U.S. Internal Migration: Recent Patterns and Outstanding Puzzles

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I. Introduction

Americans of all ages, levels of education, income levels, and races and ethnicities move less than they used to. Figure 1 provides an illustration of this trend (for the aggregate population). The percent of individuals (all ages) in the Current Population Survey (CPS) who moved within the U.S. at some point in the year (black line) was about 17 percent on average in the 1980s and 10 percent in 2017. About half of the overall decline in mobility reflects a decline in short-distance moves: the percent changing residences within a county (blue line) fell by about 4 percentage points over this period. However, the percent of people moving longer distances—potentially crossing labor markets—has declined substantially as well. As measured in the CPS, for example, the percent who changed states in the year (orange line) was around 3 percent in the 1980s and 1½ percent in 2017, while the percent who changed states or counties (sum of red and orange lines) fell by about 3 percentage points over this period.

The decline in longer-distance migration, particularly movement across labor markets (e.g. counties, commuting zones, or states), has received increasing attention from scholars and policymakers for a number of reasons.[2] First, the decline may suggest that the U.S. economy is less able to re-equilibrate spatially following local demand shocks or national demand shocks that vary in intensity across regions. Indeed, Dao, Furceri, and Loungani (2017) show that in response to local demand shocks, state population adjustment via net migration is less than in decades earlier. And, analyses of local labor market adjustment following the China Shock (Autor, Dorn, and Hanson, 2013; and Autor, Dorn, Hanson and Song, 2014) and the Great Recession (Yagan, forthcoming) generally find small effects of large adverse shocks on the level of population or out-migration, but larger effects on employment and/or participation. A smaller responsiveness of migration to shocks could imply significant and persistent local labor market impacts from shocks and possibly persistent national effects as a consequence. Second, the decline in migration has occurred at a time when regional convergence in employment and income has slowed[3]; internal migration would be a means of alleviating cross-regional inequality, but this equilibrating mechanism is evidently less effective than it used to be. This concern is particularly relevant for policymakers and researchers trying to understand why more people don't leave areas with declining labor markets and move to more prosperous locations. Third, declining migration may be one aspect of a more general decline in labor market dynamism. The reduction in dynamism has been a subject of growing focus (e.g. Hyatt and Spletzer, 2013; Davis and Haltiwanger, 2014; Molloy, Smith, Trezzi, and Wozniak, 2016).

[2] E.g., the November 19, 2018 blog post by Ryan Nunn, Jana Parsons, and Jay Shambaugh of the Hamilton Project, "Americans Aren't Moving to Economic Opportunity": https://www.hamiltonproject.org/blog/americans_arent_moving_to_economic_opportunity.

[3] For example, for employment see Amior and Manning (2018), and for income, see Ganong and Shoag (2017). Austin, Glaeser and Summers (2018) also provides evidence of slowing convergence for employment and income.

Although it is clear Americans move across labor markets less frequently than they used to, the reasons for this decline remain uncertain. Proposed explanations generally include those related to the labor market (e.g. workers are less likely to change employers than in the past and for that reason have less incentive to move, for instance Molloy, Smith, and Wozniak 2017) and those related to the housing market (e.g. high productivity areas are increasingly expensive to move to, and so workers from less prosperous areas are less likely to make such moves). Understanding the root causes of declining migration is important for many reasons, including for making policy recommendations regarding workers who remain in areas with declining labor markets and stagnating incomes. Whether it is more effective to incentivize people to move to more prosperous areas, or instead to target improvements in local labor market opportunities in less prosperous areas, requires a clearer understanding of why Americans are less likely to move, especially following adverse local labor demand shocks.

With this paper, we aim to address two broad issues related to the decline in internal migration in the U.S. First, we provide an updated summary of how internal migration has evolved over the last few decades, what has happened to internal migration in the aftermath of the Great Recession, and summarize evidence related to explanations for these trends. (In part this represents an update of our earlier papers documenting the multi-decade decline in migration, see Molloy, Smith, and Wozniak 2011, 2013, 2014, and 2017.) Specifically, we illustrate the previously documented facts that both short- and long-distance migration have fallen since the 1980s, and that the decline has been widespread across demographic groups. While the decline in short migration can be well explained by changing demographics, the decline in long migration cannot. We also highlight and discuss the flattening out of migration since the Great Recession, and argue that this flattening likely reflects some modest pro-cyclicality that is offset by continued trend declines in migration. We then summarize evidence related to explanations for the decline in migration between labor markets, and provide descriptive evidence that is consistent with labor-market related explanations—in particular, that the decline in migration appears to be a reflection and symptom of a broader decline in labor market dynamism more generally.

In the second part of the paper, we examine migration flows across metropolitan areas. We pay particular attention to differences between metropolitan areas with strong labor markets and those with weak labor markets, with an eye towards understanding whether these difference may help explain the long-run decline in migration or why more people do not move from weaker labor markets to stronger ones. We establish the following four findings:

1) Out-migration rates are larger on average from areas with stronger labor demand than from areas with weaker demand. In-migration rates are also larger in stronger labor markets, so there is more churn (movements in and out) in these areas; weaker labor

markets appear more sclerotic. (However, over time most metro areas have experienced a decline in in- and out-migration, regardless of labor market strength.)

2) Migrants leaving weak metro areas are more likely to move to another weak metro than a stronger metro. In contrast, migration from stronger metros is very directed towards other strong metros.
3) The geographic concentration of metropolitan areas with weak labor demand is a primary factor explaining why migration from weaker metros is not better targeted toward more prosperous area. Even migrants who are moving across metros tend to choose new locations that are closer to their origin metro, and metros with weak labor markets tend to be farther from prosperous metros. By contrast, we find little role for housing regulation or geographic housing supply constraints in preventing people from moving from low-demand to high-demand areas.
4) Migrants moving out a metropolitan area are younger and better educated than those who remain, and this differential is even larger in weak labor markets than in strong labor markets. We interpret this result as showing that people who move out are disproportionately those who would likely benefit the most.

In summary, the principal factor that appears to describe why migration from weak to strong labor markets is at best modest is that weak and strong labor markets tend to be geographically distant. A practical implication is that inducing some workers to leave less prosperous cities for more prosperous cities may be exceedingly difficult if the target destinations are not very close by—longer-distance migration is not common, even when local labor market prospects are bleak.

II. The long-run decline in internal migration, and recent developments

In this section, we document the widespread decline in internal migration since the 1980s, focusing primarily on migration across longer distances. We focus our discussion on four key facts:

1) Long-distance migration rates (cross-county and cross-state) are significantly lower than they were decades earlier, and the decline in migration stopped (at least temporarily) around the end of the Great Recession.

2) The declines since the 1980s have been widespread across demographic characteristics, and the recent pause has also been widespread.

3) The long-run decline cannot be explained much by changes in population demographics, although changing demographics (population aging) does explain a significant amount of the decline in short-distance (within-county) migration.

4) Internal migration is pro-cyclical, after accounting for group-specific trends and demographics. The recent flattening of migration may be understood as roughly a continuation of pre-recession trends with some pro-cyclical improvement.

Fact 1: Long-distance migration rates are significantly lower than they were decades earlier, and the decline in migration stopped around the end of the Great Recession.

Figures 2A shows the fraction of Americans (all ages) that moved states in the year, as measured in three publically-available data sources commonly used to measure internal migration: the Annual Social and Economic Supplement to the Current Population Survey (ASEC CPS, black line), the IRS tax data (red line), and the American Community Survey (ACS, blue line). There is a change in recording methodology in the IRS data in 2011 that likely resulted in an upward jump in reported migration—other details on data construction and comparability are provided in the Data Appendix.[4] In the 1980s, about 3 percent of Americans changed states in a given year. This had fallen to about 2½ percent in 2000, and by 2009 had either edged down a bit further (as measured in IRS and ACS data) or, as measured in CPS data, fallen substantially further to 1½ percent.[5] Since 2009, the cross-state migration rate has been about flat in all three data sources. Figure 2B shows about 6 percent of Americans moved states

[4] Note that data plotted in these and subsequent figures are generally shifted one year from when the data were collected. This is because the CPS and ACS ask about migration in the previous year, while IRS data generally refers to migration over the calendar year prior to when taxes were filed. Thus, whenever we show migration rates by year our intention is to show the percent moving over the course of the indicated year (rather than the percent moving in the year prior to the survey).

[5] The CPS data have been adjusted for bias from changes in imputation procedures from 2000 to 2006 as noted by Kaplan and Schulhofer-Wohl, 2006. See the Data Appendix for more details.

or counties in a year in the 1980s, and this has fallen by about half in the CPS data by the 2010s while in the IRS data (discounting the uptick in 2012 when data comparability is an issue) it has fallen by about 1 percentage point.[6] In the CPS and ACS data, this measure of longer-distance migration has also been about flat since 2009.

Fact 2: The decline in longer-distance migration since the 1980s has been widespread across demographic groups, and the recent pause has also been widespread.

Figures 3A-3D show cross-state, and cross-state or cross-county, migration rates from the CPS by age (Figs A and B) and by education for 25-54 year old individuals (Figs C and D). As has been extensively documented (e.g. Bound and Holzer 2000), younger (16-24, the black line; 25-54, the blue line) and better-educated individuals (for 25-54 year olds, the orange line) have higher longer-distance migration rates in every year of the sample. The decline in long-distance migration has occurred for all age and education groups, although it has been somewhat larger for younger and better-educated individuals—consequently, internal migration rates by age and education have converged somewhat since the 1980s. More recently, the pause in the decline has also been widespread across demographic groups, with perhaps some small increase in long-distance migration since 2009 for individuals 16-24 and 25-54 years old. (As we show later, migration rates for these ages tend to be somewhat more cyclical.[7])

Table 1 shows estimates of the change in average cross-state migration rates from 1980-1984 to 2013-2017 by age, education, employment status, homeownership status (current year status), family structure, and location in the household income distribution; the last column shows the change in the share of the 25-54 population accounted for by each sub-group. For most of these characteristics, we focus on the 25-54 population to abstract away from population aging and changes in college attendance, both which affect longer-distance migration. The first thing of note is that the decline in cross-state migration over this period is extremely widespread: cross-state migration has fallen over this period for every age group; all education groups; employed and non-employed men and women; homeowners and renters; married and unmarried men and women; households with no earners, one earner, or two earners, and households where

[6] Migration across counties or states may not perfectly map into the concept of migration across local labor markets, such as commuting zones, which might be of even greater interest. However, CPS data—which will form a large component of the analysis in this paper due to its long availability (more decades of data than the ACS) and detailed information on demographics (IRS data only provides information on all migration flows between counties, without demographic detail)—doesn't consistently provide migration information in the detail required to assess moves other than those occurring within-county, cross-county but within state, or within-state.

[7] Appendix Figures 1A and 1B plot average cross-state migration rates across birth year cohorts and ages, by education. Consistent with Figures 3A and 3B, the cross-cohort difference in average migration rates is largest for younger ages. For those with at least some college experience, roughly 7 percent born in 1945-1964 (orange and red lines) moved across states when age 25, compared with 5 or 6 percent for those born in 1975 or later. Cross-cohort migration rates appear to have converged somewhat later in life, although average cross-state migration rates were still somewhat higher for older cohorts at age 45.

both earners have college degrees; households with and without kids; and households regardless of their location in the income distribution. That said, migration rates declined more for men who didn't work in the previous year, individuals currently renting, households where neither spouse worked, and lower-income households. The last column of the table also shows that educational attainment has increased and homeownership rates have decreased for the 25-54 population over this period, which should push up migration rates, all else equal. The widespread nature of the decline is also suggestive evidence against any one explanation as a primary cause—e.g. changing homeownership rates, rising dual-earner or dual-professional households, and labor market polarization or changing industry/occupation composition of employment (which should differentially affect less-educated men).

Figure 4A and 4B plot estimates of state in- and out-migration rates (again for 25-54 year olds) averaged over the nine Census divisions, to see if there are particular areas of the country where 25-54 year olds are more likely to move across state lines. There is some variation across Census divisions in terms of state in-migration rates—in-migration rates are significantly higher in Mountain states and lower in New England—while out-migration rates are more similar (except for Mountain states, where out-migration rates prior to 2005 tended to be higher than elsewhere). The general trend in migration, however, is apparent across regions—in- and out-migration rates declined to some extent for all regions through the end of the Great Recession, and have been about flat or have edged up slightly since then.

Fact 3: The decline in long-distance migration cannot be explained much by changes in population demographics, although changing demographics (population aging) does explain much of the decline in short-distance (within-county) migration.

As suggested by the widespread decline in longer-distance migration across demographic groups, changes in the demographic composition of the population since the 1980s can't explain much of the overall decline in migration. Older individuals move less frequently, so population aging has pushed down migration rates somewhat; offsetting this a little, the population has become better-educated and better-educated individuals tend to move more frequently. To show this more formally, we adjust migration rates for changes in the age, sex, race (White non-Hispanic, Black non-Hispanic, Hispanic, and other), and education (at most high school and some college or better) composition of the population, accounting for average differences across demographic groups over the 1980-2017 period, by estimating OLS regressions of migration rates (cross-state, cross-state or cross-county, and within-county) on dummies for these demographic characteristics, and year fixed effects; differences in the year fixed effects across the years provide an estimate of differences in migration rates that remain after accounting for the year-specific distribution of the characteristics. In Figure 5A we plot the actual change in cross-state or cross-county (panel 1) and within-county (panel 2) migration relative to 1980 (the black line) alongside our estimated year fixed effects (the red line). The longer-distance migration rate declined by about 3 percentage points since 1980, and changing demographics can explain about ½ percentage point of the decline (about a tenth of the 1½ percentage point decline in cross-state migration, and a few tenths of the 1½ percentage point decline in cross-county migration). In contrast, changing demographics can explain a little more than half of the decline in within-county migration—nearly 2 percentage points of the 3½ percentage point decline. The reason why demographic adjustment explains more of the within-county decline is that the age differential in within-county migration rates is larger than for longer-distance migration rates, such that population aging puts greater downward pressure on within-county migration.[8]

Fact 4: Internal migration is pro-cyclical, after accounting for demographic-specific trends and the demographic composition of the population. The recent flattening of the long-distance migration rate can be understood as a continuation of the pre-recession trends in migration with some pro-cyclical improvement.

Internal migration rates are pro-cyclical. This has been shown previously (e.g. Saks and Wozniak 2011) but to gauge the effects of recent labor market improvement on migration, we use CPS data to estimate OLS regressions of different migration rates (cross-state, cross-state or cross-county, and within-county) on dummy variables for age, sex, education, and race/ethnicity (as defined previously), time trends, and as a cyclical control the Congressional Budget Office's estimate of the national unemployment rate gap (unemployment rate minus the CBO's estimate of its natural rate). We also include the homeownership status of the respondent's current household as an additional control for expositional purposes, although as noted in footnote 7 homeownership status in the CPS is not ideally measured for estimating the impact of homeownership. Because the Great Recession and its aftermath may have been a particularly unusual period for cyclical dynamics and migration (e.g. housing bust, deep recession and slow recovery) we end our estimation in 2007. The time trends and effect of the unemployment rate gap variable are allowed to differ by age/sex/education/race/homeownership group.

Table 2 shows coefficients on the unemployment rate gap from these regressions. The dependent variable for columns 1 and 2 is whether the respondent moved across states, for columns 3 and 4 is whether the respondent moved across states or counties, and columns 5 and 6 is whether the respondent moved within the county. The first column in each set only includes the unemployment rate gap and a linear time trend; the second panel includes the listed

[8] We have also examined the contribution of changing homeownership, although this adjustment is imperfect because it is based on whether the *household* the respondent is living in *at the time of the CPS survey* is owner-occupied, rather than the respondent's *own* homeownership status in the *previous year*. With that in mind, rising homeownership as measured in the CPS is estimated to have pushed down long-migration rates by about ½ percentage point from the mid-1990s to mid-2000s and then falling homeownership is estimated to have pushed up long-migration rates by the same amount.

demographic indicator variables as main effects and these variables interacted with the unemployment rate gap, and demographic-group-specific time trends, with the omitted variable as indicated. The negative coefficient on the unemployment rate gap in columns 1, 3, and 5 indicate that the aggregate migration rate is lower when the migration rate is higher (conditional on the inclusion of a time trend). Columns 2 and 4 show that longer-distance migration tends to be more cyclical for 25-44 year olds, with few differences in estimated cyclicality across other characteristics. Column 6 shows that within-county migration rates for individuals age 45 and older are less cyclical than for other ages, and within-county migration rates for Blacks are less cyclical than for other groups.[9]

How has migration in the aftermath of the Great Recession compared to what would be expected given the usual cyclicality in migration, labor market tightness as proxied by the CBO's estimate of the unemployment rate gap, and a continuation of the demographic-group specific trends that were in train prior to the recession? To answer this question, we use the coefficient estimates from regressions similar to those described in Table 2 (e.g. using data from 1980-2006, demographic group indicator variables interacted with the unemployment rate gap, and demographic group specific time trends) to project national migration rates, which are plotted as the red lines in Figure 5B.[10] Long-distance migration rates (Panel 1) began falling before the recession and in 2009 were a little lower than would have been expected by the rise in the unemployment rate and declining group-specific migration rates. Since 2009, this simple model projected migration rates to edge down slightly as modest pro-cyclicality offsets most of the downward influence from the continuation of the group-specific pre-recession rates of decline, while the actual migration has been about flat or edged up slightly on net. Overall, though, the relative flatness of the long-distance migration rate since 2009 is roughly in line with the usual group-specific cyclical response of migration, conditional on a strong underlying downtrend. Meanwhile, the continued decline in within-county migration (Panel B) is quite unexpected by this model, as within-county migration tends to exhibit stronger cyclicality than does long-distance migration.

[9] For all of these regressions, the estimated pro-cyclicality of migration is quite dependent on the inclusion of time trends and exclusion of Great Recession years and thereafter; without time trends, or with the inclusion of later years of data, we generally estimate that migration is generally acyclical (i.e. the coefficient on the unemployment rate gap is small and statistically insignificant).

[10] Specifically, we estimate individual level OLS regressions using data from 1980-2007. The dependent variable is whether the individual moved across states or counties, or within-county. The covariates are indicator variables for sex, education, race, and age, as main effects and interacted with the unemployment rate gap, and group-specific time trends. We do not include homeownership status in these regressions, for the reasons discussed in footnote 8. Individual-level migration probabilities are projected from these covariates and estimated regression coefficients, and aggregated up to form national migration rates.

Summary

To summarize, long-distance migration rates fell noticeably from the late 1980s to the end of the Great Recession or so, and changing demographics (population aging) can explain only a small amount of this decline. The frequency that Americans move longer distance (cross-state or cross-county) has been about unchanged on net in the aggregate since 2009, and migration for younger and better educated individuals has picked up a little. Overall, the behavior of the aggregate long-distance migration rate over this period is fairly consistent with a simple model that projects migration by assuming a continuation of the pre-recession demographic-group-specific trends, with this downtrend mostly offset by some modest cyclicality in internal migration. Given this interpretation of the behavior in migration over the last decade, it seems plausible to expect that longer-distance internal migration rates might turn down again if the labor market were to weaken, thus allowing the influence of forces shaping the trend migration rate to show through without the offsetting, pro-cyclical upward pressure of a tight labor market. Of course, this prediction assumes that longer distance migration remains on a downward trend, outside of the supportive influence of a strong economy. While there is no way of knowing with certainty whether this assumption is reasonable, the fact that longer-distance migration in the aggregate has been essentially flat for a decade despite the continued economic expansion suggests that whatever factors were depressing migration prior to the Great Recession continue to exert a downward influence.

