

# POPULATION AGING, MIGRATION SPILLOVERS, AND THE DECLINE IN INTERSTATE MIGRATION\*

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## Abstract

Does population aging explain the declining interstate migration in the United States since the mid-1980s? We document that an increase in the share of middle-aged workers in one state causes a fall in the migration of all local workers. We develop an island model in which firms prefer hiring local workers with high moving costs as they command lower wages. Population aging causes firms to recruit more from the local market instead of from elsewhere, increasing local job prospects and reducing everyone's migration rate. Empirical evidence is provided for the mechanism. Our model explains half of the observed decline.

**JEL Codes:** D83, J11, J24, J61, R12, R23

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# 1 Introduction

The rate of interstate migration in the United States has declined steadily from 3 percent in the mid-1980s to less than 1.5 percent in 2010. Had the rate of interstate migration stayed constant at its 1980 level, an additional 3.6 million workers per year would have changed their residential states in 2010. A large fraction of interstate migrants report having moved for a new job, for job search, or for other job-related reasons.<sup>1</sup> Given the importance of interstate migration for individual labor market outcomes, the decline in migration raises the concern that it might adversely affect the labor market.<sup>2</sup> To draw conclusions about the labor market consequences of lower labor mobility, this paper studies its causes.

Specifically, we study the effect of the aging population on the decline in interstate migration. Population aging is a natural candidate for explaining lower mobility, because migration rates decline sharply over the life cycle. The migration rate of workers below age 40 is about twice as large as that of workers older than 40.<sup>3</sup> The age composition of the U.S. population has changed substantially over the period in which declining migration rates occurred: the share of individuals above age 40 in the working-age population increased from 62 percent in the 1980s to 75 percent in 2010.

However, as we show in section 2 in an accounting exercise, the direct effect of the aging population can account for only 20 percent of the decline. Both [Kaplan and Schulhofer-Wohl \(2013\)](#) and [Molloy et al. \(2013\)](#) evaluate the role of changes in demographics (for example, age, education, and household structure) and find that the direct effect of such changes is too small to explain much of the decline. Instead, most of the decline is accounted for by a declining trend common across all groups. These empirical observations lead them to rule out population aging as a quantitatively viable explanation and look for common factors affecting migration decisions of everyone in the labor force.<sup>4</sup> This paper argues that aging population is associated with a sizable

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<sup>1</sup>For example, on average, 50 percent of all interstate moves during the 2000s were job related (March CPS; authors' calculations).

<sup>2</sup>Several recent papers study the effect of migration on individual labor market outcomes. [Kennan and Walker \(2011\)](#) find that interstate migration decisions are influenced to a substantial extent by income prospects. [Gemici \(2011\)](#) documents that wages of single women increase upon a move, whereas those of married women decrease.

<sup>3</sup>March CPS; authors' calculation. Throughout the paper, we restrict attention to workers between the ages of 25 and 60. We label workers older than 40 as middle aged.

<sup>4</sup>[Kaplan and Schulhofer-Wohl \(2013\)](#) argue that the development of information technology and the decrease in the geographic specificity of occupations are responsible for lower migration rates. [Molloy et al. \(2013\)](#) propose a

general equilibrium effect. More specifically, we show that an increase in the share of middle-aged workers in the labor force induces a lower equilibrium migration rate for *all* workers (*migration spillovers*), thereby explaining a sizable portion of the decline in within-group migration.

To provide an empirical underpinning to our study of indirect effects, we start by analyzing the cross-state variation in the age composition of labor force and migration rates. We find that an increase in the share of middle-aged workers in a state is associated with lower mobility for workers at *all* ages. One possible (and simple) explanation for this finding is that middle-aged workers sort into locations with a less dynamic labor market. If this is the case, both young and old workers residing in those states would be less likely to move. Following [Shimer \(2001\)](#), we control for the possible endogeneity of the age structure in a state by instrumenting it with lagged birthrates and find even larger elasticities. Our preferred specification suggests that “young” workers (between the ages of 25 and 40) are 35 percent less likely to move if they reside in a state with a 10 percent larger share of middle-aged workers. The corresponding figure for middle-aged workers is almost 60 percent. These results point to sizable indirect effects of changes in the age composition of the labor force. To properly account for these effects, we need to understand the economic forces at play. This paper focuses on that task.

We first investigate several candidate theories. The positive comovement of mobility across various age groups can be explained by (1) an increase in the relative wage of young workers in response to an aging local population; (2) an increase in the wages of all age groups due to the relatively limited mobility of capital; or (3) intergenerational informal care arrangements. In [section 2.4](#), we claim that these theories are not viable explanations as they are inconsistent with other aspects of the data: the first two are inconsistent with the evidence on inflow rates, whereas the last one is inconsistent with the mobility behavior of the elderly.

Our theory is that an aging local population leads firms to change their recruiting method and direct more jobs toward local workers. To test this theory quantitatively, we develop an equilibrium search model consisting of many locations that differ in their attractiveness to workers at different ages. Each location is populated by various types of workers whose moving costs differ. Workers can look for jobs in the local market, where they meet local firms, or in the global market, where they meet a firm from any location. Similarly, firms in a given location can advertise a position in

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decline in labor turnover as a possible explanation.

the local market or in the global market. An important outcome is that high-moving-cost workers (middle-aged workers) in the local market are the most attractive to firms, because their lower outside option allows firms to hire them at lower wages. Consequently, an increase in their share in a location causes firms to optimally recruit more heavily from the local market. This change in the recruiting strategy of firms raises the local job-finding rate, resulting in lower mobility for all workers in that location.

We calibrate a version of the model with 50 locations by targeting several labor market and migration-related moments during the 1980s. While we do not target any state-specific moment, the model reproduces remarkably well the negative cross-sectional relationship between population flows and the share of middle-aged workers: as expected profits associated with hiring from the local market rise, firms find it more profitable to hire through local means than through a global search. Therefore, workers in such states find local jobs at a higher pace and do not need to move as much, regardless of their age, compared to those in other locations. In a similar fashion, we provide empirical evidence in favor of this mechanism, by exploiting cross-state heterogeneity in the age composition: we document that the share of local hires in a state—that is hires that come from within the state—is higher in states with a higher share of middle-aged workers.

Given the quantitative success of the model and the empirical evidence in favor of the mechanism, we turn to the time series of migration. Keeping all parameters of the model constant, we change only the population composition to mimic the U.S. population at various points in time. The model generates a decline in migration of 0.8 percentage points. This decline corresponds to more than half of the decline in the data. About 75 percent of this model-generated decline is due to the equilibrium effect, and just 25 percent is due to the direct effect of compositional change. Consistent with the data, our model generates sizable declines in migration rates for workers at *all* ages through the indirect effect. Thus, our results suggest that accounting for migration spillovers is important in evaluating the effect of compositional changes in the population.

Finally, we use our model to assess the implications of lower geographic mobility for aggregate unemployment. Our explanation for the long-run decline in migration suggests that the labor market concern may be misplaced. We find that the large decline in migration causes a *decline* in aggregate unemployment. The upward pressure on unemployment caused by the limited search opportunities of older workers is largely offset by the general equilibrium effect that increases the

job-finding rate of all workers.

Our paper is most closely related to [Kaplan and Schulhofer-Wohl \(2013\)](#) and [Molloy et al. \(2013\)](#), who study the decline in gross mobility over the last two decades. While they differ in their explanation of this phenomenon, both papers show that migration has been declining for various groups of workers, which accounts for a large portion of the decline in the aggregate. They conclude that compositional changes cannot be quantitatively important and pursue other theories instead. Our paper argues that the within-group decline in migration is consistent with compositional changes once the equilibrium effects are taken into account.

Another paper that argues for the importance of compositional changes in understanding the decline in interstate migration is [Guler and Taskin \(2012\)](#). Their focus is on the rise in female labor force participation and the consequent increase in the share of dual-income households. Their findings suggest that the rise in dual-earner households can explain 35 percent of the decline. We differ from their work most notably by our ability to explain the decline in within-group migration rates, which accounts for most of the decline in the data.<sup>5</sup>

While studying a very different topic, our paper is also closely related to [Shimer \(2001\)](#), who exploits cross-state variation in the share of young workers to argue that an increase in a state's share of young workers causes a decline in that state's unemployment rate. Our work is analogous to his in that we document facts of a similar nature and argue that equilibrium effects are important for explaining cross-sectional facts.

This paper is also related to the extensive literature that studies various types of reallocation. [Coen-Pirani \(2010\)](#) documents several stylized facts about gross and net worker flows across U.S. states and argues that they are inconsistent with several models of worker reallocation. He then proposes a unifying theory of gross and net worker reallocation to explain these empirical regularities. We differ from [Coen-Pirani \(2010\)](#) in that our focus is on the time series of gross mobility and in our emphasis on equilibrium effects. [Kambourov et al. \(2008\)](#) study trends in occupational and geographic mobility of single and married men and women over the last 40 years. [Fujita \(2011\)](#) studies the decline in labor turnover, and [Davis et al. \(2010\)](#) study the decline in the flow rate into unemployment from the 1980s to the mid-1990s.

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<sup>5</sup>[Gemici \(2011\)](#) estimates a structural model of migration to understand the role of dual-income families in mobility decisions. [Guler et al. \(2012\)](#) use a search model to understand the aggregate implications of the job search behavior of couples.

Our paper is broadly related to the literature studying the link between geographic mobility and the labor market. In their seminal paper, [Blanchard and Katz \(1992\)](#) find evidence that population flows are an important adjustment mechanism for recovery following adverse local shocks. In response to their work, there is an extensive empirical and theoretical literature trying to understand worker flows and their interactions with regional labor markets and potential frictions. Following the Great Recession, several recent papers study the interactions between the housing market, gross and net worker geographic reallocation, and geographic mismatch. Some examples include [Aaronson and Davis \(2011\)](#), [Barnichon and Figura \(2011\)](#), [Valletta \(2013\)](#), [Ferreira et al. \(2012\)](#), [Schulhofer-Wohl \(2011\)](#), [Sahin et al. \(2012\)](#), [Modestino and Dennett \(2013\)](#), [Davis et al. \(2010\)](#), [Nenov \(2012\)](#), and [Karahan and Rhee \(2013\)](#).

On the theoretical front, we build on the island framework in [Lucas and Prescott \(1974\)](#) and model the local labor market with search frictions as in [Mortensen and Pissarides \(1994\)](#). [Alvarez and Shimer \(2011\)](#) develop a tractable island model to study rest- and search-unemployment. Similar to ours, [Lkhagvasuren \(2011\)](#) uses an island model with frictional local labor markets to understand the coexistence of high migration rates and a large dispersion of unemployment rates across states. In our model, workers' job search options are not limited to local jobs and include jobs in any location. We focus on the interaction between the local and the global markets that this setup brings about, which turns out to be crucial for the general equilibrium effect. Similar to us, [Lutgen and Van der Linden \(2013\)](#) study an island model allowing workers to search in multiple locations simultaneously to examine the efficiency of search in multiple locations. A key dimension of heterogeneity across workers in our model is moving costs. The differences in these costs generate variation in workers' search scope. Analogous to our setup, the model in [Piazzesi et al. \(2014\)](#) features segmented housing markets with individuals that are heterogeneous in their search range.

The rest of the paper is organized as follows. Section 2 documents the stylized facts on the decline in interstate migration and presents the cross-state analysis. Section 3 presents the quantitative model, while section 4 discusses our calibration and the results. Finally, section 5 concludes.

## 2 Empirical analysis

We now document the long-run decline in interstate migration in the United States and explore its various components. This is followed by an investigation of the effects of population aging exploiting cross-state variation.

### 2.1 Data

Our analysis focuses on the period 1980–2012. Throughout the paper, we consider two age groups: young workers (25–39) and middle-aged workers (40–60). We compile a state-level dataset on migration, population and its age composition, unemployment, personal income, homeownership rates, and lagged birthrates. More information about the data is provided in appendix C.

### 2.2 Aggregate facts

The blue line in figure 1 plots the evolution of interstate gross migration rates from the March Supplement to the Current Population Survey (March CPS), and the red solid line is the long-run trend of the same. Figure 1 points to a long-run decline starting in the mid-1980s with little business-cycle variation. The decline is substantial: the interstate migration rate in 2010 is only 50 percent of the rate in the 1980s.

Is the decline concentrated in certain states? One conjecture is that interstate migration might have slowed down because of lower net flows. For example, the 1980s were a time of relatively large flows out of the so-called Rust Belt area. Net flows across states are an order of magnitude smaller than gross flows, as has been documented many times before (see, e.g., [Coen-Pirani 2010](#) and [Davis et al. 2010](#)), so the large fall in gross migration is unlikely to be explained by changes in net flows. Figure A.1 in appendix A shows the spatial nature of the fall in migration rates. While the magnitude of the fall is different across states, which is an important variation for testing various theories, migration has fallen in virtually all states. This paper aims to explain a nontrivial portion of the decline as well as its spatial heterogeneity.

