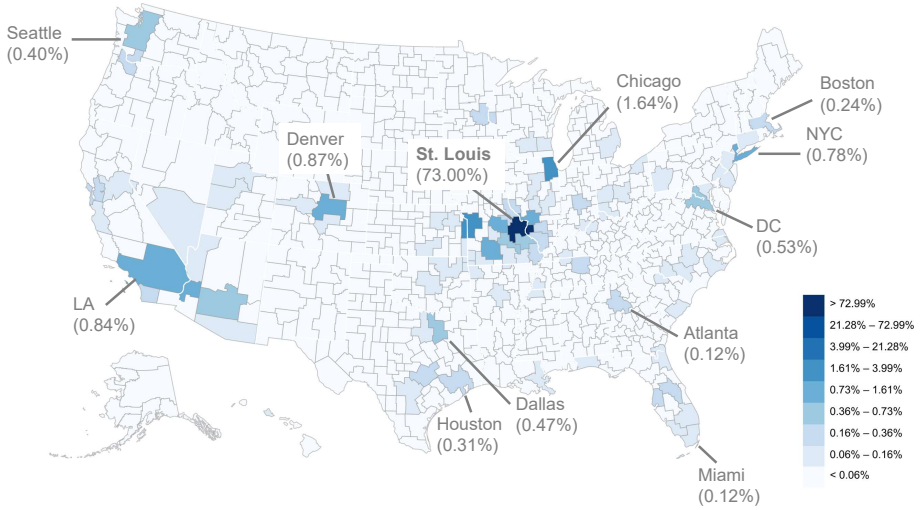
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 4: Migration Destinations Conditional On Growing Up in St. Louis, by Race/Ethnicity

**A. Black Young Adults**

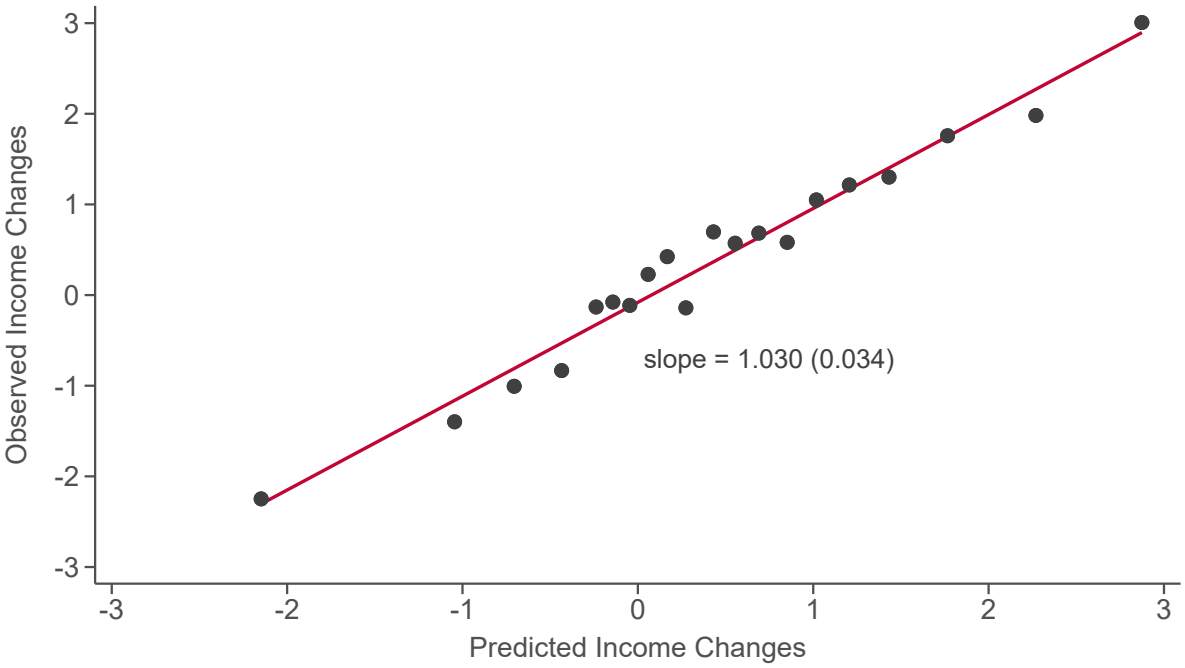



**B. White Young Adults**



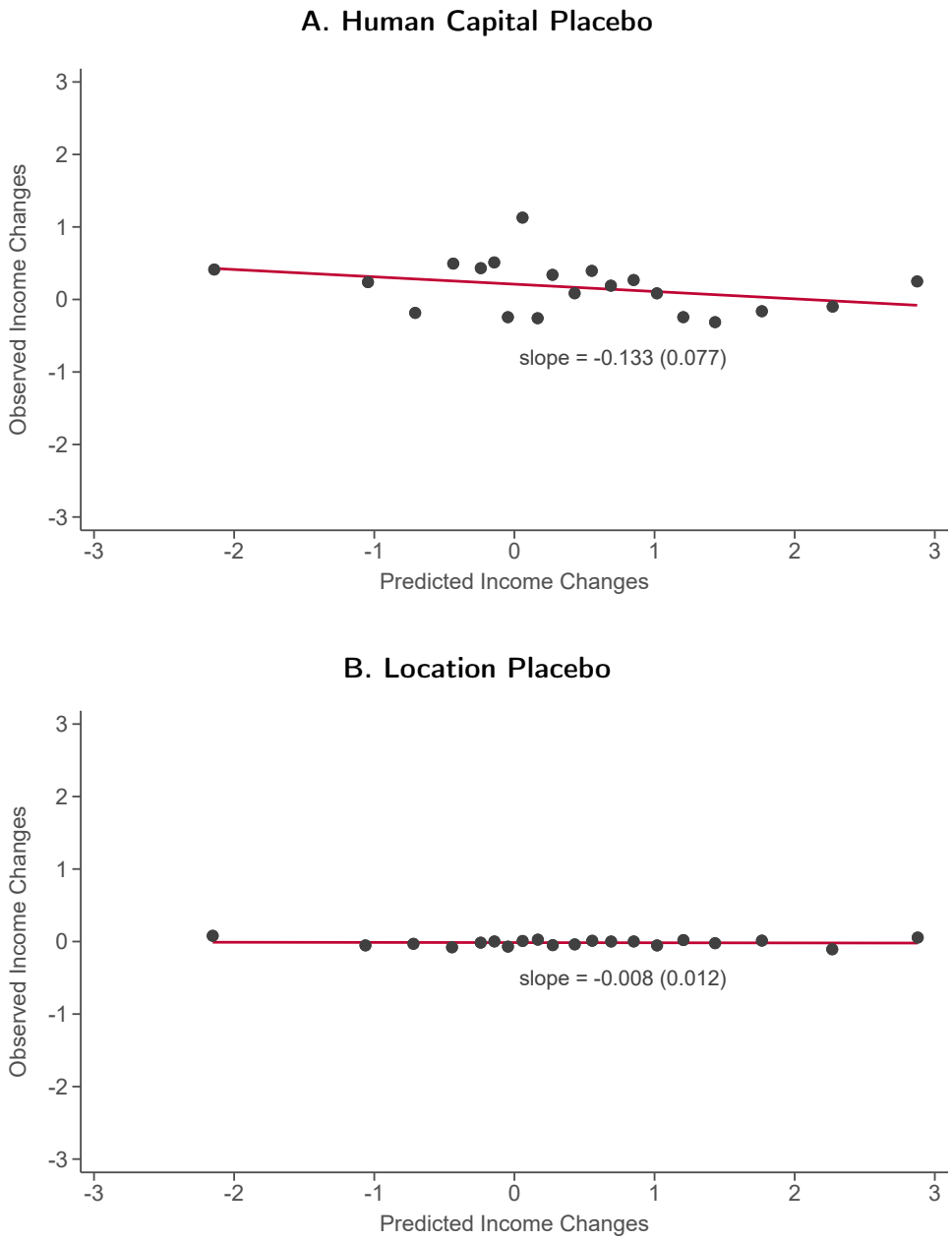

*Notes:* This figure presents the probability of living in each destination CZ in young adulthood conditional on growing up in St. Louis, MO. Panel A shows the migration patterns for Black young adults and Panel B shows the migration patterns for White young adults.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 5: Testing for Skill-Biased Sorting




*Notes:* This figure presents results for the test of skill-biased sorting, outlined in Section 5 of the text. We first construct the predicted change in incomes, $X_{od}$, given the instrumental variation and form the predicted values, $dZ_{od}$. For each origin, we then construct the migration-weighted average of these predicted values, $\sum_d M_{d|o} dZ_{od}$. We present the binned scatter plot of the change in incomes in each origin, $dY_o$ , on these migration-weighted average predicted outcomes based on the change in $dZ_{od}$ on the x-axis. We report the coefficient from the regression in the micro-data. *Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

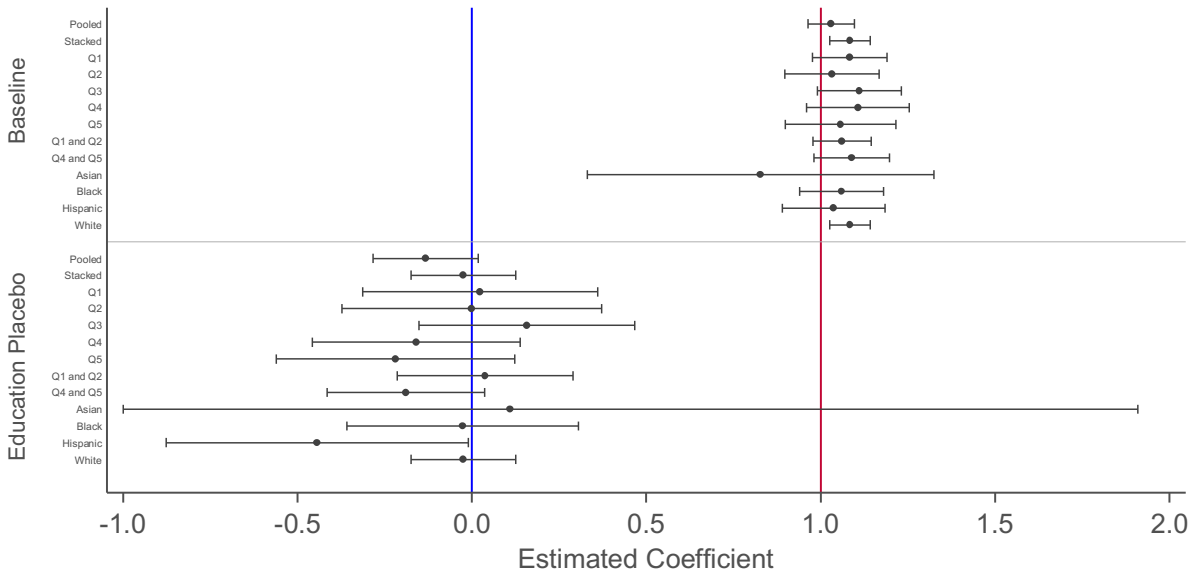
FIGURE 6: Testing for Skill-Biased Sorting: Placebos




*Notes:* This figure presents results for the test of skill-biased sorting, outlined in Section 5 of the text. We begin by forming the proposed wage change measure, $dZ_{od}$, by regressing $dX_{od}$ on the instruments $dW_{od}$ in Equation (7). We then form the predicted change in origin incomes based on the probability of migrating to each destination, $\sum_d M_{d|o} dZ_{od}$, using the pre-period migration matrix, $M_{d|o}$. We then present the binned scatter plot of the change in incomes in each origin, $dY_o$ , on the predicted change in outcomes, $\sum_d M_{d|o} dZ_{od}$. This provides a visual representation of the slope $\kappa$ in equation (6) that estimates the fraction of the variation in $dZ_{od}$ that reflects changes in wage offers as opposed to skill-biased sorting. The figure reports the slope coefficient, $\kappa$, from the regression in the micro-data along with robust standard errors.