III. Explaining the decline in migration: The role of the labor market

Two primary explanations proposed for the decline in longer-distance migration include housing market related factors, such as trends in homeownership (since homeowners tend to be less mobile) or growing dispersion in housing costs (since it could be more difficult to move from an area of low costs to an area of high costs), and labor market related factors, such as the employment distribution of occupations becoming more similar across localities (reducing the need to move to find employment in a particular occupation, e.g. Kaplan and Schulhofer-Wohl 2017), or workers' unwillingness or inability to change jobs reducing the need to relocate for work reasons (e.g. Molloy, Smith and Wozniak 2017).[11]

[11] Of course not all explanations fit neatly into these two categories. For example, other possible causes include changing family structure, for example the rise in dual-earning households, which could complicate work-related relocation decisions. (However, we showed earlier that migration has fallen regardless of the number of earners in the household.) Kaplan and Schulhofer-Wohl (2017) also suggest that improvement in telecommunication technology could have improved potential migrants' information about possible migration locations, reducing the need to migrate to "sample" different locations.

In this section, we focus on evidence related to labor-market explanations, which is in part an update and extension of evidence from Molloy, Smith, and Wozniak (2017). We do not present a review of a full set of potential explanations, or list the evidence for and against each one. Instead, before moving on to a discussion of why we think labor-related explanations are particularly attractive, we offer a few comments on housing related explanations. While the idea that high housing costs in strong labor markets (due, for example, to strict restrictions on new construction) could be contributing to the decline in migration is an intuitively appealing one, empirical support for this notion is not entirely clear-cut. Some examples that support this notion include Barkema and Bayoumi (2019), which estimates that larger housing price differentials between metros are associated with less long distance migration from low to high house price areas; Plantinga, Detand-Dessendre, Hunt, and Piguet (2013), which shows that higher housing prices in a metro area are associated with lower in-migration for college-educated men; and Ganong and Shoag (2017), which provides some evidence that high housing costs in richer states can explain why less-educated individuals are less likely to move to more prosperous states than decades earlier. On the other hand, Molloy, Smith, Trezzi, and Wozniak (2016) show that the labor market fluidity (measured with a broader index that incorporates information on migration) hasn't fallen more in states with stricter housing supply regulations, and Zabel (2012) finds that the responsiveness of in-migration to a city in response to a shocks doesn't depend on the housing supply elasticity of the city. Moreover, it seems implausible that housing costs would be able to explain the downward trend in labor market churning, since people frequently change jobs without moving. On net, we are somewhat skeptical that rising housing costs in some highly-productive cities have been a material factor contributing to the downward trend in long-distance migration, even if these costs may still be an important impediment to migration in any particular point in time. We will return to this issue in the next section of the paper by examining whether housing supply constraints appear to be reducing migration from metropolitan areas with low labor demand to areas with high demand.

Labor market explanations

Labor-market explanations relate to reasons why the benefit of moving to a new location, either to search for a new job or with a new job in hand, have declined. Possibilities include that the costs of being unemployed have risen (e.g. greater risk of human capital loss, Fujita 2018) reducing incentives to job hop, with or without an intervening unemployment spell; the set of jobs is more similar across locations than it used to be or there is less regional variation in the returns to particular occupations (e.g. Kaplan and Schulhoffer-Wohl, 2017); or the pecuniary benefits gains associated with job changing (e.g. wage gains) have declined. Whatever the reason, in our view the decline in cross-labor market migration seems very much rooted in labor market related reasons.

One piece of supporting evidence is that the primary reason given in the CPS for cross-state or cross-county moves is "job related" rather than housing or family related. And, the decline in cross-state or long-distance mobility since 2000 is almost entirely concentrated among people moving for job related reasons. In contrast, the decline in within-county migration is almost entirely housing-related. Figures 6A, 6B, and 6C display the fraction of the population who reported moving across states (6A), states or counties (6B), or within-county (6C) and who reported that the primary reason for moving was job related, family related, housing related, due to retirement, attending college, or something else.[12] Figures 7A and 7B divide job-related moves for longer-distance moves into job-related sub-categories, and Figure 7C splits within-county housing-related moves into housing-related sub-categories. The primary reason given for a cross-state or cross-county move is job-related, the bulk of the decline in long-distance migration through 2009 is attributable to a decline in job-related migration, and the flattening out of the decline after 2009 is also most apparent in job-related long-distance migration; the primary reason for a job-related move is "new job or job transfer" and the bulk of the decline in job-related long-distance moves is from this category as well. Hence, at least based on CPS respondents' self-assessment, the decline in longer distance migration appears attributable to a decline in job-based migration rather than other reasons. (One caveat to this interpretation is that the decline in long distance migration that appears as a decline in job-related moves could in fact be housing-related if job-related moves have been impeded by housing-related factors, for instance because housing in the destination labor market was too expensive.) In contrast, the primary reason given for a within-county move is housing-related, and the entirety of the decline in within-county moves appears attributable to a decline in moves for housing-related reasons.[13]

Second, the decline in migration appears to be related to a broader decline in labor market dynamism more generally, and the decline in migration seems likely to be a symptom of (or reflection of) this phenomenon rather than a cause of the more general decline in dynamism. As an illustration of these general trends, Figure 8A plots the fraction of the prime-age population with two or more primarily employers in the previous year (unconditional on employment status for the year), as estimated from the ASEC CPS supplement, alongside the fraction moving across

[12] Reasons for job-related moves are: "new job or job transfer," "to look for work or lost job," or "for easier commute." Reasons for family-related moves are: "change in marital status," "to establish own household," or "other family reason." Reasons for housing-related moves are: "wanted to own home and not rent," "wanted new or btter housing," "for cheaper housing," or "other housing related reason." Reasons for other moves are: "change of climate," "health reasons," "other reasons," "natural disaster."

[13] From Figure 7C, the decline in housing-related within-county moves is attributable to wanting new and better housing, wanting to own rather than renting, or other housing-related reasons.

states.[14] Both measures peaked in the late 1980s and have come down significantly since then. Also note that since the end of the Great Recession, the job-changing number has turned up; this is apparent in other worker-based measures of dynamism and labor market churning, such as the JOLTS quit rate and hiring rate. The reason for the decline in job switching is still not fully understood, but similar to the decline in migration, it cannot be fully explained by demographics (Hyatt and Spletzer, 2013; Molloy, Smith and Wozniak, 2017). Declining labor market dynamism has been shown for other metrics, including job finding and separation rates, job creation and destruction rates, and firm birth and deaths (e.g. Hyatt and Splezter, 2013; Davis and Haltiwanger, 2014; Decker, Haltiwanger, Jarmin, and Miranda, 2016).

In principle a decline in migration spurred by factors external to the labor market could lead to a decline in job switching and labor market dynamism more generally. However, it seems unlikely that causality runs in this direction, because the decline in labor market dynamism implied by these other measures has been larger in magnitude than the decline in migration. For example, the share of all prime-age individuals who changed jobs in the previous year fell by about 4 percentage points on net from 1990 to 2009 and has recovered some since then, while the fraction changing states fell by 2 percentage points and has subsequently been about flat. Also, as shown in Figure 8B, the fraction of prime-age individuals who changed jobs but not states fell by 4 percentage points from 1990 to 2009 and remains a few percentage points below its highs earlier in the 1990s—so, there has been a sizeable decline in the fraction that changed jobs without a change in state, suggesting that something else was driving the decline in job changing. Indeed, job changing is less associated with changing locations than it used to be. Figure 9 shows that of those who change jobs, the percent not changing states or counties has grown from 82½ percent in 1980 to nearly 90 percent more recently, and the percent not changing states has grown from about 90 percent to 92½ percent.

As a final illustration of the relationship between job changing and labor dynamism, we examine the cross-state relationship between job changing and migration. Figure 10A plots by the state the percent of 25-54 year olds changing states in the previous year (y-axis) against the percent of 25-54 year olds changing employers (x-axis); the state used for these estimates refers to the CPS respondent's state in the *previous* year, so migration rates can be understood as out-migration rates from each state. Figure 10B plots for each measure the change from its 1983-87 average to its 2013-2017 average. These plots show that state with higher job changing rates also have higher migration rates, and states where the job changing rate declined the most had larger declines in out-migration. Also of note in Figure 10B is that nearly every state

[14] This measure tracks closely the monthly job-to-job transition measure commonly estimated from the monthly CPS, computed by estimating the number of respondents who report being at the same employer from one month to the next (as pioneered by Fallick and Fleischman 2004). The benefit of the ASEC-based measure is that it has been recorded since the 1980s, whereas the monthly measure is available only since the CPS redesign in 1994.

experienced a decline in job changing and out-migration over this period, and on average the decline in job changing was three times as large as the decline in out-migration—again suggesting that the decline in labor market dynamism has been broader than the decline in migration.

To summarize, in our view the decline in long-distance migration is most likely a reflection of declining labor dynamism more broadly, and hence the reasons for the decline in longer distance migration seem rooted in the labor market. Left out of this discussion, of course, are the reasons for the longer-run decline in labor market dynamism—this question remains unsettled and there is a large and burgeoning literature on this issue that we don't delve into here (e.g. increased market concentration and declining business formation, see for example Decker, Haltiwanger, Jarmin, and Miranda, 2016), but instead note that a richer understanding of the factors behind declining labor market dynamism can also help explain why longer distance migration has also fallen.

IV. Migration across weaker and stronger labor markets

In light of the evidence that the decline in migration is rooted in the labor market, we next turn our focus towards exploring how in- and out-migration rates vary across metropolitan areas based on the strength of their labor markets and other characteristics. Not only does this analysis aid in understanding whether the connection between migration and labor demand has changed over time, it also provides insight into the types of factors that may be acting as barriers to prevent more population adjustment in response to labor market conditions.

A. Defining strong and weak labor markets

The first step in our analysis is defining a local labor market and determining a measure of labor market strength. We use cities—specifically, core-based statistical areas (CBSAs) which we will refer to as "metros" throughout—as our unit of analysis, for a few reasons. First, metros are more related to a local labor market concept than are counties, since cross-county commuting is common. Second, measures related to labor market strength (e.g. employment levels and employment growth, unemployment rates) and related to the housing market (e.g. house prices, regulations on building, and geographic constraints related to housing supply elasticities) are more readily available at the metro level. Commuting zones may be a more natural unit of analysis than metros, with the added benefit that they encompass the entire U.S. (whereas our measure will leave out rural areas), but our need for labor and housing market related data constraints us to metros.

To determine whether a metro is a strong or weak labor market, we decided against using contemporaneous real labor market outcomes such as unemployment or employment rates or wages, since these will be determined by both labor supply and demand and affected by any internal migration over our period of analysis. So instead we adopt what has become standard practice in local labor market analysis and construct a Bartik-style measure of employment growth in a metro, using a metro's composition of employment across industries in 2000 (based on the Quarterly Census of Employment and Wages, or QCEW) and national employment growth by industry from 2001 to 2016 (again using the QCEW). We have about 360 metros for which we have this measure, and we rank these metros by predicted employment growth and refer to this ranking as a metro's "labor demand." Generally, when we refer to a metro as having "weak or low labor demand," or being in the bottom of the distribution, we mean a metro in the bottom third of the distribution; "strong or high labor demand," or being in the top of the distribution, refers to those in the top third of the distribution. (In some parts of our analysis, we consider quintiles and deciles of the distribution as well.)

Appendix Table 1A shows the top and bottom 50 metros by this measure, and Figure 11 provides a map where metros are color-coded with this classification (lighter green metros are lower in the distribution). Lower labor demand metros include many metros in the "Eastern Heartland" (following Austin, Glaeser, and Summers 2018 classification), while high labor demand metros are generally clustered around the coasts.

B. Differences in migration by labor demand

Next, we examine differences in inflow and outflow rates based on our measure of a metro's labor market strength. We use IRS data to compute average inflow and outflow rates (i.e. as a share of each metro's population) from 2001-2015 for each metro, and in Figure 12 we plot these inflow and outflow rates against the metro's measure of predicted employment growth. Inflow rates to stronger labor markets are higher than inflow rates to weaker labor markets, but somewhat surprisingly, outflow rates are also higher from stronger labor markets. Figure 13 shows average inflow and outflow rates by year across each tercile of the predicted employment growth distribution, and shows that for every year of the 1994-2016 period the average inflow rate for the strongest labor market was well above the average inflow rate to middle or weak labor markets. Outflow rates from the middle and strongest labor markets are similar, and above outflows from the weakest labor markets. Figure 13 also illustrates that the decline in internal migration over this period is apparent across the demand distribution—average inflow and outflow rates decline for each tercile of our labor demand measure.

Our primary takeaway from these figures is that, contrary to what one might expect from a simple model of migration where individuals move from weak to strong labor markets, outflow rates are on average greater in strong labor markets than weak labor markets. Instead, there appears to be more churn overall—more people moving in and out—in stronger labor markets, and less churn in weaker labor markets. Weaker labor markets appear to be more sclerotic.

For those who do migrate from weak labor markets, where do they go—and how does this compare to the direction of outflows from strong labor markets? Again using IRS data, we compute for each metro in each year the share of outflows from that metro to low, middle, and high demand metros. We then average these outflow shares across each tercile in each year and plot the trends in Figure 14. The panel on the left shows the average share of outflows to low demand cities from low (red line), middle (orange line), and high (green line) demand metros, the middle panel shows the average share of outflows to middle demand metros, and the right panel shows the average share of outflows to high demand metros. Focusing first on outflows from high demand metros, 65 to 70 percent of all outflows from high demand metros on average go to other high demand metros, about 25 percent go to middle demand metros, and less than 10 percent go to low demand cities. In contrast, migration from low demand metros is more evenly split across the distribution—25 to 30 percent to low demand cities, 40 percent to middle demand cities, and 30 to 35 percent to high demand cities. (The pattern of outflows from middle demand cities looks more similar to outflows from high demand metros than outflows from low demand metros.)

In summary, not only do fewer people leave low demand metros, but when they do leave, migration is not strongly directed towards strong demand metros. In contrast, migration rates from high demand metros are larger, and this migration is on average very strongly directed towards other high demand metros.

C. Understanding migration flows between weak and strong labor markets

1. Characterizing migration flows between metros

These findings raise the question: "why aren't outflows from low demand metros more targeted towards high demand metros, similar to outflows from other high demand metros?" Understanding the reasons why migration from less prosperous cities is not more strongly directed towards high demand metros may help clarify why migration from low demand metros is not more significant and what barriers may exist that impede migration from labor markets that have experienced adverse demand shocks.

To explore this question, we begin by forming a dataset of migration flows between every metro pair for 2001-2015. We then calculate the outflow rate from each originating metro to every receiving metro by dividing by the originating metro's population in the year. We then average over all years in the sample to generate the average outflow rate from each originating metro to every possible receiving metro.[15]

As a baseline, with this dataset we regress these outflow rates on dummy variables for whether the receiving metros are in the middle or top tercile of the demand distribution (panel A of Table 3). Using these coefficients we then estimate the predicted outflow rate from each metro to low, middle, and high demand receiving metros. We average these predicted outflows over all originating metros in the low, middle, and high tercile of the distribution and divide by the total average outflow rate for each group. This gives us the average share of outflows from each tercile of the distribution to metros in each tercile—effectively just backing out the average of the time series shown in Figure 13. The red line in Figure 15 plots this average outflow share. Panel A shows the average outflow shares from low demand metros to low, middle, and high demand metros (each of the three delineations on the x-axis), while panel B shows the average outflow shares from high demand metros.[16] As we found earlier, outflows from high demand metros are very directed towards other high demand metros, while outflows from low demand metros are more evenly split between low, middle, and high demand metros.[17] Our aim in the following analysis is to understand why outflows from high demand metros are strongly directed towards other high demand metros, while outflows from low demand metros are more evenly split—that is, why the red line in the right panel slopes strongly upward while the red line in the left panel does not.

The first factor of importance is population—high demand metros tend to be more populous than low demand metros, and larger cities tend to attract more migrants. We include in our regressions the log of the receiving metro's population in addition to dummy variables for the receiving metro's location in the labor demand distribution (panel B in Table 3). Next, we compute predicted outflow rates from each receiving metro to every other metro using the dummy variables for receiving metro labor demand, the coefficient on log population from the regression, and the average population across all metros (i.e. generating predicted outflows holding receiving metro population at the average across all metros). Finally, we compute

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[15] This gives us a dataset with 88,179 number of observations (357 originating metros multiplied by 246 receiving metros). We can form the predicted employment measure for about 360 metros, but our measure of housing regulation is available for only about 260 metros. In our analysis, we restrict our set of receiving metros to only those that have available values for predicted employment, the regulatory variable, and geographic constraints. Hence, our sample of originating metros is larger than our sample of receiving metros.

[16] We omit outflows from middle demand metros for ease of visual exposition. Outflows from middle demand metros are also more directed towards high demand metros, though less so than are outflows from high demand metros—about 10 percent of outflows from middle demand metros go to low demand metros on average, 40 percent go to middle demand metros, and 50 percent go to high demand metros.

[17] The outflow shares shown by the red line in Figure 15 do not exactly correspond with the average of the time series shown in Figure 13. The reason is that the measures of metro-level characteristics that we include as covariates in subsequent regressions are not available for all metros. We use a consistent set of metros across all regressions in this section and hence exclude a few that are included in Figure 13.

average outflows using this regression-based outflow rate. The blue line shows the outcome from this exercise. Adjusting for population boosts outflow shares to low demand metros by about 10 percentage points and reduce outflow shares to high demand metros by the same amount. Consequently, outflow shares from high demand metros after adjusting for receiving metro population are somewhat less directed towards other high demand metros—the blue line in the right panel is less steeply sloped than the red line. But outflows from low demand metros are even more tilted away from high demand metros—after adjusting for receiving metro population, only 20 percent of outflows on average from low demand metros go to high demand metros. We view adjusting for receiving metro population as a key control for this analysis, since larger cities clearly attract more migrants, regardless of how prosperous they are, and so we view the blue line in Figure 15 as the new baseline for the rest of the analysis. This also deepens the mystery—in addition to the blue line for low demand metros (in the left panel) not sloping upward line like the blue line for high demand metros (in the right panel), we seek to understand why on average only 20 percent of outflows from low demand metros go towards high demand metros.

2. Distance matters!

Figure 16A and 16B provide one possible explanation. In these figures, we have divided metros into deciles of the demand distribution (on the x-axis) and plotted the average or median distance to the closest high demand metro (metro in the top tercile of the demand distribution). Both average and median distance is declining in labor demand—metros in the bottom decile of the demand distribution are on average 120 miles from the nearest high demand metro, while metros in the top decile are 70 miles away. In other words, weak labor markets are on average farther from strong labor markets than strong labor markets are from other strong labor markets.

As another way of seeing this phenomenon, we compute for each metro the number of nearby (within 200 miles) strong (top tercile) labor markets, and compute the average and median number of nearby strong labor markets by the originating metro's decile in the demand distribution—we plot our findings in Figure 16B.[18] Weak (bottom decile) labor markets have on average 3 strong labor markets nearby, while strong labor markets have on average 7 nearby strong labor markets. Hence, these figures collectively suggest another reason why migration from low demand metros may not be better targeted towards high demand metros—distance matters when choosing a migration destination, and low demand metros are on average more

[18] We choose 200 miles because on average migration flows between cities that are 200 miles apart or more tend to be much smaller than migration flows between cities within 200 miles of each other, and distances above 200 miles seem to matter less for explaining migration flows. That said, our subsequent findings are largely the same if we control for distance between cities more flexibly or use other cutoffs for defining whether metros are "nearby" (e.g. 100 miles).

geographically distant from high demand metros than high demand metros are from high demand metros (and high demand metros tend to be more geographically clustered).