To better understand the nature of the decline in migration, figure 2 shows the fraction of the working-age population that changed its residential state for various reasons.<sup>6</sup> Of the variety of

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<sup>6</sup>These reasons include job-related factors (e.g., for a new job, job transfer, job search, easier commute, etc.),

reasons to move, moves motivated by job-related factors have declined sharply, whereas other moves have not changed noticeably. This observation rules out theories based on increases in direct moving costs, as such increases would cause lower migration rates in all categories. Instead, it is the job-related component that explains most of the trend.

One natural candidate for explaining the decline in migration is the aging of the population over the last 30 years. As shown in figure 3, the U.S. population has aged substantially: the fraction of the working-age population older than 40 has increased from 62 percent in the 1980s to 75 percent in 2010. It is well known that there are large migration differences across age groups. To illustrate this, figure 4 plots the interstate migration rate over the working life.<sup>7</sup> People between the ages of 25 and 29 are almost four times more likely to move across states than those aged 50 to 54.

The effects of the aging population on interstate migration fall into two categories. The first is a direct effect. Mechanically, the aggregate migration rate is a weighted average of age-specific migration rates. Thus, demographic changes alter the weights and the migration rate, without affecting the “within-group” migration rates. To evaluate the direct effect of compositional change, we conduct a simple accounting exercise. At any point in time, the migration rate can be written as a weighted sum of group-specific migration rates:

$$m_t \equiv \sum_i s_{i,t} \times m_{i,t},$$

where  $s_{i,t}$  and  $m_{i,t}$  are group-specific shares and migration rates at time  $t$ , respectively. Fixing the migration rate of every age group to its level in 1980, we construct a counterfactual migration rate by changing only the shares of age groups:

$$\hat{m}_t = \sum_i s_{i,t} \times \bar{m}_{i,t}.$$

Under this formulation, any change in the migration rate,  $\Delta\hat{m}$ , is driven by the change in the share of each age group; that is,

$$\Delta\hat{m} = \sum_i \Delta s_{i,t} \times \bar{m}_{i,t}.$$

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family-related factors (e.g., changes in marital status, to establish one’s own household, etc.), housing-related factors (e.g., to own, better housing, better neighborhood, etc.), and other reasons (e.g., foreclosure, natural disaster, etc.).

<sup>7</sup>We do not control for time or cohort effects in this figure. The results for either case are available upon request and point to similar declining life-cycle pattern of mobility.



The red line in figure 5 plots the resulting counterfactual migration rates. The result suggests that the direct effect of the aging population accounts for about 20 percent of the decline. Instead, most of the decline is accounted for by declines in “within-group” migration rates. Figure 6 plots the migration rates of various age groups in various years and shows that migration has declined for everyone. This across-the-board decline accounts for most of the trend. Our paper argues that the population aging can explain the within-group decline. Next, we exploit heterogeneity in the age composition across the U.S. states to investigate this issue.

### 2.3 Cross-state variation in population aging and migration rates

Changes in the age composition may have indirect effects on migration by affecting the age-specific (within-group) migration rates. At this point, we remain agnostic as to what the mechanisms could be and conduct an empirical analysis to identify and measure this component. The main empirical analysis for testing and measuring the indirect effect relies on cross-state differences in the age composition of the labor force and the consequent variation in migration rates. The goal is to figure out what would happen to the mobility of a worker if she were to be transferred to a location with an older population. To that end, we compute the aggregate and age-specific outflow rates for each state. The sample size of the CPS is too small at the state level to yield reliable estimates of age-specific mobility. To have sufficient precision, we focus on two age groups: individuals between the ages of 25 and 39 and those older than 40 and younger than 65. With a slight abuse of language, we refer to the first group as “young workers” and to the second group as “middle-aged workers.”

**OLS Results** The main empirical specification looks at how the outflow rate in state  $i$  and year  $t$  depends on the share of the labor force older than 40,  $share_{it}$ :

$$\log mobility_{it} = \alpha_i + \beta_t + \gamma \log share_{it} + \varepsilon_{it}. \quad (1)$$

Here,  $\alpha_i$  and  $\beta_t$  denote state and time fixed effects, respectively.  $\varepsilon_{it}$  captures other sources of variation. State fixed effects are needed to dispose of any unmeasured state-level fixed factor that might simultaneously affect the age composition as well as the mobility in a state. Similarly, time

fixed effects are needed to take out the effects of the various aggregate shocks that may have hit the U.S. economy during our sample period. We first estimate equation (1) with OLS and later instrument for the variation in the age composition with lagged birthrates. In both cases, we follow [Bertrand et al. \(2004\)](#) and report state-clustered standard errors to account for serial correlation within states.

Table 1 reports the OLS results. Panel 1 shows the results from estimating equation (1) using aggregate migration-rate data from 1984 to 2006.<sup>8</sup> The estimated elasticity of migration with respect to the share of “old” workers is -2.5. This coefficient is significantly different from zero at any commonly used confidence level. A 10 percent increase in the share of workers older than 40 is associated with a 25 percent decline in the migration rate out of that location. It is possible that the regression picks up the effect of some other variation across states that is correlated with the age composition. Column (2) in panel A investigates this correlation controlling for various state-level variables. The negative correlation is not driven by differences in homeownership rates, personal income, or unemployment. Finally, column (3) controls for state-specific time trends and finds similar results.

Clearly, there is a mechanical caveat with this estimate. Since older workers have a lower migration propensity, one would expect the migration rate to be lower in states with more older workers. It is possible that this relationship is driven by the composition effect. We argue that this is not the case. Panels B and C show that an increase in the share of middle-aged workers in a state is associated with a significant reduction in the migration rate of *all* workers. Quantitatively, the elasticity is larger for workers older than 40 (-2.8) than that for young workers (-2.4).<sup>9</sup> Similarly, these findings are robust to other controls, as illustrated in columns (5) and (8), and to state-specific linear time trends, as illustrated in columns (6) and (9).

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<sup>8</sup>We stop in 2006 to avoid confounding the estimates with the effects of the Great Recession. This omission does not affect the results in any meaningful way.

<sup>9</sup>Note that while all columns use the same sample period (1984–2006), every specification is estimated on a slightly different sample. This difference occurs because some variables take on a value of zero for some state-year observations (for example, the mobility rate of middle-aged workers). Such observations are omitted as the equations are estimated in logs. We have analogous results for all tables estimated on a (smaller) common sample, which we can provide on request. These results support the same conclusions but differ from the baseline estimates in their significance. More specifically, several columns in table 1 become significant at 5 percent instead of 1 percent. Similar comments apply to the tables that follow.

**IV Results** One possible explanation for these results is that older workers move to states with a less dynamic labor market, say, with a lower separation rate, and thus do not need to move as much. As a result, both young and older workers residing in those states move less than identical workers in other states. Note that if a state has a less dynamic labor market throughout our sample, this factor would be captured by state fixed effects. A bias in the coefficient would arise if a state has a temporary change in its labor market that temporarily attracts more older workers. To establish causal inference, we follow [Shimer \(2001\)](#) and exploit the variation in the age composition in a state induced by the birthrates in that state in the past. More specifically, our instrument in state  $i$  and year  $t$  is defined as the sum of all birthrates in state  $i$  from year  $t - 39$  to  $t - 25$ . The instrument turns out to do a good job of inducing variation in the age composition. In the first stage, we regress the share of middle-aged workers on a full set of state and time dummies and the birthrate. This yields a coefficient of 0.40 and a standard error of 0.02. Birthrates explain about 21 percent of the residual variation in age composition, after accounting for fixed effects. Together with the fixed effects, the specification explains 96 percent of the variation.

Table 2 presents the results of the IV regression. The resulting elasticities are strikingly larger than the OLS estimates: A 10 percent increase in a state's share of middle-aged workers causes outflow rates in that state to go down by almost 38 percent. There is also a remarkable difference in the elasticity of young and middle-aged workers. A young worker would be 35 percent less likely to move if she were to live in a state with a 10 percent larger share of middle-aged workers. The same figure for a middle-aged worker is 60 percent. If older workers were moving to states with a less dynamic labor market, the IV estimates would have been substantially lower. The finding that IV results in larger elasticities is indicative of a measurement error in the population estimates.

An alternative way to compute population is using data from the Internal Revenue Service (IRS). In contrast to the CPS, IRS data are administrative and arguably contain very little measurement error.<sup>10</sup> Table A.1 provides the results of a similar analysis using IRS flows and confirms that states with a higher share of middle-aged workers have lower outflow rates. The estimated magnitudes are remarkably close to the benchmark estimates and confirm our results that population aging has an indirect effect on migration.

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<sup>10</sup>The sample that the IRS uses to compute population flows is based on tax returns and is different from the CPS sample that we use, most notably in age. We do not have access to the micro-data and cannot condition on specific age groups.

Our benchmark analysis uses year-to-year variation in population composition to estimate the effects of migration. As a check for robustness, we use lower-frequency movements. To do so, we turn to the decennial census and repeat the same analysis. The results are presented in table A.2 and confirm our main finding that population aging affects within-group migration rates.

**Standard errors** Our approach in tables 1 and 2 can account for any serial correlation in residuals by state. However, Foote (2007) shows that it is important to account for much wider covariance patterns among residuals to make consistent inference when exploiting geographic variation. Importantly, if migration rates and shares of middle-aged workers are jointly affected by state-level economic shocks, which are likely to be spatially correlated, failing to account for this type of correlation can lead to misleading standard errors. Moreover, since state-wide economic conditions are potentially correlated over time as well, the error of one state in a year might be correlated with a nearby state’s error in the following years. In Appendix B, we analyze this issue thoroughly and find our conclusions to be robust.<sup>11</sup>

## 2.4 Possible explanations for the cross-sectional facts

Before turning to our theory of general equilibrium effects, we now discuss several possible (and simple) explanations of these facts and rule them out by empirically investigating their implications.

One such explanation is based on the change in relative prices that may affect workers’ mobility. This argument is based on the premise that workers of different ages are not perfect substitutes in the production function (see Borjas 2003; and Wasmer 2003). Suppose that the share of middle-aged workers increases, say, due to fewer births 25 years ago, as in the IV analysis. Then, the relative scarcity of young workers would push up their relative wages and cause them to move less. While this simple explanation could potentially explain the lower outmigration rate of young workers in response to an increase in the share of middle-aged workers, it is inconsistent with the facts on inflow rates. Note that the increase in relative prices of young workers in this location

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<sup>11</sup>In contrast to Foote (2007), who shows the findings in Shimer (2001) to be weakest when accounting for spatial correlation, we find that standard errors are largest when accounting for serial correlation. Perhaps, this difference arises because the shocks that drive the variation in migration rates are less spatially correlated than the ones that drive unemployment rates, as in Shimer (2001).

should attract more younger workers, resulting in a larger share of young workers in total inflows. Our analysis of the share of young workers in inflows rejects this hypothesis (column 3 of table 3).

Yet another explanation is based on changes in prices. Suppose that unlike labor, capital is immobile. Note that in the IV analysis, an increase in the share of middle-aged workers in a state results from low birthrates in the past and is likely associated with a decrease in the (relative) population of this state. In a world with no capital mobility, this would push up wages at all ages and result in lower outmigration rates for all workers. An immediate implication of this explanation is that inflows should rise as this state should attract more workers. Our analysis of the inflow rate suggests that these states receive fewer inflows in response to an exogenous increase in the share of middle-aged workers (column 1 and 2 of table 3). Note also that the OLS specifications explicitly controlled for state population and found the results to be robust—see columns (2), (4), and (6) of table 1.

Another explanation is based on informal care arrangements between parents and their children. If a group of workers, say, the middle-aged, moves less frequently, this may reduce the mobility of their children if the children anticipate a need for their parents' help to insure against labor market shocks (Kaplan 2012) or if the children provide informal care to their parents (Groneck and Krehl 2014). If our facts are driven by intergenerational relationships, such as these informal care arrangements, then the cross-sectional correlations should also manifest themselves in the mobility of the elderly. We have investigated this possibility and found no such relationship in the data. The mobility of the elderly, defined as those older than 65, do not respond to changes in local age composition.<sup>12</sup>

While none of these possible explanations seems consistent with the data, we now present (and test) our own theory of migration spillovers.

### 3 The Model

Our theory is based on a composition externality of middle-aged workers on the local labor market. It predicts that an increase in the share of middle-aged workers in a local labor market causes firms to recruit locally from that labor market thereby lowering the equilibrium migration rate for *all*

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<sup>12</sup>We do not present these results for the sake of brevity, but they are available upon request.

individuals (migration spillovers).

**The Environment** Time is continuous. The economy consists of a finite number of “islands,” indexed by  $i = 1, 2, \dots, N$ . There is a unit measure of infinitely lived, risk-neutral workers and a continuum of firms that are distributed across these locations.