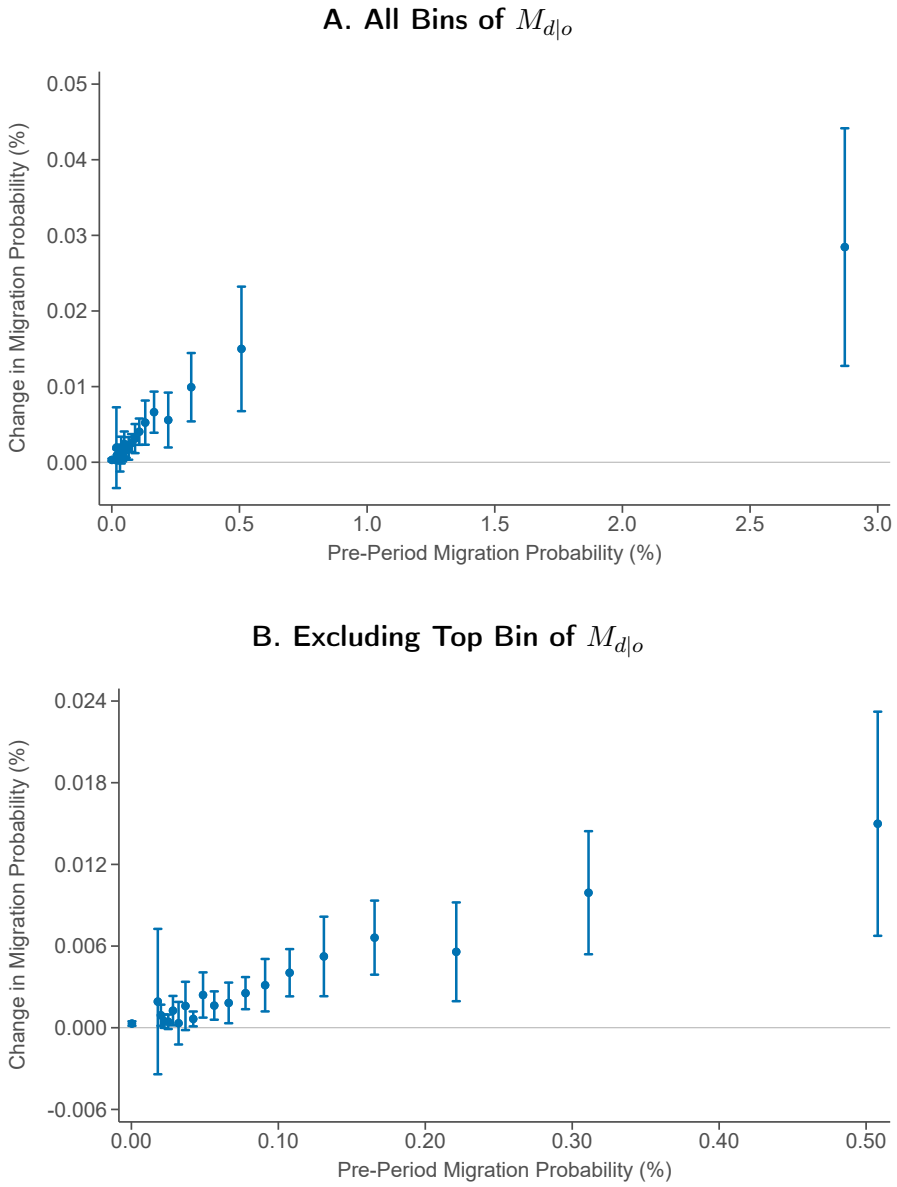
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 7: Testing for Skill-Biased Sorting




*Notes:* This figure presents results for the test of skill-biased sorting, outlined in Section 5 of the text. The first set of results present the baseline test of a regression of the change in incomes for those from each origin CZ, $dY_o$, on the migration-weighted average of the change in $dZ_{od}$, $\sum_{d|o} M_{d|o} dZ_{od}$, where $M_{d|o}$ is constructed using the pre-period (1982-83) migration patterns. We report results from the pooled specification analogous to the specification in Figure 5 and then report estimates by demographic subgroup. The education placebo results replace $dY_o$ with the change in predicted incomes conditional on years of education, parental income, and child race/ethnicity, for the sub-sample that completed the American Community Survey in 2010 and 2017.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

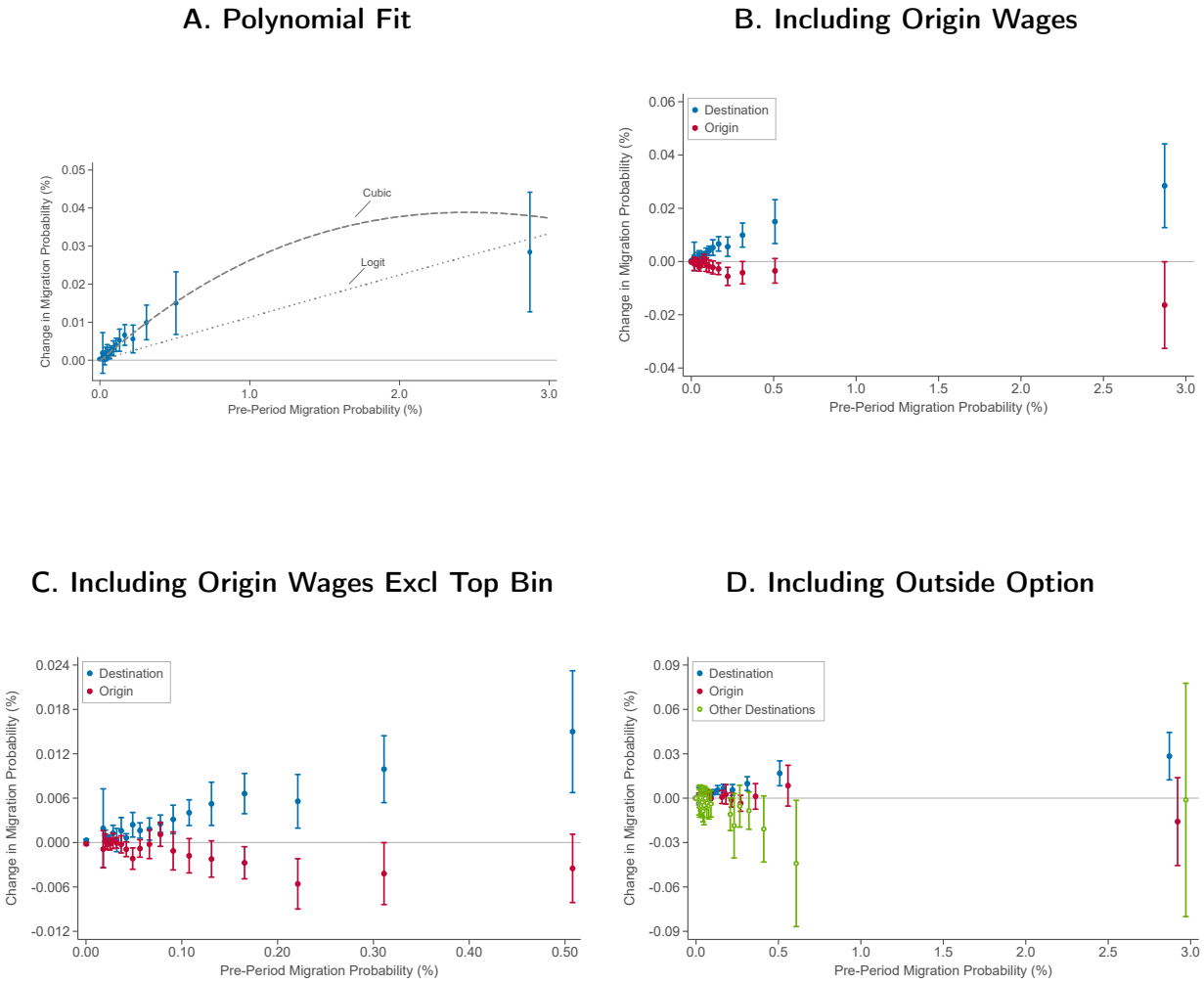
FIGURE 8: Migration Response to Changes in Wage Offers




*Notes:* This figure presents the results from regressions of the change in migration responses to changes in wage offers. We present the coefficients $\beta_g^{dest}$ for each grouping of pre-period migration probability, $M_{d|o}$. We use 21 bins – one bin for the below-median migration probability, and 20 equal-mass bins for above median $M_{d|o}$ values. Panel B excludes the top-most bin to zoom in on lower probability destinations. The horizontal axis then reports the mean of $M_{d|o}$ in each bin, and the vertical axis reports the coefficient $\beta_g^{dest}$ as defined in equation (8). $\beta_g^{dest}$ measures the effect of a 1 rank ($800) increase in wages in the CZ on the probability of migrating to the $CZ$. The grey dashed line reports the predicted impacts of a 1 rank change in wages by replacing $\beta_g^{dest}$ with a cubic polynomial in $M_{d|o}$. The red dashed "Logit" line presents estimates from fitting the dots in Panel A to a curve proportional to $M_{d|o}\left(1 - M_{d|o}\right)$ running through the origin.

*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

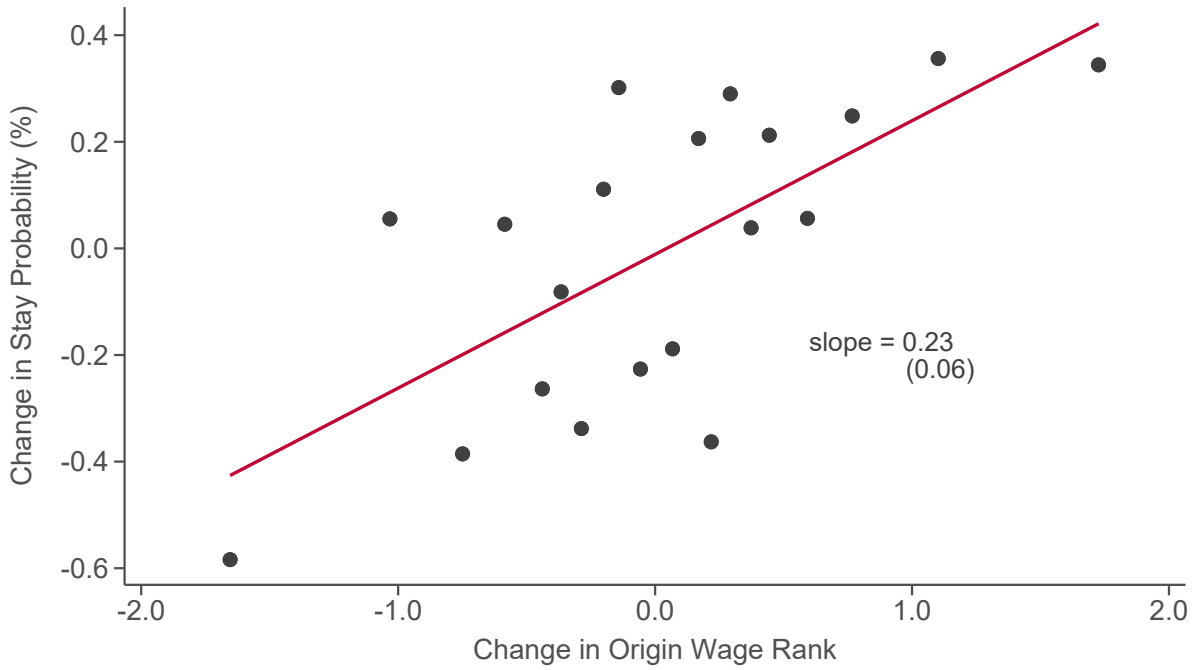
FIGURE 9: Migration Response to Changes in Wage Offers: Alternative Specifications




*Notes:* This figure presents the results from regressions of the change in migration responses to changes in wage offers using various specifications. Panel A presents the same coefficients as in Figure 8A overlaid with two lines: the dashed line reports the predicted impacts of a 1 rank change in wages by replacing $\beta_g^{dest}$ with a cubic polynomial in $M_{d|o}$. The dotted line presents estimates from fitting the dots in Panel A to a curve proportional to $M_{d|o}\left(1 - M_{d|o}\right)$ running through the origin. Panel B presents the coefficients corresponding to equation (8). Panel C zooms in to the first 19 bins of $M_{d|o}$ to help visualize the coefficients for smaller values of $M_{d|o}$. Panel D adds controls for the outside option and presents the coefficients $\beta_g^{dest}$, $\beta_g^{orig}$, and $\beta_g^{out}$ for each grouping of pre-period migration probability, $M_{d|o}$. The origin and other destination coefficients in the top 4 bins are staggered by 0.0005 and 0.0010% respectively along the x-axis to ease visualization.

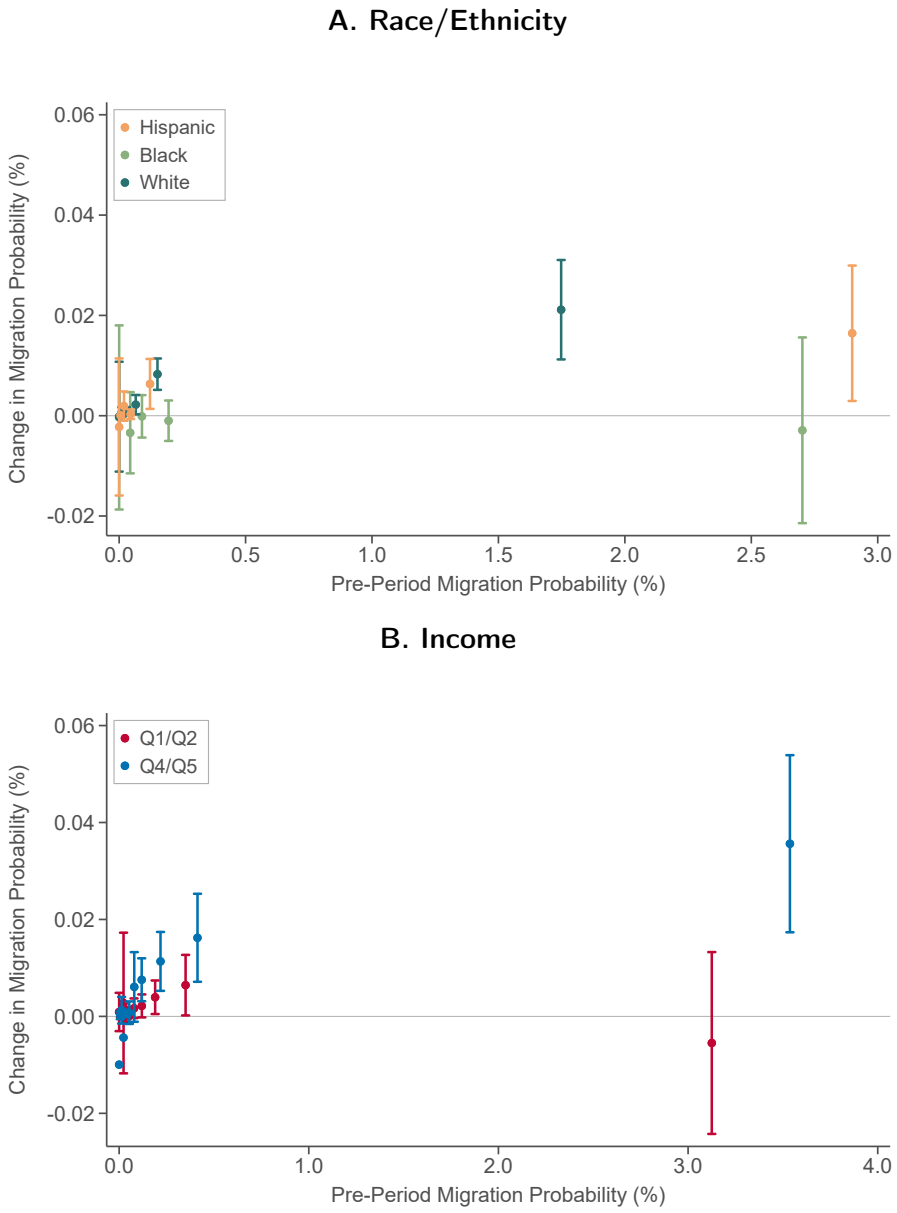
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 10: Change in Stay Probabilities With Respect to a 1 Rank Change in Origin Wages