To explore the implications of this, we also include in the regressions a dummy variable for whether the metros are 200 miles apart or more. Panel C displays the regression results—outflow rates are meaningfully smaller for metros that are 200 miles apart or more. Also note that in Panel C the coefficients on the middle and high labor demand dummy variables in the first column (outflows from low demand areas) are no longer negative as they were in panel B—indicating that after controlling for distance between metros, outflows from low demand areas are now larger to middle and high demand metros than to low demand metros. Even after adjusting for distance, migration flows from high demand metros are still much more targeted towards other high demand metros (the coefficient on the high labor demand dummy in the third column is still quite large). The orange line in figure 15 adjusts for distance as well as receiving metro population (as with population, we adjust outflows using the coefficient on distance multiplied by the average distance between metros in our sample). Now, outflows from low demand areas are more evenly balanced towards low, middle, and high demand metros. And, while the orange line for high demand metros in the right panel still slopes upward, the composition of outflows from low demand metros appear more similar to outflows from high demand metros than they did in the unadjusted data (red line) or population adjusted data (blue line).

3. Factors related to the housing market in receiving metros

How important are higher housing prices in high demand metros for explaining migration flows to weak and strong labor markets? Rather than including house prices directly in our regressions—which would be influenced by demand for housing and hence migration—we include measures of regulatory and geographic constraints that have previously been shown to be related to the elasticity of local housing supply. (That said, our findings are robust to using house prices or rent instead of these constraints.) Specifically, we measure regulatory constraints on housing supply using the Wharton Residential Land Use Regulation Index (Gyouko, Saiz, and Summers, 2008), and we measure geographic constraints on housing availability using estimates from Saiz (2010). We rank metros by their location in the distribution of the regulatory and geographic constraints variables and classify them as being low, middle, or high regulatory or geographically constrained metros based on their tercile in these distributions.[19] Finally, we include dummy variables for whether the metro is in the middle or top of the regulatory and geographic constraint distribution in our regressions. Panel D of Table 3 shows the coefficient estimates on our new set of covariates. As before, migration from low demand metros to middle

[19] Appendix Table 1B and 1C list the top and bottom 50 metros for each variable.

and high demand metros is somewhat greater than migration to low demand areas, and migration from high demand metros remains strongly directed towards other high demand metros. The regulatory and geographic constraints dummies generally have negative coefficients and these coefficients are sometimes statistically significant. But the magnitudes are fairly small.

The green line in Figure 15 shows adjusted outflow shares based on coefficient estimates from these regressions. The green line lies almost exactly on top of the orange line, indicating that adjustment of outflow shares for housing constraints in the receiving metros makes almost no difference for explaining the direction of outflows towards low, middle, and high demand metros.[20]

To continue our focus on the importance of housing supply constraints, we flip our analysis from describing flows into metros based on their tercile of the labor demand distribution to their tercile in the housing regulation or geographic constraints distribution. We repeat our analysis of running metro-level regressions of outflow rates on receiving metro characteristics, including population, distance, and dummy variables for whether the receiving metro is in the bottom, middle, or top of the regulation/constraints distribution. In Figure 17A we plot outflows from low and high demand metros to low, middle, and high regulation metros, and in Figure 17B we plot outflows to low, middle, and high geographic constraint metros. After adjusting for population and distance (the orange line), average outflow shares to low, middle, and high regulation and geographic constraint metros are all very similar—the orange line in the left and right panels of both figures are reasonably flat. The one exception is that outflows from low demand areas are more tilted towards areas with low geographic constraints—the average outflow share from low demand metros to low constraint metros is about 40 percent, while the average outflow share to metros with high constraints is less than 30 percent.

4. Summary

Overall, our interpretation of these findings is that migration flows are not much associated with constraints on housing in receiving cities, and that housing constraints in more prosperous metros cannot explain why outflows from low demand metros *on average* are not more strongly directed towards high demand metros, in the manner that outflows from high demand metros are directed towards other high demand metros. The "*on average*" is an important caveat—we do not mean to imply that housing constraints are irrelevant for all prosperous, high productivity cities. Indeed, there are some cities—San Francisco, for example—where housing constraints seem like a plausible impediment to in-migration. But, for

[20] We have repeated our analysis controlling for the receiving metro's tercile in the house price distribution (and, separately, rental price distribution). The share of outflows from low, middle, and high labor demand metros to low, middle, and high labor demand receiving metros look very similar when controlling for house price or rent instead of using the housing regulation and geographic constraint variables.

every highly constrained, highly prosperous area like San Francisco, there are also other less constrained but still prosperous areas—think Houston—so on average, migration flows do not seem to be much associated with the degree of housing constraints in the receiving city, regardless of where they sit in the labor demand distribution.

D. Characteristics of migrants from low and high demand areas

Finally, we are interested in understanding the characteristics of migrants who leave low demand areas. To answer this question, we use microdata from the American Community Survey for 2005 to 2016 and estimate individual level regressions where the dependent variable is whether the respondent moved out of his or her metro over the last year, and covariates include dummies for age, sex, education, home ownership, race and ethnicity, and location in the metro's income distribution.[21] We estimate these regressions separately based on the originating metro's quintile in the labor demand distribution. Table 4 displays the coefficient estimates on these variables, with "—" indicating the omitted category in each set of variables.

A couple of interesting findings emerge. First, as has been noted elsewhere, younger and better educated individuals are more likely to move than are older and less educated individuals, regardless of the original metro's labor demand. However, this pattern is especially pronounced for individuals living in low demand areas. For example, for individuals from metros in the lowest quintile of labor demand, individuals age 22-29 are about 7 percentage points more likely to move than individuals 50-64. For people living in high demand metros, 22-29 year olds are about 4.5 percentage points more likely to move than 50-64 year olds. And people with 4 or more years of college are about 3 percentage points more likely to move out of low demand metros than are high school graduates, whereas the differential is about 1 percentage point in high demand metros. These relationships are consistent with disproportionate out-migration from less prosperous areas by individuals who may stand to benefit the most: younger workers have the longest time left in their working career to reap the labor market returns from moving to a higher-wage area, and others have shown that college-educated workers have especially benefited from moving to highly prosperous cities (e.g. Diamond 2016).

Also, there are some interesting differentials by race. Regardless of a metro's quintile of labor demand, whites are more mobile than other races. But black non-Hispanics who live in low demand areas are slightly less mobile relative to whites than are black non-Hispanics who live in high demand areas. Because our analysis adjusts for the individual's relative income within the metropolitan area, this finding cannot be explained by racial differences in income. Rather, it could be that black individuals have less financial wealth (conditional on income) or less non-monetary resources that would help them move out of low demand areas. Another

[21] We use data downloaded from the Integrated Public Use Microdata Series (Ruggles et. al. 2019).

possible factor that might contribute to this result is that the presence of an African American community may be an important location attribute for many black people, and the number of metropolitan areas with such communities may be limited.

E. Summary

To summarize, in this section we have examined differences in in- and out-migration rates between less prosperous and more prosperous metros, using data on migration flows between all metros from the IRS and proxying for the strength of an area's labor market using a Bartik-style measure (a metro's industry composition of employment in 2000 crossed with national employment trends by industry from 2001 to 2016). We have shown that in- and out-migration rates are on average higher over this period for metros with stronger labor markets, so that less prosperous metros appear more sclerotic—that said, in- and out-migration rates have declined for most cities, regardless of how strong their labor markets have been. Not only do outflows from low demand areas appear lower on average than outflows from more prosperous areas, but outflows from low demand areas tend to be directed towards other less prosperous labor markets. Meanwhile, outflows from high labor demand metros tend to be very directed towards other high demand metros.

What accounts for this asymmetry in migration from low to high demand metros, compared with migration flows from high demand to high demand metros? It appears that a primary explanation is distance: less prosperous areas tend to be far from more prosperous areas, while more prosperous areas tend to be close to other prosperous areas. Since distance is a significant impediment to migration, the greater distance on average from weak to strong labor markets appears to be a primary explanation for why migration from weak labor markets isn't better directed to strong labor markets (as migration from strong labor markets is). On the other hand, housing constraints (regulatory or geographic) do not appear to much explain differential migration patterns between weak and strong metros. Indeed, on average migration flows to metros with greater housing constraints don't appear to be much different from flows to metros with less significant constraints. Finally, we have shown that the age and education migration differential is larger for migrants from lower demand areas—these are groups that may be expected to benefit the most from migrating from a less prosperous labor market, and it appears that (relative to older and less educated individuals) they are indeed more likely to move from less prosperous areas than are younger and better educated residents in more prosperous areas.

V. Conclusion

Americans now are significantly less likely to move than they were in the 1980s. This is true regardless of sex, age, education, or race. It is also true for people moving in and out of areas with strong labor markets as well as for people moving in and out of areas with weak labor markets. The decline in migration appears to have paused at the end of the Great Recession, but it has not reversed. This lack of reversal, despite the relatively strong economy of the last several and the usual pro-cyclical pattern of migration, suggests that whatever factors were depressing internal migration for the decades prior to the Great Recession have continued to exert downward influence.

What factors have contributed to falling migration rates? Changing demographics—in particular, population aging—seems like it should be a primary candidate explanation. Population aging can account for a large fraction of the decline in migration across short distances, but only a small percent of the decline in migration across longer distances, such as across states or across counties. In our view, the most significant contributors to the decline in long-distance migration are likely rooted in the labor market, and seem likely to be related to declining labor market dynamism more generally. Indeed, the most common reason given for a long-distance move is labor market related, and the biggest decline in long-distance migration is apparent in job-related moves. Further, job changes sometimes involve a location change, and job changing has also declined substantially since the 1980s. The decline in job changing seems more likely to drive the decline in migration, rather than the other way around, because the decline in the job changing rate is much larger in magnitude than is the decline in migration (in terms of the number of people affected), and also because there is a sizeable decline in job changing even for people who don't move locations.

One reason why low long-distance migration rates have been raised as a policy concern is because if people do not move out following adverse local demand shocks, residents of areas experiencing persistent adverse shocks may face increasingly bleak labor market prospects. Indeed, we confirm that migration from less prosperous areas tend to be smaller than migration from more prosperous areas, and those who move from less prosperous areas tend *not* to go to more prosperous areas; in contrast, migrants from more prosperous areas are much more likely to go to other prosperous areas. We show that a primary explanation for this asymmetry is that areas with weaker labor markets tend to be farther from areas with stronger labor markets—that is, labor markets tend to be clustered based on their labor market strength. As a consequence, those looking to move from weak labor markets have fewer nearby strong destination labor markets to choose from. That said, we do find that younger and better educated people are especially likely to migrate from lower demand metros—and these are the individuals who likely benefit most from a move to a better labor market (in terms of increases to lifetime income).

We also examine the relationship between migration flows and a metro's housing supply constraints from regulation and geography. We find that the level of housing constraints in more prosperous metros cannot account for the low level of migration from weak labor demand metros to more prosperous areas. Indeed, average migration flows into metros look similar regardless of the metro's housing constraints. We caution that our conclusions are drawn from differences in *average* migration flows across metros groups—we cannot rule out housing constraints being a significant impediment to migration into *some* particularly constrained areas (e.g. San Francisco). More research on the importance of housing supply constraints and rising housing costs, especially in more prosperous labor markets, as an area where additional rigorous empirical research would be greatly valuable.

Our analysis raises additional concerns about the U.S. economy's ability to adjust quickly to adverse shocks at the national or local level, for a few reasons. First, the lack of significant improvement in internal migration rates over the last decade, during a time when improving labor market conditions would all else equal support an increase in relocation, suggests that whatever forces have been depressing migration in the decades prior to the Great Recession remain in effect, and as a consequence internal migration may resume its decline if general economic conditions were to weaken. In other words, if ten years of economic expansion hasn't been sufficient to reverse *any* of the previous decades' slide, it is unclear what, if anything, it would take to do so. Second, and relatedly, the decline in migration appears symptomatic of declining labor market dynamism more generally, which is likely an exceedingly difficult structural issue for policy to address.[22] Third, a significant impediment to migration out of weak labor markets appears to be that weak labor markets tend to be geographically distant from strong labor markets. Given how infrequently migrants move very long distances, even to move from poor labor markets to strong ones and especially for non-college educated individuals, interventions to improve labor market outcomes for workers in areas that experience large adverse shocks may need to be specifically tailored for the characteristics, experiences, and needs of the area (e.g. "place-based policies") rather than aimed at incentivizing movement to more prosperous areas.

[22] That said, if declining worker-level dynamism—as indicated from measures like the quit rate and job-to-job transitions—reflects improved matching between firms and workers (reducing incentives to move and change jobs) then the decline in migration may have positive implications for worker welfare and productivity more generally.

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Data Appendix

CPS data. We use microdata from the ASEC supplement to the CPS as provided by IPUMS. When using these data to estimate migration rates, we exclude all individuals with imputed or missing migration (using the qmigrat1 imputed value flag). In addition, we merge in the NBER extracts of the ASEC to include the "fl_665" variable that indicates whole-case imputation. Excluding respondents with imputed responses to the whole survey (from fl_665) or to the migration questions (from qmigrat1) addresses the issue identified in Kaplan and Schulhofer-Wohl (2013) for which hot deck imputation of migration responses resulted in an overestimate of the decline in migration over some of the early 2000s. The migration variables in the ASEC refer to migration over the previous year. Since the survey is administered in March, we assign internal migration rates from a survey administered in March of a given year to the previous year, e.g. we take migration over the previous year as measured in the March 2018 survey to correspond with migration in 2017.

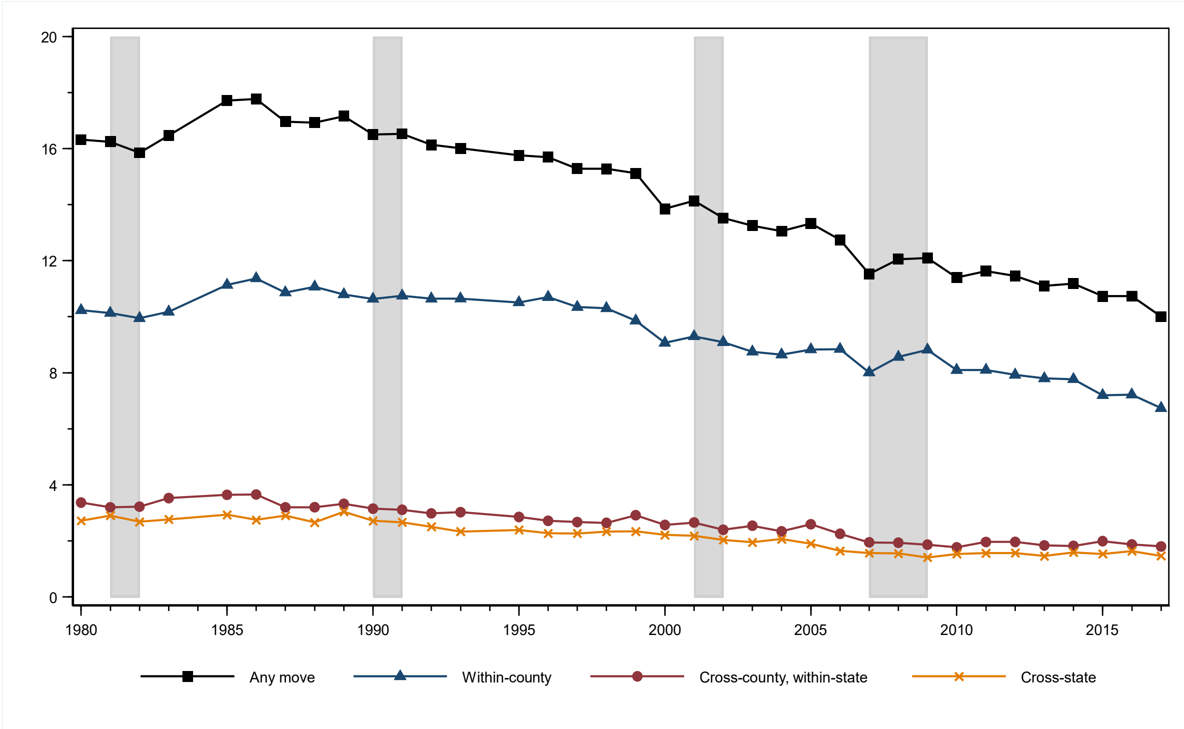
ACS data. We use microdata from the ACS as provided by IPUMS. As with the CPS data, we exclude all individuals with imputed or missing migration (using the qmigrat1 imputed value flag.) Survey questions refer to migration over the previous year, but the ACS is administered throughout the year and the date that a respondent replied to the ACS is not provided, so it is uncertain exactly which calendar year (the year of the survey or the previous year) best corresponds with data collected over a particular year. We assign internal migration rates from a survey administered in a given year to the previous year, e.g. we take migration over the previous year as measured in the 2018 ACS survey to correspond with migration in 2017.

IRS data. We use publically provided data from the IRS on migration flows between counties, which is available for tax years 1991 to 2016.[23] The IRS generates this data from year-to-year address changes reported on individual income tax returns filed to the IRS, and reports the number of tax returns and personal exemptions claimed (approximately the number of individuals covered by the tax return) moving between every county and staying in each county. Based on the mapping of counties to metros, we then generate metro-to-metro migration flows. IRS data is dated by the tax filing year and measures change in filing location from one filing year to the next; since filing generally occurs early in the calendar year, we take migration estimated from these IRS data to refer to moves that occurred in the year before the filing year. The methodology the IRS uses to record locational moves from changes in tax filing residence was changed in the 2012 tax filing year. Prior to 2012, individuals who were primarily filers in one year but secondary filers in the next, or the reverse, were excluded from calculations; in 2012 data and thereafter, they were included. This likely prevents data from tax year 2012 and

[23] https://www.irs.gov/statistics/soi-tax-stats-migration-data

thereafter from being strictly comparable to other years. Therefore, in our analysis, we generally include a break in time series at this point. We also exclude 2015 from our analysis; in conversations with the IRS, data from 2015 suffer from some quality issues that prevent comparability to other years.