Workers move across locations by paying a moving cost of  $c$ . There are  $j = 1, \dots, J$  types of workers, with type  $j$  making up  $\omega^j$  measure of workers. An individual of type  $j$  faces a stochastic moving cost, which is i.i.d. and follows a type-specific distribution  $G^j$ . Workers have preferences across locations: for a worker of type  $j$  residing in location  $i$  is associated with a flow utility of  $\varepsilon_i^j$ .<sup>13</sup> While unemployed, workers search for job opportunities. Upon a successful job search, they negotiate a wage contract and start an employment spell, which lasts until the job dissolves exogenously at type-specific rate  $\delta^j$ . For simplicity, we assume Nash bargaining.<sup>14</sup>

Firms have access to a linear production technology that turns one unit of labor into one unit of output.<sup>15</sup> A firm can recruit workers *locally* from its location or *globally* from any other location. More specifically, each location has a local market that is accessible only to local workers and firms. Positions advertised in the local market of a location  $i$  are directed to residents of  $i$  only. Firms post a vacancy by paying a cost  $\kappa$ , and matches are determined randomly by a constant-returns-to-scale matching function,  $m(v_i, u_i)$ , where  $v_i$  and  $u_i = \sum_j u_i^j$  are the measures of vacancies and unemployed workers in  $i$ , respectively. Letting  $\theta_i = v_i/u_i$  denote the tightness in this market, the job finding rate for workers and the contact rate for firms in this market are  $p(\theta_i) = m/u_i$  and  $q(\theta_i) = m/v_i$ , respectively.

There is also a global market for firms and workers where they can search. Matches are random across types and locations and are given by the same matching function  $m$  as in the local market. The tightness of the global market is given by  $\theta_g = \sum_{i=1}^N v_{gi} / \sum_{i=1}^N u_i$ , where  $v_{gi}$  is vacancies of

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<sup>13</sup>Without this heterogeneity in preferences across locations, all locations will be identical. This parameter is introduced to generate exogenous variation across locations so that one can assess the model’s success in matching the cross-sectional facts.

<sup>14</sup>An alternative to this setup is to have large firms and study the intra-firm bargaining as in Cahuc et al. (2008). The advantage of this framework is to allow for a nontrivial complementarity between workers of different types, which is shown to have some empirical support in Wasmer (2003). As we discussed at the end of section 2, this feature can help explain the lower outmigration rate of young workers in response to an aging local population. However, such a model would also imply an increase in inflows to the aging location, a feature inconsistent with the data. Thus, we choose a simpler approach and consider a setup with single-worker firms.

<sup>15</sup>We assume that locations are identical in productivity. Labor productivity is set to one as a normalization and without loss of generality.

firms in location  $i$  that are advertised in the global market.<sup>16</sup>

**Value functions** Let  $U_i^j$  and  $W_i^j(w)$  denote the value to a worker of type  $j$  in location  $i$  of being unemployed and employed, respectively. Then, the following equations characterize workers' decision problem:

$$rW_i^j(w) = w + \varepsilon_i^j + \delta^j (U_i^j - W_i^j(w)) \quad (2)$$

$$rU_i^j = b + \varepsilon_i^j + \left( p_{il} + p_g \frac{v_{ig}}{v_g} \right) (W_i^j(w_{il}^j) - U_i^j) + p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} \mathbb{E} \max \left\{ 0, W_{kg}^j(w_{kg}^j(c)) - U_i^j - c \right\}, \quad (3)$$

where  $w_{il}^j$  is the wage in the local market of  $i$  and  $w_{kg}^j(c)$  is the wage in the global market for a firm in  $k$ . Equation (2) states that a worker employed at wage  $w$  keeps receiving this wage until the match dissolves at rate  $\delta^j$ . As stated in equation (3), an unemployed worker receives a flow utility of leisure  $b$  and the location- and type-specific utility,  $\varepsilon_i^j$  and engages in job search in two markets: the local market of location  $i$  and the global market. Meeting with a local firm happens in the local market, at rate  $p_{il}$ , as well as in the global market, at rate  $p_g v_{ig}/v_g$ . In the latter expression,  $p_g$  is the rate at which any meeting occurs in the global market and  $v_{ig}/v_g$  is the probability that the meeting is with a local firm. Because no moving cost has to be paid, a meeting with a local firm in both markets turns into a job. Unemployed workers meet nonlocal prospective employers in the global market. In this case, they draw a moving cost  $c$  from the type-specific moving cost distribution and determine if a job is mutually beneficial.<sup>17</sup> Upon negotiating the wage, the firm subsidizes the workers' relocation expenses.

It is easy to show that the decision to accept a distant job offer and move in the global market is characterized by a cutoff rule. We let  $c_{ik}^j$  denote the cutoff moving cost such that workers in location  $i$  who meet a firm in  $k$  in the global market move if and only if  $c < c_{ik}^j$ .

Let  $J$  denote the value a firm matched with a worker at wage  $w$ , and let  $V_{il}$  and  $V_{ig}$  denote the

<sup>16</sup>For workers, there are no costs to searching in any market. Thus, all unemployed workers search in their local market as well as in the global market. Therefore, the relevant unemployment when defining the global market tightness is the measure of unemployed workers across all locations.

<sup>17</sup>Note that we assume moving cost is revealed to the worker upon meeting a firm in a different location. The i.i.d. assumption simplifies the analysis of the model and has no meaningful effect on our results. In fact, an earlier version of the paper modeled moving cost as a permanent trait of the worker and reached similar conclusions.

values of creating a job opening in the local and global market, respectively. These values are given by the following equations:

$$rJ^j(w) = y - w - \delta^j J^j(w)$$

$$rV_{il} = -\kappa + q_l \sum_{j=1}^J \frac{u_i^j}{u_i} \left[ J^j(w_{il}^j) - V_{il} \right] \quad (4)$$

$$rV_{ig} = -\kappa + q_g \left[ \sum_{j=1}^J \frac{u_i^j}{u} \left\{ J^j(w_{il}^j) - V_{ig} \right\} \right. \\ \left. + \sum_{k \neq i} \sum_{j=1}^J \frac{u_k^j}{u} \mathbb{E} \max \left\{ 0, J^j(w_{kg}^j(c)) - V_{ig} \right\} \right], \quad (5)$$

where  $u = \sum_i u_i$ . Equation (4) states that a firm pays the fixed vacancy posting cost  $\kappa$  and hires a local worker of type  $j$  with probability  $q_l u_i^j / u_i$ . Equation (5) is the value of creating a job in the global market and takes into account the fact that a firm meets a local worker, at rate  $q_g u_i^j / u$ , and a nonlocal worker from another location  $k$  at rate  $q_g u_k^j / u$ . In the latter event, the firm-worker pair decides if it is profitable to form a match and decides on the wage.

**Wage setting** We assume that matches are set through Nash bargaining and let  $\eta$  denote workers' bargaining power. This assumption implies that workers capture  $\eta$ -share of the match surplus and that firms capture the rest. There are two surplus functions that we need to solve for: the surplus of a local firm-worker pair and the surplus of a firm matched with a nonlocal worker. Let  $S_i^j$  denote the local match in location  $i$  with a worker of type  $j$  and let  $S_{ki}^j(c)$  denote the match surplus of a worker of type  $j$  that currently resides in  $k$  with a firm in  $i$ . These objects are given by

$$S_i^j \equiv J_i^j + W_i^j - U_i^j$$

$$S_{ki}^j(c) \equiv J_i^j + W_i^j - U_k^j - c.$$

In appendix D.1, we derive a system of equations that characterizes the surplus functions in terms of the fundamentals of the model.



**Law of motion** The following equations define the laws of motion for the measures of employed and unemployed workers across locations and types:

$$\begin{aligned}
\dot{u}_i^j &= - \left( p_{il} + p_g \left[ \frac{v_i}{v} + \sum_{k \neq i} \frac{v_k}{v} G^j(c_{ik}^j) \right] \right) u_i^j + \delta^j e_i^j \\
\dot{e}_i^j &= -\delta^j e_i^j + (p_{il} + p_g) u_i^j + p_g \sum_{k \neq i} G(c_{ki}^j) u_k^j \\
1 &= \sum_{i=1}^N (u_i^j + e_i^j).
\end{aligned} \tag{6}$$

We study the steady state of this environment and thus impose  $\dot{u}_i^j = \dot{e}_i^j = 0$ .

**Free-entry conditions** We assume free entry of firms in all markets so that firms make no ex-ante profits in equilibrium. Equations (7) and (8) show the zero-profit conditions in local and global markets:

$$\kappa = (1 - \eta) q_{il} \sum_{j=1}^J \frac{u_i^j}{u_i} S_i^j \tag{7}$$

$$\kappa = (1 - \eta) q_g \left\{ \sum_{j=1}^J \frac{u_i^j}{u} S_i^j + \sum_{k \neq i} \sum_{j=1}^J \frac{u_k^j}{u} \mathbb{E} \max(0, S_{ki}^j(c)) \right\}. \tag{8}$$

We note once again that all meetings in the local market turn into a job spell, whereas some of the nonlocal meetings in the global market may end without one.

**Equilibrium** We are now ready to define equilibrium for this environment.

**Definition 1.** Steady-state equilibrium

A steady-state equilibrium consists of cutoff values for moving,  $\{c_{ik}^j\}$ , wages in local and global markets,  $w_{il}^j$  and  $w_{kg}^j(c)$ , measures of unemployed by type and location,  $\{u_i^j\}$ , market tightnesses  $\{\theta_{il}\}$  and  $\theta_g$ , and vacancy shares of firms in the global market by location,  $\{v_{ig}/v_g\}$ , such that

1. Cutoff values  $\{c_{ik}^j\}$  solve workers' migration problem in (2) and (3).
2. Wages in the local market,  $w_{il}^j$ , and the global market,  $w_{kg}^j(c)$ , solve the Nash bargaining problem.

3. Measures of employed and unemployed by location and type,  $e_i^j$  and  $u_i^j$ , satisfy the laws of motion in steady-state given in (6).
4. Zero-profit conditions hold in all markets so that equations (7) and (8) are satisfied.

Recall that the paper argues for the existence of general equilibrium effects of compositional changes. In the context of the model, we argue that a change in  $\{w^j\}$  affects the equilibrium migration rate of all workers. We now point to the main force in the model that generates this effect.

Workers of different types differ in their job opportunities as those with higher moving costs are less likely to get distant jobs. This difference is reflected in their outside option in the bargaining problem: high-moving-cost workers are associated with a higher surplus in the local market and a lower surplus in the global market. When the share of such workers increases in the economy, say, through population aging, firms find it more profitable to create more jobs in the local market. Equation (7) dictates that market tightness rises in the local market. This rise in local market tightness further depresses the profits in the global market by increasing workers' outside option. Moreover, the compositional change implies that jobs advertised globally are less profitable as they attract higher-moving-cost workers on average. As a result of these effects, firms advertise fewer jobs in the global market than in the local market. Consequently, workers of any type find jobs locally at a faster rate than they do globally and end up moving less. The next section of the paper is dedicated to testing and quantifying this mechanism.

## 4 Quantitative analysis

We have presented a quantitative model to study the effect of compositional changes in the population on migration.<sup>18</sup> We now calibrate the model and test it by comparing the cross-sectional predictions to the data. Finally, the model is used to evaluate the role of population aging in declining migration rates.

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<sup>18</sup>It is worth emphasizing that the model is general and can be used to study the implications of changes in the U.S. population other than the aging population. Some examples are the rise in the share of dual-income households and changes in the homeownership rate. We focus in this paper on the aging of the population, because (1) the magnitude of demographic change is large; (2) the timing lines up well with the trend in migration; and (3) population aging is plausibly exogenous to migration and the labor market.

## 4.1 Calibration

We calibrate a version of the model with identical locations.<sup>19</sup> Each type of worker in the model corresponds to a specific age group in the data. We ask the model to match a number of targets related to mobility and labor markets, as explained below. Appendix D.2 presents the details of the computational algorithm used to solve for a steady-state equilibrium of the model.

**Calibration strategy** The calibration proceeds in two steps. In the first step, we exogenously set values for parameters that have direct counterparts in the data or that can be taken from previous studies because the estimates are not model dependent. The second step uses an exactly identified simulated method of moments (SMM) and targets moments computed using data from around the 1980s. Importantly, we do not target any data about the cross-section of states and instead test the model’s performance on this aspect.

**Functional forms** The matching function is Cobb-Douglas. The contact rate functions for both local and global markets are given by,

$$p(\theta) = v\theta^{1-\gamma}, \quad q(\theta) = v\theta^\gamma.$$

The parameter  $\gamma$  governs the elasticity of the matching function, and  $v$  is the matching efficiency.

**Parameters calibrated a priori** We set  $N$ , the number of locations, to 50. We focus on seven age groups between the ages of 25 and 60 and set the number of age groups,  $J$ , to seven. These age groups correspond to individuals aged 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, and 55–60. The share of each age group in the population is computed from the March CPS using data in 1981. To calibrate the job destruction rates by age group,  $\delta^j$ , we follow Shimer (2012) and compute the continuous time analog of separation probabilities by age group for the entire sample period. We then take the average over 1981.<sup>20</sup> The time discount rate  $r$  is set to match a quarterly discount

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<sup>19</sup>*Symmetric version* means that we are turning off location preference parameters,  $\varepsilon_i^j$ , by setting them to zero. This enables us to solve the model efficiently. The nonsymmetric version, a perturbation of the symmetric model, is used later to evaluate the model by studying its cross-sectional implications.

