Population Aging, Migration Spillovers, and the Decline in Interstate Migration*

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Abstract

Interstate migration in the United States has declined by 50 percent since the mid-1980s. We study the role of the aging population in this long-run decline. We document that an increase in the share of old workers in the working age population in one state *causes* a large fall in the migration rate of all workers in that state, regardless of their age. To understand this finding, we develop an equilibrium search model of many locations populated by workers that differ in their moving cost. Firms prefer hiring workers through local channels as this increases their chance of finding local workers who have higher moving costs and thus command lower wages. We show that a change in the composition toward older workers causes firms to recruit more from the local labor market. This increase in the local job-finding rate reduces the migration incentives of all workers, regardless of their age ("migration spillovers"). When calibrated, our model reproduces remarkably well the cross-sectional relationship between population flows and the age structure of the labor force across states. The theory makes strong predictions regarding the behavior of wages and the share of hires from within a state, which we show to be consistent with the data. We use the model to quantify the contribution of the aging population to the long-run decline in migration. Our findings suggest that population aging accounts for as much as 60 percent of the observed decline. Of this effect, almost 80 percent is attributable to the indirect general equilibrium effect.

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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 a job search, or for other job-related reasons.[1] 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.[2] 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 the decline in migration, because migration rates decrease sharply over the life cycle. The migration rate of workers below age 40 is around two times higher than that of workers older than 40.[3] 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 compositional changes in the population is too small to explain much of the decline. Most of the decline is accounted for by a declining trend common across all groups. These empirical observations have led researchers to rule out population aging as a quantitatively viable explanation and look for common factors affecting the migration decisions of everyone in the economy.[4]

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

[2] 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 these of married women decrease.

[3] March CPS; authors' calculation.

[4] 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.

Such logic, however, ignores the possibility that compositional changes may have an indirect general equilibrium effect on migration through the labor market. In this paper, we show, and empirically support, that, in addition to the direct compositonal effect on migration, an increase in the share of old workers in the labor force reduces migration by inducing a lower equilibrium migration rate for *all* workers (*migration spillovers*).

To provide an empirical underpinning to our study of indirect effects, we start by analyzing the cross-state variation in the age composition of population and migration rates. We find that an increase in the share of "old" workers is associated with a lower mobility rate for workers at *all* ages. One possible (and simple) explanation for this finding is that old 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. However, controlling for the possible endogeneity of the age structure in a state by instrumenting it with lagged birth rates, we find even larger elasticities. Our preferred specification suggests that workers between the ages of 25 and 40 are 28 percent less likely to move if they live in a state with a ten percent larger share of old workers. The same figure for those workers older than 40 is almost 60 percent! These results point to massive indirect effects of changes in the age structure of the labor force. To properly account for these effects, we need to understand the economic forces at play. The rest of the paper is dedicated to this task.

Our theory is that an increase in the age composition in a location leads firms to change their recruiting method and direct jobs more towards local workers. If exists, this force can lead all workers to find local jobs at a faster pace, which would explain their low migration rates. To test this theory, we write down an equilibrium search model consisting of many locations that differ in their attractiveness to workers at different ages.[5] Each location is populated by various types of workers whose moving costs differ. Workers can look for jobs in the local market, where they can meet local firms, or in the global market, where they can meet a firm from any location. Similarly, firms in a location can advertise for a position in the local market or in the global market. An important outcome is that high-moving-cost workers in the local market are the most attractive to firms, because their lower outside

(2013) propose a decline in labor turnover as a possible explanation.

[5]This feature is needed to induce heterogeneity across locations in the age composition in a way that is exogenous to the labor market in that location.

option allows firms to hire them at lower wages.

We calibrate a version of the model with 51 states. The model is calibrated it by targeting several labor market and migration-related moments during the 1980s as well as the cross-sectional dispersion of age composition in the data. At no point in the calibration do we target state-specific migration rates. The model reproduces remarkably well the cross-sectional relationship between population flows and the age composition. The mechanism at play is that local job finding rate is higher in states with a higher old population share, so that the migration incentives of all workers decline, resulting in lower mobility for workers in that state, independent of age. We provide evidence in favor of this mechanism, in a much similar fashion, by exploiting cross-state heterogeneity in the age structure. Here, we document that the share of local hires in a state–hires that come from within the state–are higher in states with an older population.

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 only change the population composition to mimic the U.S. population in 2010. The calibrated model generates a decline in migration of 0.9 percentage points. This decline corresponds to around two-thirds of the decline in the data. We find that, of this 0.9 percentage point decline, almost 80 percent is due to migration spillovers and just 20 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 the 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 geographical 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 only a slight increase 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 related to several strands of the literature on migration and labor market. In their seminal 1992 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 which tries to understand worker flows and their interactions with regional labor markets. One such paper, Coen-Pirani (2010), studies cross-sectional properties of gross and net worker flows across states. We differ from Coen-Pirani (2010) in that our emphasis is on the time series of gross flows. Recent literature also studies the interactions between the housing market and gross and net worker flows.[6]

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) develops a tractable island model to study rest and search unemployment. Similar to ours, Lkhagvasuren (2011) and Carrillo-Tueda and Visschers (2013) use an island model with search frictions.[7]

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, our calibration, and the results. Finally, section 4 concludes.

2 Empirical Analysis

We start this section by describing the various data sources used in the analysis. We then 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 using cross-state variation.

2.1 Data

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

[6]Some examples include Aaronson and Davis (2011), Valletta (2013), Ferreira et al. (2012), Schulhofer-Wohl (2011), Modestino and Dennett (2013), Davis et al. (2010), Nenov (2012), and Karahan and Rhee (2013).

[7]Lutgen and Van der Linden (2013) study the efficiency implications of job search opportunities in multiple locations. Similar to Lutgen and Van der Linden (2013), in our paper the worker's job search is not limited to his or her current location.

is not motivated by changes in schooling (for example, 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 is obtained from the Integrated Public Use Micro data Series (King et al. (2010)).[8] After 1996, we exclude observations with imputed migration data to avoid complications arising due to changes in CPS imputation procedures.[9]

We obtain annual population estimates for various age groups in each state from the Census.[10] 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 have verified the robustness of our results.

Following Shimer (2001), we obtain exogenous variation in age-composition by instrumenting with lagged birth rates. These are measured in births per thousand of residents and are available in the various Statistical Abstracts of the United States. We are grateful to Rob Shimer for providing us with his data. As explained in Shimer (2001), data are unavailable for Hawaii and Alaska prior to 1960. We drop these states from the analysis.[11]

To validate the mechanism proposed in this paper, we construct a measure of the share of local hires for each state. More specifically, we want to obtain the fraction of the share of people that find a job in a state that were already residing in the same state during the unemployment spell. This requires the use of a proper panel of workers. We therefore turn to the Survey of Income and Program Participation (SIPP). We provide more details about the SIPP as it is less commonly used in the migration literature.[12] 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. We have around 4.2 million individual-wave observations between 1984 and 2012. Migration information can be constructed in all but the first wave of each panel. Some summary statistics are presented in Appendix B. As explained in Aaronson and Davis

[8] The data can be obtained on https://cps.ipums.org/cps/.

[9] See Kaplan and Schulhofer-Wohl (2012) for a detailed explanation.

[10] All population files are downloaded from `http://www.census.gov/popest/data/historical/index.html`. More detailed information about population estimates is provided in the Appendix.

[11] The omission does not affect the results in any meaningful way.

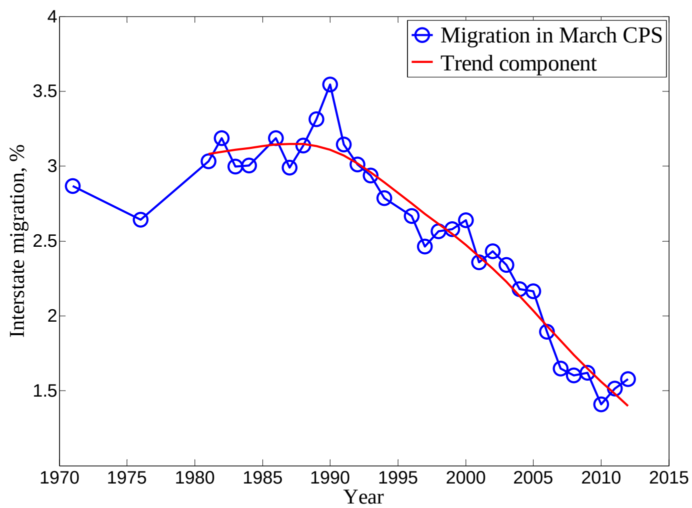
[12] Two exceptions we are aware of are Aaronson and Davis (2011) and Guler and Taskin (2012).

(2011), SIPP is useful to study migration behavior because it tracks households when they move to different addresses, and because it contains various demographic information.[13]

2.2 Aggregate facts

The blue line in figure 1 plots the evolution of interstate gross migration rates from the 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: Interstate migration rate in 2010 is only 50 percent of the same figure in 1980s.