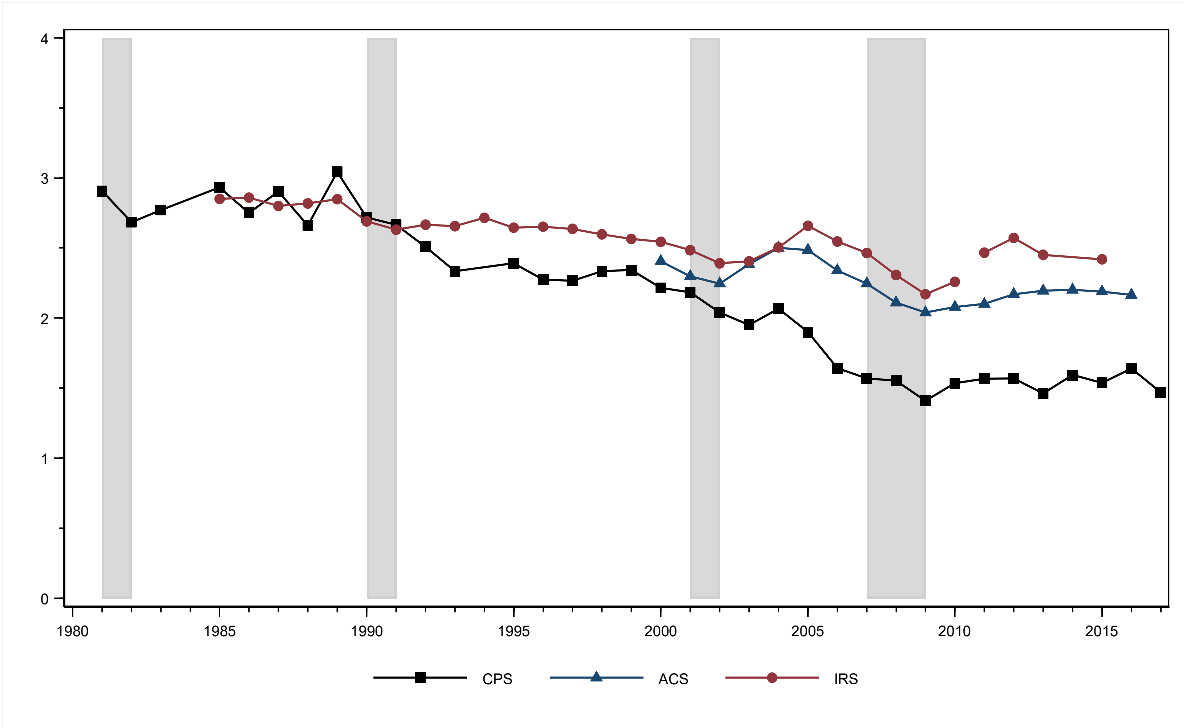
Figure 1. Measures of internal migration, CPS (in percent)



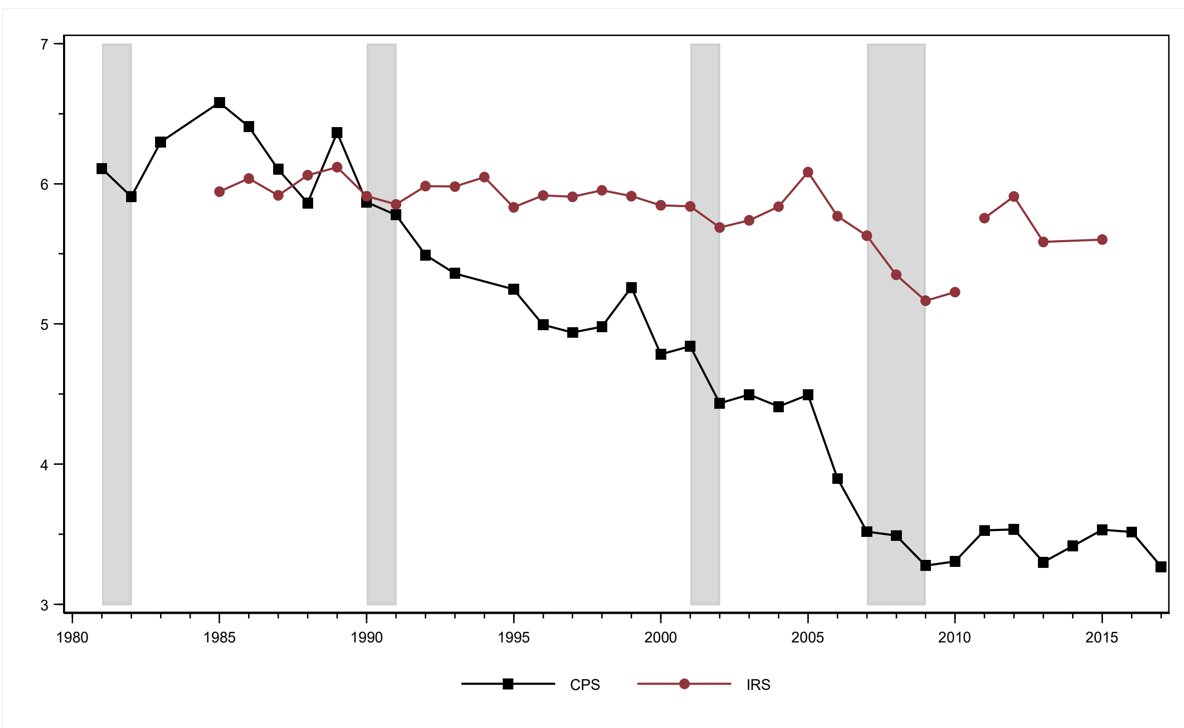
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are computed for all ages, and respondents with imputed values for migration are excluded from the calculations. The black line plots the percent moving residences in the previous year, the blue line plots the percent reporting a within-county move, the red line plots the percent reporting cross-county but within-state moves, and the orange line plots the percent reporting cross-state moves; the blue, red, and orange lines sum to the black line. The data plotted are shifted 1 year back from the date of the survey since survey responses refer to migration over the previous year, e.g. the point labeled 2017 is from the 2018 ASEC. NBER recessions are shaded.

Figure 2. Comparing measures of internal migration (in percent)

A. Cross-state migration

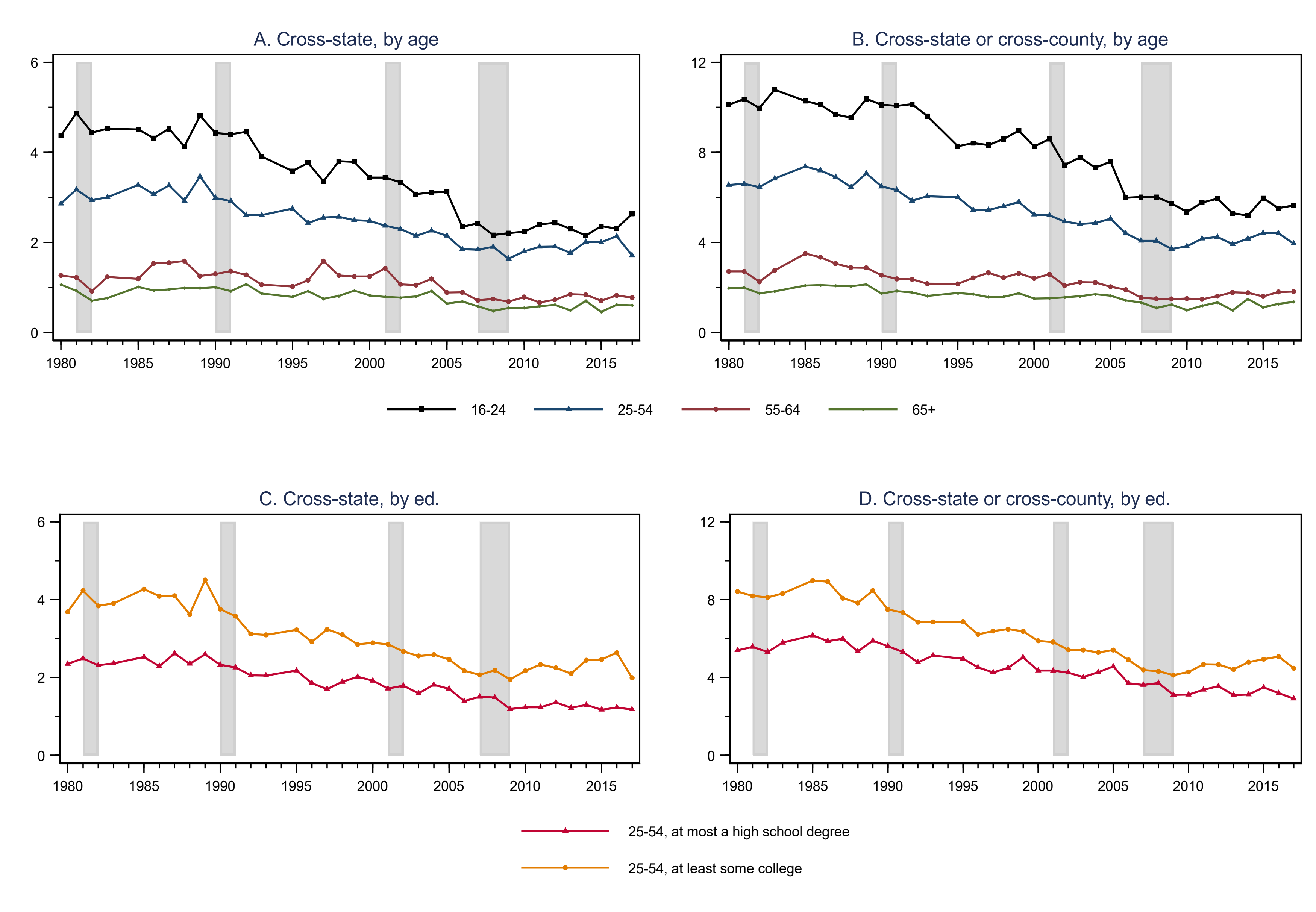


B. Cross-state migration or cross-county



Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS (black line); publically available data on county-to-county migration flows from the IRS (red line); and ACS data, as provided by IPUMS (blue line). Estimates are computed for all ages, and for CPS and ACS estimates respondents with imputed values for migration are excluded from the calculations. For the CPS and ACS estimates, the data plotted are shifted 1 year back from the date of the survey since survey responses refer to migration over the previous year, e.g. the point labeled 2017 is from the 2018 ASEC. IRS data are also shifted back one year from the published date, since the published date refers to the year of tax filing and migration references the tax year (which is primarily in the year before filing). NBER recessions are shaded.

Figure 3. Longer distance moves, by age and education (in percent)



Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Panels A and C plot the percent of the age or education group moving across states in the indicated year, and Panels B and D plot the percent moving across states or counties. Imputed values for migration are excluded from the calculations. The data plotted are shifted 1 year back from the date of the survey since survey responses refer to migration over the previous year, e.g. the point labeled 2017 is from the 2018 ASEC. NBER recessions are shaded.

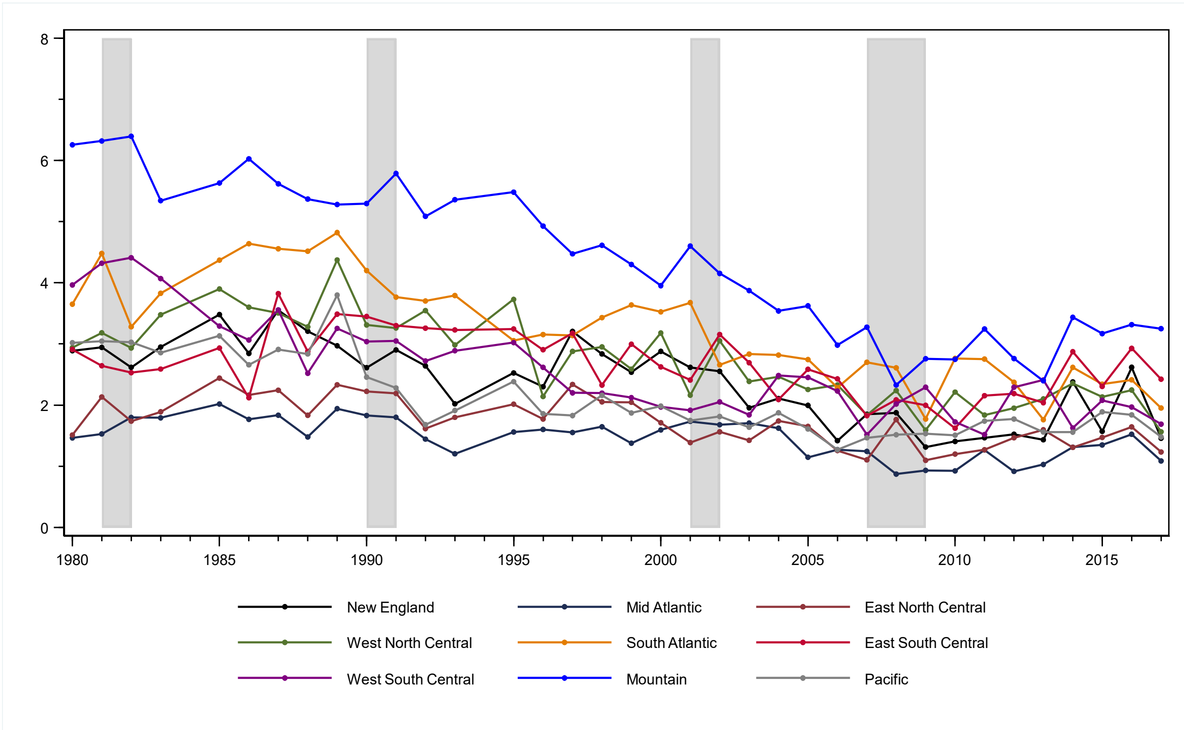
Table 1. Change in cross-state migration, by demographic characteristics

	Average cross-state migration rate: 1980 - 1984	2013 - 2017	Change	Change in pop. share (25-54)
All	**2.2**	**1.5**	**-0.7**	
A. By age				
16+	2.2	1.5	-0.7	
25-54	2.4	1.9	-0.4	
55-64	0.9	0.8	-0.1	
65+	0.7	0.6	-0.1	
B. By education (25-54 only)				
Less than high school degree	1.7	1.0	-0.7	-8.7
High school degree, no college	2.0	1.3	-0.7	-14.8
Some college	2.7	1.8	-0.9	9.0
4 year degree or more	3.4	2.7	-0.7	14.5
C. By employment status (25-54 only)				
Worked in previous year, men	2.4	2.0	-0.4	-1.6
Didn't work in previous year, men	4.6	1.7	-2.9	2.1
Worked in previous year, women	2.2	1.8	-0.3	1.7
Didn't work in previous year, women	2.2	2.0	-0.2	-2.2
D. By homeowner status (current year status, 25-54 only)				
Homeowner	1.3	0.9	-0.4	-7.9
Renter	4.9	3.6	-1.3	7.9
E. By family structure/work status (25-54 only)				
Unmarried, men	3.4	2.2	-1.2	8.1
Unmarried, women	2.5	2.2	-0.3	5.9
Married	2.2	1.7	-0.4	-14.0
Neither spouse with employment in prev. year	4.7	1.7	-3.0	-0.3
Only one spouse with employment in prev. year	2.6	2.2	-0.4	-6.0
Both spouses with emp. in prev. year	1.8	1.5	-0.3	-7.6
Both spouses with emp. in prev. year, both with college degrees	3.9	2.9	-1.0	1.6
Kids in household	2.0	1.5	-0.5	-8.7
No kids in household	2.9	2.5	-0.4	8.7
F. By household earning (25-54 only)				
Bottom quartile of household income dist.	3.1	2.1	-1.0	
Middle two quartiles of household income dist.	2.3	1.9	-0.4	
Top quartile of household income dist.	2.1	1.8	-0.2	

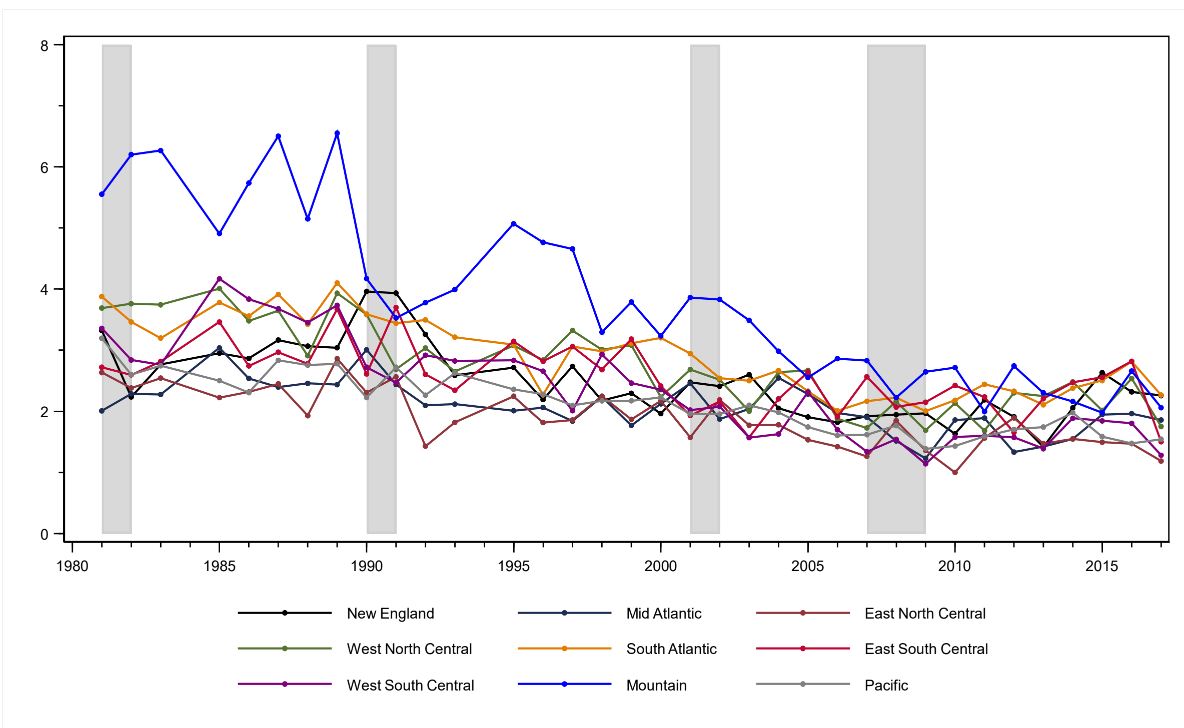
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Respondents with imputed values for migration are excluded from the calculations. The first two columns display average cross-state migration rates for 1980-1984 (column 1) or 2013-2017 (column 2), for the group listed in the row. The third column is the difference in the first two columns. The last column displays the change in the share of the 25-54 population represented by the group in each row, from 1980-1984 to 2013-2017.

Figure 4. Cross-state migration rates, by Census division (25-54 year olds, in percent)

A. Percent who moved into a state in the Census division



B. Percent who moved out of a state in the Census division

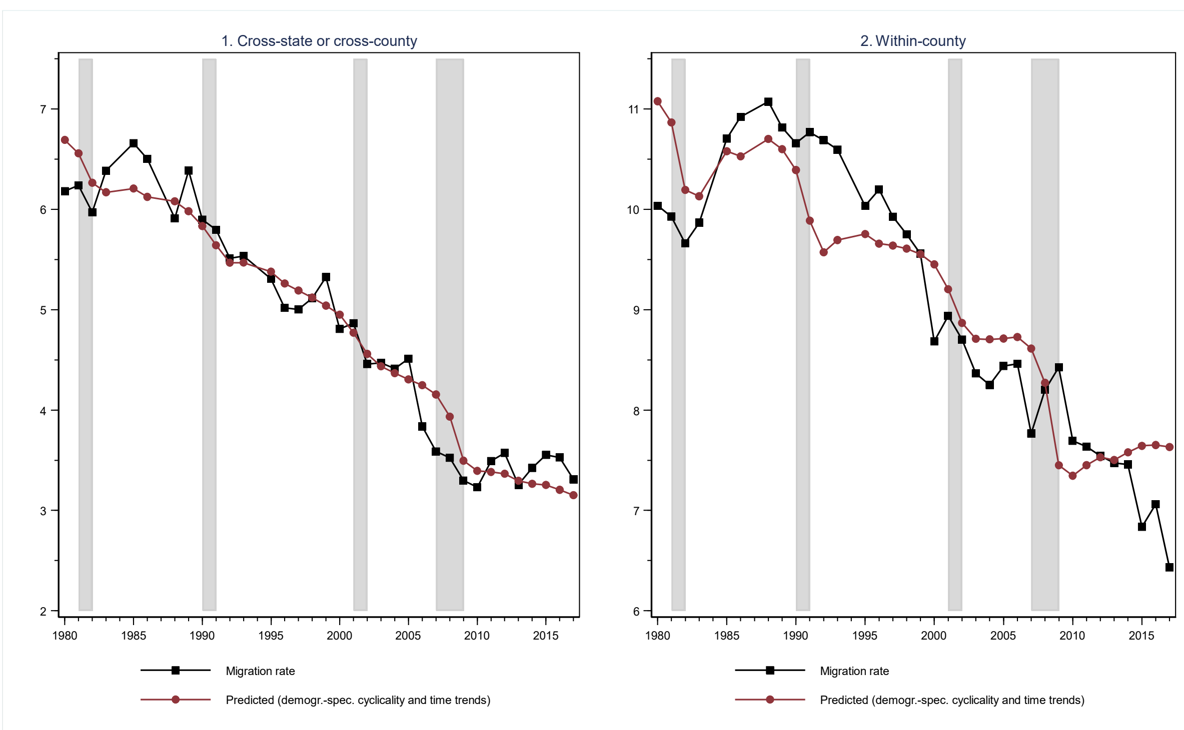


Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Rrespondents with imputed values for migration are excluded from the calculations. The lines plotted in Panel A are estimates of the percent of respondents who moved states in the given year, by current Census division of residence. The lines plotted in Panel B are estimates of the percent of respondents who moved states in the given year, by previous Census division of residence. The data plotted are shifted 1 year back from the date of the survey since survey responses refer to migration over the previous year, e.g. the point labeled 2017 is from the 2018 ASEC. NBER recessions are shaded.