<sup>20</sup>These data were constructed by Robert Shimer. For additional details, please see Shimer (2012) and his web page <http://sites.google.com/site/robertshimer/research/flows>.

rate of 1 percent. This requires setting  $r = 0.0033$ . The bargaining parameter  $\eta$  is set to 0.5. The flow utility of unemployment is taken from [Hall and Milgrom \(2008\)](#) and set to 0.71. Finally, to set the matching function parameters  $\nu$  and  $\gamma$ , we follow [Diamond and Sahin \(2014\)](#) and construct a measure of the monthly job-finding rate for the period 1977–85 as the sum of E–E, U–E and N–E transition rates from the CPS. This series is then regressed (in logs) on a constant and the market tightness series constructed in [Barnichon \(2010\)](#). We obtain an estimate of 0.77 for  $\nu$  and 0.25 for  $\gamma$ .<sup>21</sup> Parameters calibrated outside the model are summarized in table 4.

**Parameters calibrated with the simulated method of moments** There are eight remaining parameters to be estimated. These are the vacancy posting cost,  $\kappa$ , and the moving cost distribution for each age group. We assume that the moving cost for each age group is distributed exponentially with mean  $\mu_i$  for  $i = 1, \dots, J$ .<sup>22</sup> We use a simplex-based algorithm to minimize the percentage deviation of model-generated moments from their empirical counterparts.

**Targeted moments and their model counterparts** We follow [Shimer \(2012\)](#) and compute the continuous time job-finding rate. We target the average rate in 1981. The model counterpart of this measure is the average of job-finding rates across age groups and locations, weighted by the measure of unemployed. Note that the model counterpart of the job-finding rate for a worker that resides in  $i$  and is in age group  $j$ ,  $f_i^j$ , is given by

$$f_i^j = p_{il} + p_g \frac{v_{ig}}{v_g} + p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} G^j(c_{ik}^j),$$

where the first two terms sum to the rate at which the worker gets a local job and the last term accounts for the rate of getting a job elsewhere. The model analog of the job finding rate is then defined as

$$f = \sum_{i=1}^N \sum_{j=1}^J u_i^j f_i^j.$$

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<sup>21</sup>While there are limited estimates for these parameters for the period of interest, there is a much wider range for later periods, especially for  $\gamma$ . To check the robustness of our results to this value, we also estimate the model with  $\gamma = 0.5$  and perform the main counterfactual analysis.

<sup>22</sup>We choose this distribution as it takes only positive values and leaves us with only one parameter to be estimated per age group.

Finally, we target the trend component of interstate migration rates for each of the seven age groups in 1981. Taking out the cyclical component helps us deal with the fact that the early 1980s were a recessionary period and that migration could be off its trend. To extract the trend component, we apply a Hodrick-Prescott filter on the aggregate migration series with a smoothing parameter of 100. Let  $\sigma$  denote the ratio of the raw aggregate migration rate in 1981,  $\hat{m}_{1981}$ , to its trend component,  $trend_t$ :  $\sigma_t = trend_t / \hat{m}_t$ .<sup>23</sup> Finally, we obtain the trend component of the age-specific migration rates by scaling the raw numbers by  $\sigma_t$ :

$$trend_{j,t} = \sigma_t \cdot \hat{m}_{j,t}.$$

Note that this approach assumes that the cycle component is the same across all age groups.<sup>24</sup> We target the values in 1981,  $trend_{j,1981}$  for  $j = 1, \dots, J$ .

The model counterpart of the annual migration rate is computed as the fraction of workers who change their location at least once over the course of a year. This is achieved by first computing this object separately for each age group, location, and employment status and then obtaining the average by weighting with the respective population shares. Note that even though only unemployed workers are allowed to move in the model at any instant, employed workers may move over the course of a year if they have an unemployment spell in between. We assume that an unemployed worker meets with at most one job within a month and use monthly migration rates to compute the annual migration rate, taking into account time aggregation.<sup>25</sup> Let  $m_{e,i,t}^j$  and  $m_{u,i,t}^j$  denote the  $t$ -period migration probabilities for an employed and unemployed worker of type  $j$  residing in  $i$ , respectively. In other words, these objects measure the probability that a worker will move at least once in the next  $t$  periods. We are interested in computing  $m_{e,i,12}^j$  and  $m_{u,i,12}^j$ . Equations 9–12

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<sup>23</sup>We obtain  $\sigma_{1981} = 1.0155$ .

<sup>24</sup>An alternative approach is to detrend each of the series separately. This has no material effect on our results. We prefer this approach, because it ensures that the trend components by age groups aggregate perfectly to the trend component of the aggregate series. This is the only rationale for choosing this approach.

<sup>25</sup>While this assumption is not necessary to compute migration rates in a continuous time environment, we find that it is the fastest approach numerically and easiest to implement. One can approximate the continuous time version arbitrarily well by shortening the length of a “period.” We found that our approach provides a good approximation to the continuous-time counterpart.

define these objects recursively:

$$m_{e,i,1}^j = 0 \quad (9)$$

$$m_{u,i,1}^j = P_{ig}^j \quad (10)$$

$$m_{e,i,t+1}^j = (1 - \Lambda) m_{e,i,t}^j + \Lambda m_{u,i,t}^j \quad (11)$$

$$m_{u,i,t+1}^j = P_{ig}^j + (1 - P_{ig}^j) P_{il} m_{e,i,t}^j + (1 - P_{ig}^j) (1 - P_{il}) m_{u,i,t}, \quad (12)$$

where  $P_{ig}^j$  denotes the monthly probability of finding a job in another location,  $P_{il}$  denotes the monthly probability of a local job offer and  $\Lambda$  denotes the monthly separation probability. These are given by the following expressions:

$$P_{ig}^j = 1 - \exp \left\{ -p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} G^j(c_{ik}^j) \right\}, \text{ for } k \neq i.$$

$$P_{il} = 1 - \exp \left\{ - \left( p_{il} + \frac{v_{ig}}{g} p_g \right) \right\}$$

$$\Lambda = 1 - \exp \{ -\lambda \}.$$

The estimation minimizes the equally weighted sum of squared percentage deviations of model moments from the targets. Table 5 summarizes the moments used in the estimation and provides the fit of the model to the targeted moments. The estimated parameters are summarized in table 6. The model does an excellent job of matching the calibration targets. Recall that migration decreases with age in the data. This monotonicity might lead someone to conjecture that the moving cost should increase with age.<sup>26</sup> Note, however, that this is not necessarily the case in this model. For example, while individuals between 45 and 49 have a lower migration rate than those between 40 and 44, the average moving cost is higher for the latter group.<sup>27</sup>

<sup>26</sup>Kennan and Walker (2011) use a structural model to estimate moving costs and find them to be large, much larger than our estimates. The difference is likely driven by the search frictions in our model, which makes it difficult for workers to move even in the absence of explicit costs. For a group of workers that face no moving cost, interstate migration would be less than 4 percent. In contrast, the model in Kennan and Walker (2011) features no additional friction so that their estimate of moving cost is a composite of various costs and frictions.

<sup>27</sup>If the cutoff costs were the same across types, then trivially the mobility rate would be decreasing in the mean of the moving cost distribution. However, it is easy to show that the cutoff cost is increasing in the mean in a way that the relationship between the mean and the migration rate is ambiguous.

## 4.2 Testing the model on cross-sectional data

The main goal of the model is to quantify the effect of aging population on interstate migration. Before turning to this ultimate exercise, we study the model’s cross-sectional implications and compare them to their empirical counterparts. Recall that the calibration did not target any moments on the cross section, so that this section can be thought of as an exercise validating the model. Recall that section 2 documented a new stylized fact on population composition and flows: workers in states with an older population have higher migration rates than those in other states. In this section, we document that the fraction of local hires–hires to local firms from among state residents–is larger in states with an older workforce. We compute the model counterparts of these elasticities and compare them to the data. The model is quantitatively consistent with both features.

Note that the calibrated model is symmetric across locations, as the preference values,  $\varepsilon_i^j$ , are all set to zero. We introduce heterogeneity across locations by changing these preference parameters,  $\Phi = [\varepsilon_i^j]$  for  $i = 1, \dots, N$  and  $j = 1, \dots, J$ . We take the calibrated parameter values as given and perturb the first column of the matrix  $\Phi$ , which corresponds to location 1, randomly around zero. This perturbation ensures that the preference for all other locations is unchanged and thus that these locations remain identical.<sup>28</sup> We draw 100 such perturbations and compute the relevant cross-sectional elasticity for each equilibrium as explained below.<sup>29</sup> We report the average elasticity across simulations.<sup>30</sup>

**Age composition and migration rates** Let  $m_{\leq 40,i}$  and  $m_{>40,i}$  denote the model outmigration rates of workers in location  $i$  between 25 and 40 and between 40 and 60, respectively. These are computed analogous to the aggregate migration rate, by taking into account the time aggregation to measure the probability of at least one move and aggregating across the relevant age groups. Let  $\xi$

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<sup>28</sup>Thus, while there are 50 locations in the model, solving for an equilibrium in this setup requires solving all objects for only two locations: location 1 and the rest. Despite the fact that this perturbation reduces the model effectively to a two-location model, the number of locations is important in determining the size of the general equilibrium effect, especially across locations. For example, if there were only two locations in the model, a change in the population composition in one location would exert a big effect on equilibrium objects of the other location. Specifying the number of locations disciplines the magnitude of the general equilibrium effect. An alternative approach would be to consider a nonrestrictive perturbation to the entire  $\Phi$  matrix. To solve the model for this case is computationally challenging and requires linearization techniques. Instead of making an approximation to the equilibrium, we chose to simplify the perturbation but solve the resulting model accurately.

<sup>29</sup>The number of repetitions has no effect on the estimated elasticity. We run several repetitions to make sure that the results are not driven by a particular realization of the matrix  $\Phi$ .

<sup>30</sup>While the elasticities differ across simulations, they all have the same sign.

denote the model counterpart of the cross-sectional elasticity of migration with respect to the share of middle-aged workers. Similarly, let  $\xi_{\leq 40}$  and  $\xi_{>40}$  denote the same for young and middle-aged workers. Then these are given by<sup>31</sup>

$$\begin{aligned}\xi &= \frac{\log(m_1) - \log(m_2)}{\log(\text{share}_1) - \log(\text{share}_2)} \\ \xi_{\leq 40} &= \frac{\log(m_{\leq 40,1}) - \log(m_{\leq 40,2})}{\log(\text{share}_{\leq 40,1}) - \log(\text{share}_{\leq 40,2})} \\ \xi_{>40} &= \frac{\log(m_{>40,1}) - \log(m_{>40,2})}{\log(\text{share}_{>40,1}) - \log(\text{share}_{>40,2})}.\end{aligned}$$

The results are reported in table 7 and compared to the OLS and IV estimates. Note that while the model elasticities lie below the point estimates, they are within the confidence intervals. Interestingly, consistent with the data, the elasticity of the older group is larger than that of the young, also consistent with the data. We note that the model agrees with the data on the cross-sectional elasticity of migration.

**Age composition and fraction of local hires** Our second fact pertains to the relationship between the age composition in the population and hiring patterns across states. This feature of the data is especially important as it directly speaks to the main mechanism in the model. Using data from the Survey of Income and Program Participation (SIPP), we compute the fraction of local hires out of total hires for each state-year combination.<sup>32</sup> The number of total hires is defined as everyone in the state who reports being unemployed one month prior to the survey month but is employed by the time of the survey. Local hires are then defined as those among the total hires that did not move across states over this period. In the data, we compute the elasticity of the share of local hires with respect to the share of population older than 40 to be 0.4515, significant at 10 percent.

The model counterpart of the share of local hires,  $lh_i$ , is computed by simply dividing the measure of workers that are hired locally to all hires in that location. The associated cross-sectional

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<sup>31</sup>Note that we use location 1 and location 2 to compute these elasticities. The choice of location 2 is arbitrary as it is identical to location  $i = 2, \dots, 50$ .

<sup>32</sup>Further details about the SIPP sample are given in appendix C.



elasticity,  $\zeta$ , is then given by

$$\zeta = \frac{\log(lh_1) - \log(lh_2)}{\log(\text{share}_{>40,1}) - \log(\text{share}_{>40,2})}.$$

The resulting elasticity is reported in table 8 and compared to the empirical estimate.<sup>33</sup> We find the magnitude of the cross-sectional correlation computed in the model to be remarkably in line with that in the data.

**Explaining the cross-sectional facts** How does the model explain the cross-sectional correlations between age composition and population flows? The intuition behind this feature is based on a general equilibrium effect that we have elaborated on at the end of section 3. In short, in the location with an older population, hiring a worker from the local market is more profitable than recruiting globally. Consequently, firms in this location advertise locally, and the job-finding rate in the local market is higher. These differences in the recruiting behavior of firms across locations cause workers in older locations to move less as they find local jobs at a faster pace. The same mechanism is responsible for the higher local hires in the older location. In this location, firms advertise a higher share of their vacancies in the local labor market and end up hiring more of their workforce from the resident pool.