FIGURE 1
INTERSTATE MIGRATION IN THE UNITED STATES



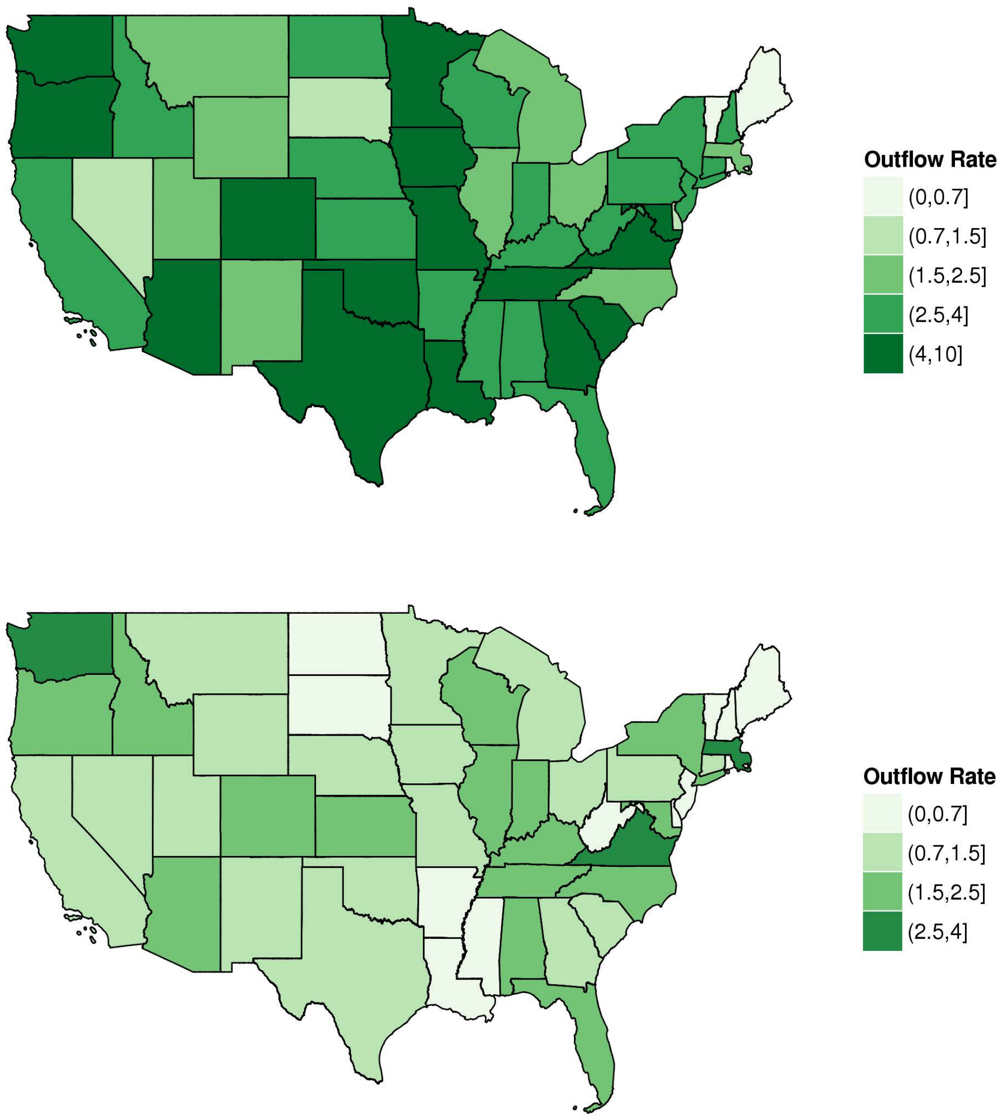
Note: Figure 1 shows the time series of annual interstate migration rates computed from the March CPS. The blue line is the migration rate in the March CPS for the period 1970-2012. Migration rates are computed based on non-imputed observations. The solid red line is the long-run trend of interstate migration rates using Hodrick-Prescott filter for the period 1980-2012.

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 (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 2 shows the spatial nature of the fall

[13]Data can be downloaded from http://thedataweb.rm.census.gov/ftp/sipp_ftp.html.

in migration rates. While the magnitude of the fall is different across states, an important variation to test various theories, migration has fallen virtually in all states. This paper will explain a nontrivial portion of the decline as well as its spatial heterogeneity.

FIGURE 2
SPATIAL NATURE OF MIGRATION RATES

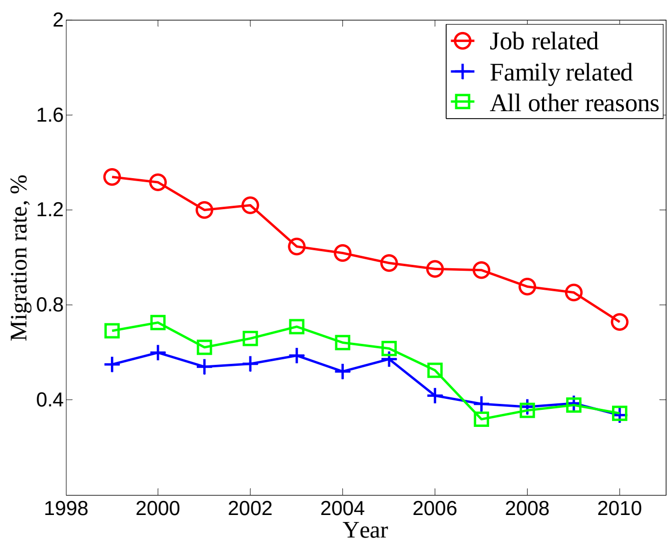


This figure shows two heatmaps that show snapshots of outflow rates across states in the U.S in two different times. The top panel shows the data for 1986 and the bottom panel shows the same for 2010. As these maps show, the decline in migration is a widespread phenomenon across states.

To better understand the nature of the decline in migration, figure 3 shows the fraction of the working-age population that moved across states for different reasons.[14] Of the variety of reasons to move, moves motivated by job-related factors have declined sharply, whereas other moves have changed unnoticeably. This observation rules out theories based on increases in direct moving costs, as such increases would cause lower migration rates in all categories.

One natural candidate for explaining the decline in migration is the aging of the population over the last 30 years. As shown in figure 4, the U.S. population has aged substantially: The fraction of 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 5 plots the interstate migration rate over the working life. People between the ages of 25 and 29 are almost four times more likely to move across states than those aged 50 to 54.

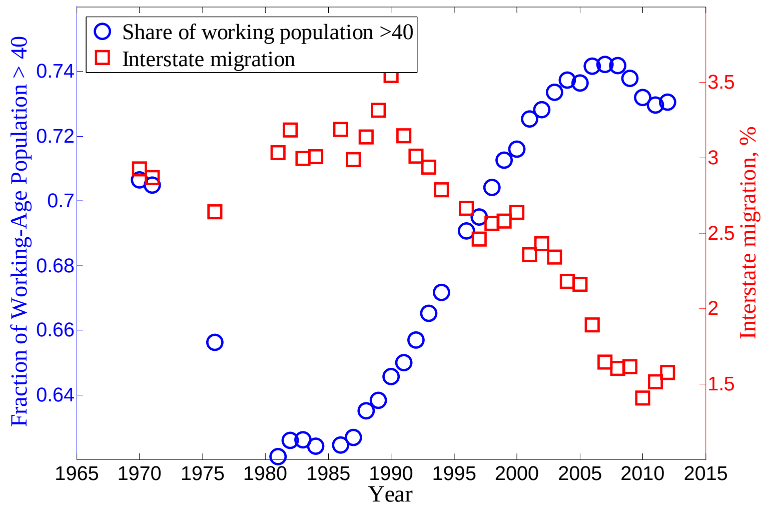
FIGURE 3
REASONS TO MOVE IN THE UNITED STATES



Note: Figure 3 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.

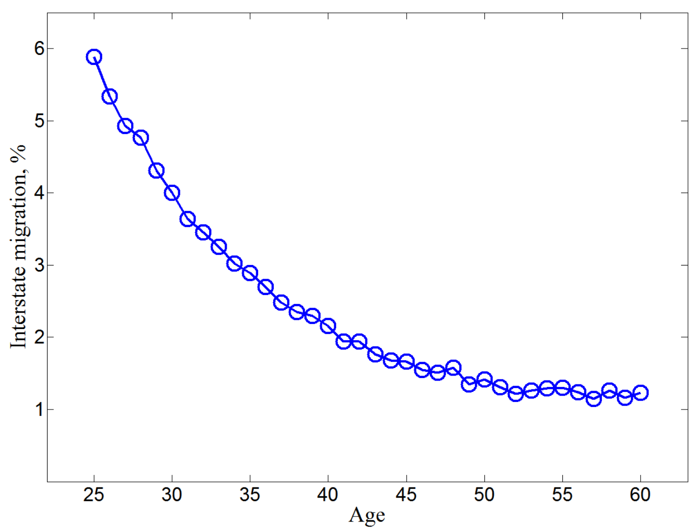
[14] These reasons include job-related factors (e.g., for a new job, job-transfer, job search, easier commute, etc.), family-related factors (e.g., changes in marital status, to establish one's own household, etc.), housing-related factors (e.g., to own, better housing, better neighborhood, etc.), and other reasons (e.g., foreclosure, natural disaster, etc.).