Figure 5. Adjusting migration rates (16+) for demographics, the cycle, and trends

A. Demographic adjustment

B. Sim. migration rates, controlling for demog., pre-2006 trends, and cyclicality



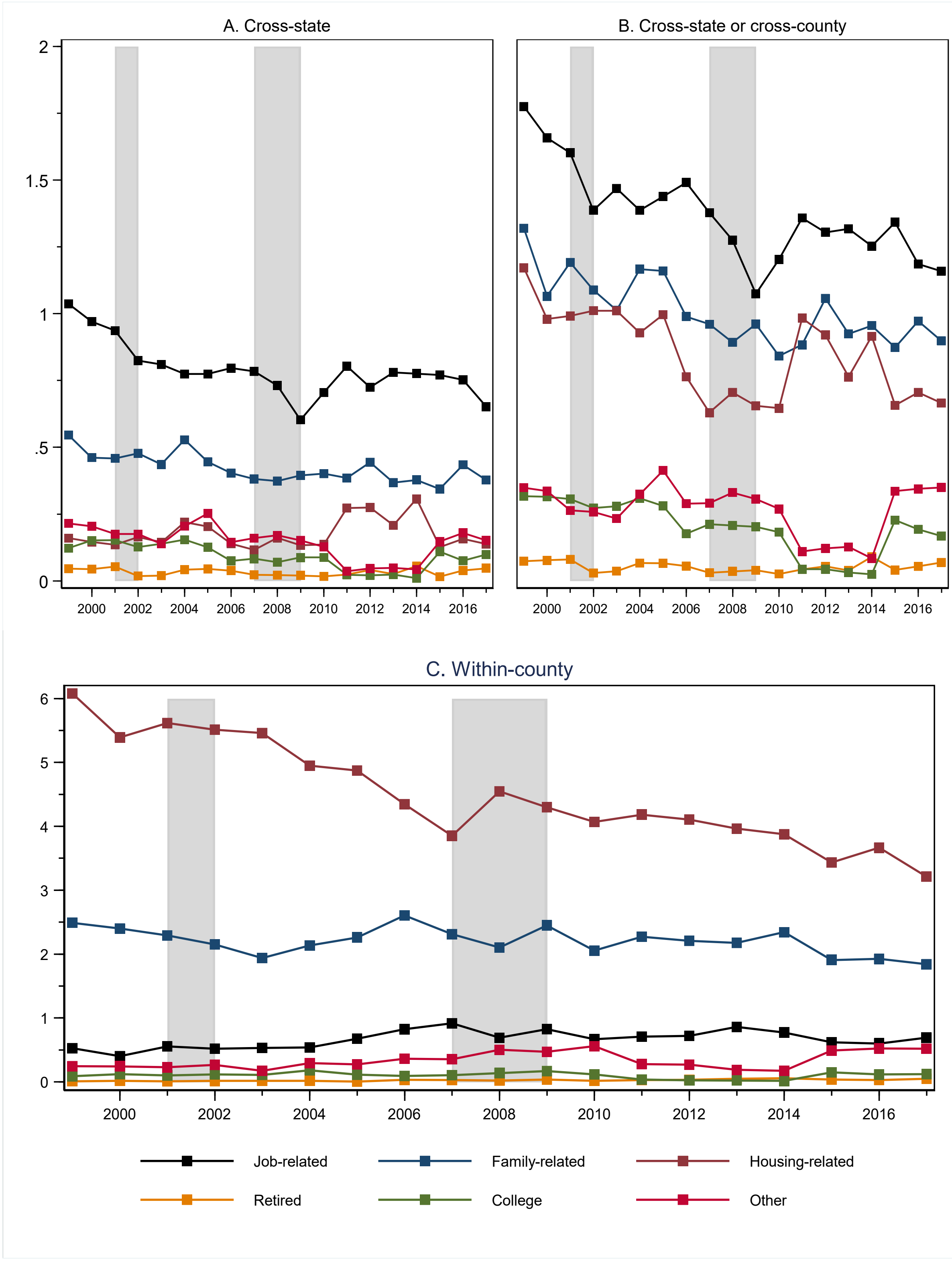
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 16+ population. Figure A plots the change in actual migration rates relative to 1980 (black line) compared with the change implied by changes in the age, sex, race, and education (the red line)--see text for more details. Figure B plots the actual migration rate along the simulated migration rate from a model that predicts migration from the age, sex, race, and education, the Congressional Budget Office's estimate of the unemployment rate gap, and demographic-group specific pretrends, all estimated based on data from 2006 and earlier--see text for more details.

Table 2. Relationship between cross-state migration and unemployment rate gap

	Dependent variable: Dummy variable for whether respondent (16+) moved indicated location in previous year (x 100)					
	Cross-state		Cross-state or cross-county		Within county	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate gap	-0.08	0.03	-0.10	0.03	-0.26	-0.49
	(0.01)	(0.03)	(0.02)	(0.05)	(0.02)	(0.06)
Coefficient on unemployment rate gap interacted with indicator variables for:						
Age (16-24 is omitted group):						
Age 25-34		-0.08		-0.12		0.09
		(0.02)		(0.04)		(0.04)
Age 35-44		-0.12		-0.23		0.11
		(0.05)		(0.07)		(0.08)
Age 45-54		-0.02		0.00		0.27
		(0.04)		(0.06)		(0.08)
Age 55-64		0.04		0.02		0.33
		(0.04)		(0.06)		(0.07)
Age 65+		-0.09		-0.14		0.36
		(0.04)		(0.06)		(0.07)
Race (White is omitted group):						
Black		-0.03		-0.05		0.42
		(0.04)		(0.05)		(0.07)
Hispanic		0.13		0.08		-0.01
		(0.04)		(0.05)		(0.08)
Other		0.22		0.62		-0.44
		(0.31)		(0.47)		(0.61)
Education (at most high school degree is omitted group):						
Some college or more		0.10		0.24		0.04
		(0.07)		(0.10)		(0.12)
Sex (male is omitted group):						
Female		-0.02		-0.02		0.04
		(0.02)		(0.03)		(0.04)
Homeownership status (owner is omitted group):						
Renter		-0.14		-0.04		-0.09
		(0.03)		(0.05)		(0.06)

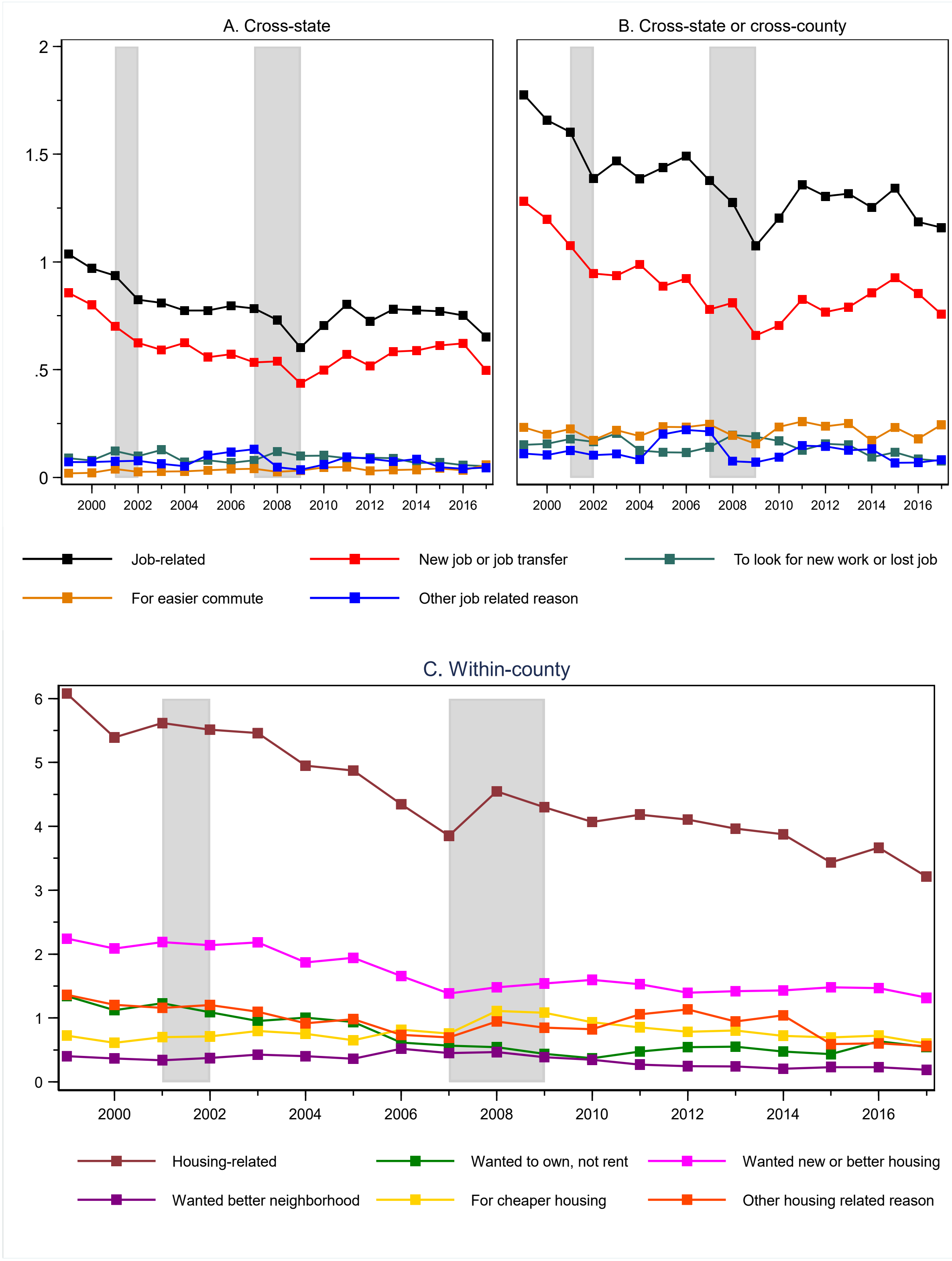
Note: Each column presents the coefficient on the unemployment rate gap (standard error in parentheses) for a separate regression. All regressions are estimated at the individual level for the 16+ population, use CPS ASEC surveys from 1980-2017, and have an observation count of 2,743,808. Regressions in columns (1), (3), and (5) only include the national unemployment rate gap and a linear time trend as covariates. Regressions in columns (2), (4), and (6) include dummy variables for the age, race, education, sex, and homeownership groups as listed in the table; dummies for the demographic groups interacted with the national unemployment rate gap; and group-specific time trends. The coefficient on the unemployment rate gap interactions are provided for each group.

Figure 6. Self-reported reasons for moving as a percent of pop. (16+)



Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 16+ population, and respondents with imputed values are dropped. Panel A plots the percent of the 16+ population who moved states in the previous year and reported the reason for the move as listed. Panel B plots similar estimates for respondents who moved states or counties, while Panel C plots the percent moving within county by self-reported reason for the move. NBER recessions are shaded. Job-related reasons include: New job or job transfer, to look for work or lost job, for easier commute. Family-related reasons include changein marital status, to establish own household, or other family reason. Housing-related reasons include wanted to own home and not rent, wanted new or better housing, for cheaper housing, other housing-related reason. Other includes change of climate, health reasons, other reasons, natural disaster.

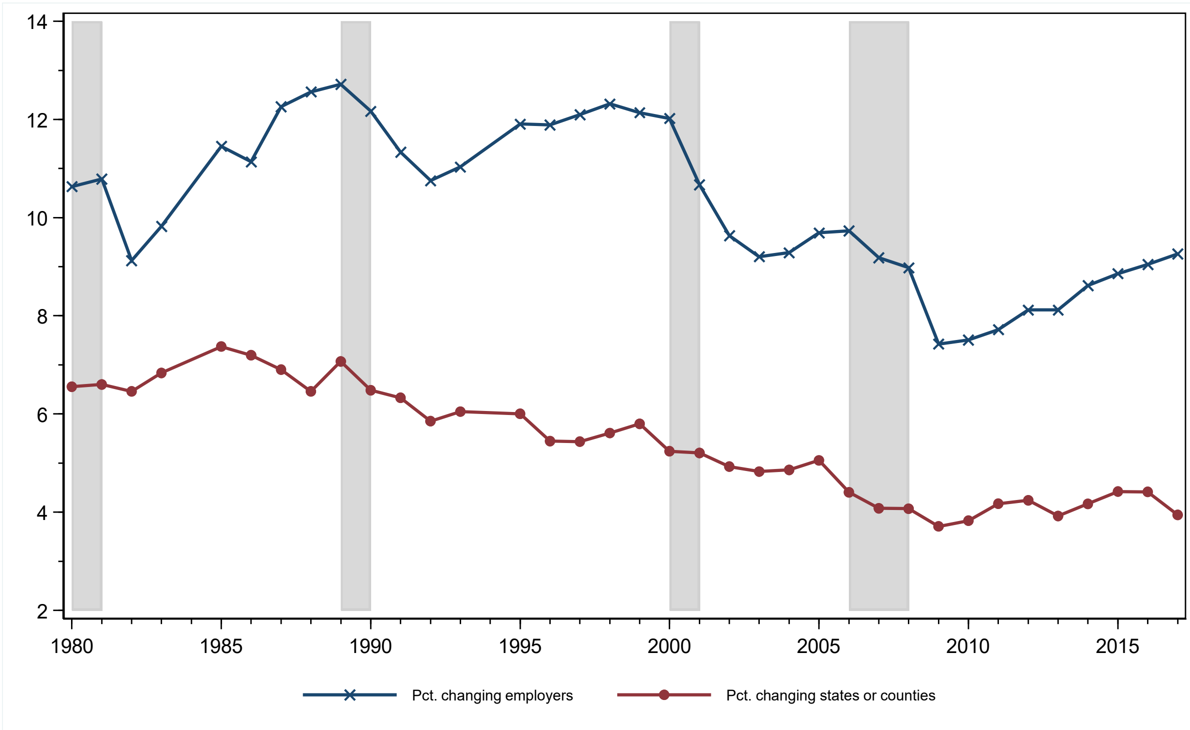
Figure 7. Job and housing related reasons for moving as a percent of pop. (16+)



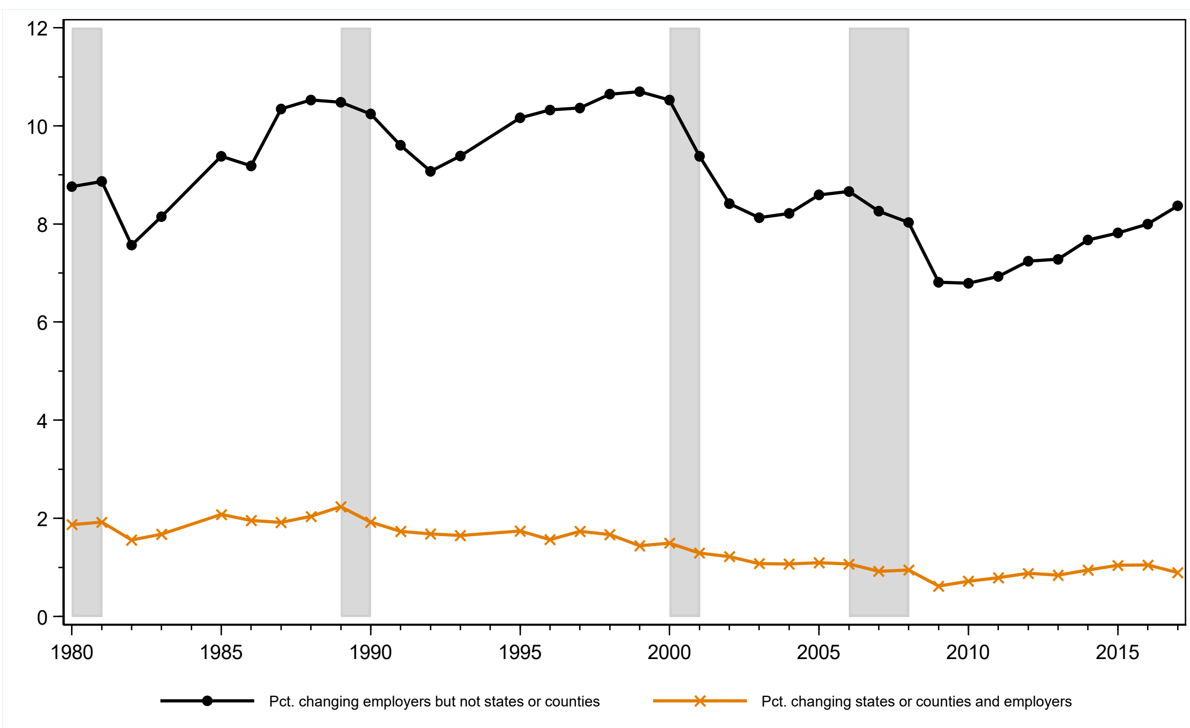
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 16+ population, and respondents with imputed values are dropped. Panel A plots the percent of the 16+ population who moved states in the previous year and reported job related reasons as the reason for the move. Panel B plots the percent of 16+ who changed states or counties and reported job related reasons as the reasons for the move. Panel C plots the percent of 16+ who moved within county in the previous year and reported housing related reasons for the move. NBER recessions are shaded.

Figure 8. Job changing and migration (25-54 years)

A. Percent changing employers or states and counties over the prev. year

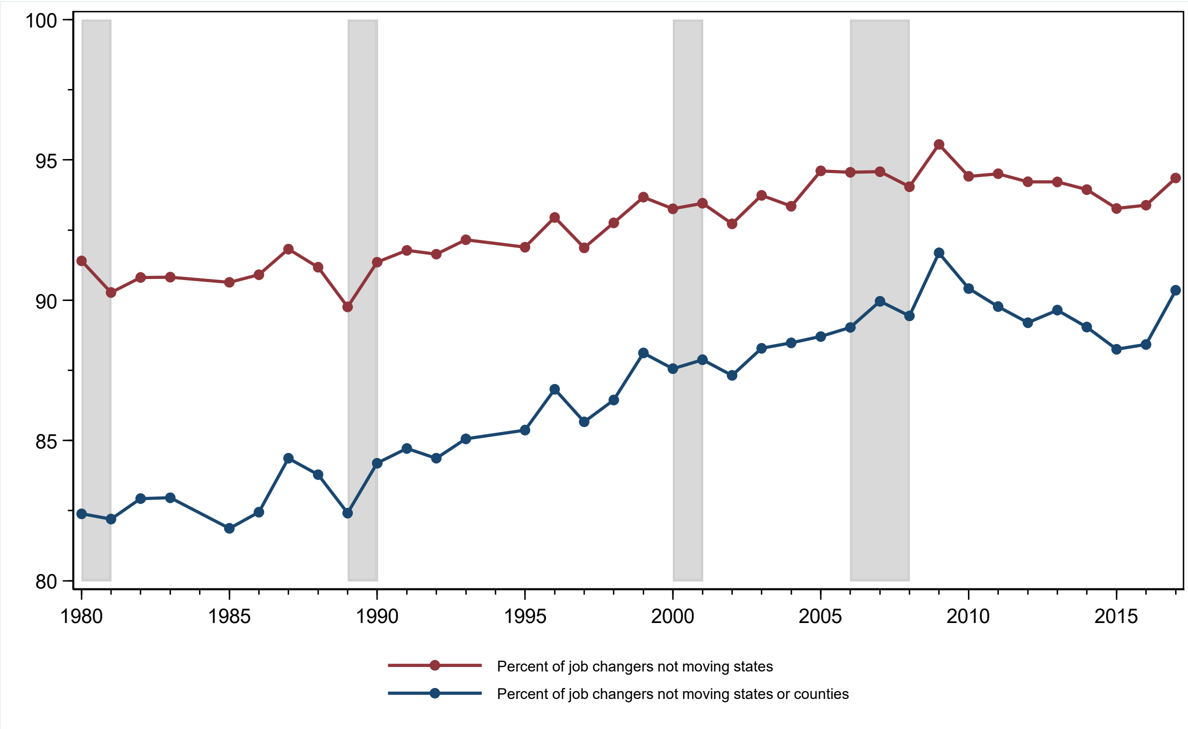


B. Percent changing employers, with or without a location change



Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 25-54 population, and respondents with imputed values are dropped. Panel A plots the percent of the 25-54 population who moved states or counties in the previous year, and the percent reporting two or more primary employers. Panel B plots the percent of 25-54 who changed employers and also states or counties, and the percent who changed employers but did not change states or counties. NBER recessions are shaded.