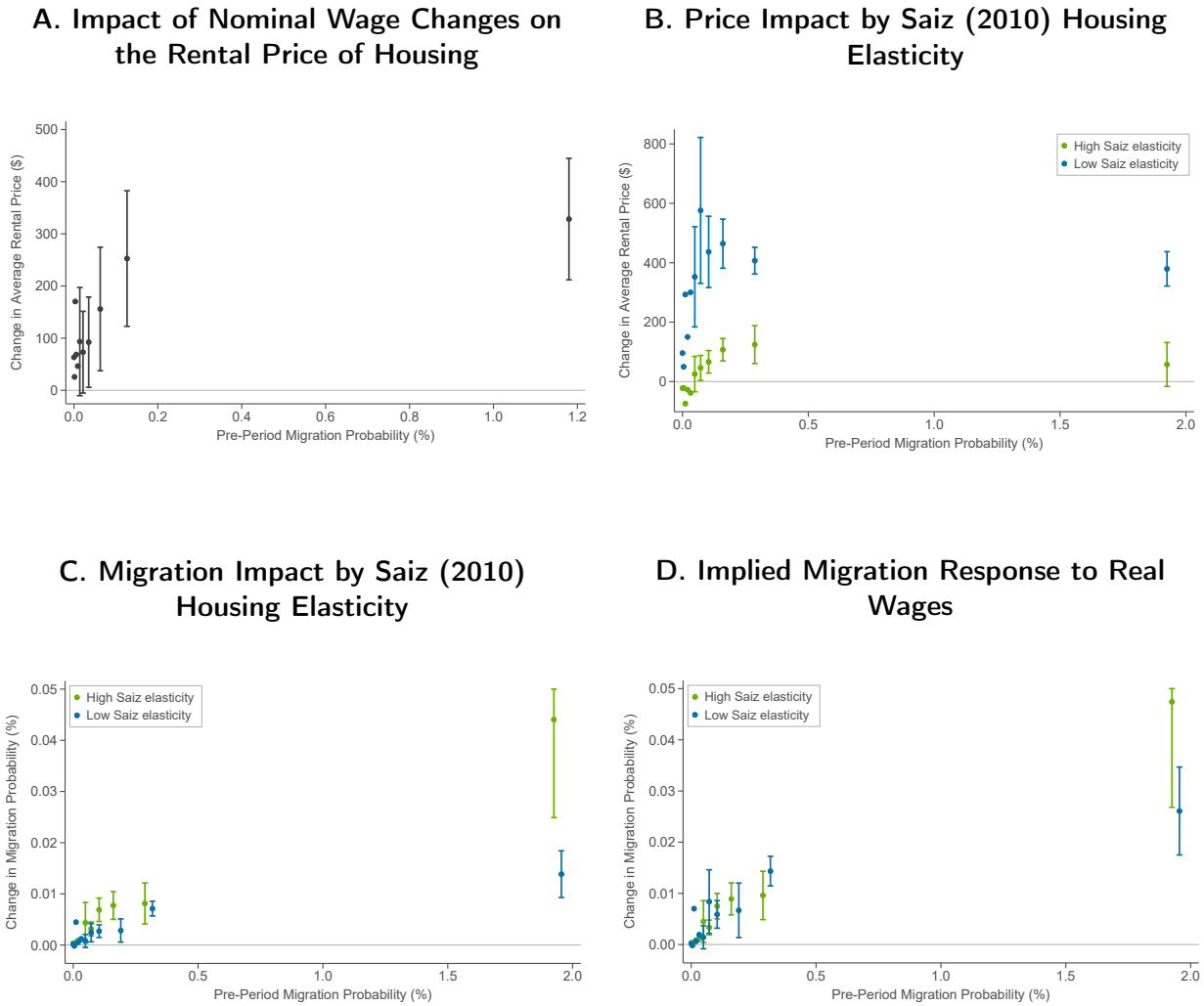

*Notes:* This figure presents the impact of changes in wage offers in one's origin on the likelihood of staying in the origin. We present a binned scatter plot of the relationship between changes in the fraction of children who remain in their childhood CZ on the changes in wages in the origin. The x-axis corresponds to the predictions from the first stage regression of changes in stayer wages, $dX_{oo}$, on changes in the wages of 27-28 year olds in the origin, $dZ_{oo}$.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 11: Change in Migration Probabilities With Respect to a 1 Rank Change in Destination Wages by Demographic Groups




*Notes:* This figure presents the results from regressions of the change in migration responses to changes in wage offers separately by select demographic subgroups. Panel A presents the estimated coefficients $\beta_g^{dest}$ from equation (10) separately for Hispanic, White, and Black young adults. Panel B presents the estimated coefficients $\beta_g^{dest}$ from equation (10) separately for the bottom two (Q1/Q2) and top two (Q4/Q5) quintiles of parental income. We report the coefficients for each subgroup-specific decile of the $M_{d|os}$ distribution. The Q4/Q5 coefficients in the second and third highest deciles are staggered by 0.0003 and 0.0006% respectively along the x-axis to ease visualization.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

FIGURE 12: Change in Migration Probabilities With Respect to a 1 Rank Change in Destination Wages




*Notes:* This figure explores the impact of changes in wage offers on the rental price of housing and the migration response to real as opposed to nominal wages. Panel A presents estimates of $\beta_g^{dest}$ from equation (9) when replacing $dM_{d|o}$ with the change in the rental price of housing, as measured by the average rent for a 2-3 bedroom unit in the destination CZ. Panel B repeats the results in Panel A but considers a sample of high and low housing supply elasticity destinations, where low elasticity destinations are defined as those in the lowest 30 MSAs in Saiz (2010). Panel C presents the corresponding heterogeneity in migration response ($\beta_g^{dest}$ from equation (9)) by high and low housing supply elasticity destinations. Panel D takes the migration responses in Panel C and divides by $1 - dp/dw$ to present estimates of the response of migration to changes in real prices using the translation of 1 rank of wage income = \$800. In Panels C and D the low Saiz elasticity coefficients in the top three bins are staggered 0.03% along the x-axis and in Panel D the top confidence interval is capped at 0.05% to ease visualization.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

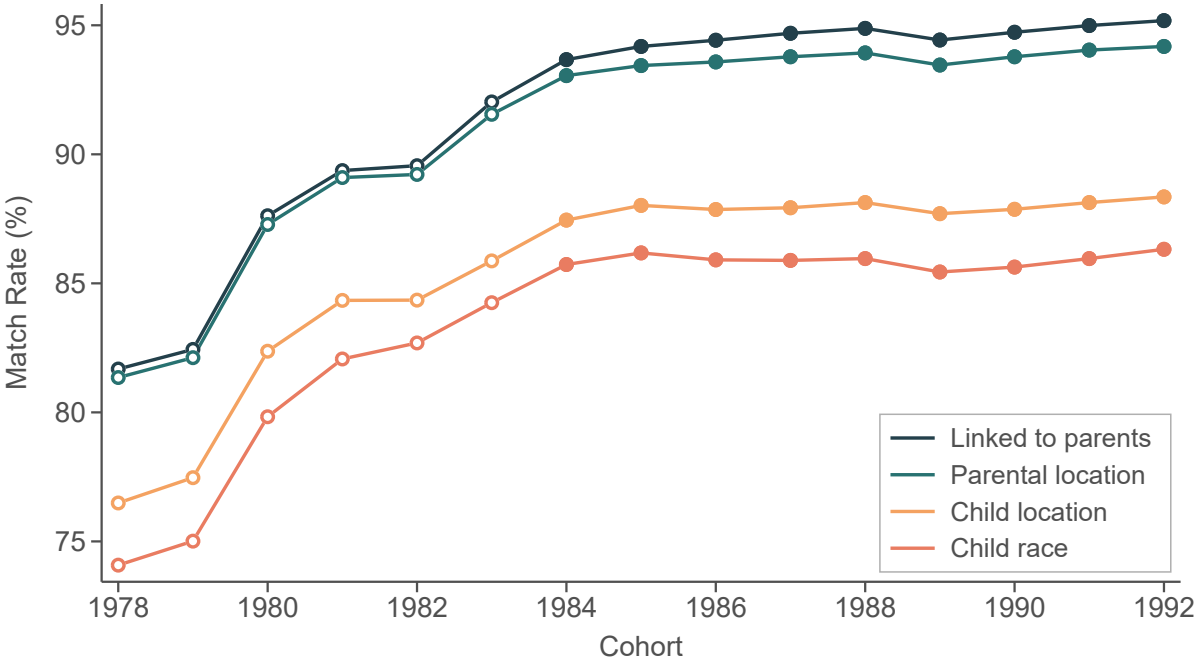
Table 1
Top 10 Most Common Destinations for Movers

| | Pooled | | White | | Black | | Hispanic | | Asian | |
|---|---|---|---|---|---|---|---|---|---|---|
| Rank | Destination | % Movers | Destination | % Movers | Destination | % Movers | Destination | % Movers | Destination | % Movers |
| 1 | New York, NY | 3.19 | New York, NY | 3.15 | Atlanta, GA | 6.68 | Los Angeles, CA | 5.16 | Los Angeles, CA | 8.38 |
| 2 | Los Angeles, CA | 3.05 | Los Angeles,CA | 2.64 | Houston, TX | 3.03 | New York, NY | 3.19 | New York, NY | 8.29 |
| 3 | Washington, DC | 2.22 | Washington, DC | 2.25 | Washington, DC | 2.77 | San Antonio, TX | 3.11 | San Francisco, CA | 7.61 |
| 4 | Atlanta, GA | 1.89 | Denver, CO | 1.99 | New York, NY | 2.71 | Phoenix, AZ | 2.99 | Washington, DC | 3.52 |
| 5 | Seattle, WA | 1.81 | Chicago, IL | 1.93 | Dallas, TX | 2.65 | Houston, TX | 2.75 | San Diego, CA | 3.3 |
| 6 | Chicago, IL | 1.79 | Seattle, WA | 1.88 | Los Angeles, CA | 2.31 | San Diego, CA | 2.72 | Seattle, WA | 3.26 |
| 7 | Denver, CO | 1.72 | Boston, MA | 1.72 | Charlotte, NC | 1.94 | Austin, TX | 2.50 | San Jose, CA | 3.05 |
| 8 | San Francisco, CA | 1.72 | San Francisco, CA | 1.54 | Raleigh, NC | 1.65 | San Francisco, CA | 2.40 | Boston, MA | 2.85 |
| 9 | Dallas, TX | 1.65 | Dallas, TX | 1.41 | Chicago, IL | 1.45 | Dallas, TX | 2.27 | Sacramento, CA | 2.65 |
| 10 | Houston, TX | 1.62 | Phoenix, AZ | 1.41 | Fort Worth, TX | 1.44 | Orlando, FL | 2.09 | Chicago, IL | 2.59 |

Notes: This table presents the top 10 most common destinations that young adults who leave their childhood CZ move to. Each subpanel presents the results separately for each racial/ethnic group. Within each pa
the first column lists the destinations (ordered by the fraction of young adults moving there) and the second column reports the share of young adults who left their childhood CZ that moved there.
Source: Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address informati
DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