Figure 4
Aging Population in the United States



Note: Figure 4 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 5
Interstate Migration over Working Ages



Note: Figure 5 shows annual interstate migration rates over the working life. Migration rates are computed based on non-imputed observations. The interstate migration rate decreases sharply over the working life and most of the decline occurs before age 40.

The effect of the aging population on interstate migration can be categorized 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 an 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:

$$\hat{m_t} = \sum_i s_{i,t} \times \overline{m}_{i,t}.$$

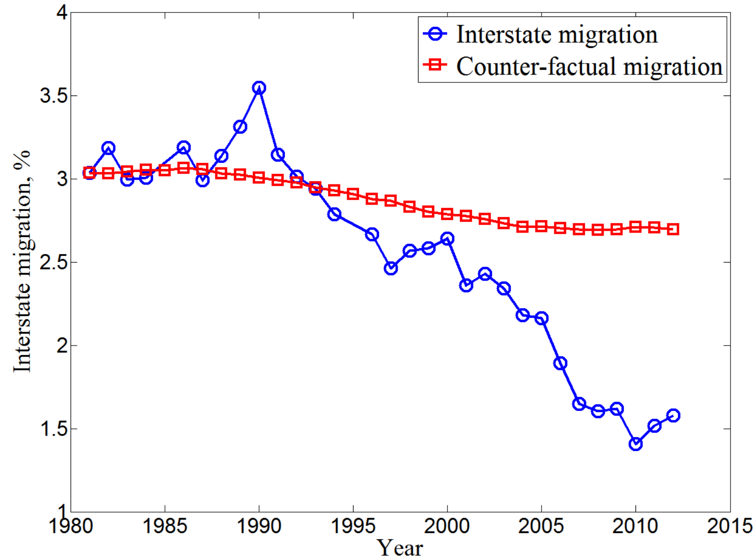
Under this formulation, any change in the migration rate, $\Delta\hat{m}$, is driven by the change in the share of each age group; that is,

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

The red line in figure 6 plots the resulting counterfactual migration rates. The result suggests that the direct effect of the aging population accounts for 20% of the decline.

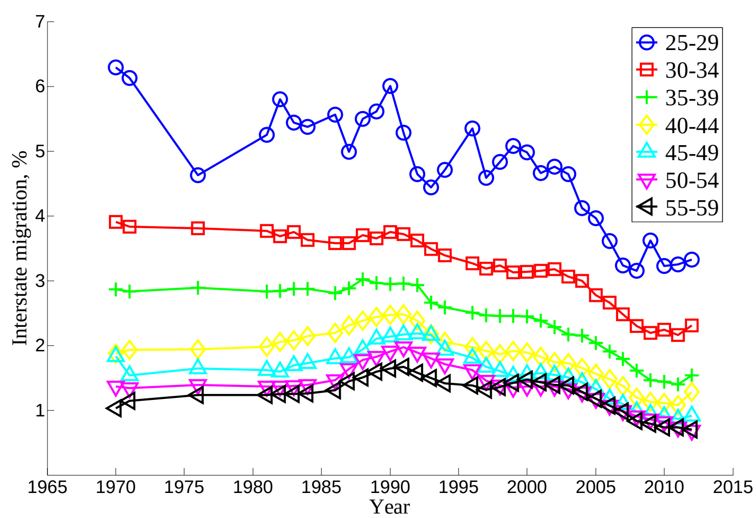
Based on this finding, we investigate how the life-cycle pattern of migration has evolved. Figure 7 plots the migration rates of different age groups. Interstate migration has declined for all ages. This common decline across ages accounts for most of the observed decline in interstate migration. Thus, to understand why migration has declined, we need to understand why migration has fallen for workers at all ages.

Figure 6
Quantifying the Direct Effect of Aging on Interstate Migration



Note: Figure 6 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 7
Time Trend of Interstate Migration over Working Ages



Note: Figure 7 shows the 5-year moving average of interstate migration rates for each age group.

2.3 Cross-state Variation in Population Aging and Migration Rates

Second, changes in the age composition may have indirect effects on migration by changing the age-specific migration rates. 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 young and an old worker if she were to be transferred to a location with a higher share of older workers. 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 the second group as "old 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, $share_{it}$.

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

Here, α_i and β_t denote state and time fixed effects, respectively. ϵ_{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 birth rates across states. To deal with the serial correlation in the residual, standard errors are clustered around state and year.

Table 1
Mobility and the Age Composition

	Panel A: OLS			Panel B: IV		
	Aggregate	25-40	40-60	Aggregate	25-40	40-60
Share 40-60	-1.8102^{***}	-1.7665^{***}	-2.1465^{***}	-3.7902^{**}	-3.7671^{**}	-5.9853^{***}
	(0.512)	(0.621)	(0.734)	(1.655)	(1.850)	(2.258)
R^2	0.686	0.625	0.472	0.686	0.626	0.465
N	1,127	1,124	1,096	1,127	1,124	1,096

Note: Panel A of table 1 shows the OLS estimates of the panel model in (1). Panel B shows the IV estimates, estimated via 2 stage least squares, instrumenting for the age composition with lagged cumulative birth rates. In both panels, standard errors are clustered around state and year.

The left panel of table 1 reports the OLS results. Column 1 shows the results from estimating equation (1) using aggregate migration rate data from 1980 to 2010. The estimated elasticity of migration with respect to the share of "old" workers is -1.8. This coefficient is significantly different from zero at any commonly used confidence level. A ten-percent increase in the share of workers older than 40 is associated with an 18 percent decline in the migration rate out of that location.

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 older states. The magnitude and significance of this coefficient could be entirely driven by the composition effect. More interesting results are presented in the second and third columns of panel A of table 1. An increase in the share of old workers in a state is correlated with a significant reduction in the migration rate of *all* workers, conditional on their age. Quantitatively, the elasticity is twice as large for workers older than 40 (-2.15) than the elasticity of younger workers (-1.77).

IV Results One possible explanation for these results is that old 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 old workers residing in those states move less compared to identical workers in other states. Note that if a state has a less dynamic labor market throughout our sample, this 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. One way to control this issue is to include more controls. While we have established the robustness of our findings in table 1 to other controls, we pursue an alternative route here and use an instrument to establish causal inference.[15] Our instrumental variable strategy follows Shimer (2001) and exploits 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 birth rates in state i from year $t-39$ to $t-25$. The instrument turns out to do a good job in inducing variation in the age composition. In the first stage, we regress the share of old workers on a full set of state and time dummies and the birth rate. 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.

Panel B of table 1 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 old 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 old workers. A young worker would be 37 percent less likely to move if she were to live in a state with a ten percent larger share of old workers. The same figure for an old worker is 60 percent.[16]

The next question that we tackle in this paper is what explains these patterns? What is it that makes workers that live in states with an older population move less? Section 3 presents a mechanism through which compositional changes affect group-specific migration rates. The theory that we propose is based on a composition externality of old workers on the local labor market. It predicts that an increase in the share of old workers in a local labor market causes firms to recruit from their local labor market and thereby lowers the

[15] We have included state-wide measures of personal income, industrial composition, homeownership rate, college completion rate, and marriage rate to the specification in (1). The coefficient on age composition is always negative and significant for all age groups and is quantitatively similar, in a statistical sense, to those reported in table 1.

[16] If old 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 measurement error in the population estimates.

equilibrium migration rate for *all* individuals (migration spillovers).

3 Understanding Cross-sectional Facts

The economy consists of two locations, A and B, that are populated by N types of infinitely lived workers. Workers of various types differ in their moving costs and their permanent preference for A over B. Workers have preferences that are ordered according to

$$\Sigma_{t=0}^{\infty} u_j \left(c_t, \epsilon_i \right),$$

where i is the worker's type, j denotes his location in period t, c_t is his consumption, and ϵ_i is his preference for A. We assume linear utility and express the utility function u as

$$u_j \left(c, \epsilon \right) = \begin{cases} c + \epsilon & \text{if } j = A \\ c - \epsilon & \text{if } j = B. \end{cases}$$

ϵ is distributed according to a normal distribution with mean $\mu_{\epsilon,i}$ and variance σ^2.