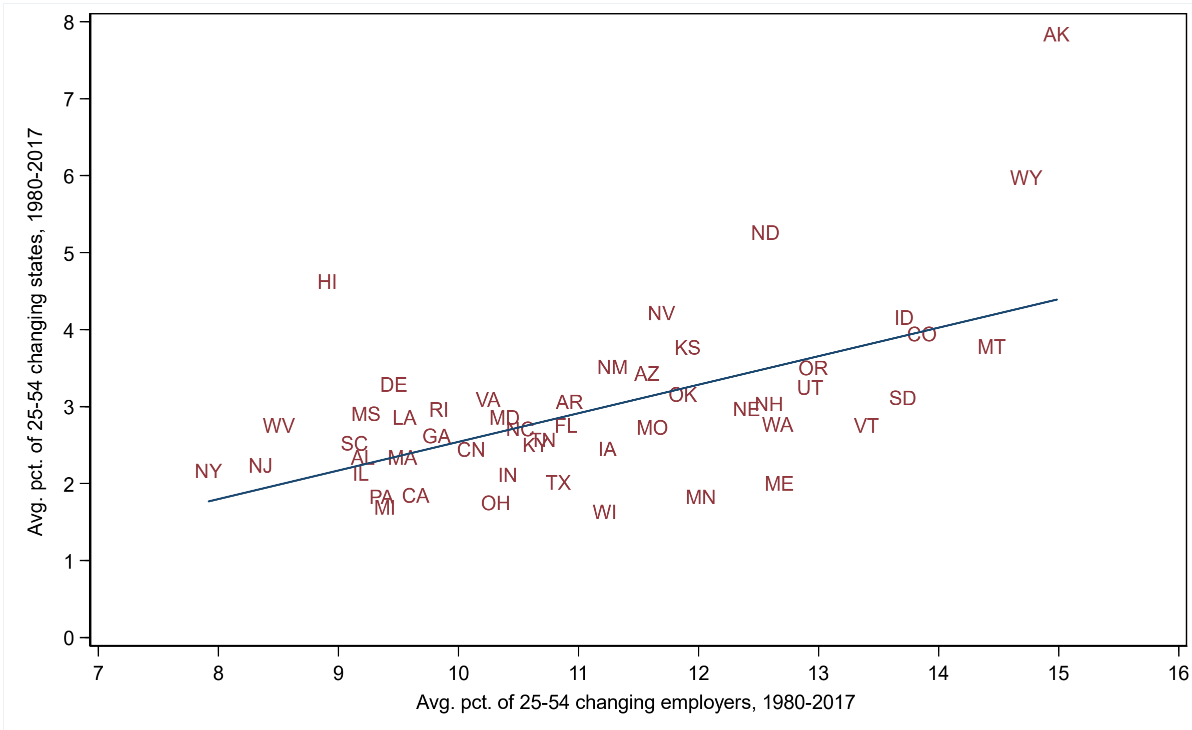
Figure 9. Percent of job changers who do not change states or counties (25-54 years)



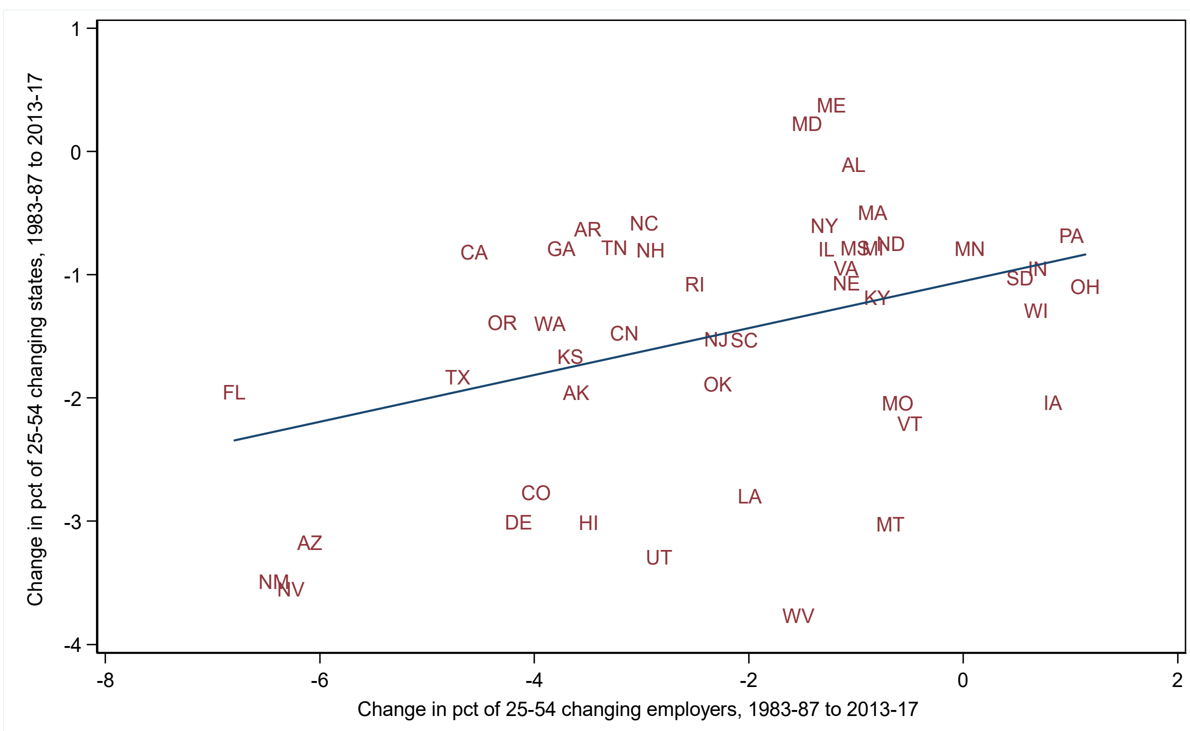
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 25-54 population, and respondents with imputed values are dropped. Figure plots the percent of job changers (respondents with two or more primary employers in the previous year) who report not changing states or counties (blue line) or not changing states (red line). NBER recessions are shaded.

Figure 10. Cross-state relationship between job changing and cross-state migration (25-54 years)

A. Average job and state changing, 1980-2017

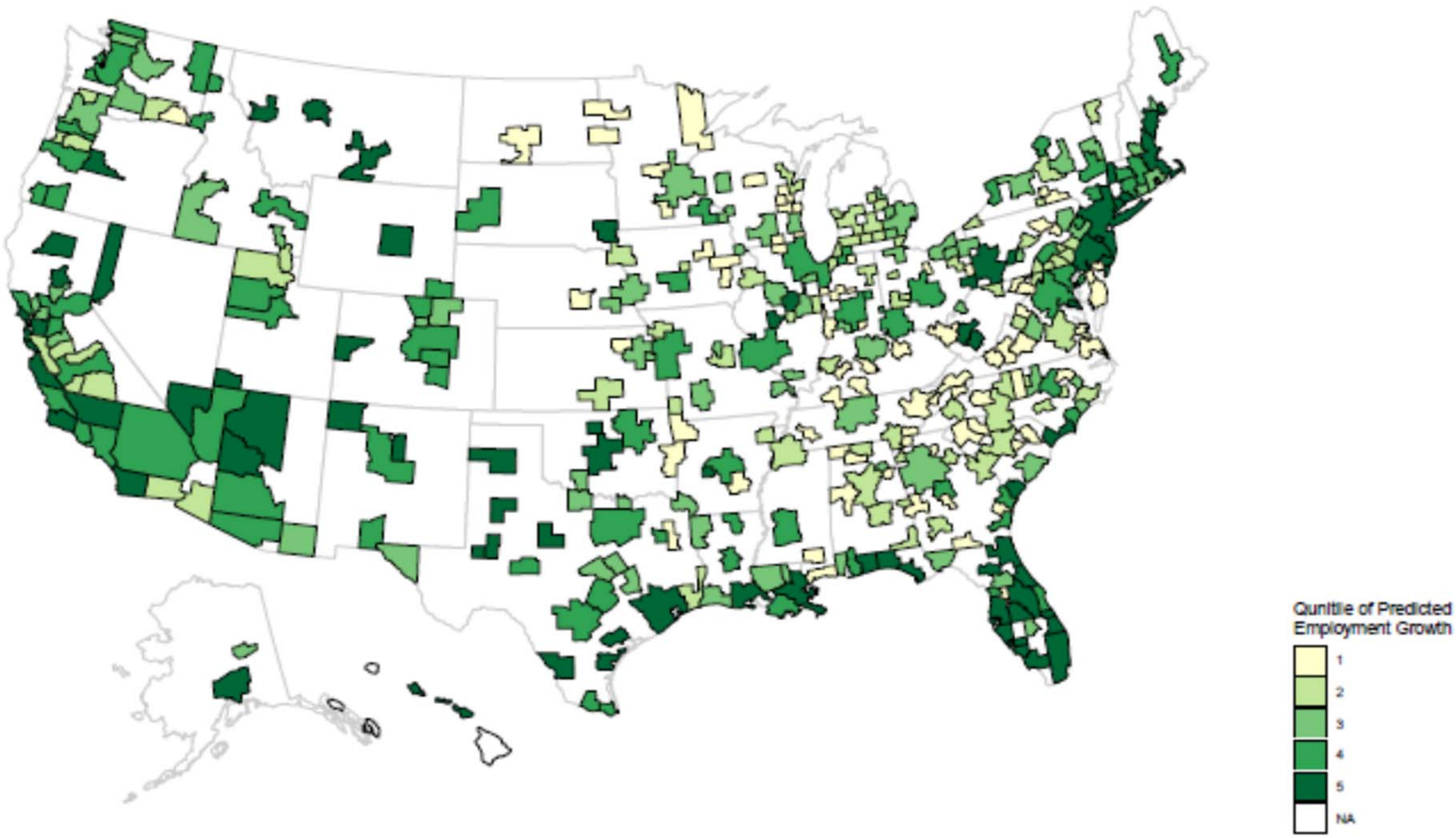


B. Change in percent changing jobs and changing states, 1983-1987 to 2013-2017



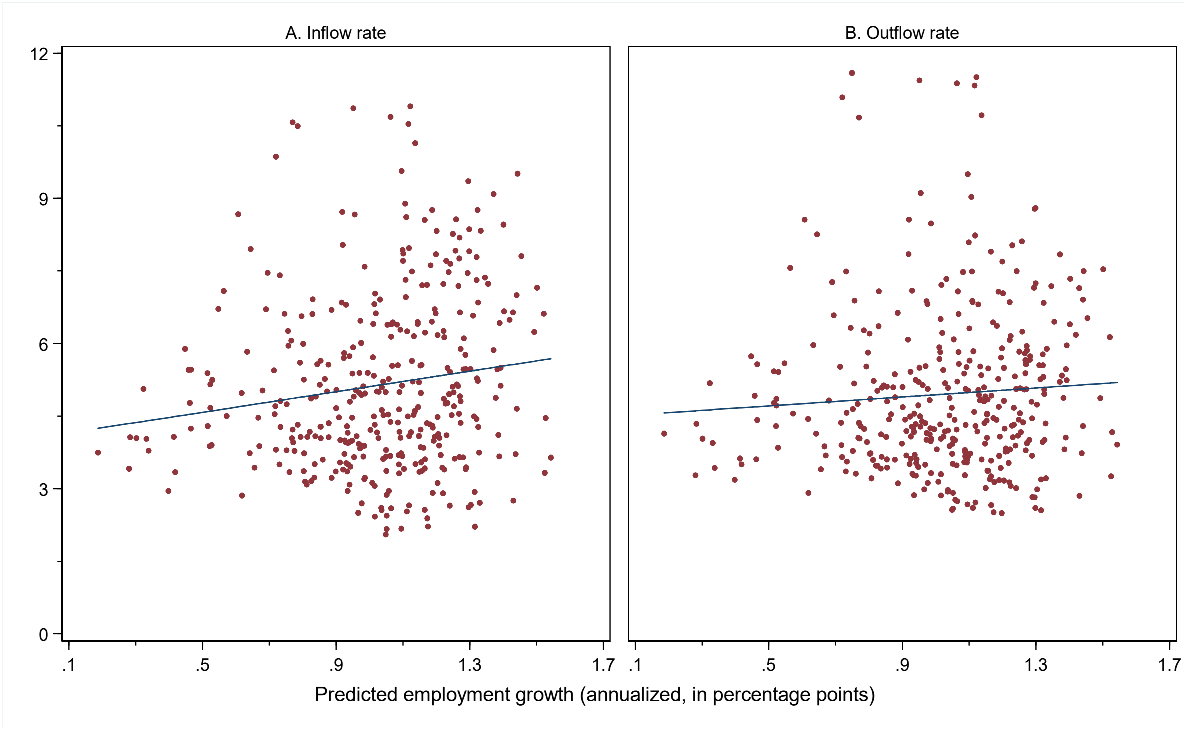
Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Estimates are for 25-54 population, and respondents with imputed values are dropped. Figure A plots the average percent of 25-54 changing states in the previous year (x axis) against the average percent changing employers, over the 1980-2017 period. The CPS respondents' state of residence in the previous year is used for the state averages, so cross-state migration rates by rate can be interpreted as out-migration rates. Figure B plots the change in the average of the rate (by state) for 1983-87 to 2013-17. In Figure A, the estimated equation for the regression line (with standard errors in parentheses) is: percent moving states = -1.17 (0.92) + percent changing employers x 0.37 (0.08). In Figure B, the estimated equation is: change in cross-state migration = 1.05 (0.21) + change in job changing x 0.19 (0.07).

Figure 11. Map of metros, color-coded by their quantile in the distribution of predicted employment growth for 2001-2016



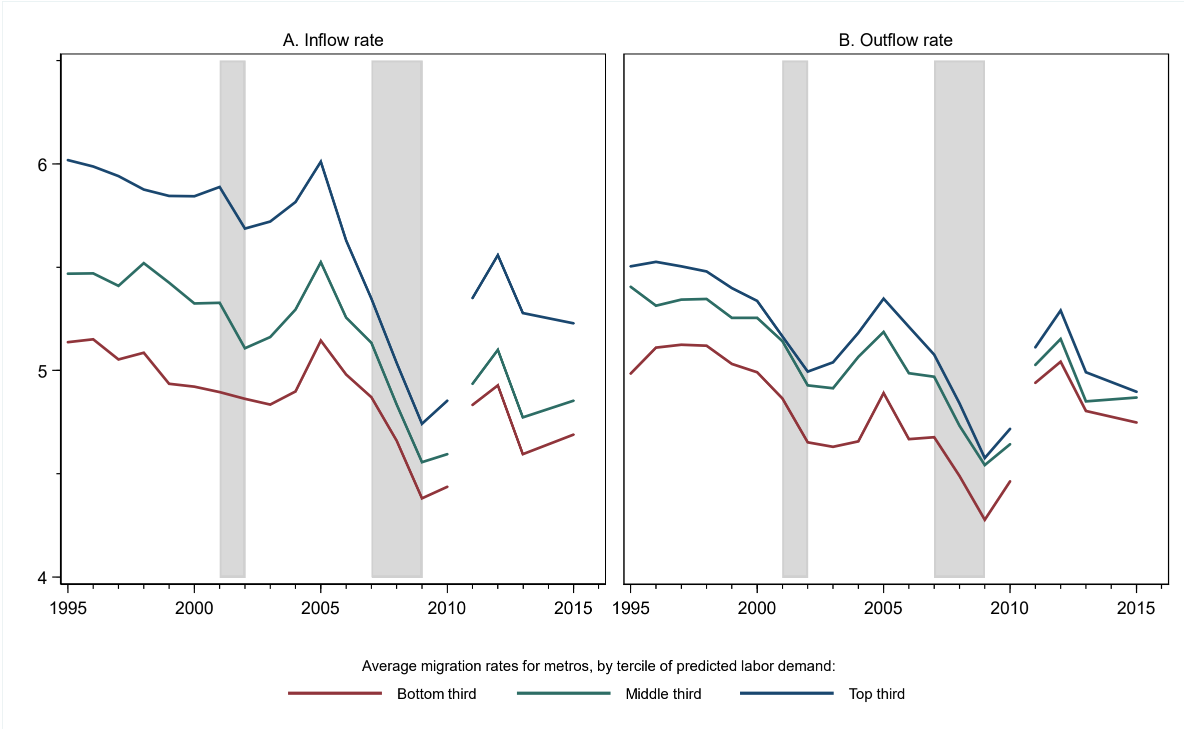
Note. Figure color-codes each metro in our sample by its location in the distribution of our measure of predicted employment growth, where predicted employment growth is based on the metro's industry composition in 2000 and national trends in employment growth by industry from 2001-2016. See text for more details.

Figure 12. Cross-metro relationship between average inflow and outflow rates (in percent) and predicted employment growth (annualized, in percentage points), 2001-2016



Note: Figure shows the relationship between a metro's average inflow and outflow rate from 2001-2016, as estimated from IRS data, and the metro's predicted employment growth (annualized, in percentage points), as defined in the text. The blue line represents the relationship from an OLS regression of average inflow or outflow rate on predicted employment growth (371 observations). The estimated regression line in Panel A: Inflow rate = 4.05 (0.39) + 1.06 (0.37) x pred. employment growth. The estimated regression line in Panel B: Outflow rate = 4.48 (0.36) + 0.46 (0.34) x pred. employment growth. See notes to Figure 11 or text for details on the construction of the measure of predicted employment growth.

Figure 13. Average inflow and outflow rates for metros, by tercile of predicted labor demand



Note: Figure shows average inflow and outflow rates for metros in the top, middle, and bottom third of the predicted labor demand distribution. See notes to Figure 11 and text for details on construction of the measure of predicted labor demand.

Figure 14. Average share of outflows, by origin and destination metro's tercile of predicted labor demand distribution

Note: Figure shows the average share of all outflows, by origin metro's tercile of the predicted labor demand distribution, to metros in each tercile of the predicted labor demand distribution. Panel A shows the average share of outflows going to metros in the top tercile, from bottom tercile metros (red line), middle tercile metros (orange line), and bottom tercile metros (green line). Panel B shows the average share going to middle-tercile metros, and Panel C shows the average share going to bottom-tercile metros. For each year, each color line adds to 100 across the three panels.