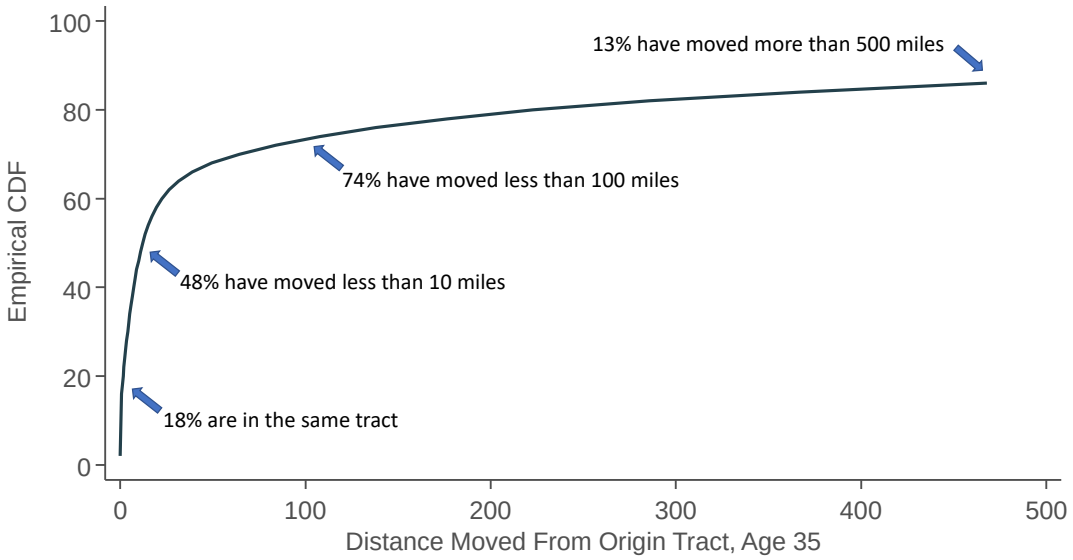
## Appendix Figures and Tables

APPENDIX FIGURE A1: Match Rates by Birth Cohort



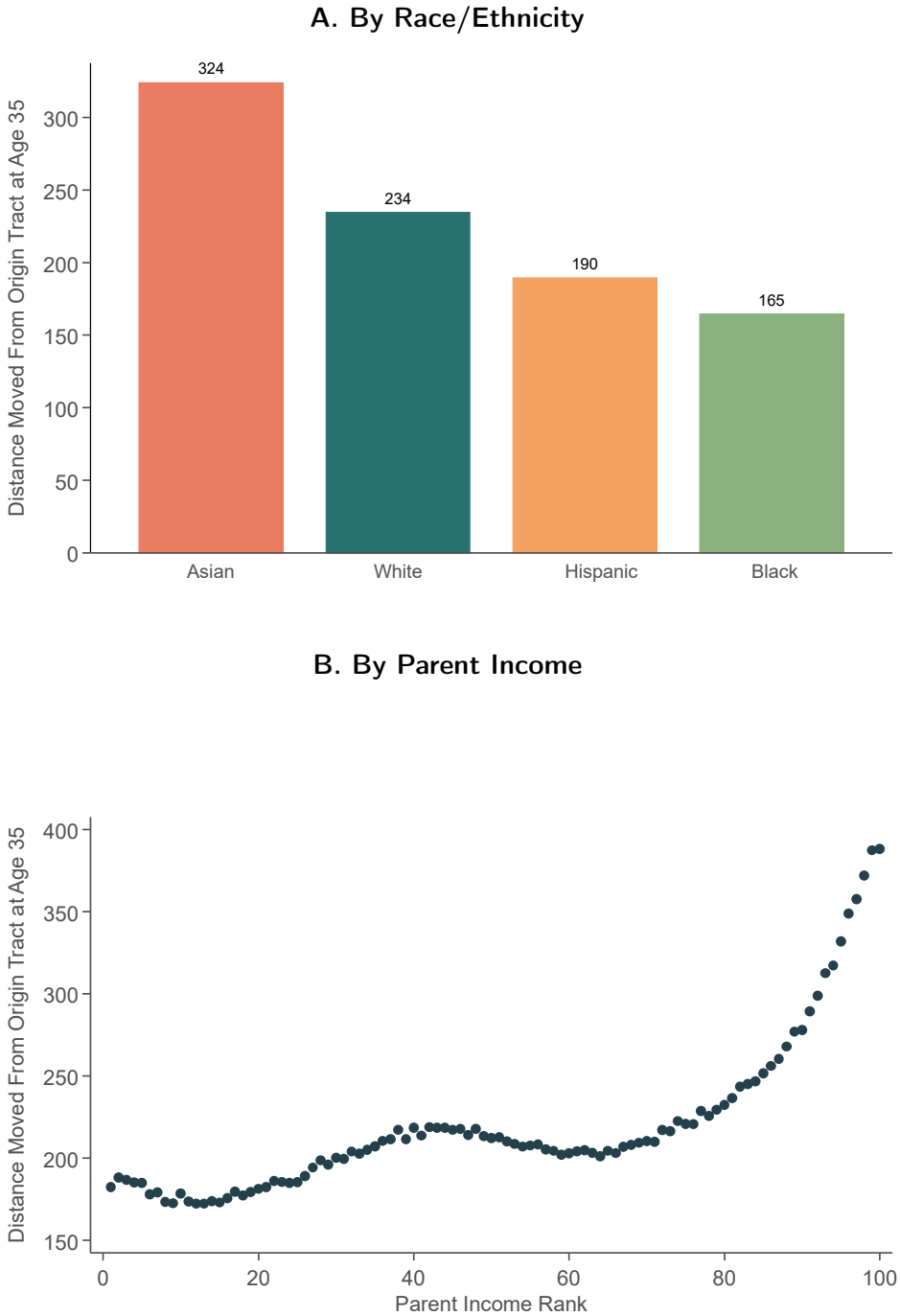

*Notes:* This figure presents sample match rates by cohort. The top line presents the fraction of US born children who we are able to match to parents over ages 14-18. The next line presents the fraction who we can also match to a parental location between ages 14-18. The next line presents the fraction of children who we are also able to match to a child location at age 26. The lowest line presents the fraction of children who we are also able to match to race and ethnicity information in the Decennial Census or American Community Survey. We represent the match rates for our primary sample (1984-92 birth cohorts) in solid dots as opposed to hollow dots for earlier cohorts not included in the publicly released migration matrix.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A2: Cumulative Distribution of Distance Traveled at Age 35




*Notes:* This figure presents the cumulative distribution of distances moved for each child in our sample. We measure distance as the distance between the centroid of the childhood Census Tract (at age 16) and the Census Tract in which the child resides at age 35.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

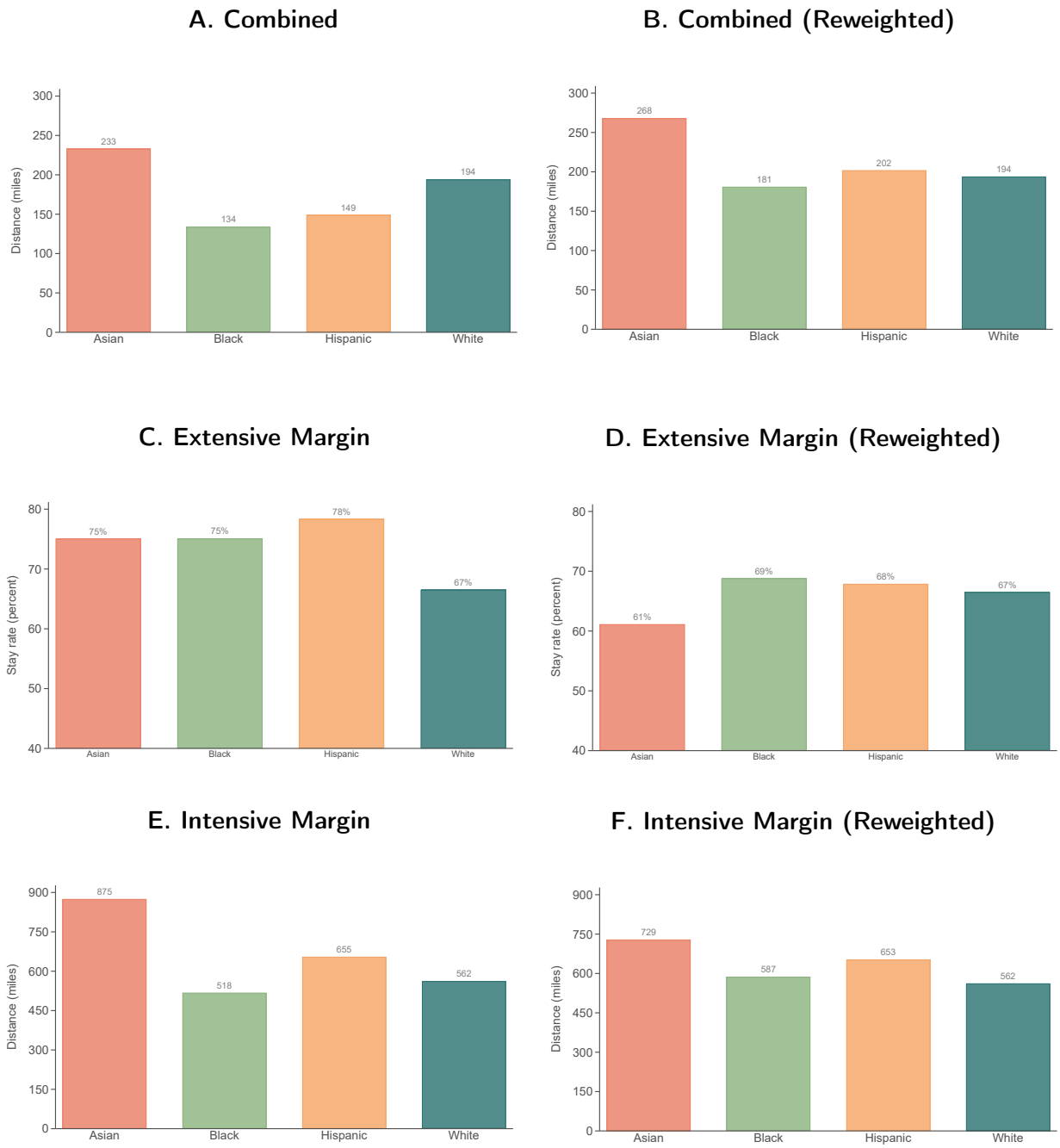
APPENDIX FIGURE A3: Average Distance Traveled by Parent Income and Child Race at Age 35




*Notes:* This figure repeats panels A and B in Figure 3 using distances measured at age 35 as opposed to age 26. Panel A reports the mean distance traveled by child race/ethnicity for our four child race/ethnicity categories: Hispanic, Non-Hispanic Black, Non-Hispanic White, and Non-Hispanic Asian. Panel B reports the mean distance traveled by parental income quantile.

*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

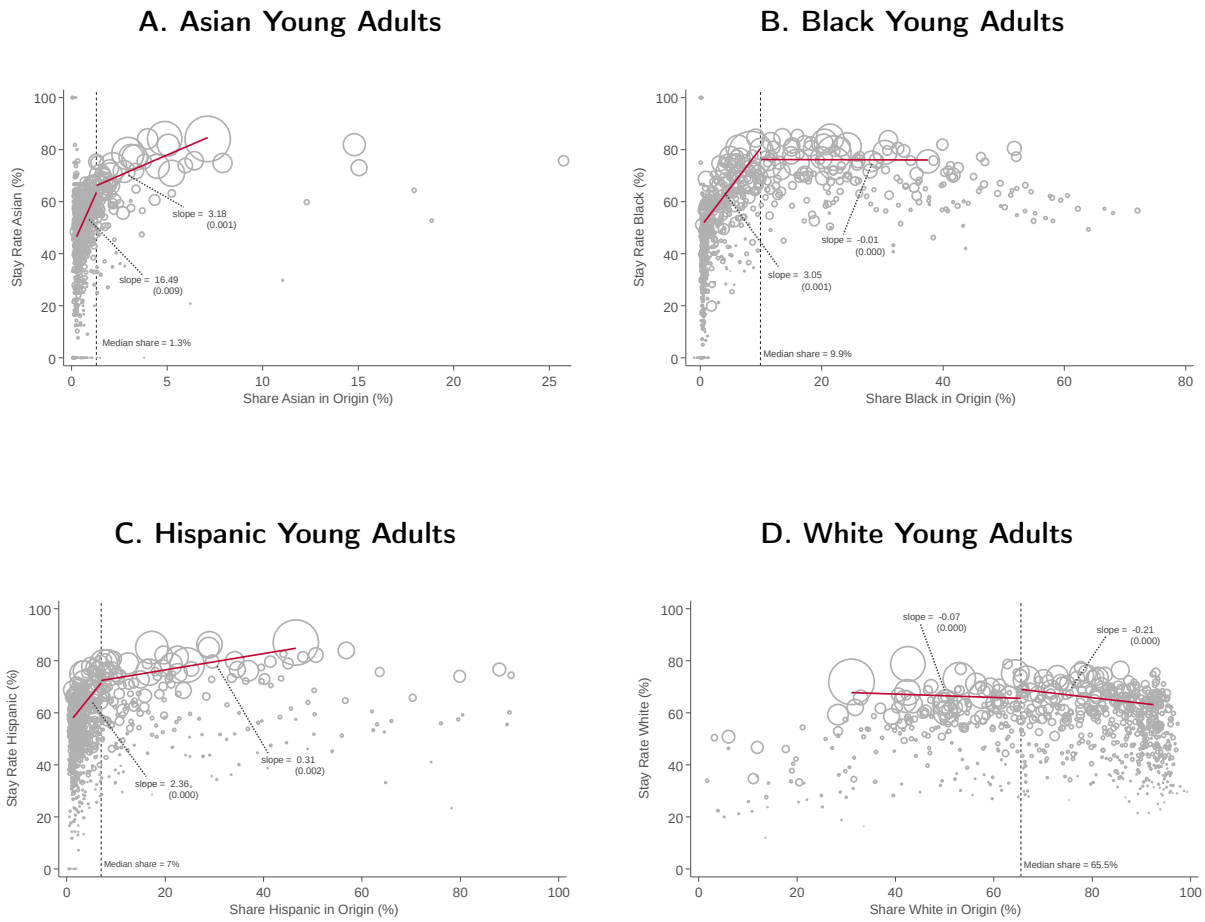
APPENDIX FIGURE A4: Extensive vs. Intensive Margin by Race/Ethnicity




*Notes:* This figure plots CZ-to-CZ distances between childhood and young adult location by race/ethnicity. Panel A reports the aggregate distances moved for each race/ethnicity. Panel C reports the fraction of people who stay in their childhood CZ. Panel E reports the distance moved conditional on leaving the childhood CZ. Panels B, D, and F repeat these panels but re-weight the distribution of young adults across CZs to match the distribution of White young adults across CZs.