We conclude that the general equilibrium effect is important to understanding these new cross-sectional facts.

### 4.3 Effects of the aging population on interstate migration

To isolate the role of the aging population, we compute the model-generated migration rate for each year between 1981 and 2010 by changing only the shares of each age group to their empirical counterpart for that year. These shares are reported in table A.3 in appendix A. We solve for the steady-state equilibrium of the estimated model and report equilibrium migration rates. Figure 7

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<sup>33</sup>Note that the sample size of the SIPP is relatively small for this exercise. Using a one-month period to calculate the share of local hires results in many observations being either 0 or 1. As the zeros are dropped in estimating the elasticity, table 8 uses 781 observations to estimate the elasticity. We also estimate the relationship using the level of the share as opposed to its log and find a coefficient of 0.3923 with a  $p$ -value of 0.09. It is reassuring that the qualitative results are not an artifact of dropping the zero observations. Using a longer period of, say, three or six months to compute the local hires share, we also find a positive elasticity.

plots the resulting series and compares it to the data. The model generates a decline in interstate migration by 0.8 percentage point. This is about 53 percent of the 1.5 percentage point decline in the data. Note also that the model is exceptionally successful in explaining declining mobility until the early 2000s but does not explain much of the decline in the later period. This unexplained portion could be attributable to changes in information technology as articulated in [Kaplan and Schulhofer-Wohl \(2013\)](#).

How much of this decline can be attributed to the migration spillovers? The direct compositional effect can be measured simply by taking the weighted average of 1981 migration rates using the working-age population shares at some point in time. This effect accounts for a 0.2 percentage point decline, as shown in the accounting exercise in section 2. The remainder of the decline in migration, 0.6 percentage point, should be attributed to the migration spillovers. This large effect can best be understood by focusing on the changes in age-specific migration rates: figure 8 illustrates that our model is able to generate, through only a change in the composition, quite sizable declines in the migration rates of *all* age groups. We plot the age profile of migration every 5 year starting in 1996. In fact, the model explains roughly 50 percent of the within-group decline.<sup>34</sup> This observation suggests that accounting for the general equilibrium effects is important for properly assessing the role of population aging. Studies quantifying only the direct effect understate the total effect.<sup>35</sup>

#### 4.4 Understanding the mechanism

A direct implication of our theory of migration spillovers is that the share of distant hires, hires from outside the state, should fall over time. Figure 9 plots the model counterpart of this share and compares it to the data.<sup>36</sup> It is also interesting to note that this share has fallen steadily until early 2000s and has levelled around 1 percent. Note that similar to the data, our model predicts this share to fall steadily until mid-2000s and then remain flat. While the model overstates the level of this

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<sup>34</sup>There have been other studies to explain this across-the-board decline in migration. The unexplained portion of the within-group decline can be attributable to the mechanisms explained in [Kaplan and Schulhofer-Wohl \(2013\)](#) and [Molloy et al. \(2013\)](#). [Kaplan and Schulhofer-Wohl \(2013\)](#) argue that the decline in the geographic-specificity of occupations and changes in information technology can account for at least one-third of the decline.

<sup>35</sup>While not shown on this plot, the model does an extremely good job of explaining the decline in within-group migration until 2001. Migration rates keep falling after 2001, but the model generates little decline for this period.

<sup>36</sup>We plot the 5-year moving average from the data.

share, the data support the implication of the theory that this share has fallen over time, thereby lending support to our theory.

## 4.5 The decline in migration and aggregate unemployment

A common concern is that lower migration rates might cause higher aggregate unemployment. One popular theory is that a decline in migration might indicate a lower ability of workers to take on distant jobs, which in turn can cause aggregate unemployment to rise. This concern is particularly important in the context of our model, because migration in the model is directly linked to job offers from the distant location. Moreover, the model predicts a large decline in migration due to aging. This decline might suggest that aging causes an increase in unemployment. Based on these concerns, we use the estimated model to study the implications of aging for aggregate unemployment.

Figure 10 plots the time series for aggregate unemployment in the model. Note that population aging causes lower mobility for all workers and mobility is an important means of finding jobs in the model. Thus, one might suspect that population aging leads to an increase in unemployment. We find the opposite: despite the large fall in migration, unemployment *falls* in response to aging population by about 0.3 percentage points. As explained before, migration decreases because firms post more jobs aimed at attracting local workers. Workers are not moving as much because they have less incentive to move to find jobs. This seemingly counterintuitive result occurs because the increase in local job-finding rates more than offsets the negative effect from the compositional change and raises the job-finding rate of all workers.

## 5 Conclusion

This paper studied the long-run decline in interstate migration in the United States over the last several decades. Our study illustrates that compositional changes have not only a direct effect on migration but also an indirect effect through general equilibrium that we label *migration spillovers*: as the local population ages, local jobs become easier to find, and the migration rates of *all* workers decline in equilibrium. We found strong evidence for this mechanism in the cross-section of U.S. states. Our quantitative analysis suggested that population aging explains a large part of the lower

mobility and that most of this decline is accounted for by the general equilibrium effect.

The spillovers that we argue for in this paper are quite general and have implications for other questions in the mobility literature. The theory applies not only to the aging population but also to any compositional change such as the rise in dual-income households or changes in homeownership rates. A similar spillover may exist in response to changes in frictions faced by a group of workers. More specifically, a large literature examines the mobility effects of frictions arising in the housing market. Most of the empirical literature in this field is based on comparing the outcomes of homeowners to that of renters. These studies implicitly assume that renters are not affected by such frictions. Our theory, however, implies that these imperfections could affect the migration rate of renters through spillovers, thus invalidating the identification strategy employed in the empirical literature. In a companion paper, [Kapon et al. \(2014\)](#), we quantify these spillovers to assess the magnitude of the bias.

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## 6 Tables and Figures

TABLE 2  
MOBILITY AND THE AGE COMPOSITION

	Aggregate	25–40	40–60
Share 40–60	–3.8348** (1.655)	–3.4940** (1.850)	–5.9770** (2.386)
$R^2$	0.302	0.190	0.185
$N$	1,028	1,026	996

Table 2 shows the IV estimates of the reduced-form model in (1) estimated by least squares and instrumenting for the age composition with lagged cumulative birthrates. The dependent variable is the aggregate migration-rate by state and year in the first column, the migration rate of those 25–39 in the second, and the migration rate of those 40–60 in the third. To account for the serial correlation in the standard errors, we use a nonparametric block bootstrap and cluster around state. Standard errors are in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.



TABLE 1  
MIGRATION AND AGE COMPOSITION: OLS RESULTS

	Panel A: Aggregate			Panel B: 25–40			Panel C: 40–60		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share 40–60	-2.510*** (0.835)	-2.601*** (0.812)	-3.286*** (0.938)	-2.423*** (0.878)	-2.630*** (0.878)	-2.337** (0.954)	-2.800*** (0.992)	-2.885*** (0.985)	-5.093*** (1.160)
Home ownership		-0.784 (0.554)			-0.895 (0.576)			-0.927 (0.742)	
Personal inc. (p.c.)		0.927 (0.657)			0.942 (0.704)			1.127 (0.750)	
Unemp. rate		0.071 (0.102)			0.048 (0.129)			0.123 (0.130)	
Population		1.196 (0.753)			1.065 (0.804)			1.437* (0.795)	
Industrial comp.		Yes			Yes			Yes	
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-time effects			Yes			Yes			Yes
$R^2$	0.306	0.312	0.732	0.192	0.197	0.656	0.198	0.203	0.538
$N$	1,028	1,028	1,028	1,026	1,026	1,026	996	996	996

Note: Table 1 shows the OLS estimates of the panel model in (1). The dependent variable is the aggregate migration rate by state and year in panel A, the migration rate of those 25–39 in panel B and the migration rate of those 40–60 in panel C. The first column in each panel presents the simple regressions. The second column controls for various state-level observables, and the third column includes state-specific linear time trends to the simple regression. To account for the serial correlation in the standard errors, we use a nonparametric block bootstrap and cluster around state. Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

TABLE 3  
MOBILITY AND THE AGE COMPOSITION

	Inflow rate (IRS)	Inflow rate (CPS)	Young share in inflows
Share 40-60	−0.6767*** (0.093)	0.3568 (1.672)	−1.2449*** (.237)
$R^2$	0.370	0.395	0.838
$N$	735	1,029	1,029

Table 3 shows the IV estimates of the reduced-form model in (1) estimated by least squares and instrumenting for the age composition with lagged cumulative birthrates. The dependent variable is the inflow rate to a state in a given year, computed from IRS flows, in column 1, the same computed from March CPS in column 2 and the share of young workers (25–39) in total inflows to that state. To account for the serial correlation in the standard errors, we use a nonparametric block bootstrap and cluster around state. Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

TABLE 4  
PARAMETERS CALIBRATED OUTSIDE THE MODEL

Parameter	Value
Time discount rate, $r$	0.0033
Value of leisure, $b$	0.71
# Locations, $N$	50
Workers' bargaining power, $\eta$	0.50
Matching efficiency, $v$	0.77
Elasticity of the matching function, $\gamma$	0.25
Population share by age group	25–29 16.11%
	30–34 14.88%
	35–39 11.61%
	40–44 9.58%
	45–49 9.15%
	50–54 9.36%
	55–60 11.08%
Separation rate by age group	25–29 .0425
	30–34 .0310
	35–39 .0250
	40–44 .0210
	45–49 .0192
	50–54 .0176
	55–60 .0158

Note: Table 4 reports the values for parameters calibrated outside the model.

TABLE 5  
MATCHING THE CALIBRATION TARGETS

Moment	Data	Model
Average job-finding rate	0.5379	0.5379
Annual migration rate by age group	25–29	5.42%
	30–34	3.93%
	35–39	3.06%
	40–44	2.03%
	45–49	1.97%
	50–54	1.44%
	55–60	1.43%

Note: Table 5 shows the model's fit on targeted moments of the data.

TABLE 6  
PARAMETERS CALIBRATED THROUGH SIMULATED METHOD OF MOMENTS

Parameter	Value
Vacancy posting cost, $\kappa$	0.4430
Mean of the moving-cost distribution by age group, $\mu$	25–29
	30–34
	35–39
	40–44
	45–49
	50–54
	55–60

Note: Table 6 reports the values of parameters calibrated through SMM.

TABLE 7  
ELASTICITY OF MIGRATION: MODEL VS. DATA

	Aggregate	25–40	41–60
Model	-1.450	-0.870	-2.148
Data (OLS)	-2.510 (0.835)	-2.423 (0.878)	-2.800 (0.992)
Data (IV)	-3.8348 (1.655)	-3.4940 (1.850)	-5.9770 (2.258)

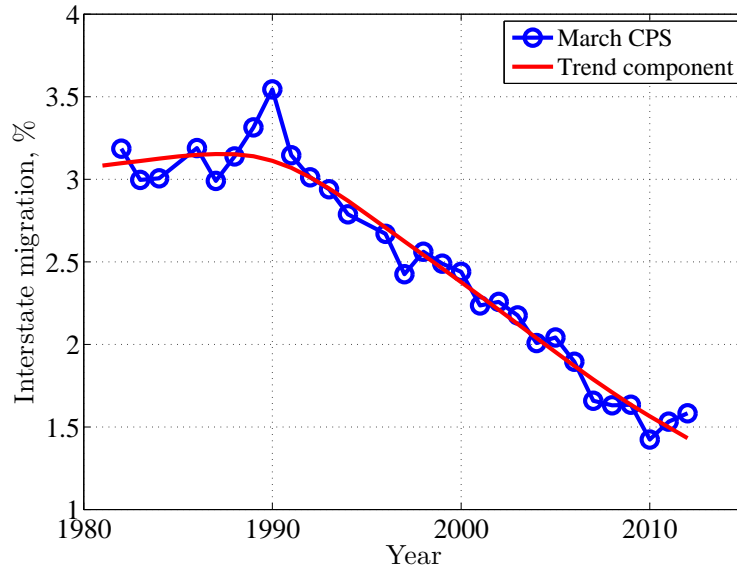
Table 7 shows the cross-sectional elasticity of outmigration computed from the model (first row) and compares it to the OLS (second row) and IV estimates (third row) of the reduced-form model in (1). The dependent variable in the first column is the outmigration at the state level, whereas for the second and third variables it is the outmigration rates of young and middle-aged workers, respectively. Standard errors are in parentheses. All coefficients are significant at least at 5 percent.