Table 3. Relationship between outflow rate and receiving metro characteristics

Dependent variable: Outflow rate (as a share of pop.) from originating metro to receiving metro

	Labor Demand of Originating Metropolitan Area		
	Low Demand	Middle Demand	High Demand
A. Only controlling for labor demand of receiving metros			
Constant	0.0060	0.0028	0.0020
	(0.0007)	(0.0007)	(0.0007)
Indicator variable for:			
Receiving metro is middle labor demand	0.0023	0.0069	0.0059
	(0.0009)	(0.0009)	(0.0009)
Receiving metro is high labor demand	0.0010	0.0107	0.0164
	(0.0009)	(0.0010)	(0.0009)
B. Also controlling for log population in receiving metros			
Constant	-0.0751	-0.1135	-0.1253
	(0.0044)	(0.0046)	(0.0042)
Log population in receiving metro	0.0066	0.0094	0.0103
	(0.0004)	(0.0004)	(0.0003)
Indicator variable for:			
Receiving metro is middle labor demand	-0.0011	0.0020	0.0006
	(0.0009)	(0.0010)	(0.0009)
Receiving metro is high labor demand	-0.0048	0.0023	0.0072
	(0.0010)	(0.0010)	(0.0009)
C. Also controlling for distance between metros			
Constant	-0.0003	-0.0225	-0.0134
	(0.0044)	(0.0045)	(0.0042)
Log population in receiving metro	0.0063	0.0095	0.0102
	(0.0003)	(0.0003)	(0.0003)
Distance between metros>200 miles	-0.0800	-0.0976	-0.1138
	(0.0014)	(0.0016)	(0.0016)
Indicator variable for:			
Receiving metro is middle labor demand	0.0025	0.0026	0.0001
	(0.0009)	(0.0009)	(0.0008)
Receiving metro is high labor demand	0.0008	0.0045	0.0055
	(0.0009)	(0.0010)	(0.0009)

Note: Each column in each panel is from a separate regression. The dependent variable in each regression is the average share of the origin metro's population migrating to the receiving metro over the 2001-2016 period, with the included covariates listed in each panel. In column 1, the sample of originating metros is limited to bottom tercile metros, in column 2 the sample is middle-tercile metros, and in column 3 the sample is top-tercile metros. Standard errors are in parentheses. The indicator variables are dummies for whether the receiving metro is in the indicated tercile of the predicted labor demand, housing regulation, or geographic constraint distribution--see text for details on the construction of these variables. The average outflow rate (between any originating and receiving metro) in the sample used for the regression is 0.01 (as a percent of the originating metro's population), there are 357 originating metros used in the regression sample and 247 receiving metros, for 88,179 total observations (357 originating metros x 246 receiving metros different from originating metro).

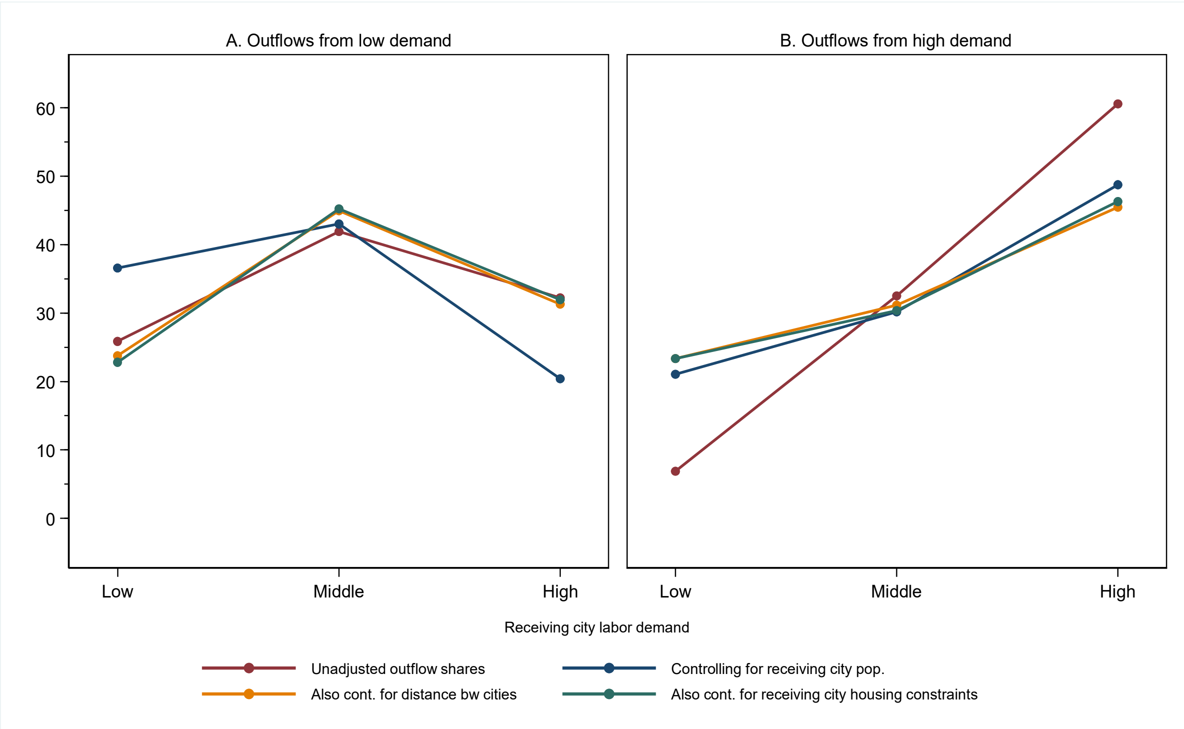
Table 3, cont. Relationship between outflow rate and receiving metro characteristics

Dependent variable: Outflow rate (as a share of pop.) from originating metro to receiving

	Labor Demand of Originating Metropolitan Area		
	Low Demand	Middle Demand	High Demand
D. Also controlling for measures of constraints on housing supply in receiving metros			
Constant	0.0000	-0.0217	-0.0136
	(0.0045)	(0.0046)	(0.0043)
Log population in receiving metro	0.0063	0.0095	0.0103
	(0.0004)	(0.0004)	(0.0003)
Distance between metros>200 miles	-0.0800	-0.0976	-0.1137
	(0.0014)	(0.0016)	(0.0016)
Indicator variable for:			
Receiving metro is middle labor demand	0.0028	0.0022	-0.0001
	(0.0009)	(0.0009)	(0.0008)
Receiving metro is high labor demand	0.0012	0.0046	0.0057
	(0.0010)	(0.0010)	(0.0009)
Receiving metro has mid-housing reg.	-0.0003	-0.0010	-0.0017
	(0.0009)	(0.0009)	(0.0008)
Receiving metro has high housing reg.	-0.0015	0.0028	0.0012
	(0.0010)	(0.0010)	(0.0009)
Receiving metro has mid-geographic consts.	0.0012	-0.0027	-0.0017
	(0.0009)	(0.0009)	(0.0008)
Receiving metro has high geographic consts.	-0.0011	-0.0022	-0.0013
	(0.0009)	(0.0009)	(0.0008)

Note: Each column in each panel is from a separate regression. The dependent variable in each regression is the average share of the origin metro's population migrating to the receiving metro over the 2001-2016 period, with the included covariates listed in each panel. In column 1, the sample of originating metros is limited to bottom tercile metros, in column 2 the sample is middle-tercile metros, and in column 3 the sample is top-tercile metros. Standard errors are in parentheses. The indicator variables are dummies for whether the receiving metro is in the indicated tercile of the predicted labor demand, housing regulation, or geographic constraint distribution--see text for details on the construction of these variables. The average outflow rate (between any originating and receiving metro) in the sample used for the regression is 0.01 (as a percent of the originating metro's population), there are 357 originating metros used in the regression sample and 247 receiving metros, for 88,179 total observations (357 originating metros x 246 receiving metros different from originating metro).

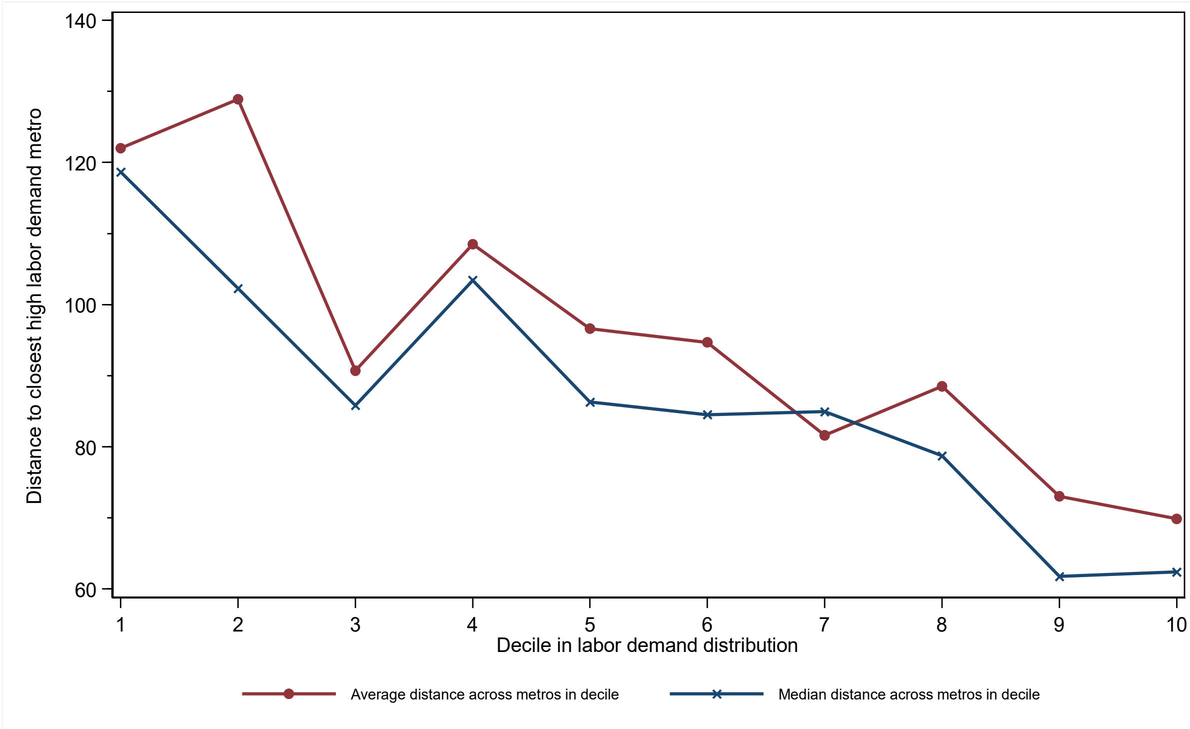
Figure 15. Share of outflows from metros in the bottom and top tercile of the labor demand distribution, to metros in the bottom, middle, and top of the labor demand distribution



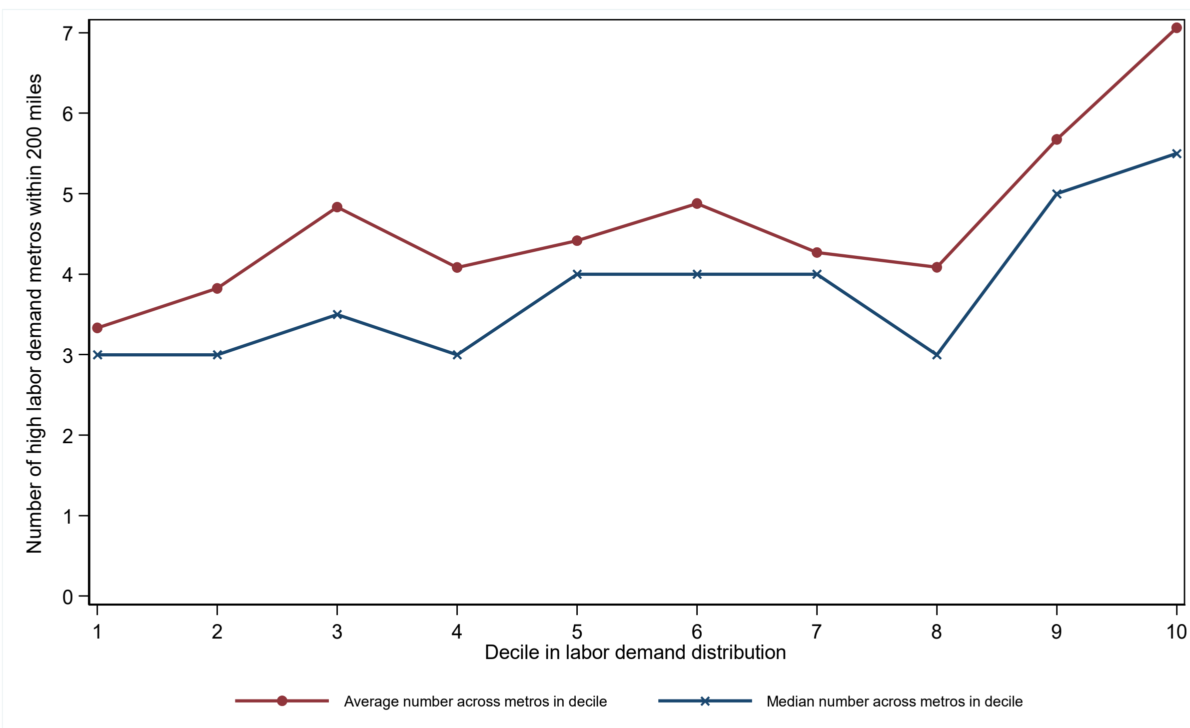
Note: Figure shows the average share of all outflows, by origin metro's tercile of the predicted labor demand distribution, to metros in each tercile of the predicted labor demand distribution. Panel A shows the average share of outflows from metros in the bottom tercile to bottom/middle/high demand metros, while Panel B shows the average share of outflows from metros in the top tercile. The three points for each line add to 100. The red line is unadjusted data. The blue line is the resulting outflow shares after adjusting for receiving metro population. The orange is the outflow share after also adjusting for distance between cities, and the green line additionally adjusts for the receiving city's housing regulation and geographic constraints. Adjusted outflow shares are based on regressions described in table 3.

Figure 16. Distance to nearest metros in the top tercile of the demand distribution

A. Average and median distance to metros in the top tercile of the demand distribution



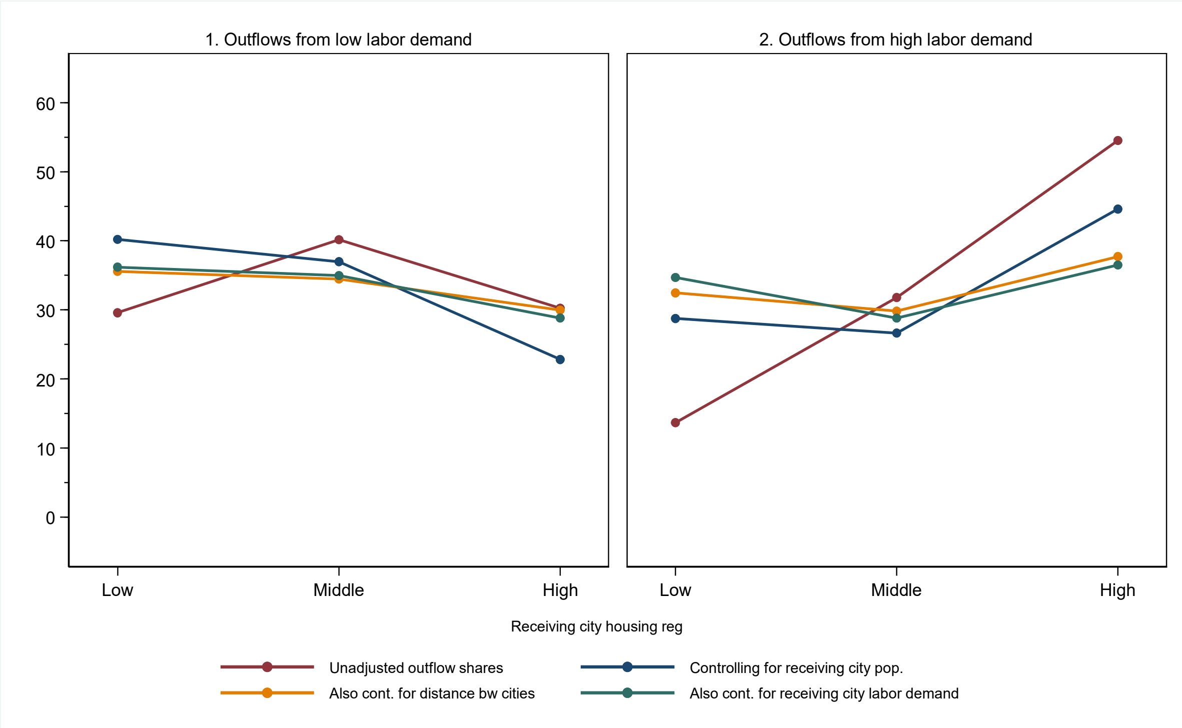
B. Average and median number of metros in the top tercile of the demand dist. within 200



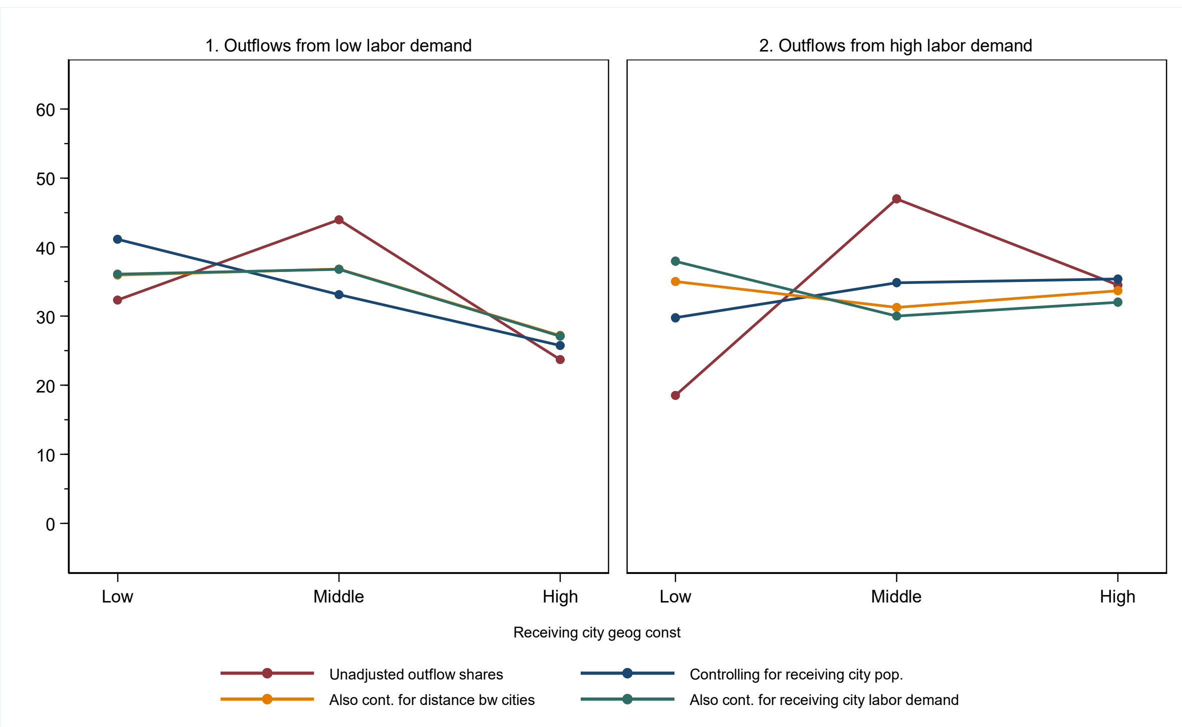
Note: Panel A shows the average (red) or median (blue) distance to the nearest metro in the top tercile of the predicted demand distribution, by the originating metro's decile in the labor demand distribution. Panel B shows the average (red) or median (blue) number of metros in the top tercile of the demand distribution that are within 200 miles of the originating metro, by the originating metro's decile in the labor demand distribution.