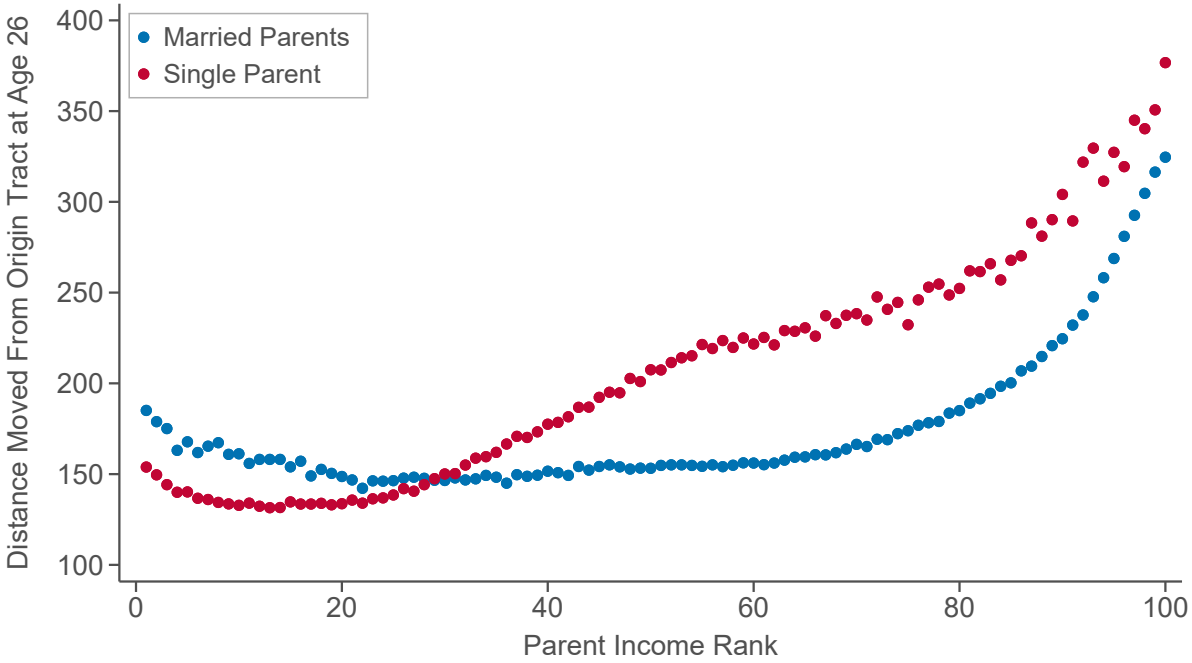
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A5: Stay Rates Vs. Origin Own-Race/Own-Ethnicity Share



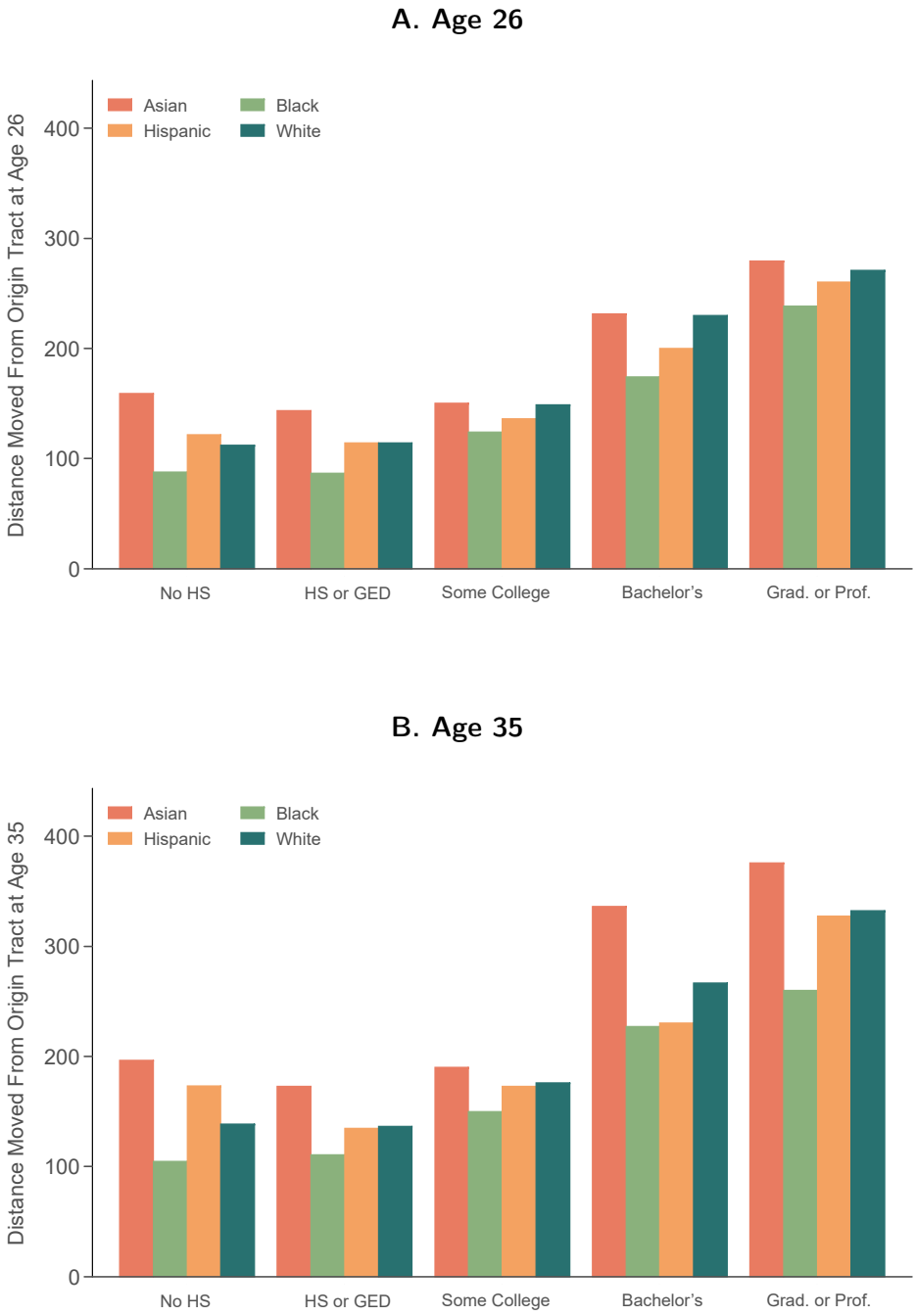

*Notes:* This figure plots the share of individuals who reside in their childhood CZ against the share of same-race/same-ethnicity individuals in that origin CZ. The dashed line shows the median racial/ethnic share across all origins (weighted by origin counts in the sample). The linear prediction for origin's in the 5-50$^{\text{th}}$ percentile and 50-95$^{\text{th}}$ percentile are show in red. Circle size is proportional to the number of observations in each CZ.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A6: Distance Moved by Parental Income and Marital Status



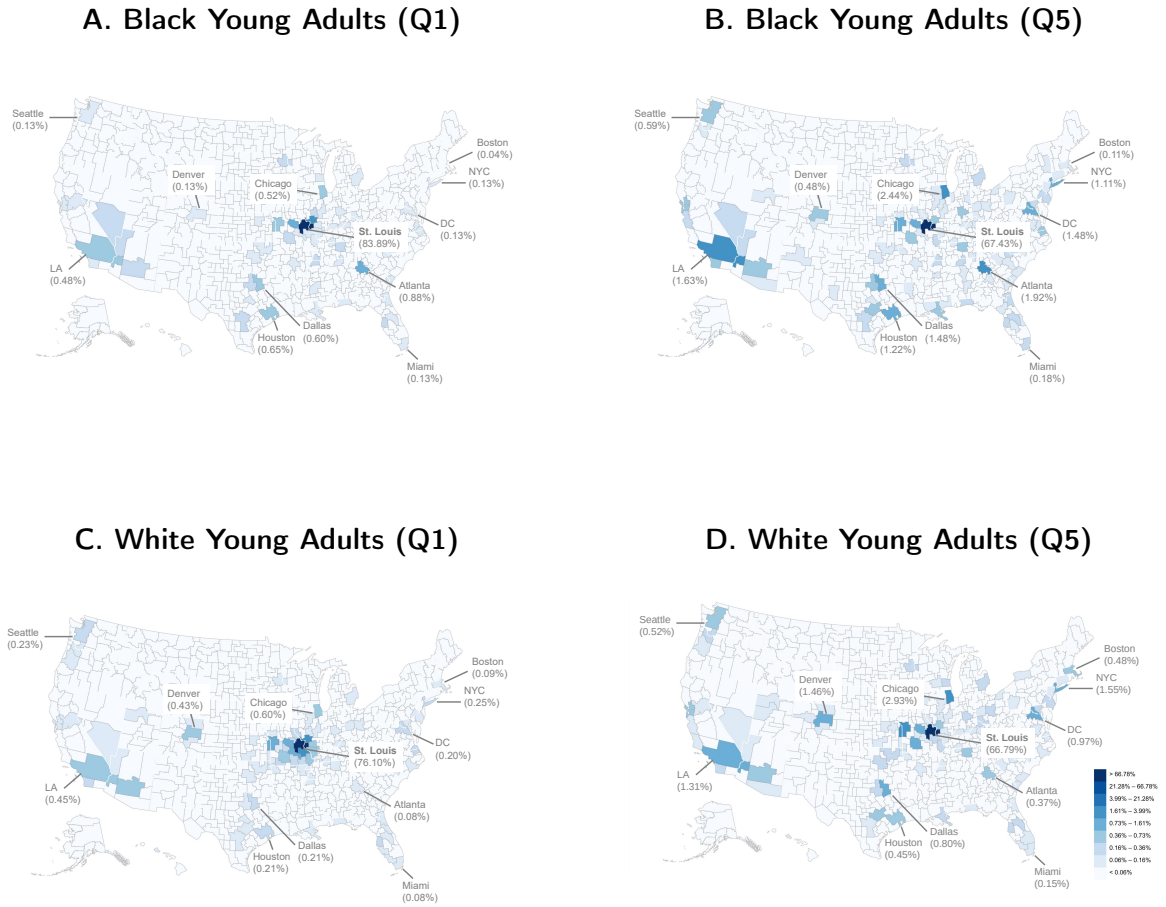

*Notes:* This figure presents the average distance moved at age 26 by parental income percentile separately for children in single versus married parents (as defined by whether the parent is married versus single on the tax form used to link the parent(s) to the child).
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

Appendix Figure A7: Distance Travelled by Education and Race




*Notes:* This figure presents the average distance traveled between the origin at age 16 and young adulthood at age 26 (Panel A) and age 35 (Panel B), separately by race and educational attainment measured in the American Community Survey.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

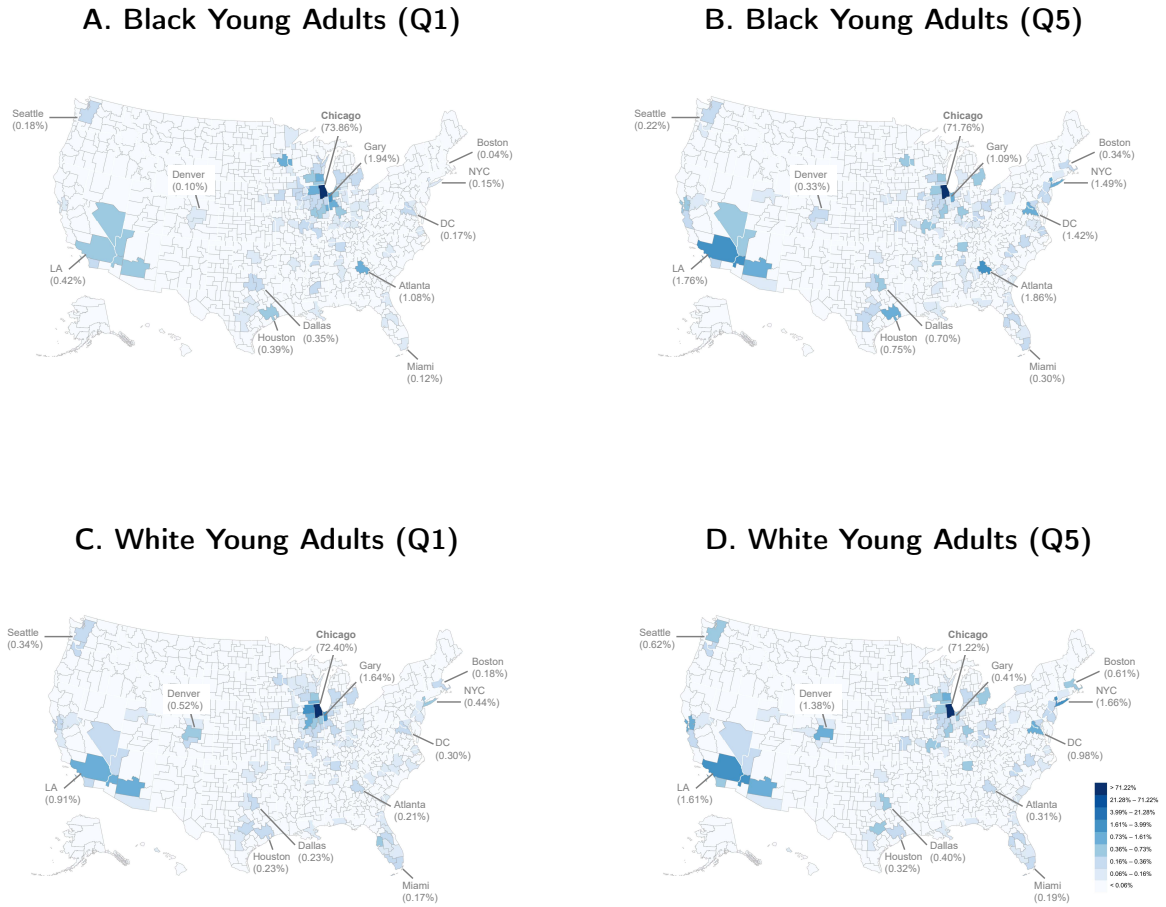
APPENDIX FIGURE A8: Migration Destinations Conditional On Growing Up in St. Louis, by Race/Ethnicity and Parental Income




*Notes:* This figure presents the probability of living in each destination CZ in young adulthood conditional on growing up in St. Louis. Panel A shows the results for Black young adults with parents in the lowest income quintile (Q1), Panel B shows Black young adults with parents in the highest income quintile (Q5), Panels C-D show these same results for White young adults.

*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A9: Migration Destinations Conditional On Growing Up in Chicago, by Race/Ethnicity and Parental Income

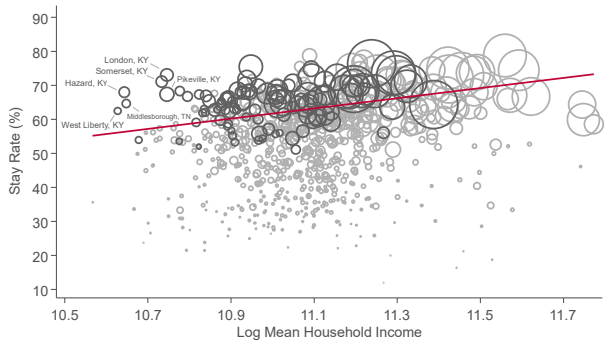



*Notes:* This figure presents the probability of living in each destination CZ in young adulthood conditional on growing up in Chicago. Panel A shows the results for Black young adults with parents in the lowest income quintile (Q1), Panel B shows Black young adults with parents in the highest income quintile (Q5), Panels C-D show these same results for White young adults.