A worker can be employed or unemployed. At the beginning of the period, unemployed workers decide whether they want to move to the other location. After job destruction, shocks are realized and labor markets open. Firms post vacancies, and unemployed workers look for jobs. Job search consists of two stages. In the local job search stage, workers apply for jobs in their own location. This is followed by a distant search, in which those workers that were unable to secure a local job decide whether to look for a job in the other location. Once all local and distant matches are formed, the migration stage opens. Finally, production is made, and wages are paid out. The following describes the timing of events within a period:

1. Unemployed workers migrate to their preferred location.

2. Separation shock hits existing matches with probability δ.

3. The local labor market opens: unemployed workers look for local jobs.

4. The distant labor market opens: unemployed workers that could not find a local job decide whether to look for a job in the other location.

5. Workers who accept an offer from the other location pay the moving cost and move.

6. Production is made, and wages are paid.

Similar to the simple model, there are four different market tightnesses that govern job- and worker-finding probabilities for workers and firms, respectively. Let θ_l^j and θ_d^j denote the market tightnesses in the local and distant labor markets in location j.

3.0.1 Value Functions and Decision Rules

The following equations describe the value of employment and unemployment to workers residing in A and B:

$$\begin{aligned}
W^A(w,\epsilon,\mu) &= w+\epsilon+\beta\left[(1-\delta)W^A(w,\epsilon,\mu)+\delta U^A(\epsilon,\mu)\right] \\
W^B(w,\epsilon,\mu) &= w-\epsilon+\beta\left[(1-\delta)W^B(w,\epsilon,\mu)+\delta U^B(\epsilon,\mu)\right] \\
U^A(\epsilon,\mu) &= b+\epsilon+\beta\left[\max\left\{\Sigma^A(\epsilon,\mu),\Sigma^B(\epsilon,\mu)-\mu\right\}\right] \\
U^B(\epsilon,\mu) &= b-\epsilon+\beta\left[\max\left\{\Sigma^A(\epsilon,\mu)-\mu,\Sigma^B(\epsilon,\mu)\right\}\right],
\end{aligned} \tag{2}$$

where Σ^j is the value of being in location j at the beginning of the local job search stage. It is given by

$$\begin{aligned}
\Sigma^j(\epsilon,\mu) &= p\left(\theta_l^j\right)W^j\left(w_l^j(\epsilon,\mu),\epsilon,\mu\right)+\left(1-p\left(\theta_l^j\right)\right)\Delta^j(\epsilon,\mu) \\
&= \Delta^j(\epsilon,\mu)+p\left(\theta_l^j\right)\left\{W^j\left(w_l^j(\epsilon,\mu),\epsilon,\mu\right)-\Delta^j(\epsilon,\mu)\right\}.
\end{aligned}$$

Here, $w_l^j(\epsilon,\mu)$ is the equilibrium wage in the local labor market of j to a worker with preference ϵ and moving costs μ, and Δ^j represents the value of participating in the distant job search in the other location, $-j$, while residing in location j, and is given by

$$\begin{aligned}\Delta^{j}\left(\epsilon,\mu\right) &= \max\left\{U^{j}\left(\epsilon,\mu\right),p\left(\theta_{d}^{-j}\right)\left(W^{-j}\left(w_{d}^{-j}\left(\epsilon,\mu\right),\epsilon,\mu\right)-\mu\right)+\left(1-p\left(\theta_{d}^{-j}\right)\right)U^{j}\left(\epsilon,\mu\right)\right\} \\ &= U^{j}\left(\epsilon,\mu\right)+\max\left\{0,p\left(\theta_{d}^{-j}\right)\left(W^{-j}\left(w_{d}^{-j}\left(\epsilon,\mu\right),\epsilon,\mu\right)-\mu-U^{j}\left(\epsilon,\mu\right)\right)\right\}.\end{aligned}$$

Here, $w_{d}^{-j}\left(\epsilon,\mu\right)$ is the equilibrium wage in the distant labor market of $-j$ to a worker with preference ϵ and moving cost μ.

For firms, the value of employing a worker at a fixed wage w is denoted by $J(w)$ and is given by

$$J\left(w\right)=y-w+\beta\left(1-\delta\right)J\left(w\right). \tag{3}$$

It is easy to show that the migration behavior of all types of workers is characterized by cutoff rules. For each type, these rules are summarized by four cutoff preferences: $\epsilon_{A,l}\left(\mu\right),\epsilon_{B,l}\left(\mu\right),\epsilon_{A,d}\left(\mu\right)$, and $\epsilon_{B,d}\left(\mu\right)$.[17] The cutoff $\epsilon_{A,l}$ governs the migration decision for a worker residing in A at the beginning of the period. Workers with $\epsilon\geq\epsilon_{A,l}\left(\mu\right)$ decide to stay in A and engage in a local job search there. Workers with $\epsilon<\epsilon_{A,l}\left(\mu\right)$ move to B before a local job search begins. This cutoff is defined by the following equation:

$$\Sigma^{A}\left(\epsilon_{A,l}\left(\mu\right),\mu\right)=\Sigma^{B}\left(\epsilon_{A,l}\left(\mu\right),\mu\right)-\mu. \tag{4}$$

Similarly, we define $\epsilon_{B,l}\left(\mu\right)$ as follows:

$$\Sigma^{A}\left(\epsilon_{B,l}\left(\mu\right),\mu\right)-\mu=\Sigma^{B}\left(\epsilon_{B,l}\left(\mu\right),\mu\right). \tag{5}$$

Workers residing in B move to A at the beginning of the period, only if their preference parameter ϵ is higher than $\epsilon_{B,l}\left(\mu\right)$.

$\epsilon_{A,d}\left(\mu\right)$ and $\epsilon_{B,d}\left(\mu\right)$ govern the cutoff preferences for participating in the distant labor

[17] This cutoff property arises because the auxiliary value functions $\left\{\Sigma^{j},U^{j},W^{j}\right\}_{j\in\{A,B\}}$ are strictly monotonic with respect to ϵ.

market, and they are defined by the following equations:

$$U^A\left(\epsilon_{A,d}\left(\mu\right),\mu\right) = W^B\left(w,\epsilon_{A,d}\left(\mu\right),\mu\right)-\mu \tag{6}$$

$$U^B\left(\epsilon_{B,d}\left(\mu\right),\mu\right) = W^A\left(w,\epsilon_{B,d}\left(\mu\right),\mu\right)-\mu. \tag{7}$$

An individual living in A that could not find a local job decides to try his chance in the distant job market of B if and only if $\epsilon < \epsilon_{A,d}\left(\mu\right)$. Similarly, residents of B that did not secure a job in B apply for positions in A if and only if $\epsilon > \epsilon_{B,d}\left(\mu\right)$.

A consequence of having four cutoff values describing migration behavior in the model is that there are five possible categories of migration patterns:

1. A-lover: $\epsilon_{A,d} \leq \epsilon$. A worker in this category always lives in A and does not look for a job in B.

2. Weak preference for A: $\epsilon_{A,l} < \epsilon < \epsilon_{A,d}$ and $\epsilon > \epsilon_{B,l}$. A worker in this category lives in A and moves to B only if he cannot find a job in A and finds a job in B. This worker moves back to A immediately upon losing the job in B.

3. Status quo: $\epsilon_{A,l} < \epsilon < \epsilon_{A,d}$ and $\epsilon_{B,d} < \epsilon < \epsilon_{B,l}$. A worker in this range prefers his current location and moves only if the local job search turns out to be unsuccessful and a distant offer comes along.

4. Weak preference for B: $\epsilon_{B,d} < \epsilon < \epsilon_{B,l}$ and $\epsilon < \epsilon_{B,l}$. Such a worker stays in B while unemployed and moves to A only in the event of a job offer from A. He returns to B immediately after the job in A is terminated.

5. B-lover: $\epsilon < \epsilon_{B,d}$. A worker in this category always stays in B and never participates in the distant labor market of A.