TABLE 8  
ELASTICITY OF LOCAL HIRES: MODEL VS. DATA

	Data	Model
Elasticity of the share of local hires w.r.t. share of population > 40	0.4515* (0.273)	0.4513

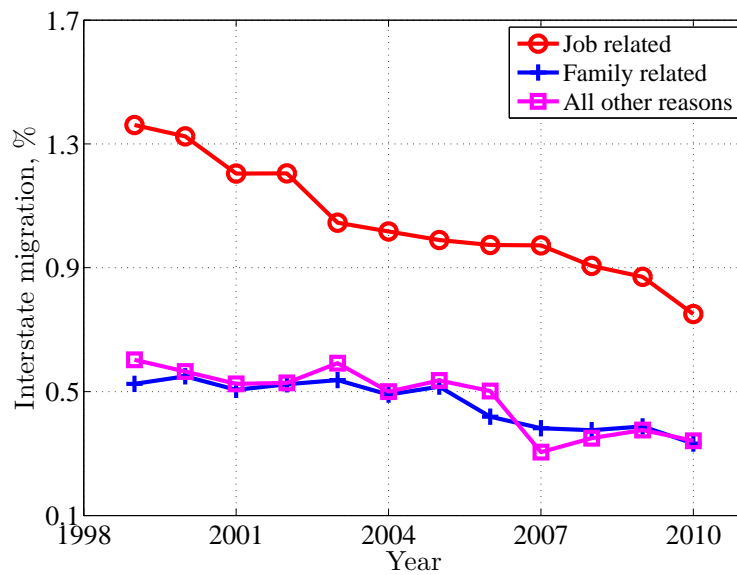
Table 8 shows the IV estimate (first column) of the cross-sectional elasticity of local hires and compares it to the model counterpart (second column). The dependent variable in the first column is the share of local hires in a month at the state level. Standard errors are in parentheses.

FIGURE 1  
INTERSTATE MIGRATION IN THE UNITED STATES



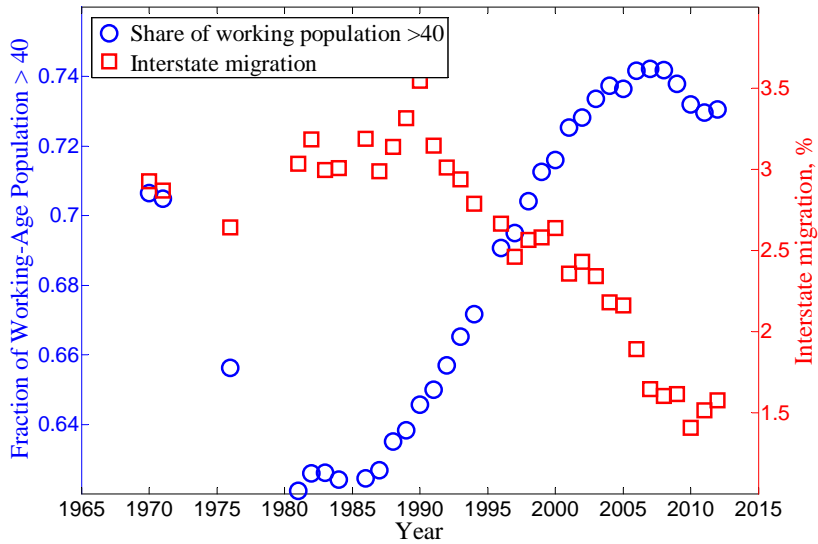
Note: Figure 1 shows the time series of annual interstate migration rates computed from the March CPS. The blue line is the migration rate in the March CPS for the period 1980–2012. Migration rates are computed based on nonimputed observations. The solid red line is the long-run trend of interstate migration rates using a Hodrick-Prescott filter with a scaling parameter of 100 for the period 1980–2012.

FIGURE 2  
REASONS TO MOVE IN THE UNITED STATES



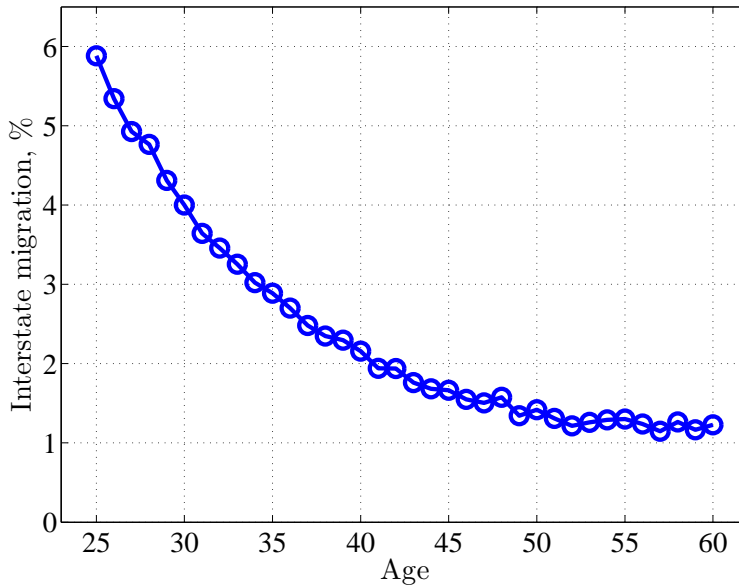
Note: Figure 2 shows the fraction of the working-age population that moved across states for different reasons, computed from the March CPS. The red line is the share of migrants who moved for job-related reasons. The blue line is the fraction of moves related to family reasons. The green line is the share of migrations for all other reasons.

FIGURE 3  
AGING POPULATION IN THE UNITED STATES



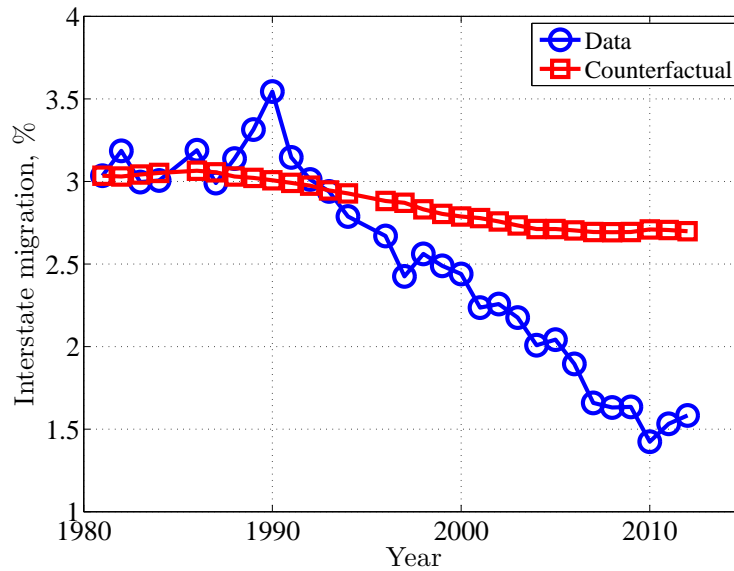
Note: Figure 3 shows the aging of the U.S. population over the period 1980–2010. The blue dots indicate the share of individuals older than 40 among individuals between the ages of 25 and 60. The red squares show interstate migration rates during the same time period (March CPS; authors’ calculations).

FIGURE 4  
INTERSTATE MIGRATION OVER WORKING AGES



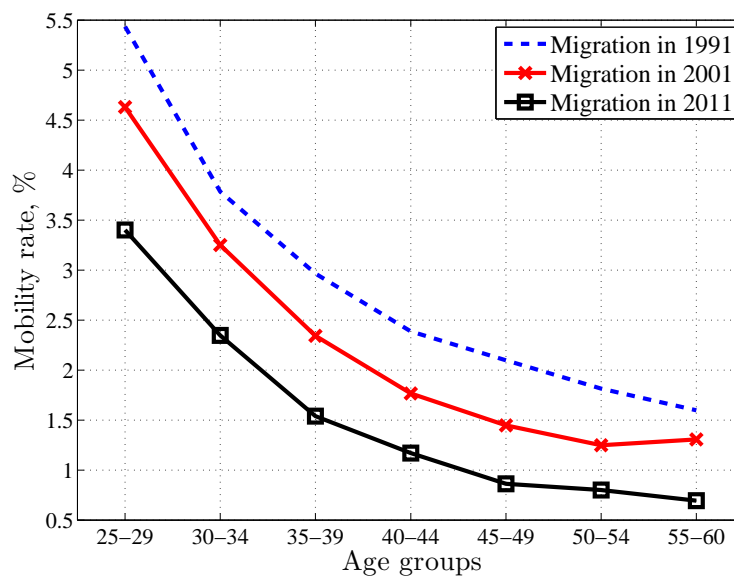
Note: Figure 4 shows annual interstate migration rates over the working life. Migration rates are computed based on nonimputed observations. The interstate migration rate decreases sharply over the working life, and most of the decline occurs before age 40.

FIGURE 5  
 QUANTIFYING THE DIRECT EFFECT OF AGING ON INTERSTATE MIGRATION



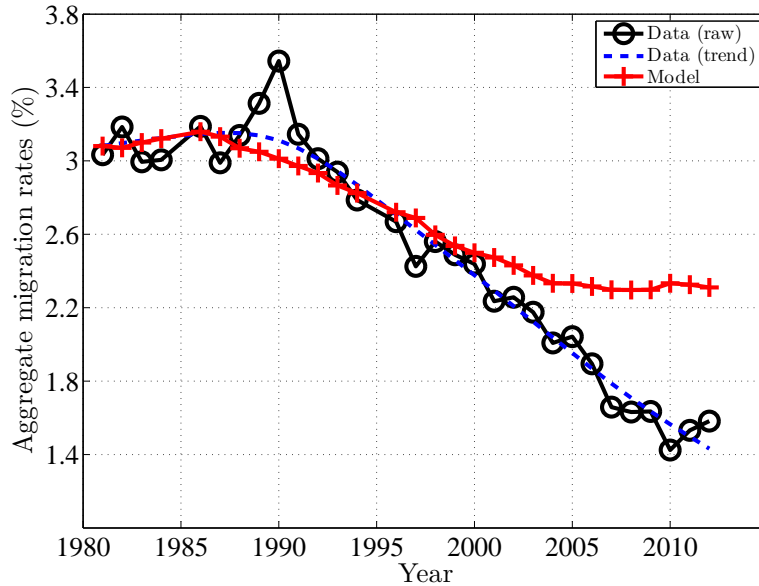
Note: Figure 5 shows the direct effect of the aging population on interstate migration. The blue line with circles is the interstate migration rate in the March CPS. The red line shows the counterfactual migration rate obtained by fixing the migration rate of each age group to its 1980 level and changing the share of each group in line with the data (March CPS; authors' calculations).

FIGURE 6  
 TIME TREND OF INTERSTATE MIGRATION OVER WORKING AGES



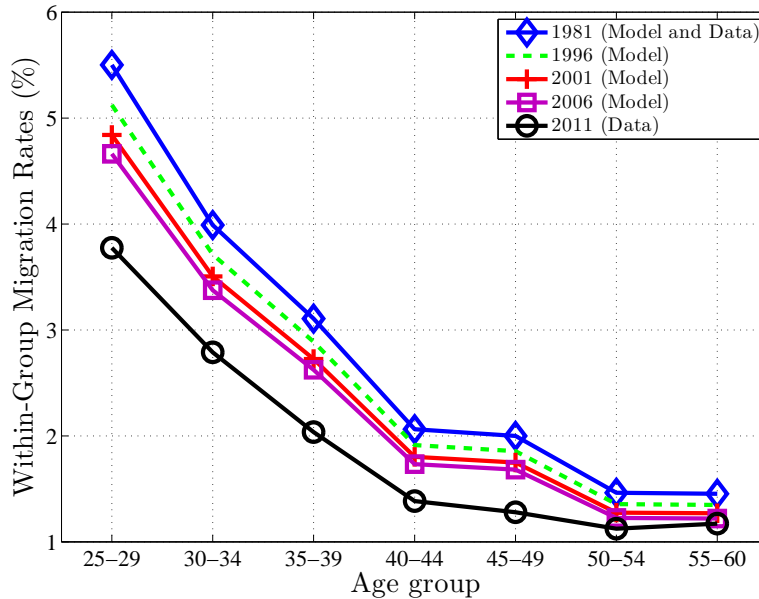
Note: Figure 6 shows the interstate migration rate across seven age groups for three years: 1991, 2001, and 2011.

FIGURE 7  
AGING POPULATION AND THE DECLINE IN MIGRATION: DATA VS. MODEL



Note: Figure 7 plots the model-implied interstate migration rates from 1981 to 2012 and compares them to the data. Annual migration in the model is computed as the fraction of all population who move at least once in a 12-month period. The trend component of the series is obtained with an HP filter with a scaling parameter of 100.