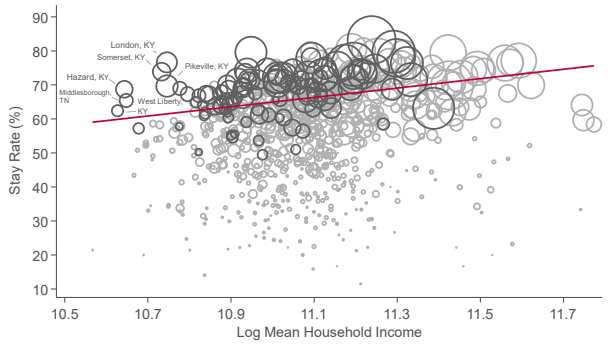
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A10: White Stay Rates vs. Mean Household Income in Origin CZ

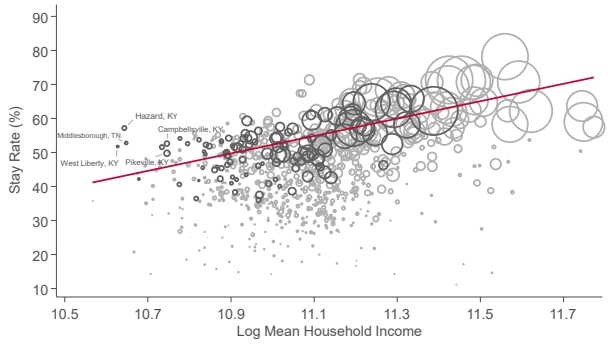
**A. White Young Adults**




**B. White Young Adults (Q1)**



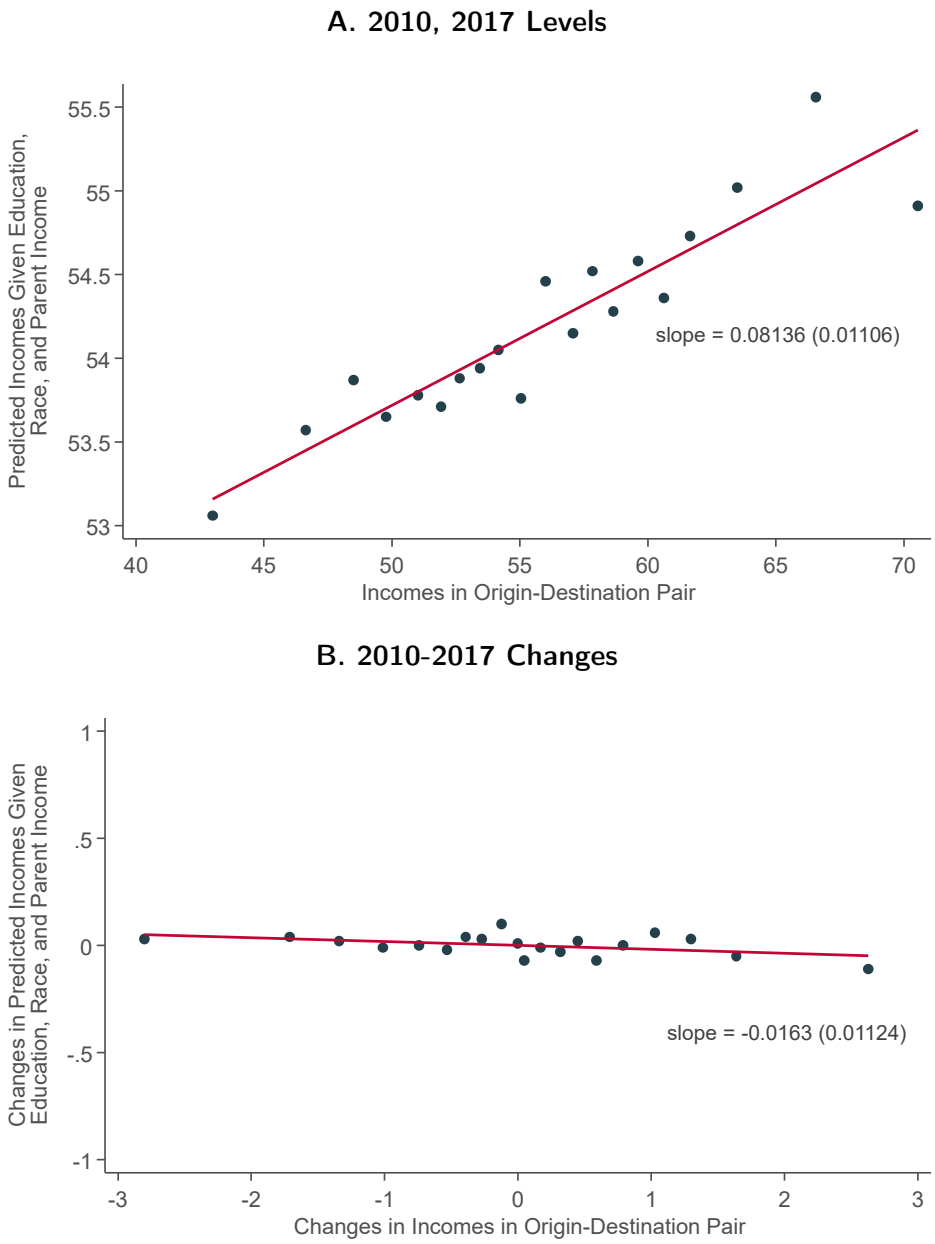

**C. White Young Adults (Q5)**




*Notes:* This plots the fraction of White young adults who remain in their origin CZ against the natural logarithm of mean household income in their childhood CZ. These results are shows for all White young adults (Panel A), and White young adults with parental incomes in the bottom (Panel B) and top (Panel C) income quintile. CZ-level average household income is a 5-year average obtained from the 2013-2017 American Community Survey (ACS). The figure shows CZs in the Appalachian region in dark gray and all other CZs in light gray. The Appalachian region is identified from 423 county definition provided by the Appalachian Region Commission (ARC). We crosswalk these 423 counties to the CZ-level and define an area as an Appalachian CZ if it contains at least one county identified by ARC.

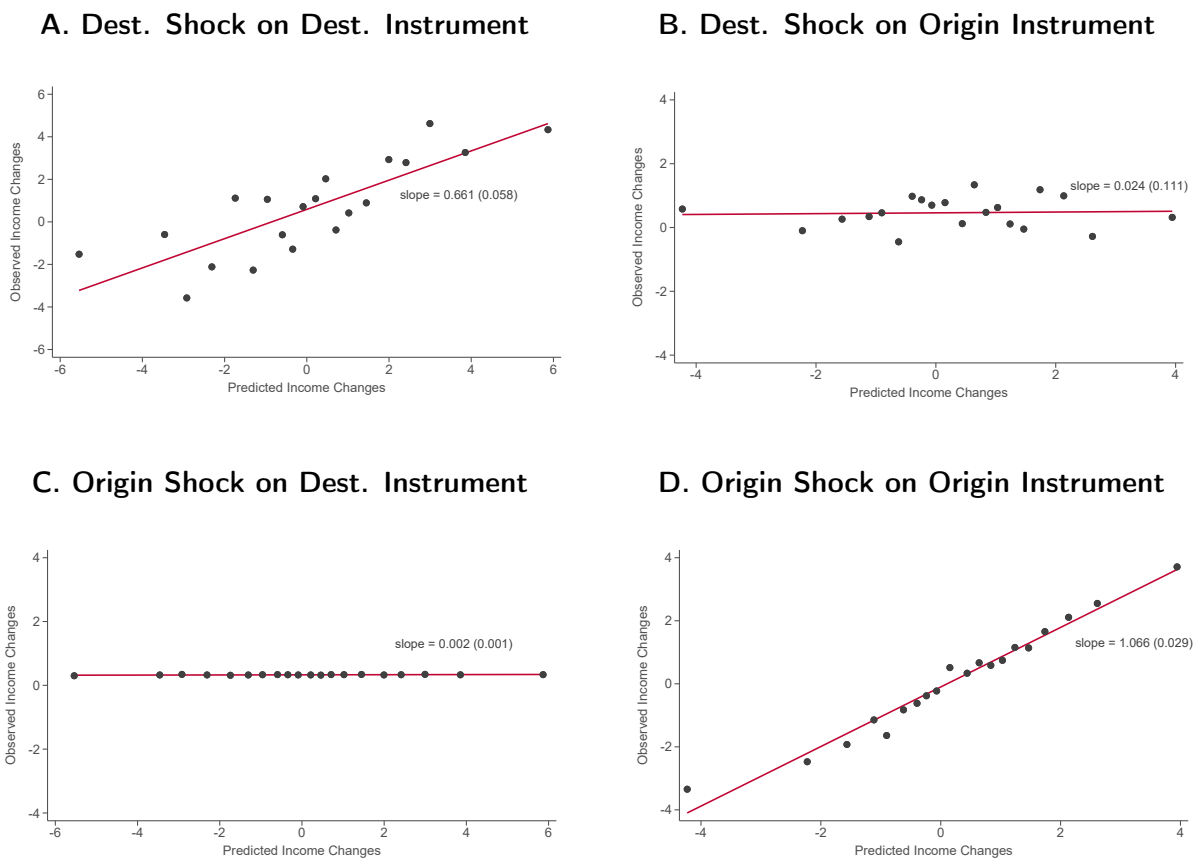
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A11: Income versus Predicted Incomes by CZ




*Notes:* This figure shows the CZ-level relationship between average incomes and the average predicted incomes for those in the American Community Survey. We construct predicted incomes in 2010 and 2017 by first conducting a national-level regression of individual income at age 26 on the fully saturated interactions of parent income quintile, child race category (5 categories), and the exact number of years of education. We then use these estimated coefficients to construct predicted incomes in 2010 and 2017 in each CZ. Panel A presents a binned scatter plot of the levels of predicted incomes incomes conditional on education, child race/ethnicity, and parental income in each destination CZ and the actual average incomes on the x-axis. Panel B then adds CZ fixed effects so that it presents the patterns for the 2010-2017 change in predicted incomes against the 2010-2017 realized income change.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

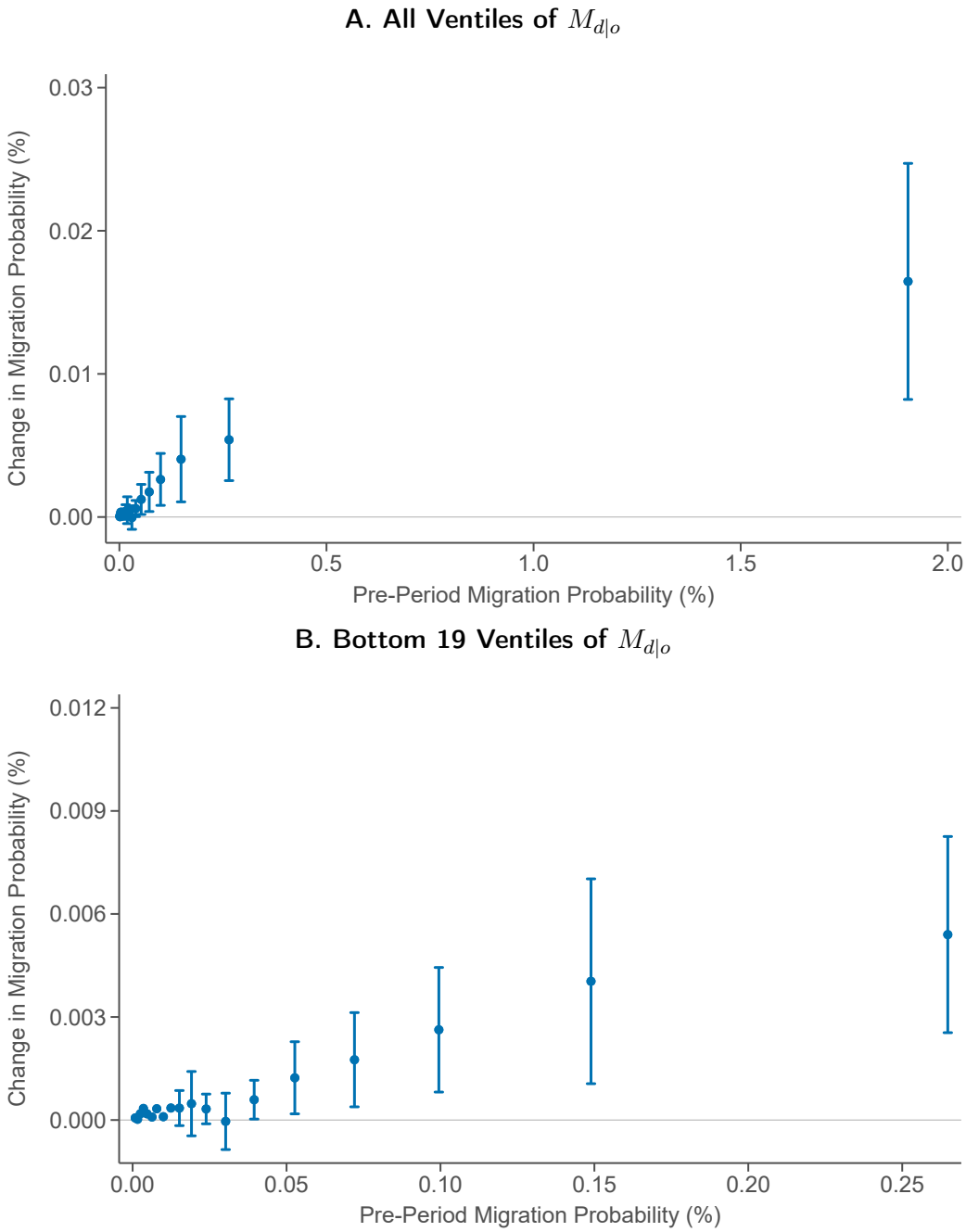
APPENDIX FIGURE A12: First Stage Relationships




*Notes:* This figure presents binned scatter plot corresponding to the first stage regressions of $dX_{od}$ and $dX_{oo}$ on the destination, $dW_{od}$ and origin, $dW_{oo}$, instruments. We present regression coefficients and standard errors corresponding to the multivariate linear regression coefficients, clustering standard errors two-way at the origin and destination CZ level.