3.0.2 Wage Determination

We now describe the wage determination between a worker and a firm. Workers and firms meet in the local and distant labor markets. Upon meeting, they decide on the wage by engaging in Nash bargaining. For simplicity, we assume that firms offer a fixed-wage contract.[18] The bargaining problem in the local labor market is given by

$$w_l^j(\epsilon,\mu) = \arg\max\left[W^j(w,\epsilon,\mu) - \Delta^j(w,\epsilon,\mu)\right]^{\eta} J(w)^{1-\eta}. \tag{8}$$

Note that the outside option of the worker in the local bargaining problem is Δ^j and includes the option value of searching in the distant labor market. Similarly, the bargaining problem in the distant market is given by

$$w_d^j(\epsilon,\mu) = \arg\max\left[W^j(w,\epsilon,\mu) - \mu - U^{-j}(w,\epsilon,\mu)\right]^{\eta} J(w)^{1-\eta}. \tag{9}$$

3.0.3 Steady-State Equilibrium

We now define a steady-state equilibrium of this model. Let $u^j(\epsilon,\mu)$ denote the steady-state measure of unemployed workers with preference ϵ and moving cost μ in location j.[19] We assume free entry of firms. This ensures that in equilibrium, firms expect to make zero profit from creating a vacancy in each market. Equations (10)−(12) describe the zero profit conditions in the distant and local markets of A and B:

$$\kappa = q\left(\theta_l^j\right)\sum_{i=1}^{N}\frac{\int u^j(\mu_i,\epsilon)\, J\left(w_l^j(\mu_i,\epsilon)\right)}{\sum_{i=1}^{N}\int u^j(\mu_i,\epsilon)}, \quad j\in\{A,B\} \tag{10}$$

$$\kappa = q\left(\theta_d^A\right)\sum_{i=1}^{N}\frac{\int u^B(\mu_i,\epsilon)\, J\left(w_d^A(\mu_i,\epsilon)\right)\mathbb{I}_{\left\{\epsilon>\epsilon_{B,d}(\mu_i)\right\}}}{\sum_{j=1}^{N}\left(1-p_l^B\right)\int u^B(\mu_j,\epsilon)\,\mathbb{I}_{\left\{\epsilon>\epsilon_{B,d}(\mu_i)\right\}}} \tag{11}$$

$$\kappa = q\left(\theta_d^B\right)\sum_{i=1}^{N}\frac{\int u^A(\mu_i,\epsilon)\, J\left(w_d^B(\mu_i,\epsilon)\right)\mathbb{I}_{\left\{\epsilon<\epsilon_{A,d}(\mu_i)\right\}}}{\sum_{j=1}^{N}\left(1-p_l^A\right)\int u^A(\mu_j,\epsilon)\,\mathbb{I}_{\left\{\epsilon<\epsilon_{A,d}(\mu_i)\right\}}} \tag{12}$$

Definition 1. A steady-state equilibrium consists of value functions $\{W^j, U^j, J\}_{j\in\{A,B\}}$, a set of cutoff values $\{\epsilon_{j,l},\epsilon_{j,d}\}_{j\in\{A,B\}}$, a set of wages $\left\{w_l^j, w_d^j\right\}_{j\in\{A,B\}}$, a set of steady-state unemployment measures $\{u^j\}_{j\in\{A,B\}}$, and a set of market tightnesses $\left\{\theta_l^j,\theta_d^j\right\}_{j\in\{A,B\}}$, such that:

[18] Because of the assumption of risk-neutral preferences and exogenous match destruction, this assumption is innocuous.

[19] Derivation of these steady-state unemployment measures are in appendix C.

1. The value functions satisfy equations in (2) and (3),
2. The cutoff values solve (4)−(7),
3. Wages solve the Nash bargaining problems in (8) and (9),
4. Steady-state unemployment measures satisfy the law of for labor market,
5. Market tightnesses satisfy the free-entry conditions in (10)−(12).

Given the tractability of the model, one can derive closed-form equations for the cutoff values and express these values in terms of labor market tightnesses. Further details on computation can be found in appendix C.4.

3.1 Calibration

We have presented a quantitative model to study the effect of compositional changes in the population on migration.[20] We now turn to the calibration of this model and evaluate the role of population aging in declining migration rates. Each type of worker in the model corresponds to a specific age group in the data. We calibrate the model to match a number of targets related to mobility and labor markets. This section provides the details of the calibration.

3.1.1 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 the Simulated Method of Moments and targets moments computed using data from around the 1980s.

[20]It is worth emphasizing that the model is general and that it 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.

Functional Forms: Following Menzio and Shi (2011) and Schaal (2012), we pick the contact rate functions with a constant elasticity of substitution,

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

for both local and distant labor markets. The parameter γ governs the elasticity of the matching function. We assume that the preference for A is distributed according to a normal distribution with a type-specific mean and a constant variance.

Parameters Calibrated a Priori: A period in the model corresponds to a month. We focus on seven age groups between the ages of 25 and 59 and set the number of types, N, to seven. These age groups correspond to individuals aged 25−29, 30−34, 35−39, 40−44, 45−49, 50−54, and 55−59. The share of each age group in the population is computed from the March CPS using data in 1981. These shares are reported in column 3 of table 2.

Table 2
Migration rates across age groups

Age group	Average interstate migration rate	Share in 1980	Share in 2010
25-29	5.0%	19.9%	13.0%
30-34	3.5%	18.4%	13.8%
35-39	2.6%	15.3%	14.6%
40-44	1.9%	12.4%	15.2%
45-49	1.5%	11.0%	15.7%
50-54	1.3%	11.5%	14.1%
55-59	1.2%	11.6%	13.6%

Note: Table 2 shows migration rates for people in various age groups computed over the period 1980-1985. Source: March CPS and authors' calculations.

To calibrate the job destruction rate, we take the average of job destruction rates in Shimer (2012) over the period 1950−1985.[21] As a result, δ is set to 3.4 percent. The time discount rate β is set to $0.99^{1/12} = 0.99916$ to match an annual discount rate of 0.99. The bargaining parameter η is set to 0.5. The flow utility of unemployment is taken from Hall and Milgrom (2008) and set to 0.71.

[21] 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.

Table 3
Model Parameters

Parameter	Value	Description
Pre-calibrated		
β	$0.99^{1/12}$	time discount rate
δ	3.4%	job destruction probability
b	0.71	flow utility of being unemployed
η	0.5	Nash Bargaining power of workers
Within-the-Model		
γ	1.1	elasticity of matching function
κ	0.24	cost of posting a vacancy
σ_ϵ	0.0006	standard deviation of preference type
$\mathbb{E}\epsilon_1$	-0.0007	mean of preference distribution by age group
$\mathbb{E}\epsilon_2$	-0.0008	
$\mathbb{E}\epsilon_3$	-0.0015	
$\mathbb{E}\epsilon_5$	0.0012	
$\mathbb{E}\epsilon_6$	0.0013	
$\mathbb{E}\epsilon_7$	0.0016	
μ_1	0.11	moving cost by age group
μ_2	0.20	
μ_3	0.25	
μ_4	0.31	
μ_5	0.32	
μ_6	0.42	
μ_7	0.42	

Note: Table 3 reports the estimated values of model parameters.

Parameters Calibrated with the Simulated Method of Moments: There are 16 remaining parameters to be estimated. These are the elasticity of the matching function, γ, the vacancy posting cost, κ, the variance of the preference distribution, the σ_ϵ, means of the preference distribution for each age group, $\{\mathbb{E}_i\epsilon\}_{i=1}^N$, and the moving cost for each age group, $\{\mu_i\}_{i=1}^N$.[22] We use a simplex-based algorithm to minimize the percentage deviation of model-generated moments from their empirical counterparts. The parameters and their estimated values are summarized in table 3.

3.1.2 Targets

We now describe the empirical targets that we use in the estimation. We target the average job-finding rate, the elasticity of the job-finding rate with respect to market tightness, and

[22] The mean of ϵ for type 4 is normalized to 0 to achieve identification.

the elasticity of out-migration with respect to the local unemployment rate. In the data, the elasticity of out-migration with respect to local unemployment is around 0.21. The model counterpart of this measure is defined as the ratio of the log difference in the outflow of workers divided by the log difference in unemployment rates between A and B. To get estimates of the moving-cost parameter for each type, μ_j, we target the interstate migration rates for each of the seven age groups in 1981.

TABLE 4
MATCHING THE CALIBRATION TARGETS

Moment		Data	Model
Average job finding rate		0.395	0.398
Elasticity of job finding rate w.r.t. market tightness		0.72	0.79
Elasticity of out migration w.r.t. local unemployment rate		0.21	0.42
Annual migration rate by age group	25 – 29	5.42%	5.21%
	30 – 34	3.93%	3.98%
	35 – 39	3.06%	2.87%
	40 – 45	2.03%	2.30%
	45 – 49	1.97%	2.06%
	50 – 54	1.44%	1.48%
	55 – 59	1.43%	1.43%
Population share difference by age group: A-B	25 – 29	1.03%	0.96%
	30 – 34	0.90%	0.81%
	35 – 39	1.37%	1.59%
	40 – 45	−0.63%	−0.22%
	45 – 49	−0.85%	−0.88%
	50 – 54	−0.96%	−1.0%
	55 – 59	−1.35%	−1.70%

Note: Table 4 shows the model's fit on targeted moments of the data.

Finally, we need to specify how much heterogeneity to generate between A and B in the age composition of the population. To get the targets, we construct for each state-year observation, the share of the seven age groups in that state. We then take the standard deviation of these shares across all observations. We require the difference between the share of age group i in A and that in B to differ by one standard deviation.

The estimation minimizes the equally weighted sum of squared percentage deviations of model moments from the targets. Table 4 summarizes the moments used in the estimation and provides the fit of the model to the targeted moments.