Figure 17. Share of outflows from metros in the bottom and top tercile of the labor demand

A. To metros based on their tercile of housing regulation distribution



B. To metros based on their tercile of geographic constraint distribution



Note: Figure shows the average share of all outflows, by origin metro's tercile of the predicted labor demand distribution, to metros in each tercile of the housing reg. (panel A) or geog. constraints (panel B) distribution. Panel 1 shows the average share of outflows from metros in the bottom tercile to bottom/middle/high demand metros, while Panel 2 shows the average share of outflows from metros in the top tercile. The three points for each line add to 100. The red line is unadjusted data. The blue line is the resulting outflow shares after adjusting for receiving metro population. The orange is the outflow share after also adjusting for distance between cities, and the green line additionally adjusts for the receiving city's housing regulation and geographic constraints. Adjusted outflow shares are based on regressions described in table 3.

Table 4. Relationship between moving in previous year and respondent characteristics, by originating metro's quintile in pred. demand distribution

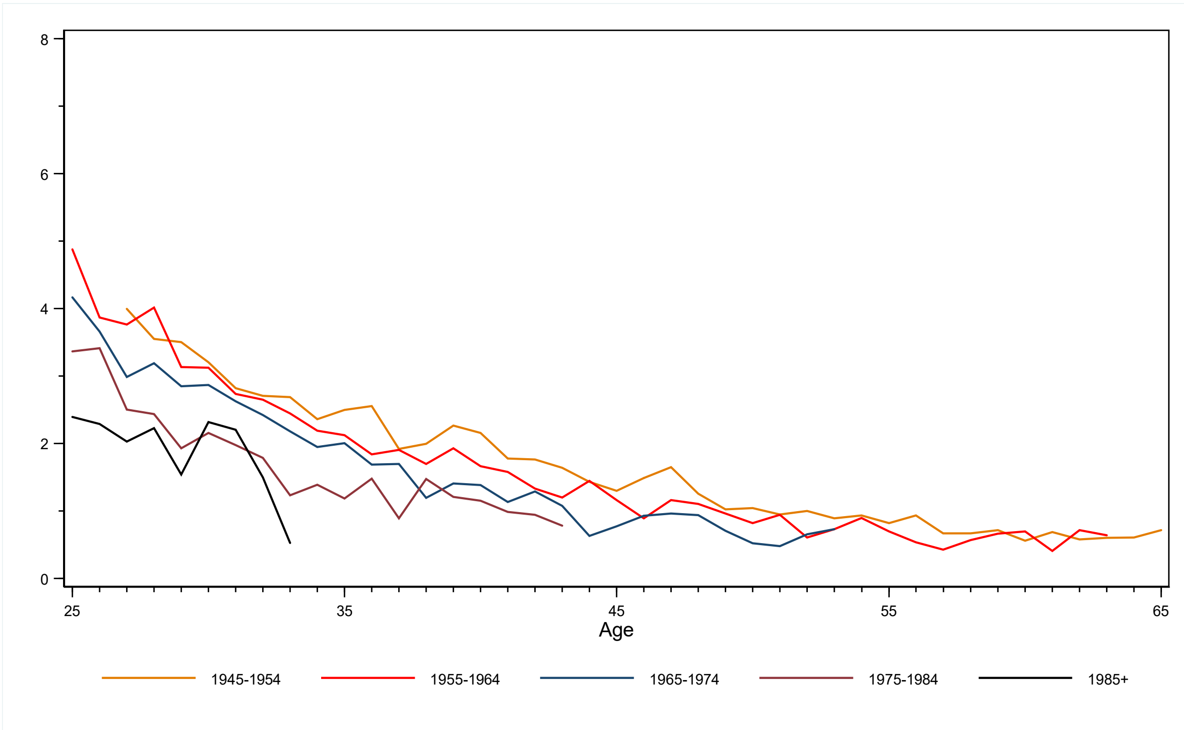
Dependent variable: Indicator for having moved in previous year

	Labor Demand of Originating Metropolitan Area				
	Bottom Quintile	20^{th} – 40^{th} percentile	40^{th} – 60^{th} percentile	60^{th} – 80^{th} percentile	Top Quintile
Age					
18-21	0.058**	0.053**	0.047**	0.042**	0.035**
22-29	0.071**	0.073**	0.055**	0.048**	0.045**
30-39	0.025**	0.026**	0.019**	0.019**	0.019**
40-49	0.009**	0.006**	0.004**	0.004**	0.004**
50-64	--	--	--	--	--
65 +	-0.004**	-0.006**	-0.005**	-0.004**	-0.003**
Education					
Less Than High School	-0.005**	-0.006**	-0.005**	-0.004**	-0.005**
High School	--	--	--	--	--
1 to 3 Years of College	0.009**	0.007**	0.007**	0.006**	0.005**
4+ Years of College	0.028**	0.031**	0.021**	0.018**	0.013**
Home ownership					
Renter-occupied HH	--	--	--	--	--
Owner-occupied HH	-0.080**	-0.083**	-0.064**	-0.050**	-0.039**
Race and ethnicity					
White, non-Hispanic	--	--	--	--	--
Black, non-Hispanic	-0.028**	-0.020**	-0.020**	-0.017**	-0.013**
Hispanic	-0.018**	-0.016**	-0.016**	-0.021**	-0.020**
Asian	0.012**	0.002*	0.007**	-0.001**	-0.006**
Other	-0.001	0.004**	-0.003**	-0.002**	0
Income in previous year relative to distribution in origination metro					
Bottom quartile	0.009**	0.008**	0.007**	0.008**	0.006**
25^{th} to 75^{th} percentile	--	--	--	--	--
Top quartile	0.001**	-0.01**	0.001*	0	-0.002**
Sex					
Male					
Female	-0.003**	-0.004**	-0.003	-0.002**	-0.002**
Year indicators	yes	yes	yes	yes	yes
Number of observations	695,592	1,556,739	2,616,267	5,924,322	5,434,108

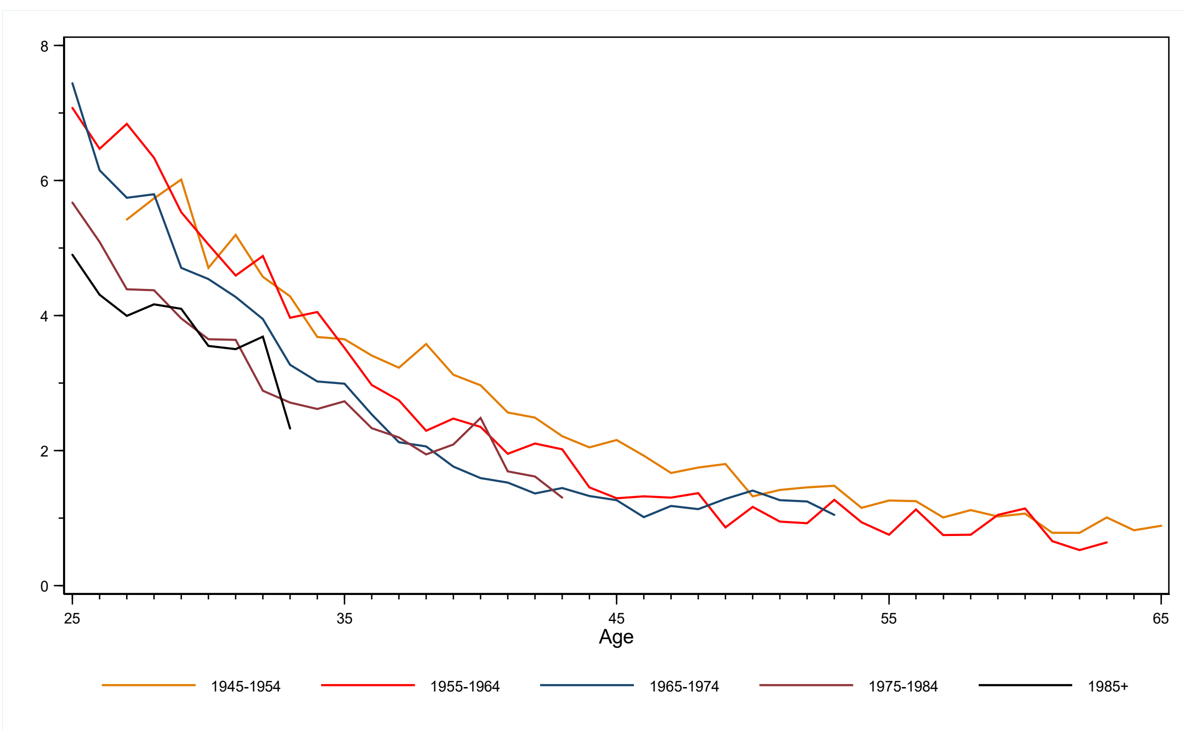
Note. Authors' estimates from microdata to the American Community Survey annual surveys, 2005 to 2016, as provided by IPUMS. Each column represents a separate regression, where the dependent variable in all regressions is whether the respondent moved in the previous year, and the included covariates are year dummies and the demographic characteristics shown in the table. The omitted category is indicated by "--". * and ** indicate significance at the 5% and 1% level, respectively.

Appendix Figure 1: Cross-state migration rates by cohort and education (in percent)

A. At most a high school degree



B. Some college or more



Note: Authors' calculations from the ASEC supplement to the CPS, as provided by IPUMS. Respondents with imputed values for migration are excluded from the calculations. Each line plot the average cross-state migration rates for the birth-year cohorts indicated in the legend, by age.

Appendix Table 1A. Metropolitain areas, by predicted labor demand

Predicted labor demand: Top 50	Predicted labor demand: Bottom 50
Abilene, TX	Appleton, WI
Amarillo, TX	Battle Creek, MI
Atlantic City-Hammonton, NJ	Binghamton, NY
Bakersfield, CA	Bismarck, ND
Billings, MT	Burlington, NC
Bloomington, IL	Cedar Rapids, IA
Boston-Cambridge-Newton, MA-NH	Decatur, IL
Bremerton-Silverdale, WA	Dothan, AL
Bridgeport-Stamford-Norwalk, CT	Duluth, MN-WI
Cape Coral-Fort Myers, FL	Elkhart-Goshen, IN
Casper, WY	Fargo, ND-MN
Charleston, WV	Fayetteville-Springdale-Rogers, AR-MO
Chico, CA	Florence, SC
Corpus Christi, TX	Fort Smith, AR-OK
Crestview-Fort Walton Beach-Destin, FL	Grand Rapids-Wyoming, MI
Deltona-Daytona Beach-Ormond Beach, FL	Greensboro-High Point, NC
Denver-Aurora-Lakewood, CO	Greenville-Anderson-Mauldin, SC
Gainesville, FL	Gulfport-Biloxi-Pascagoula, MS
Great Falls, MT	Hickory-Lenoir-Morganton, NC
Houston-The Woodlands-Sugar Land, TX	Huntington-Ashland, WV-KY-OH
Jacksonville, FL	Huntsville, AL
Johnstown, PA	Iowa City, IA
Lakeland-Winter Haven, FL	Janesville-Beloit, WI
Las Vegas-Henderson-Paradise, NV	Johnson City, TN
Lubbock, TX	Kingsport-Bristol-Bristol, TN-VA
Miami-Fort Lauderdale-West Palm Beach, FL	Knoxville, TN
New Haven-Milford, CT	Kokomo, IN
New Orleans-Metairie, LA	Lafayette-West Lafayette, IN
New York-Newark-Jersey City, NY-NJ-PA	Lebanon, PA
North Port-Sarasota-Bradenton, FL	Lexington-Fayette, KY
Ocean City, NJ	Longview, TX
Oklahoma City, OK	Lynchburg, VA
Orlando-Kissimmee-Sanford, FL	Mansfield, OH
Pensacola-Ferry Pass-Brent, FL	Midland, MI
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Montgomery, AL
Pittsburgh, PA	Oshkosh-Neenah, WI
Pittsfield, MA	Pine Bluff, AR
Portland-South Portland, ME	Racine, WI
Redding, CA	Roanoke, VA
Reno, NV	Rockford, IL
Salinas, CA	Spartanburg, SC
San Diego-Carlsbad, CA	St. Cloud, MN
San Francisco-Oakland-Hayward, CA	Terre Haute, IN
Santa Cruz-Watsonville, CA	Vineland-Bridgeton, NJ
Santa Maria-Santa Barbara, CA	Virginia Beach-Norfolk-Newport News, VA-NC
Sioux Falls, SD	Warner Robins, GA
Tampa-St. Petersburg-Clearwater, FL	Waterloo-Cedar Falls, IA
Trenton, NJ	Wausau, WI
Tucson, AZ	Weirton-Steubenville, WV-OH
Wheeling, WV-OH	York-Hanover, PA

Note. Table shows metros in the top and bottom 50 of the distribution of predicted labor demand (in alphabetical order), where predicted labor demand is based on the metro's industry composition of employment in 2000 and national trends in employment by industry from 2001-2016--see text for more details. There are 251 metros with the full set of covariates in our sample, so each tercile represents about 80 metros, and each quintile is about 50 metros.

Appendix Table 1B. Metropolitain areas, by housing regulation

Housing regulation	
Top 50	Bottom 50
Albuquerque, NM	Alexandria, LA
Allentown-Bethlehem-Easton, PA-NJ	Baton Rouge, LA
Altoona, PA	Beaumont-Port Arthur, TX
Ann Arbor, MI	Burlington, NC
Atlantic City-Hammonton, NJ	Charleston, WV
Austin-Round Rock, TX	Charlottesville, VA
Boston-Cambridge-Newton, MA-NH	Chattanooga, TN-GA
Boulder, CO	Columbia, MO
Burlington-South Burlington, VT	Davenport-Moline-Rock Island, IA-IL
Chico, CA	Decatur, IL
Denver-Aurora-Lakewood, CO	Dothan, AL
Durham-Chapel Hill, NC	Dubuque, IA
Fresno, CA	Fargo, ND-MN
Greeley, CO	Fayetteville, NC
Hartford-West Hartford-East Hartford, CT	Fort Smith, AR-OK
Jacksonville, FL	Fort Wayne, IN
Kennewick-Richland, WA	Glens Falls, NY
Lincoln, NE	Huntington-Ashland, WV-KY-OH
Los Angeles-Long Beach-Anaheim, CA	Huntsville, AL
Madison, WI	Indianapolis-Carmel-Anderson, IN
Manchester-Nashua, NH	Jackson, MS
Medford, OR	Joplin, MO
Memphis, TN-MS-AR	Killeen-Temple, TX
Miami-Fort Lauderdale-West Palm Beach, FL	Kingsport-Bristol-Bristol, TN-VA
Napa, CA	Kokomo, IN
New York-Newark-Jersey City, NY-NJ-PA	Lafayette-West Lafayette, IN
North Port-Sarasota-Bradenton, FL	Lake Charles, LA
Ocean City, NJ	Little Rock-North Little Rock-Conway, AR
Oxnard-Thousand Oaks-Ventura, CA	Longview, TX
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Mansfield, OH
Phoenix-Mesa-Scottsdale, AZ	Mobile, AL
Pittsfield, MA	Montgomery, AL
Portland-South Portland, ME	New Orleans-Metairie, LA
Providence-Warwick, RI-MA	Pensacola-Ferry Pass-Brent, FL
Raleigh, NC	Pine Bluff, AR
Reading, PA	Sherman-Denison, TX
San Antonio-New Braunfels, TX	Sioux City, IA-NE-SD
San Diego-Carlsbad, CA	South Bend-Mishawaka, IN-MI
San Francisco-Oakland-Hayward, CA	Spartanburg, SC
Santa Cruz-Watsonville, CA	Springfield, OH
Santa Rosa, CA	St. Joseph, MO-KS
Seattle-Tacoma-Bellevue, WA	Syracuse, NY
Springfield, MA	Terre Haute, IN
State College, PA	Toledo, OH
Trenton, NJ	Topeka, KS
Tucson, AZ	Warner Robins, GA
Vallejo-Fairfield, CA	Waterloo-Cedar Falls, IA
Vineland-Bridgeton, NJ	Wheeling, WV-OH
Worcester, MA-CT	Wichita Falls, TX
York-Hanover, PA	Wichita, KS

Note. Table shows metros in the top and bottom 50 of the distribution of housing regulation (in alphabetical order), where housing regulation is based on the Wharton Residential Land Use Regulation Index (Gyoruko, Saize, and Summers 2008)--see text for more details. There are 251 metros with the full set of covariates in our sample, so each tercile represents about 80 metros, and each quintile is about 50 metros.

Appendix Table 1C. Metropolitain areas, by geographic Constraints

Geographic constraints	
Top 50	Bottom 50
Altoona, PA	Abilene, TX
Asheville, NC	Albany, GA
Boulder, CO	Battle Creek, MI
Bremerton-Silverdale, WA	Bloomington, IL
Burlington-South Burlington, VT	Burlington, NC
Charleston, WV	Cedar Rapids, IA
Chico, CA	Champaign-Urbana, IL
Cleveland-Elyria, OH	College Station-Bryan, TX
Elmira, NY	Dayton, OH
Erie, PA	Decatur, IL
Eugene, OR	Des Moines-West Des Moines, IA
Fort Collins, CO	Dothan, AL
Fresno, CA	Elkhart-Goshen, IN
Glens Falls, NY	Fargo, ND-MN
Huntington-Ashland, WV-KY-OH	Fayetteville, NC
Johnson City, TN	Flint, MI
Kingsport-Bristol-Bristol, TN-VA	Florence, SC
Knoxville, TN	Fort Wayne, IN
Los Angeles-Long Beach-Anaheim, CA	Greeley, CO
Medford, OR	Indianapolis-Carmel-Anderson, IN
Milwaukee-Waukesha-West Allis, WI	Iowa City, IA
Muskegon, MI	Jackson, MS
Napa, CA	Janesville-Beloit, WI
New Haven-Milford, CT	Joplin, MO
New Orleans-Metairie, LA	Kankakee, IL
Niles-Benton Harbor, MI	Kansas City, MO-KS
Ocean City, NJ	Kokomo, IN
Oxnard-Thousand Oaks-Ventura, CA	Lafayette-West Lafayette, IN
Parkersburg-Vienna, WV	Lansing-East Lansing, MI
Portland-Vancouver-Hillsboro, OR-WA	Lima, OH
Racine, WI	Lincoln, NE
Redding, CA	Longview, TX
Reno, NV	Lubbock, TX
Roanoke, VA	McAllen-Edinburg-Mission, TX
Rochester, NY	Midland, MI
Sacramento--Roseville--Arden-Arcade, CA	Oklahoma City, OK
Salem, OR	Pine Bluff, AR
Salinas, CA	Raleigh, NC
San Diego-Carlsbad, CA	Rockford, IL
San Francisco-Oakland-Hayward, CA	Saginaw, MI
San Jose-Sunnyvale-Santa Clara, CA	Sioux City, IA-NE-SD
Santa Cruz-Watsonville, CA	Sioux Falls, SD
Santa Maria-Santa Barbara, CA	Spartanburg, SC
Santa Rosa, CA	Springfield, OH
Seattle-Tacoma-Bellevue, WA	Terre Haute, IN
Spokane-Spokane Valley, WA	Topeka, KS
State College, PA	Warner Robins, GA
Visalia-Porterville, CA	Waterloo-Cedar Falls, IA
Weirton-Steubenville, WV-OH	Wichita Falls, TX
Wheeling, WV-OH	Wichita, KS

Note. Table shows metros in the top and bottom 50 of the distribution of geographic constraints on housing (in alphabetical order), where an metro's level of geographic constraints are based on Saiz (2010) estimates of housing availability--see text for more details. There are 251 metros with the full set of covariates in our sample, so each tercile represents about 80 metros, and each quintile is about 50 metros.