*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

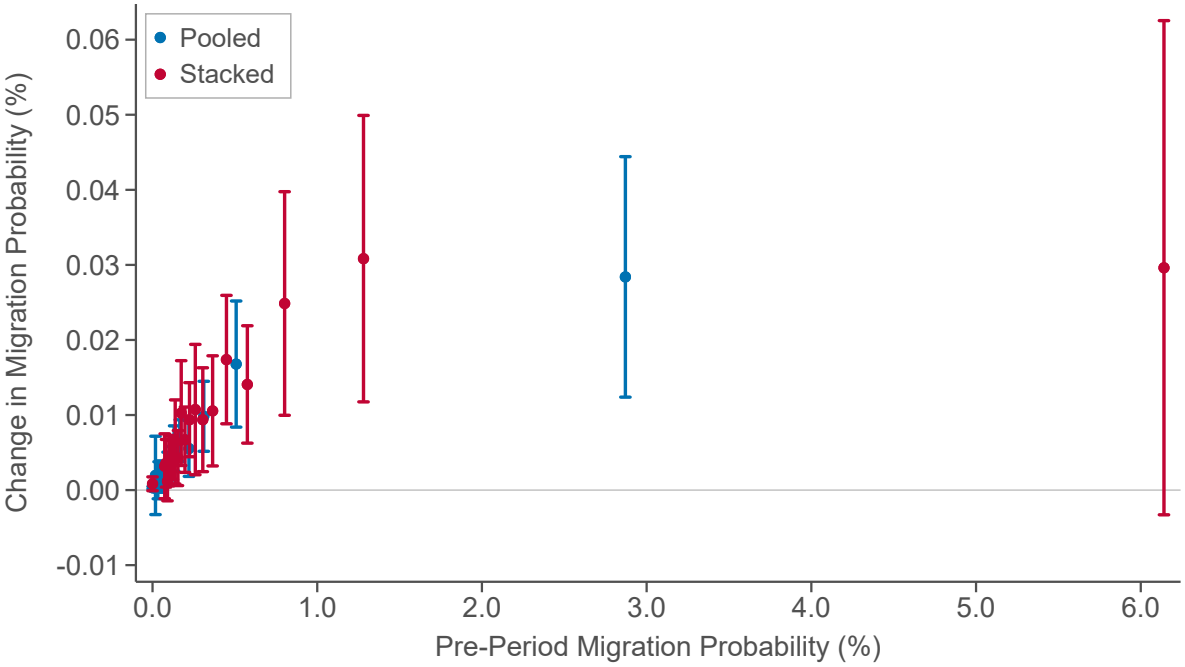
FIGURE A13: Migration Response to Changes in Family Incomes




*Notes:* This figure presents the results from regressions of the change in migration responses to changes in wage offers. We present the coefficients $\beta_g^{dest}$ for each grouping of pre-period migration probability, $M_{d|o}$. The horizontal axis reports the mean of $M_{d|o}$ in each bin, while the vertical axis reports the coefficient $\beta_g^{dest}$ from the estimation of equation (9) using 20 ventile bins of $M_{d|o}$. $\beta_g^{dest}$ measures the effect of a 1 rank ($800) increase in wages in the CZ on the probability of migrating to the $CZ$. Panel A presents results for all 20 ventile bins; panel B presents results for the bottom 19 ventile bins.

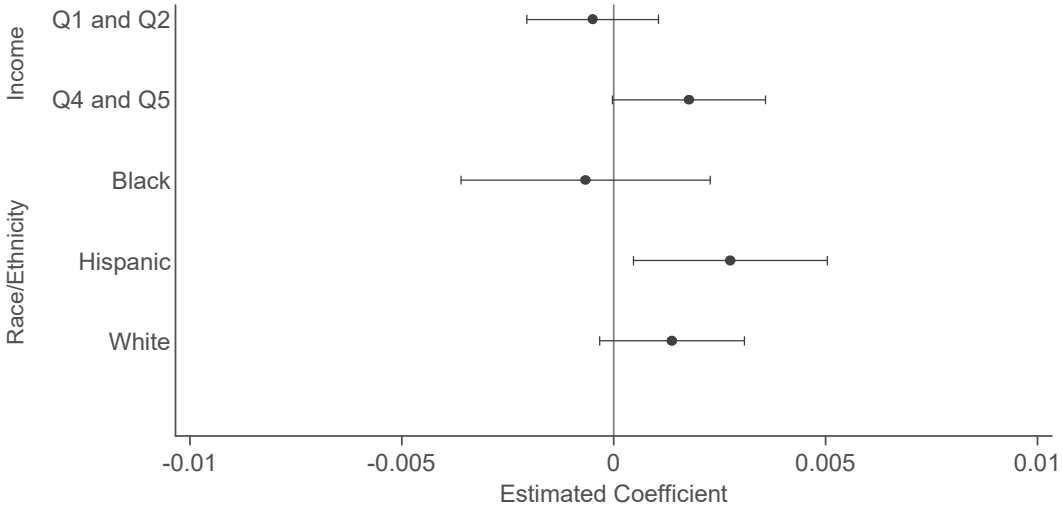
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A14: Pooled versus Demographic-Specific Bins of $M_{d|o}$




*Notes:* This figure presents the impact of changes in wage offers in one's origin on the likelihood of staying in the origin. The panel reports two series of coefficients of $\beta_g^{dest}$ for the specification in equation (9) that includes the outside option. The first series is for the pooled demographic specification. The second is for the demographic-subgroup regression outlined in equation (10). The 3rd lowest $M_{d|o}$ bin estimate appears outside the viewing window and is omitted from the graph (the point estimate is not statistically distinguishable from zero).
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

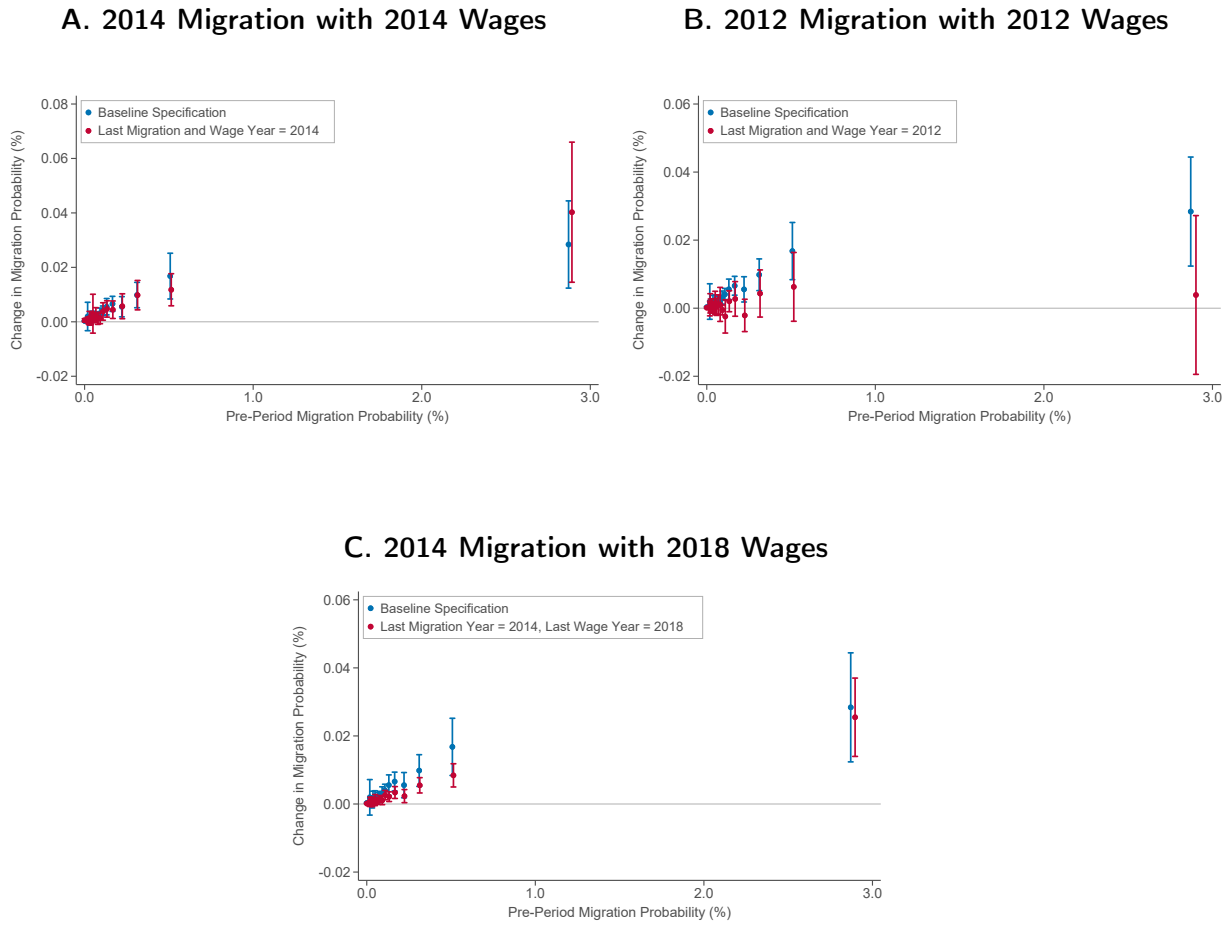
APPENDIX FIGURE A15: Impact of Wage Offers on Staying in Childhood Location by Demographics




*Notes:* This figure presents the coefficients from a regression of equation (10) focused on the likelihood of staying in one's origin CZ. We estimate versions of equation (10) that drop the collinear destination regressor due to the fact that the origin is the destination. We present results for those from high income backgrounds (Q4+Q5 parental income) and low-income backgrounds (Q1+Q2 parental income), along with estimates for Black, Hispanic, and White young adults.

*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

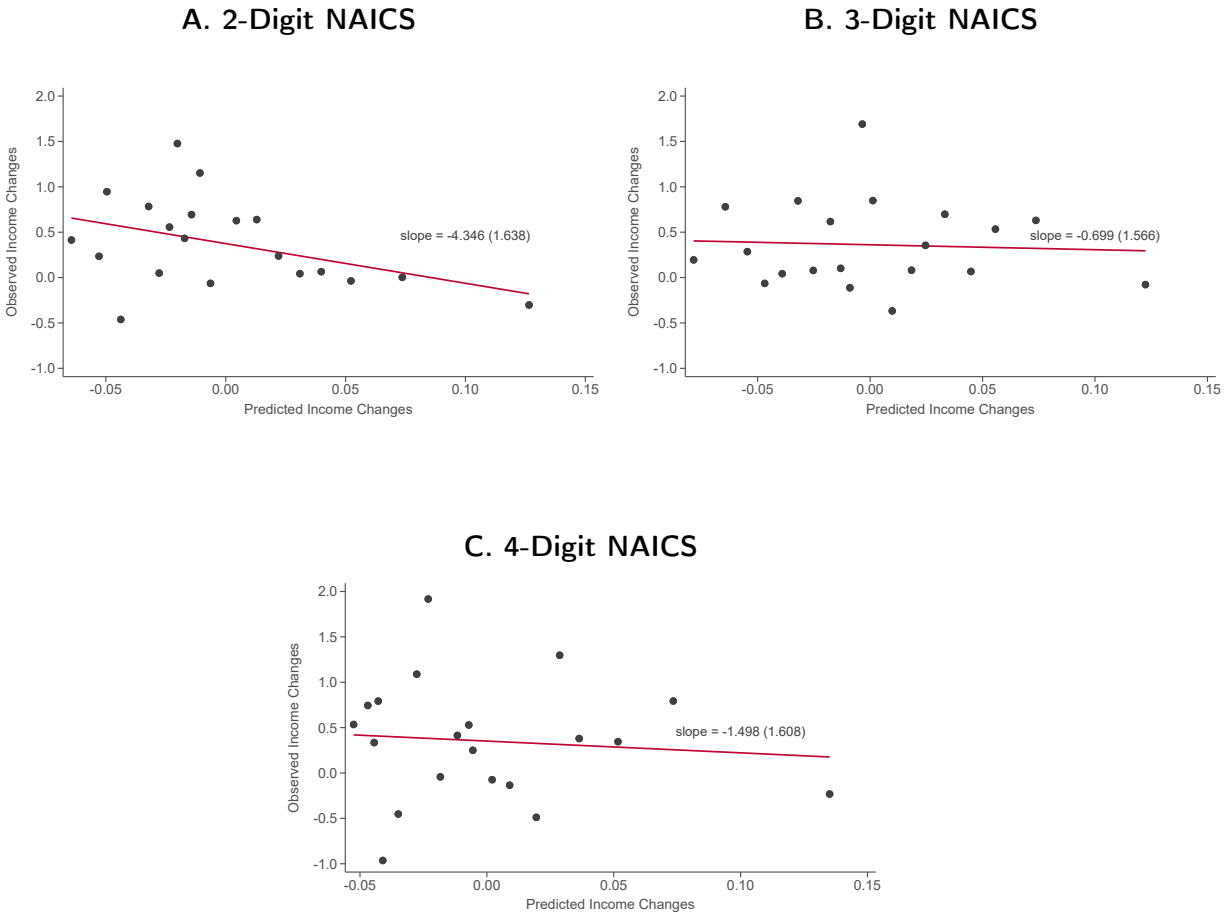
APPENDIX FIGURE A16: Dynamics and Alternative Time Windows




*Notes:* This figure explores how our baseline migration elasticity estimates vary with different specifications of the time period in we analyze migration and/or wage changes. Panel A compares the baseline specification (change in 2010 to 2017 migration rates as a function of the change in 2010 to 2017 wages, estimated over 21 bins of pretrend migration rates) to an analogous specification using 2010 to 2014 migration rates and 2010 to 2014 wage changes. Panel B shows a similar exercise with 2010 to 2012 migration rates and 2010 to 2012 wage changes. Lastly, Panel C proxies for how individuals might migrate in response to expected future wages by comparing 2010 to 2014 migration changes with 2010 to 2018 wage changes. Note that in Panel A, the confidence interval for the 2nd bin of for the 2014 specification is dropped and the coefficients in the top 5 bins are staggered aong the x-axis by +.02% to ease visualization.