3.2 Evaluating the Model's Performance on Cross-Sectional Facts

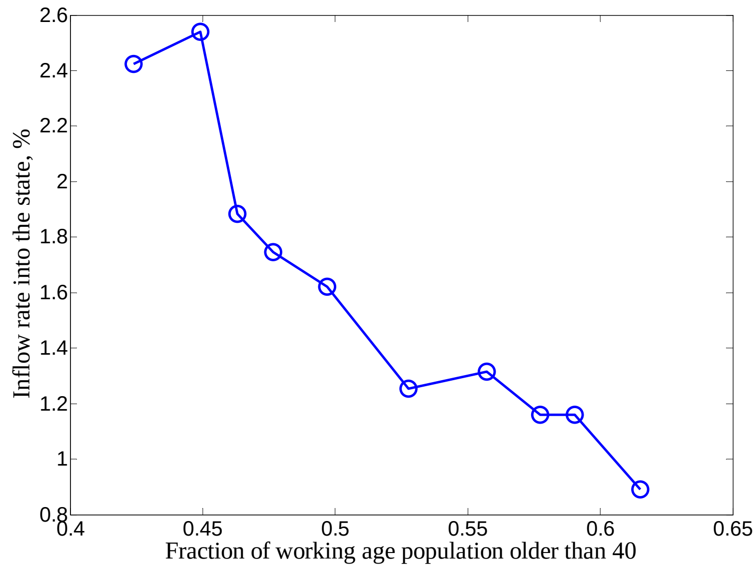
Before turning to the implications of an aging population for the time series of migration, we assess the model's performance on several nontargeted moments. We study the relationship between the age composition and population flows across states and document two new cross-sectional facts. First, states with an older population receive fewer inflows than those with a younger population. Second, for each state we compute the fraction of local hires, defined as the fraction of hires from state residents among all hires in the state. We find this fraction to be higher in states with an older population.[23] We use these facts to evaluate our estimated model and find it to be quantitatively consistent with both of these facts.

3.2.1 Age Composition and Population Inflows

Our first fact is regarding the cross-sectional relationship between inflows and age composition. Figure 8 reveals a systematic correlation between the age composition and migration flows: states with an older working population, as measured by the fraction of individuals above age 40, have a lower inflow rate. The differences are large: a state with a 10 percentage point higher share of older population receives an inflow that is around 0.9 percentage point lower.

[23] For details on data sources, sample selection, and variable definitions, see appendix B.

Figure 8
Demographics and Inflow Rate across States



Note: Figure 8 shows the cross-sectional relationship between the fraction of older population and the inflow rate across states. We first group the states in 10 percentiles according to the fraction of individuals older than 40. The x-axis is the mean of this fraction over all states in a percentile, whereas the y-axis is the average inflow rate of states in a percentile. The figure shows that states with a higher fraction of older population receive less inflows. Source: IRS population flows, March CPS, and authors' calculations.

Tables 12 and 13 in appendix A present several regression results measuring the elasticity of inflows with respect to the age composition. The tables further show that the negative relationship is robust to controlling for various state-level variables and fixed effects.[24] To compute the model counterpart of this cross-sectional elasticity, we divide the difference of the log inflow rates across the two locations by the corresponding difference in the log of age composition. The results are reported in table 5. The calibrated model is quantitatively consistent with the cross-sectional relationship.

[24]We also study the relationship between the age composition in a state and outflow rates using data from the SIPP. In particular, we are interested in how the out-migration propensities of two similar individuals that live in states with different age compositions differ. Table 10 reports the marginal effects of various regressors computed from probit regressions. Column (1) shows that among observationally similar individuals, those residing in states with an older population have lower outflow rates. Columns (2) and (3) show a similar fact across different ages: both young and old individuals living in states with an older population have lower out-migration rates. Table 11 shows that these relationships are robust to controlling for fixed effects.

Table 5
Elasticity of Inflows: Model vs. Data

	Data	Model
Elasticity of the inflow rate	−4.42	-4.83
w.r.t. share of population > 40	(0.571)	

3.2.2 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. Using data from the SIPP, we compute the fraction of local hires out of total hires for each state-year combination. The number of total hires is defined as everyone in the state who reports being unemployed three months 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.

Table 6
Elasticity of the Local Hires: Model vs. Data

	Data	Model
Elasticity of the share of local hires	0.475	0.424
w.r.t. share of population > 40	(0.209)	

In the data, we compute the elasticity of the share of local hires with respect to the share of population older than 40. The model counterpart is computed by dividing the difference of the log of the local hire share across the two locations by the corresponding difference in the log of age composition. Table 6 summarizes the result of this exercise. We find the magnitude of the cross-sectional correlation computed in the model to be in line with that in the data.

3.2.3 Migration Spillovers and the Cross-Sectional Facts

How does the model explain the cross-sectional correlations between age composition and population flows? The intuition behind the model's success in explaining the cross-sectional facts is based on a general equilibrium effect. In the location with an older population, posting a vacancy in the local market is more profitable than posting it in the distant market. Consequently, in the location with the older population, the job-finding rate in the local market is higher and the job-finding rate in the distant market lower. These differences in the recruiting behavior of firms cause the older location to receive fewer inflows. The same mechanism is responsible for the higher local hires in the older location. In this location, firms post a relatively higher share of their vacancies in the local labor market and end up hiring more of their workforce from the resident pool.

It is worth emphasizing that both cross-sectional predictions of the model are due to the general equilibrium effects: firms' recruiting behavior depends on the age composition of the population. We conclude that the general equilibrium effect is not only important to measuring correctly the effect of aging population on migration, as we find in section 3.3, but also important to understanding key cross-sectional facts.

3.3 Implications of the Aging Population on Interstate Migration

We now use the estimated model to study the implications of the aging U.S. population on interstate migration. Our main result concerns the role of aging in explaining the decline in interstate migration.

3.3.1 Effect of Aging on Aggregate Migration Rates

To evaluate the role of the aging population, we change the shares of each age group to their empirical counterparts in 2010. These shares are reported on the last column of table 2. We solve for the equilibrium of the estimated model and report equilibrium migration rates. Table 7 reports the results of this exercise. The first row of the table shows that the model generates a decline in interstate migration by 0.9 percentage point. This is about 59 percent of the 1.5 percentage point observed decline in the data.

Table 7
Migration: Data vs. Model

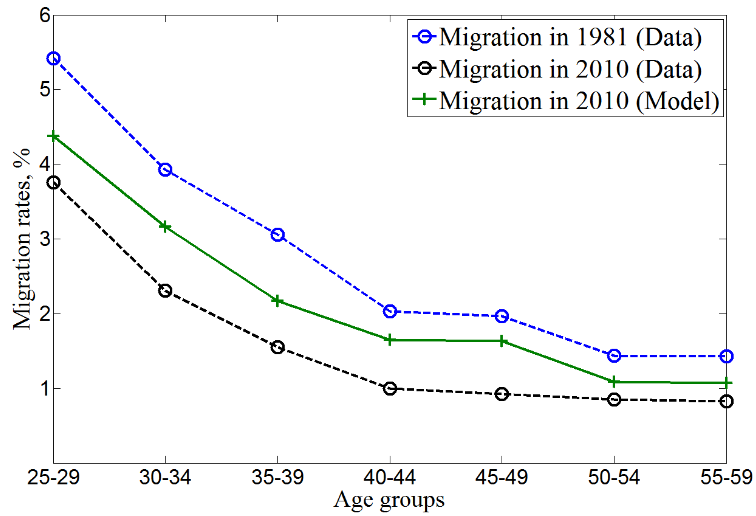
		Data		Model	
		1981	2010	1981	2010
Aggregate interstate migration		3.08%	1.56%	3.0%	2.1%
Interstate migration rate by age group	25 – 29	5.4%	3.8%	5.2%	4.4%
	30 – 34	3.9%	2.3%	4.0%	3.2%
	35 – 39	3.1%	1.6%	2.9%	2.2%
	40 – 45	2.0%	1.0%	2.3%	1.6%
	45 – 49	2.0%	0.9%	2.1%	1.6%
	50 – 54	1.4%	0.8%	1.5%	1.1%
	55 – 59	1.4%	0.8%	1.4%	1.1%

Note: Table 7 reports aggregate and age-specific migration rates in 1981 and 2010. Annual migration in the model is computed as the fraction of all population who move at least once in a 12-month period. Data counterpart is computed from the March CPS and detrended using an HP filter with a scaling parameter of 100.

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 of 2010. This effect accounts for a 0.2 percentage point decline, consistent with the accounting exercise reported in section 2. The remainder of the decline in migration, 0.7 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 9 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. 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 of aging on migration understate the effect of the aging of the U.S. population.