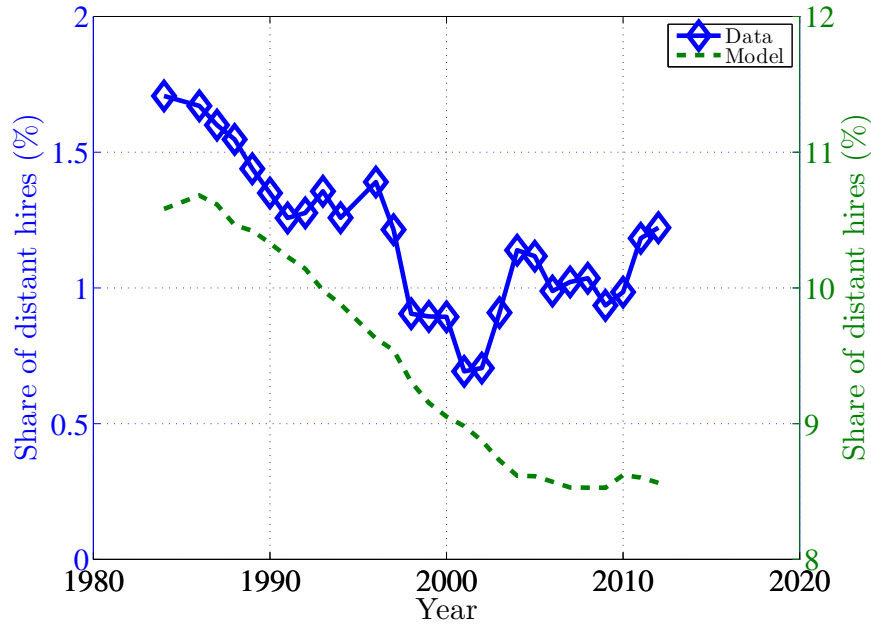
FIGURE 8  
QUANTIFYING THE IMPORTANCE OF MIGRATION SPILLOVERS



Note: Figure 8 shows the migration rates of different age groups from the data at various years. The x-axis is the seven age groups used in our estimation. The y-axis is the migration rate. The blue dashed line is the migration rate of each age group in 1980, and the black dashed line is for 2011. The green solid line is computed from the estimated model with the population shares of 1996. Similarly, the red (+) series and the square-dashed purple series show the model migration rates for 2001 and 2006, respectively.

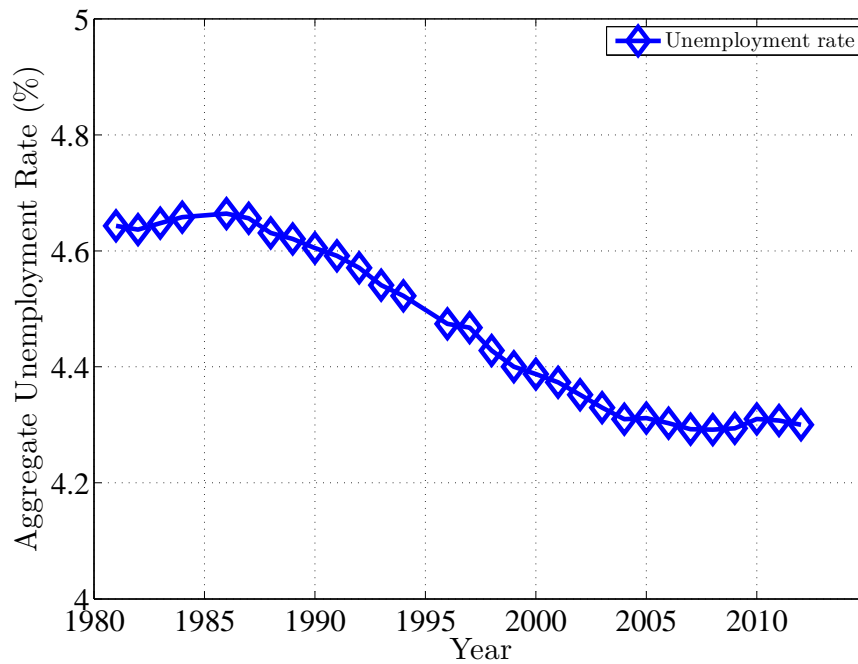


FIGURE 9  
SHARE OF DISTANT HIRES



Note: Figure 9 shows the model counterpart of the share of hires from outside the firm's own state and compares it to its empirical counterpart. The empirical counterpart is the 5-year moving average of the raw series computed from SIPP.

FIGURE 10  
DECLINING MOBILITY AND AGGREGATE UNEMPLOYMENT



Note: Figure 10 plots the series for the aggregate unemployment rate in the model.

## A Online Appendix—Not for Publication: Additional Tables and Figures

TABLE A.1  
MOBILITY AND THE AGE COMPOSITION IN IRS DATA

Aggregate Migration in IRS	
Share 40-60	−0.5893*** (0.068)
$R^2$	0.345
$N$	784

Table A.1 shows the IV estimates of the reduced-form model in (1) estimated through least squares and instrumenting for the age composition with lagged cumulative birthrates. The dependent variable is the aggregate migration rate by state and year computed using IRS flows. To account for the serial correlation in the standard errors, we use a nonparametric block bootstrap and cluster around state. Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

TABLE A.2  
MOBILITY AND THE AGE COMPOSITION IN CENSUS DATA

	Aggregate	25-40	40-60
Share 40-60	−2.1314*** (0.680)	−2.4122*** (0.650)	−1.541* (0.833)
$R^2$	0.289	0.211	0.179
$N$	98	98	98

Table A.2 shows the IV estimates of the reduced-form model in (1) estimated through least squares and instrumenting for the age composition with lagged cumulative birthrates. The dependent variable is the aggregate migration rate by state computed from the 1990 and 2000 Census. To account for the serial correlation in the standard errors, we use a nonparametric block bootstrap and cluster around state. Standard errors are in parenthesis. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

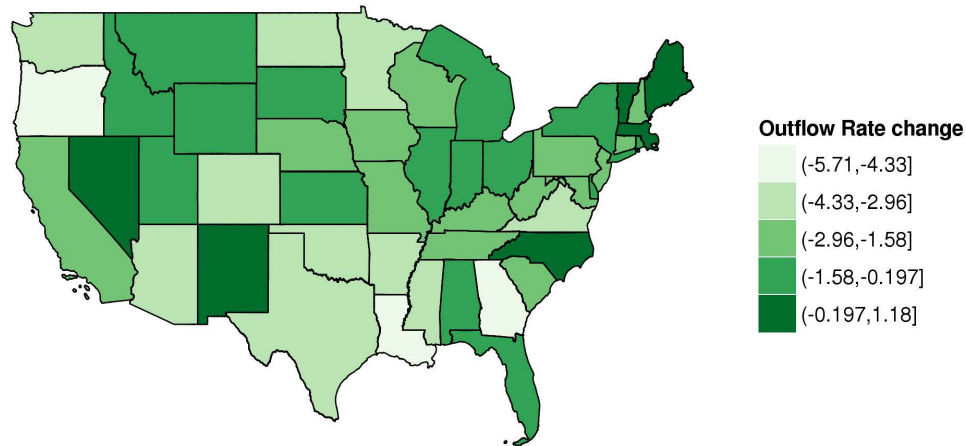
TABLE A.3  
AGE COMPOSITION OF THE U.S. POPULATION: 1981–2012

Shares of Age Groups, %

Year	25–29	30–34	35–39	40–44	45–49	50–54	55–60
1981	16.1	14.9	11.6	9.6	9.2	9.4	11.1
1982	15.9	14.7	12.2	9.9	8.8	9.2	11.0
1983	15.9	14.5	12.6	10.1	8.9	8.8	10.6
1984	16.0	14.7	12.7	10.5	8.9	8.6	10.3
1986	15.5	15.0	13.7	10.5	8.6	8.0	9.8
1987	15.2	15.1	13.5	11.2	8.8	7.8	9.5
1988	14.7	14.9	13.4	11.6	9.1	7.9	9.3
1989	14.2	14.9	13.6	11.7	9.1	7.8	9.1
1990	14.0	14.7	13.9	12.1	9.6	7.9	8.8
1991	13.7	14.6	13.7	12.7	9.7	8.0	8.6
1992	13.2	14.5	14.0	12.5	10.1	8.1	8.4
1993	12.6	14.4	13.9	12.5	10.5	8.4	8.3
1994	12.3	14.1	13.9	12.6	10.8	8.5	8.3
1996	11.8	13.4	14.3	13.0	11.7	8.6	8.5
1997	11.8	12.9	14.2	13.2	11.3	9.1	8.4
1998	11.4	12.7	13.8	13.3	11.6	9.8	8.8
1999	10.9	12.5	13.5	13.3	11.9	10.0	9.0
2000	11.0	12.2	13.2	13.2	12.0	10.5	9.1
2001	10.4	12.7	14.7	15.2	12.9	10.2	8.2
2002	10.2	12.8	14.2	15.0	13.2	10.3	8.8
2003	10.2	12.4	13.7	15.0	13.4	10.6	9.3
2004	10.1	12.2	13.1	14.7	13.6	10.9	9.9
2005	10.3	11.9	12.9	14.4	13.4	11.1	10.1
2006	10.4	11.3	13.2	14.0	13.4	11.3	10.5
2007	10.5	11.2	12.9	13.5	13.3	11.5	11.2
2008	10.6	11.1	12.7	13.2	13.3	11.6	11.3
2009	10.6	11.4	12.3	13.0	13.2	11.9	11.3
2010	10.9	11.5	12.2	12.7	13.1	11.7	11.4
2011	10.8	11.7	11.7	12.6	12.6	11.7	11.8
2012	10.6	11.7	11.6	12.5	12.0	11.9	12.2

Note: Table A.3 shows the shares of each age group from 1981 to 2012. Source: Census and authors' calculations.

FIGURE A.1  
SPATIAL NATURE OF MIGRATION RATES



Note: Figure A.1 shows a heat map of the decline in migration rates across the U.S. states from 1986 to 2010. The decline in migration is a geographically widespread phenomenon.

## B Online Appendix—Not for Publication: Accounting for Wide Patterns of Correlation in Errors

Throughout the paper, we followed [Bertrand et al. \(2004\)](#) and reported state-clustered standard errors. This approach can account for any serial correlation pattern in residuals by state. However, as [Foote \(2007\)](#) shows, it might be important to account for much wider covariance patterns among residuals to make consistent inference when exploiting geographic variation, in particular, spatial correlation.<sup>37</sup> Table A.4 investigates this issue by reporting standard errors clustered in various ways. The first row reports the coefficient estimates and the second row shows the baseline state-clustered standard errors along with the significance level shown denoted by asterisks. Panel A is for the OLS estimates, whereas Panel B is for the IV estimates. Missing in the standard errors clustered by state is spatial correlation, which could be important if the outcome variable and the dependent variables are both driven by state-level economic shocks. A simple approach to take care of spatial correlation nonparametrically is to use year-clustered standard errors. These

<sup>37</sup>This section draws heavily on [Foote \(2007\)](#).

standard errors are reported on the third row. As [Cameron et al. \(2006\)](#) and [Thompson \(2011\)](#) have shown, it is possible to cluster by state and year simultaneously. The standard errors corresponding to this two-way cluster are reported on row 4. The two-way cluster does not address all of the potential problems with correlated standard errors. Specifically, since state-wide economic shocks are likely to be serially autocorrelated, the error of one state in a year might be correlated with a nearby state's error in the following years. To account for this possibility, we implement the approach in [Driscoll and Kraay \(1998\)](#) (DK), who show how to deal with the panel-data inference problem with general serial patterns and spatial correlation. Their estimator is parameterized by a maximal lag after which the common autocorrelated disturbances are assumed to die out. Rows 5 and 6 report standard errors for maximal lags of 1 and 3, respectively. DK estimator uses the standard Newey-West estimator to account for the serial correlation, which can be biased in short panels. Note that this issue might be responsible for the fact that the DK standard errors are in general smaller than the state-clustered ones. [DellaVigna and Pollet \(2007\)](#) deals with this issue by imposing a parametric assumption on the serial correlation. We implement their approach and report the resulting standard errors on row 7. To sum up, table [A.4](#) shows that standard errors are largest when clustering by state.

These results stand in sharp contrast to [Foote \(2007\)](#), who shows that the findings in [Shimer \(2001\)](#) are the weakest with DK errors. Simply put, this finding shows spatial correlation to be less of an issue for our application. Perhaps, the shocks that drive the variation in migration rates over time are less spatially correlated than the ones that drive unemployment rates, as in [Shimer \(2001\)](#).

Another approach is to include additional regressors to soak up some of the spatial correlation in the errors. Of course, to preserve identification, these added regressors should be orthogonal to population shares. We use the measure of state-wide labor demand suggested by [Bartik \(1991\)](#), which we compute as the weighted average of national, industry-level employment growth rates, using state-specific industry employment shares as weights from 1980, as well as region dummies interacted with time. The bottom panel of table [A.4](#) shows the results for this specification using a variety of clusters. Overall, the findings of this section establish the robustness of our inference.