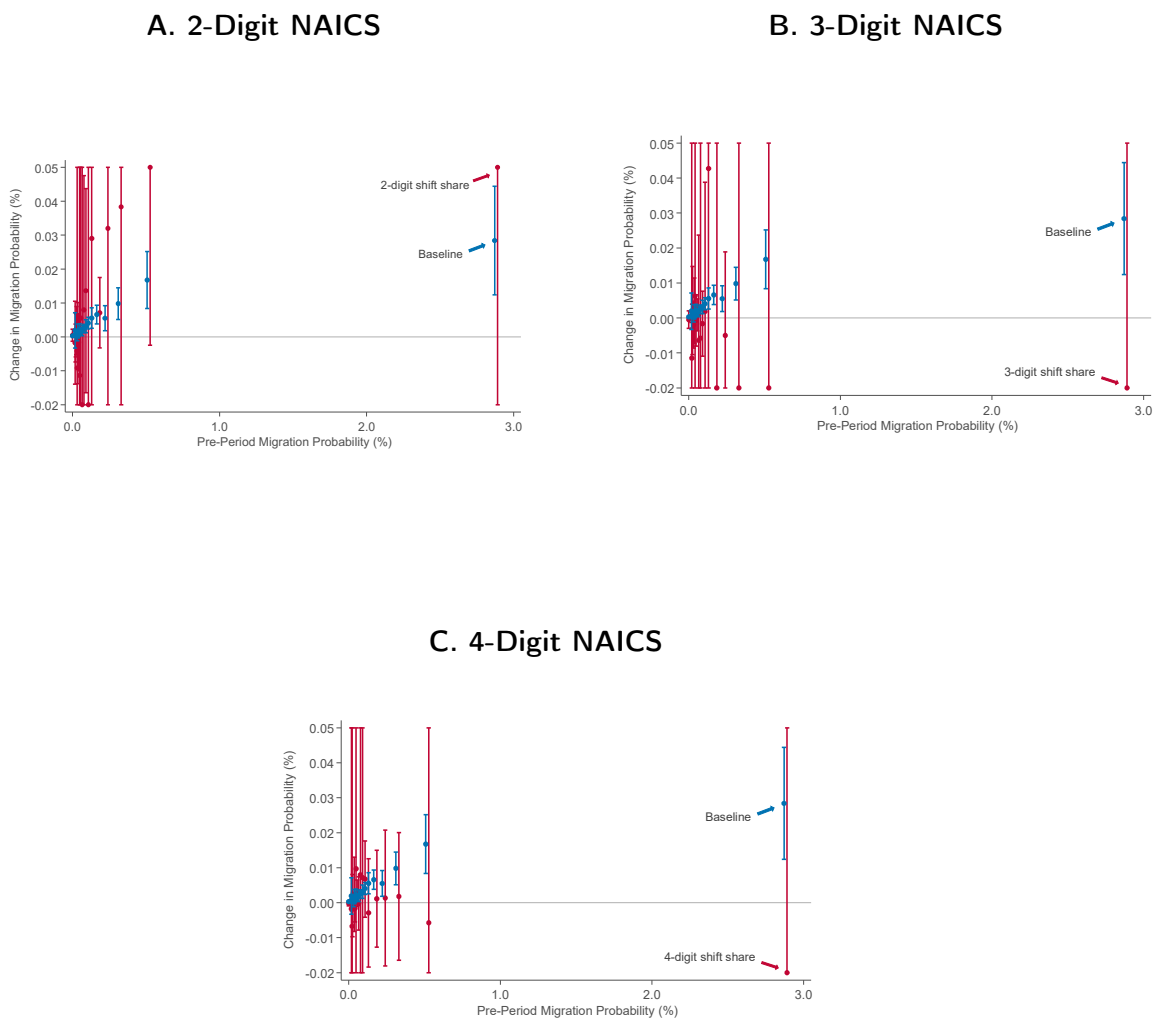
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A17: Shift-Share Instruments Test for Skill-Biased Sorting



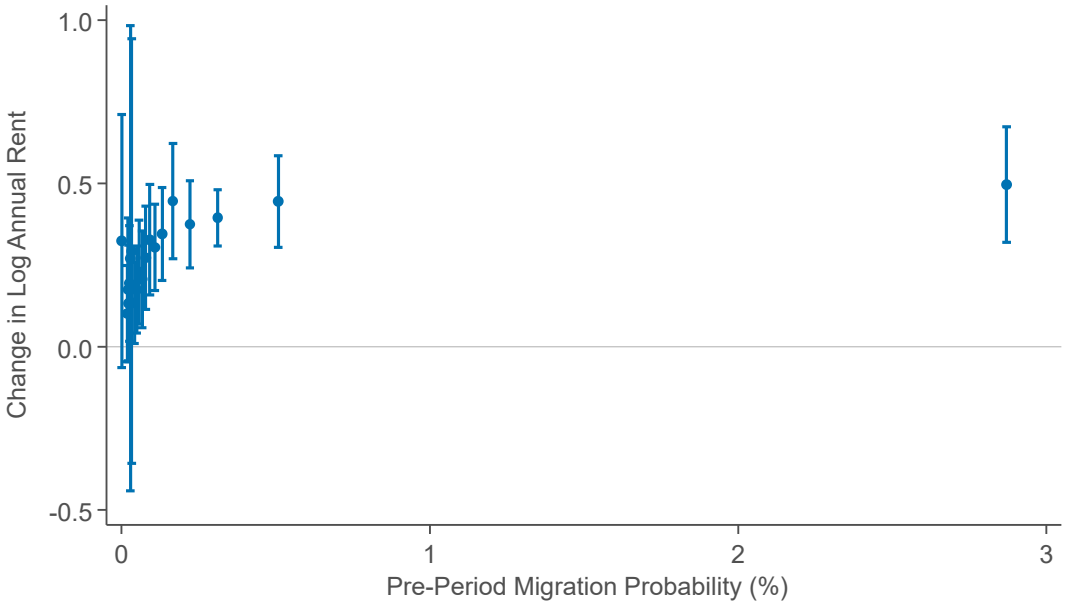

*Notes*: This figure presents the results from our test for skill-biased sorting when using shift-share instruments (the construction of which is described in section 6) as opposed to the leave-out instruments we employ throughout the paper. Panels A, B, and C, display our specifications employing shift-share instruments formed using the first 2, 3, and 4 digits of NAICS codes respectively. The binned scatter plots report the relationship between the migration weighted average of the predicted change in destination labor market strength using the shift-share instrument on the horizontal axis and the realized outcomes for those in the origin on the vertical axis. The statistics reported in this paper have been cleared by the Census Bureau Disclosure Review Board release authorization numbers CBDRB-FY22-CES014-019, CBDRB-FY2022-CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. Longitudinal Business Database (2010 and 2017) for industry NAICS information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A18: Shift-Share Instruments Impact on Migration




*Notes:* This figure presents the results of our baseline migration response to wage offer changes estimated using equation (9) but using shift-share instruments for the strength of the labor market (the construction of which is described in section 6) as opposed to the leave-out instruments we employ throughout the paper. Panels A, B, and C, display our specifications employing shift-share instruments formed using the first 2, 3, and 4 digits of NAICS codes respectively, side-by-side with our baseline estimates. Due to the large sampling variation in the shift-share estimates, in order to ease visualization we cap the coefficients and confidence intervals from below at -.01% and from above at .05%, and stagger the x-axis by +.02% for the Bartik estimates for the 5 highest bins.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. Longitudinal Business Database (2010 and 2017) for industry NAICS information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

APPENDIX FIGURE A19: Relationship of Log Rental Price of Housing and Log Nominal Wages




*Notes:* This figure presents the relationship between log rental price of housing for 2-3BR units in the CZ and the average log individual income in the CZ. We replace the LHS of equation (9) with the log rental price of housing for 2-3 bedroom units in the CZ and we use the average log child income on the RHS.
*Source:* Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

Appendix Table 1
Migration Matrix Correlations

*Panel A: Sex*

| | Male | Female |
|---|---|---|
| Male | 1 | |
| Female | 0.9936 | 1 |

*Panel B: Parental Income Quintile*

| | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| Q1 | 1 | | | | |
| Q2 | 0.9815 | 1 | | | |
| Q3 | 0.9612 | 0.9810 | 1 | | |
| Q4 | 0.9340 | 0.9630 | 0.9798 | 1 | |
| Q5 | 0.8547 | 0.8946 | 0.9208 | 0.9492 | 1 |

*Panel C: Race*

| | White | Black | Asian | Hispanic | Other |
|---|---|---|---|---|---|
| White | 1 | | | | |
| Black | 0.7843 | 1 | | | |
| Asian | 0.7490 | 0.6507 | 1 | | |
| Hispanic | 0.8758 | 0.7586 | 0.7127 | 1 | |
| Other | 0.9339 | 0.7838 | 0.7255 | 0.8712 | 1 |

*Panel D: Cohort*

| | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 |
|---|---|---|---|---|---|---|---|---|---|
| 1984 | 1 | | | | | | | | |
| 1985 | 0.9834 | 1 | | | | | | | |
| 1986 | 0.9820 | 0.9830 | 1 | | | | | | |
| 1987 | 0.9759 | 0.9769 | 0.9780 | 1 | | | | | |
| 1988 | 0.9748 | 0.9759 | 0.9770 | 0.9819 | 1 | | | | |
| 1989 | 0.9734 | 0.9746 | 0.9760 | 0.9809 | 0.9817 | 1 | | | |
| 1990 | 0.9718 | 0.9728 | 0.9744 | 0.9797 | 0.9809 | 0.9825 | 1 | | |
| 1991 | 0.9698 | 0.9713 | 0.9727 | 0.9778 | 0.9796 | 0.9808 | 0.9830 | 1 | |
| 1992 | 0.9690 | 0.9701 | 0.9713 | 0.9764 | 0.9780 | 0.9793 | 0.9816 | 0.9824 | 1 |

Notes: This table reports the correlation of migration rates (probability of moving to destination $d$ conditional on origin $o$, weighted by the population in origin o) across subgroups of the data for our primary sample of the 1984-92 birth cohorts. Panel A reports the correlation by child gender. Panel B reports the correlation by parental income quintile. Panel C reports the correlation by child race. Panel D reports the correlation by child birth cohort.
Source: Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

Appendix Table 2
Distance Moved by Race/Ethnicity

| Race/Ethnicity | Distance moved from origin tract (miles) | |
|---|---|---|
| | Age 26 | Age 35 |
| American Indian Alaska Native | 157.4 | 189.9 |
| Asian | 223.1 | 323.7 |
| Black | 130.4 | 164.5 |
| Hispanic | 143.8 | 189.5 |
| Native Hawaiian Pacific Islander | 386.0 | 428.1 |
| Other | 204.6 | 290.0 |
| White | 190.4 | 234.4 |
| 2+ races | 257.4 | 324.7 |

Notes: This table reports the average distance moved between childhood and young adulthood separately by the child's race/ethnicity. The child race/ethnicity categories include: Non-Hispanic American Indian and Alaska Native, Non-Hispanic Asian (excluding Native Hawaiian and Other Pacific Islander), Non-Hispanic Black, Hispanic, Native Hawaiian and Other Pacific Islander, Some Other Race, Non-Hispanic White, and multiple races.
Source: Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

Appendix Table 3
The Impact of Origin Wage Changes on Stay Probability

| | Individual Income Rank | |
|---|---|---|
| | (1) | (2) |
| Origin wage change | 0.0023 | 0.0001 |
| s.e. | 0.0006 | 0.0014 |
| Outside option wage change | | 0.0073 |
| s.e. | | 0.0036 |

Notes: This table presents a regression of the probability of staying in one's origin on the origin wage change along (column 1) and the origin wage change along with the migration-weighted average of destination wage changes (column 2). Robust standard errors reported below the coefficient.
Source: Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.

Appendix Table 4
Summary Statistics

*Panel A: Summary Statistics*

| Variable | Share (%) |
|---|---|
| Asian | 2.44 |
| Black | 13.65 |
| Hispanic | 13.73 |
| Other | 5.48 |
| AIAN | 0.83 |
| NHPI | 0.15 |
| Some other race | 2.35 |
| Missing race | 2.15 |
| White | 64.53 |
| Married Parents | 65.33 |
| | Mean |
| Individual Income (2010) | $23,940 |
| Individual Income (2017) | $27,090 |
| Family Income (2010) | $33,980 |
| Family Income (2017) | $33,810 |

*Panel B: Levels vs. Ranks*

| Year | Individual Income per Rank |
|---|---|
| 2010 | $808.8 |
| 2017 | $863.1 |

Notes: This table reports summary statistics for the young adults in our primary sample (1984-1992). Panel A shows the demographic composition of individuals in the sample and average parental income. Panel B shows how a 1 rank change in income translates to dollar terms. The reported coefficients are from a CZ-level regression of average individual income in the CZ on average individual income rank in the CZ, weighting by sample counts in the CZ.
Source: Federal tax data from 1994, 1995, 1998-2018 linked to the 2000 and 2010 decennial censuses, 2005-2018 Community Survey data and Department of Housing and Urban Development address information. DRB Approval Numbers: CBDRB-FY22-CES014-019, CBDRBFY2022- CES010-020, CBDRB-FY2022-CES005-013, and CBDRB-FY22-259.