Figure 9

Quantifying the Importance of Migration Spillovers



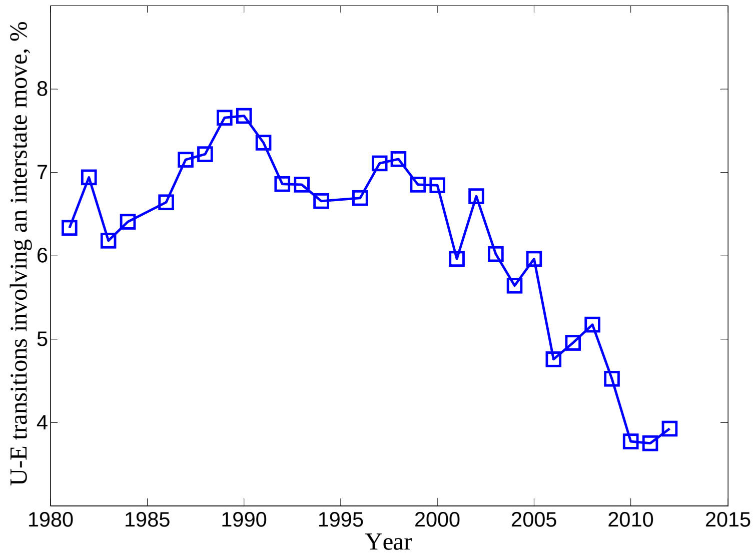
Note: Figure 9 shows the migration rates of different age groups from the data and compare the model counterparts. The x-axis is the seven age groups used in our estimation. The y-axis is the migration rate. The blue dashed line is the migration rate of each age group in 1980 and the black dashed line is for 2010. The green solid line is computed from the estimated model with population share of 2010.

3.3.2 Other Predictions of Migration Spillovers: The Share of New Hires Involving Migration

Recall that the model generates a decline in migration through the general equilibrium effect in the labor market. The local job-finding rate increases and the distant job-finding rate decreases with population aging. Thus, the theory predicts that as the population ages, a larger fraction of hires in the economy should be from the local labor market. To test this prediction, we compute the fraction of hires in CPS in a 12-month period that involves an interstate move. More specifically, we compute the number of workers that report a positive unemployment spell in the last year but are employed at the time of the survey. This is our measure of the total number of hires. We then divide the number of workers in this group that also report an interstate move by total hires. Figure 10 shows the time series of this measure and provides evidence in favor of the theory.

To compare the quantitative predictions of the model with the data, in table 8, we report the model counterpart of the fraction of hires involving an interstate move in 1981 and 2010, and compare them to the data. As table 8 shows, the model generates a 46 percent decline in hires with an interstate move, the same in magnitude as the decline in the data.

Figure 10
Fraction of Hires Involving an Interstate Move



Note: Figure 10 shows the time series of the fraction of hires that involve an interstate move. The denominator is the number of individuals aged 25-59 that report a positive number of weeks of unemployment in the last year. The numerator is those that also report an interstate move (March CPS and authors' calculations).

Table 8
Fraction of Hires with an Interstate Move: Data vs. Model

	Data	Model
Fraction of local hires in 1980, %	7.0	8.9
Fraction of local hires in 2010, %	3.7	4.8
Change: 1980-2010	−47%	−46%

Note: Table 8 shows the predictions of the model for the fraction of hires involving an interstate move and compares it to the data from the CPS. The last row shows that the model generates a decline quantitatively similar to that in the data.

3.3.3 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.

Table 9
Aging Population and Unemployment

	1980	2010	Change
Aggregate unemployment rate, %	8.16	8.37	0.21

Note: Table 9 shows the implications of the aging population for the aggregate unemployment rate in the model.

Table 9 reports the aggregate unemployment rate in the model. Despite a large drop in migration, unemployment increases only slightly in 2010 over that in 1980. As we explained earlier, 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 on the unemployment rate arises because the increase in local job-finding rates partly offsets the negative effect from the compositional change.

4 Conclusion

This paper has studied the long-run decline in interstate migration. We showed analytically that there is a positive composition externality of workers with high moving costs on the local labor market. As the share of these workers increases, local jobs become easier to find and the migration rates of *all* workers decline in equilibrium. This mechanism illustrates that changes in population composition have not only a direct effect on migration but also an indirect effect through general equilibrium.

Our quantitative analysis suggests that population aging explains nearly two-thirds of the decline in the data, and that most of this decline is accounted for by the general equilibrium effect. We also find that the general equilibrium effect is important in understanding several cross-sectional facts about population flows and the age-composition across states.

The migration spillover effect defined by this paper has implications for other themes in the mobility literature. One line of literature examines the effect of housing market imperfections on labor mobility. Our theory implies that these imperfections may also affect the migration rate of renters. Therefore, one cannot identify the effect of housing market imperfections on labor mobility by treating renters as the control group and homeowners as the treatment group. Another important trend in the labor market in the United States is the long-run decline in job-to-job transitions. A large fraction of this decline in the labor turnover rate is due to the within-group component. We think that a similar general equilibrium effect might be in place, and that the aging population may have larger impact on the decline in labor turnover than the direct compositional effect. We plan to investigate these issues in further research.

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A Additional Figures and Tables

Table 10
State demographics and outflows

VARIABLES	(1) All Population	(2) Older than 40	(3) Younger than 40
Log Income	-0.0003***	-0.0002*	-0.0005***
	(0.0000)	(0.0000)	(0.0001)
Age	-0.0009***	0.0000	-0.0021***
	(0.0000)	(0.0000)	(0.0006)
Age Squared	8.37e-06***	2.49e-07	2.37e-05***
	(0.0000)	(2.76e-06)	(0.0000)
College Binary	0.0036***	0.0014***	0.0069***
	(0.0003)	(0.0003)	(0.0004)
Employment Indicator	-0.0082***	-0.0069***	-0.0111***
	(0.0006)	(0.0006)	(0.0010)
Labor Force Indicator	0.0028***	0.0024***	0.0036***
	(0.0002)	(0.0002)	(0.0003)
Married Indicator	0.0002	0.0005***	0.0000
	(0.0002)	(0.0002)	(0.0003)
Share Above 40	-0.0101***	-0.0064**	-0.0159***
	(0.0028)	(0.0026)	(0.0052)
State Population	-0.0014***	-0.0008***	-0.0023***
	(0.0001)	(0.0001)	(0.0002)
State Unemployment	0.0000	0.0002	0.0000
	(0.0006)	(0.0004)	(0.0009)
State Income	0.0024***	0.0019***	0.0031***
	(0.0005)	(0.0005)	(0.0008)

Note: Table 10 shows the marginal effects from probit regressions using the SIPP data. The dependent variable is an outflow dummy that takes a value of 1 if the individual is living in a different location 3 months after the survey. Column (1) reports the results on the entire working age population. Column (2) and (3) report the results on a sample of workers older and younger than 40, respectively. The results show that an increase in the share of older population in a state is associated with a substantial decline in the outflow rate to that state. This effect is particularly strong for young individuals.
Standard errors in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 11
State demographics and outflows (with year fixed effects)

VARIABLES	(1) All Population	(2) Older than 40	(3) Younger than 40
Log Income	-0.0003***	-0.0002**	-0.0005***
	(0.0000)	(0.0000)	(0.0001)
Age	-0.0009***	0.0000	-0.0020***
	(0.0000)	(0.000275)	(0.0006)
Age Squared	8.32e-06***	0.0000	2.36e-05***
	(0.0000)	(0.0000)	(0.0000)
College Binary	0.0036***	0.0014***	0.0069***
	(0.0003)	(0.0002)	(0.0004)
Employment Indicator	-0.0082***	-0.0068***	-0.0111***
	(0.0006)	(0.0006)	(0.0010)
Labor Force Indicator	0.0028***	0.0024***	0.0036***
	(0.0002)	(0.0002)	(0.0003)
Married Indicator	0.0002	0.0005***	0.0000
	(0.0002)	(0.0002)	(0.0003)
Share Above 40	-0.0149**	-0.0069	-0.0274***
	(0.0063)	(0.0070)	(0.0092)
State Population	-0.0014***	-0.0008***	-0.0023***
	(0.0001)	(0.0001)	(0.0002)
State Unemployment	0.0000	0.0002	0.0000
	(0.0008)	(0.0006)	(0.0013)
State Income	0.0021***	0.0019***	0.0023**
	(0.0007)	(0.0006)	(0.0009)

Note: Table 10 shows the marginal effects from probit regressions using the SIPP data, controlling for time effects. The dependent variable is an outflow dummy that takes a value of 1 if the individual is living in a different location 3 months after the survey. Column (1) reports the results on the entire working age population. Column (2) and (3) report the results on a sample of workers older and younger than 40, respectively. The results show that an increase in the share of older population in a state is associated with a substantial decline in the outflow rate to that state. This effect is particularly strong for young individuals.
Standard errors in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 12

Cross-sectional regressions: state demographics and inflow rates

VARIABLES	(1) Log(inflow rate)	(2) Log(inflow rate)	(3) Log(inflow rate)	(4) Log(inflow rate)	(5) Log(inflow rate)
Share of pop. >40	-3.3880***	-4.3382***	-4.4225***	-3.4794***	-4.0856***
	(0.989)	(0.611)	(0.572)	(0.826)	(0.736)
Income per capita		1.0222***	1.0238***	0.8430***	0.8844***
		(0.117)	(0.116)	(0.185)	(0.169)
Unemployment			-0.0782	-0.1225	-0.0220
			(0.128)	(0.134)	(0.124)
Homeownership				-0.9316	-0.5417
				(0.708)	(0.610)
Population					-0.1246**
					(0.056)
Observations	918	918	918	918	918
R-squared	0.078	0.305	0.307	0.325	0.374

Note: Table 12 shows the cross-sectional relationship across states between the share of individuals older than 40 and the inflow rate. The regressors are all in logs except for the share of working population older than 40. The results show that an increase in the share of older population in a state is associated with a substantial decline in the inflow rate to that state. This effect prevails even after controlling for other observable differences across states.