TABLE A.4  
INVESTIGATING THE ROBUSTNESS OF INFERENCE TO RICHER CORRELATION PATTERNS IN  
THE DATA

	Panel A: OLS			Panel B: IV		
	Aggregate	25–40	40–60	Aggregate	25–40	40–60
<b>Baseline specification</b>	−2.510	−2.423	−2.800	−3.8348	−3.4940	−5.9770
Clustered by state (baseline)	0.835***	0.878***	0.992***	1.655**	1.850**	2.386**
Clustered by year	0.432***	0.602***	0.854***	1.220***	1.499**	1.993***
Clustered by state and year	0.709***	0.766***	0.954***	1.847**	1.585**	2.184***
Driscoll and Kraay, 1 lag	0.709***	0.766***	0.954***	1.847**	1.585**	2.184***
Driscoll and Kraay, 3 lags	0.655***	0.718***	0.809***	1.723**	1.470**	1.938***
DellaVigna & Pollet	0.564***	0.782***	0.981***	1.653**	2.001*	2.646**
<b>with Bartik Instruments</b>	−2.4101	−2.1431	−2.8939	−3.6624	−2.4687	−8.0793
Clustered by state	0.787***	0.950**	0.898***	2.048*	1.835*	2.493***
Clustered by year	0.537***	0.632***	1.188**	1.489**	1.541**	2.789***
Clustered by state and year	0.634***	0.757***	0.984***	1.829**	1.662**	2.656***
Driscoll and Kraay, 1 lag	0.634***	0.757***	0.984***	1.829**	1.662**	2.656***
Driscoll and Kraay, 3 lags	0.611***	0.742***	0.929***	1.768**	1.576**	2.278***
DellaVigna & Pollet	0.638***	0.779***	1.257**	0.638***	0.779***	1.257***

Note: Table A.4 shows the standard errors associated with the main variable of interest (middle-aged workers share) and the statistical significance of the coefficient using various clusters. Panel A shows the OLS results, whereas Panel B shows the IV results. The top part of the table shows the results for the baseline specification, while the bottom part adds Bartik measures of labor demand and region-year interactions as additional controls. See the discussion above for a more detailed description of the various estimators.

## C Online Appendix—Not for Publication: Data

Our analysis focuses on the period after 1980. Throughout the paper, we consider two age groups: young workers (25–39) and middle-aged workers (40–60).

Migration rates are computed using micro-data from the Annual Social and Economic Supplement to the Current Population Survey (March CPS). In order to focus on migration that is not

motivated by changes in schooling (in particular, college attendance and graduation) or retirement, we restrict the sample to nonmilitary/civilian individuals who are between the ages of 25 and 60 at the time of the survey. March CPS data are obtained from the Integrated Public Use Micro data Series (King et al. (2010)).<sup>38</sup> The migration variables are not available in 1980, 1985, and 1995. After 1996, we exclude observations with imputed migration data to avoid complications arising due to changes in CPS imputation procedures.<sup>39</sup>

We obtain annual population estimates for various age groups in each state from the Census.<sup>40</sup> Similar estimates can also be obtained using the CPS sample that is used for the computation of migration rates. We use the estimates provided by the Census; however we obtain similar results using CPS figures.

Following Shimer (2001), we obtain exogenous variation in local age composition by instrumenting with lagged birthrates. These are measured in births per thousand residents and are available in the various Statistical Abstracts of the United States.<sup>41</sup> Data are not available for 1941, 1942, and 1943. Therefore, we start using birthrates from 1944 onward. Focusing on the population share of 25–40-year-old implies that our data on lagged birthrates starts in 1984. While we have constructed the CPS inflow and outflow rates for 1981–1983, we do not use these years in the OLS estimates in order to have the same sample with the IV estimates.<sup>42</sup>

We also use other annual data at the state level. These include population, personal income per capita, homeownership rate, unemployment rate, and industrial composition. The Census Bureau provides annual homeownership rates and population estimates.<sup>43</sup> Data on personal income and unemployment are obtained from the Regional Economic Accounts at the Bureau of Economic

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<sup>38</sup>The data can be obtained on <https://cps.ipums.org/cps/>.

<sup>39</sup>See Kaplan and Schulhofer-Wohl (2012) for a detailed explanation.

<sup>40</sup>All population files are downloaded from <http://www.census.gov/popest/data/historical/index.html>.

<sup>41</sup>We are grateful to Rob Shimer for providing us with his data constructed from the Statistical Abstracts for the period 1940–91. Data are unavailable for Hawaii and Alaska prior to 1960. We drop these states entirely from the analysis. This omission does not affect the results in any meaningful way.

<sup>42</sup>We have a full set of OLS results including these years and can provide them upon request. All of the statements in this paper are valid on this larger sample as well. Note also that the elimination of 1981–84 does not guarantee that every specification is estimated on the same sample. Some variables might take on a value of zero for some state-year observations (for example, the mobility rate of middle-aged workers). Such observations are omitted as we estimate the equations in logs.

<sup>43</sup>Home ownership rates for states for the period 1984–2011 are obtained from table 15 on <http://www.census.gov/housing/hvs/data/ann11ind.html>.

Analysis and Local Area Unemployment Statistics at the Bureau of Labor Statistics, respectively.<sup>44</sup> These variables are obtained for the period 1984–2012.

To check the robustness of our findings, we compute state-level migration rates from two alternative sources. First, for the period 1991–2011, we obtain population flows constructed by the Internal Revenue Service computed from tax records. Flows are annual and refer (roughly) to moves between two consecutive Aprils. IRS reports inflow and outflow data for each state in two units: “returns” and “personal exemptions.” The returns data approximate the number of households that move, and the personal exemptions data measure the population.<sup>45</sup> We use personal exemptions.

Second, we use data from the decennial Census (1990 and 2000), which asks retrospective questions about the previous residential state in case of an interstate move. These questions allow us to compute inflow and outflow rates for each state over this period.

Last, we use data from the Income and Program Participation (SIPP). We provide more details about SIPP as it is less commonly used in the migration literature.<sup>46</sup> SIPP is a large representative sample of households interviewed every four months (a “wave”) for two to four years. The first panel begins in 1984, and a new cohort is added around the time when the previous cohort exits. The latest wave that we use was started in 2008, and contains data for years 2008–2013. We have around 10.4 million individual-month observations between 1984 and 2013. Migration information can be constructed in all but the first wave of each panel. Table A.5 presents some summary statistics of our sample. When constructing aggregate or statewide measures, we use the individual weights provided with the survey. As explained in Aaronson and Davis (2011), SIPP is useful for studying migration behavior because it tracks households when they move to different addresses and because it contains various demographic information.<sup>47</sup>

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<sup>44</sup>[http://www.bea.gov/iTable/index\\_regional.cfm](http://www.bea.gov/iTable/index_regional.cfm) and <ftp://ftp.bls.gov/pub/time.series/la/>

<sup>45</sup>Data are available for free on the IRS website for the period 1990–2011 on <http://www.irs.gov/uac/SOI-Tax-Stats-Migration-Data>. This discussion is based on Davis et al. (2010) and Karahan and Rhee (2013), who used county-county population flows to construct MSA-MSA population flows.

<sup>46</sup>Two exceptions we are aware of are Aaronson and Davis (2011) and Guler and Taskin (2012).

<sup>47</sup>Data can be downloaded from [http://thedataweb.rm.census.gov/ftp/sipp\\_ftp.html](http://thedataweb.rm.census.gov/ftp/sipp_ftp.html).



TABLE A.5  
SUMMARY STATISTICS FOR THE SIPP SAMPLE

Variable	Statistic
# Individuals	10,376,325
Married (%)	66.3
Holding a college degree (%)	25.8
In the labor force (%)	80.6
Employed (%)	77.2
Age	41.4

Note: This table shows some summary statistics of the SIPP sample that is used in the paper. Prior to 1996, we impute college attainment by years of schooling. After 1996, we observe the conferral of the degree. A person is counted as employed if they report being continuously employed for a month. A person is counted in the labor force if he is either employed or reports having looked for a job for at least one week.

## D Online Appendix—Not for Publication: Computational Details

This section describes the details of the computation of the model. We first derive the system of equations that are used to solve for the surplus functions and the cost cutoffs for mobility decisions,  $c_{ik}^j$ , in D.1 . D.2 then describes in detail the algorithm used to solve for a steady-state equilibrium.

### D.1 Surplus Functions

There are two types of surpluses that we need to solve for. Recall that  $S_i^j$  denotes the surplus associated with a firm-worker match in the local market, where the worker is of type  $j$ . Similarly,  $S_{ik}^j(c)$  denotes the surplus in the global market associated with a firm-worker match, where the firm is located in  $k$  and the worker is of type  $j$  and located in  $i$ . These objects are defined as follows:

$$S_i^j \equiv J_i^j + W_i^j - U_i^j$$

$$S_{ik}^j(c) \equiv J_k^j + W_k^j - U_i^j - c.$$

We first start with the local surplus:

$$\begin{aligned}
rS_i^j &= y - b - \delta^j S_i^j - \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) S_i^j \\
&\quad - p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} \mathbb{E} \max \left\{ 0, W_k^j - U_i^j - c \right\} \\
\left\{ r + \delta^j + \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) \right\} S_i^j &= y - b - \eta p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} \mathbb{E} \max \left\{ 0, S_{ik}^j(c) \right\} \\
\Rightarrow S_i^j &= \frac{y - b - \eta p_g \sum_{k \neq i} \frac{v_{kg}}{v_g} \mathbb{E} \max \left\{ 0, S_{ik}^j(c) \right\}}{r + \delta^j + \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right)}. \tag{13}
\end{aligned}$$

This final expression is achieved by first substituting in the expressions for the value functions, noticing that the worker always gets  $\eta$ -share of the relevant surplus (local or global) and then solving for  $S_i^j$ . The expectation is with respect to the moving cost distribution of type  $j$  worker,  $G^j$ . Turning to the global surplus function, we proceed similarly to obtain:

$$\begin{aligned}
rS_{ik}^j(c) &= y - b + \Delta_{ki}^j - rc - \delta^j S_k^j - \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) S_i^j - \eta p_g \sum_{v \neq i} \frac{v_{vg}}{v_g} \mathbb{E} \max \left\{ 0, S_{iv}^j(c) \right\} \\
S_{ik}^j(c) &= -c + \frac{1}{r} \left\{ y - b + \Delta_{ki}^j - \delta^j S_k^j - \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) S_i^j \right. \\
&\quad \left. - \eta p_g \sum_{v \neq i} \frac{v_{vg}}{v_g} \mathbb{E} \max \left\{ 0, S_{iv}^j(c) \right\} \right\}, \tag{14}
\end{aligned}$$

where  $\Delta_{ki}^j = \varepsilon_k^j - \varepsilon_i^j$  is the relative preference of the worker for  $k$  over location  $i$ .

Let  $c_{ik}^j$  denote the threshold for moving to location  $k$  from  $i$  for a worker of type  $j$ ; i.e.,  $S_{ik}^j(c_{ik}^j) = 0$ . Note that  $S_{ik}^j$  is linear in  $c$  with a slope of  $-1$ . Let  $S_{ik}^j = a_{ik}^j - c$ . Then,  $a_{ik}^j = c_{ik}^j$ , so that  $S_{ik}^j(c) = c_{ik}^j - c$ . Substituting this into the expressions (13) and (14), we arrive at the fol-

lowing expressions:

$$S_i^j = \frac{y - b - \eta p_g \sum_{v \neq i} \frac{v_{vg}}{v_g} \int^{c_{iv}^j} (c_{iv}^j - c) dG^j(c)}{r + \delta^j + \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right)}. \quad (15)$$

$$S_{ik}^j = -c + \frac{1}{r} \left\{ y - b + \Delta_{ki}^j - \delta^j S_k^j - \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) S_i^j - \eta p_g \sum_{v \neq i} \frac{v_{vg}}{v_g} \int^{c_{iv}^j} (c_{iv}^j - c) dG^j(c) \right\}$$

$$c_{ik}^j = \frac{1}{r} \left\{ y - b + \Delta_{ki}^j - \delta^j S_k^j - \eta \left( p_{il} + \frac{v_{ig}}{v_g} p_g \right) S_i^j - \eta p_g \sum_{v \neq i} \frac{v_{vg}}{v_g} \int^{c_{iv}^j} (c_{iv}^j - c) dG^j(c) \right\}. \quad (16)$$

Note that equations (15) and (16) define the cost cutoffs. Once the cutoffs are obtained, the value of the relevant surplus can be evaluated using (13) and (14).

## D.2 Overview of the Computational Algorithm

This section describes the details of the computation used in this paper.

1. Start with an initial guess of the market tightnesses,  $\{\theta_{il,0}\}$ ,  $\theta_{d,0}$  and vacancy shares,  $\left\{\frac{v_{ig}}{v_g}\right\}_0$ .
2. For each guess of  $\{\theta_{il,n}\}$ ,  $\theta_{d,n}$  and  $\left\{\frac{v_{ig}}{v_g}\right\}_n$  in iteration  $n$ :
  - (a) For each worker type, solve the system of equations given by (15) and (16) to solve the cost cutoffs,  $c_{ik}^j$ .
  - (b) Use equations (13) and (14) to obtain the surplus functions,  $S_{il}^j$  and  $S_{ik}^j$ .
  - (c) Use the law of motions to solve for the steady-state values of employment and unemployment by type and location,  $e_i^j$  and  $u_i^j$ .
  - (d) Compute the deviation from the free-entry conditions in (7) and (8).
  - (e) If the average of squared percentage deviation is less than the tolerance level,  $\varphi = 10^{-6}$ , stop. Otherwise, update the guess for  $\{\theta_{il,n}\}$ ,  $\theta_{d,n}$  and  $\left\{\frac{v_{ig}}{v_g}\right\}_n$  and move to iteration  $n + 1$ .