Standard errors in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

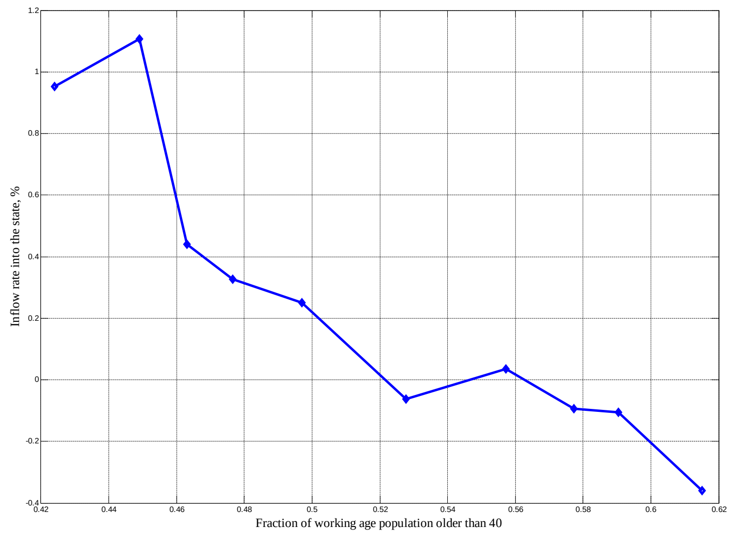
Table 13

Fixed-effect regressions: state demographics and inflow rates

VARIABLES	(1) Log(inflow rate)	(2) Log(inflow rate)	(3) Log(inflow rate)	(4) Log(inflow rate)	(5) Log(inflow rate)
Share of pop. >40	-1.0414***	-1.6721***	-1.4044***	-1.2731***	-1.1040***
	(0.214)	(0.416)	(0.434)	(0.442)	(0.377)
Income per capita		0.2337	0.0832	0.0882	0.3796***
		(0.155)	(0.158)	(0.155)	(0.121)
Unemployment			-0.1743***	-0.1792***	-0.1434***
			(0.026)	(0.027)	(0.023)
Homeownership				-0.2363	-0.0537
				(0.292)	(0.224)
Population					-0.9444***
					(0.141)
Observations	918	918	918	918	918
R-squared	0.111	0.124	0.220	0.223	0.341

Note: Table 13 shows the results of fixed effect regressions, where the dependent variable is the log of inflow rate to a state and the main regressor is the share of individuals older than 40. The regressors are all in logs except for the share of working population older than 40. The results show that an increase in the share of older population in a state is associated with a substantial decline in the inflow rate to that state. This effect prevails even after controlling for other observable differences across states.
Standard errors in parentheses, clustered by state. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 11
Demographics and Inflow Rate across States (Corrected for Time Dummies)



Note: Figure 11 shows the cross-sectional relationship between the fraction of older population and the inflow rate across states. We first group the states in 10 percentiles according to the fraction of individuals older than 40. The x-axis is the mean of this fraction over all states in a percentile, whereas the y-axis is the average inflow rate of states in a percentile. The figure shows that states with a higher fraction of older population receive less inflows. Source: IRS population flows, March CPS, and authors' calculations.

B Data

This section describes the details of the data sets used in this paper. We use micro data from the Annual Social and Economic Supplement to the Current Population Survey (March CPS) and Survey of Income and Program Participation (SIPP), and data on population flows aggregated at the state level from the IRS tax records. When using micro data, in order to focus on migration that is not motivated by changes in schooling (for example, college attendance and graduation) or retirement, we restrict the sample to nonmilitary/civilian individuals who are between 25 and 60 years of age at the time of the survey. March CPS is obtained from the Integrated Public Use Micro data Series (King et al. (2010)).[25] After 1996, we exclude observations with imputed migration data to avoid complications arising due to changes in CPS imputation procedures.[26]

[25]The data can be obtained on https://cps.ipums.org/cps/.
[26]See Kaplan and Schulhofer-Wohl (2012) for a detailed explanation.

Table 14
Summary Statistics for the SIPP Sample

Variable	Statistic
# Individuals	4200900
Married (%)	60.6
Holding a college degree (%)	26.6
In the labor force (%)	86.6
Employed (%)	81.7
Mean Age	41.7

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 to having looked for a job at least one week.

We provide more details about the SIPP as it is less commonly used in the migration literature.[27] 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 2004, and contains data for years 2003-2007. We have around 4.2 million individual-wave observations between 1984 and 2007. Migration information can be constructed in all but the first wave of each panel. Some summary statistics are presented in Appendix B. As explained in Aaronson and Davis (2011), SIPP is useful to study migration behavior because it tracks households when they move to different addresses, and because it contains various demographic information.[28]

We also use data at the state level on population flows, population, personal income, homeownership, and unemployment. Data on population flows come from tax records and are constructed by the Internal Revenue Service. Flows are annual and refer to migration over the period between two consecutive Aprils. IRS reports for each state inflow and outflow data in two units: "returns" and "personal exemptions." The returns data measures the number of households that move, and the personal exemptions data approximates the population.[29] We use personal exemptions. Census Bureau provides annual homeownership

[27] Two exceptions we are aware of are Aaronson and Davis (2011) and Guler and Taskin (2012).

[28] Data can be downloaded from http://thedataweb.rm.census.gov/ftp/sipp_ftp.html.

[29] Data from 2004 to 2012 are available for free on the IRS website 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

rates and population estimates.[30] Data on personal income and unemployment are obtained from the Regional Economic Accounts at the Bureau of Economic Analysis and Local Area Unemployment Statistics at the Bureau of Labor Statistics, respectively.[31]

C Additional Results: The Quantitative Model

C.1 Properties of the Cut-offs

1. Σ_A is increasing with respect to ϵ.

2. Σ_B is decreasing with respect to ϵ.

3. $\epsilon_{A,l} < \epsilon_{A,d}$

4. $\epsilon_{B,d} < \epsilon^B_{B,l}$

5. $\epsilon^A_l < \epsilon^B_l$

Given the above properties of the cutoffs, we know there are potentially five possible orders of four cutoffs, $\epsilon_{A,l}, \epsilon_{B,l}, \epsilon_{A,d}$, and $\epsilon_{B,d}$. For a given order of cutoff values, there are five possible migration patterns. We derive analytical solution of these functions for each possible orderings and use them for computation.

1. Order 1: $\epsilon^n_{B,d} < \epsilon^n_{A,l} < \epsilon^n_{B,l} < \epsilon^n_{A,d}$

2. Order 2: $\epsilon^n_{B,d} < \epsilon^n_{A,l} < \epsilon^n_{A,d} < \epsilon^n_{B,l}$

3. Order 3: $\epsilon^n_{A,l} < \epsilon^n_{B,d} < \epsilon^n_{B,l} < \epsilon^n_{A,d}$

4. Order 4: $\epsilon^n_{A,l} < \epsilon^n_{B,d} < \epsilon^n_{A,d} < \epsilon^n_{B,l}$

5. Order 5: $\epsilon^n_{A,l} < \epsilon^n_{A,d} < \epsilon^n_{B,d} < \epsilon^n_{B,l}$

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used county-county population flows to construct MSA-MSA population flows.

[30]Population estimates for the period 1980-2012 are available on ... Homeownership rates for states for the period 1984-2011 are obtained from Table 15 on http://www.census.gov/housing/hvs/data/ann11ind.html.

[31]http://www.bea.gov/iTable/index_regional.cfm and ftp://ftp.bls.gov/pub/time.series/la/

C.2 Steady-State Unemployment

The equations below describe the law of motion for the measure of employed and unemployed workers of all types in both locations:

$$\begin{aligned} u^A_{t+1}(\epsilon,\mu) &= u^A_t(\epsilon,\mu) + \delta e^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} + u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}} \\ &\quad -p\left(\theta^A_l\right)\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} + u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right) \\ &\quad -p\left(\theta^B_d\right)\left(1-p\left(\theta^A_l\right)\right) \\ &\quad \times\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} + u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right)\mathbb{I}_{\left\{\epsilon\le\epsilon^A_d(\mu)\right\}} \end{aligned} \tag{13}$$

$$\begin{aligned} e^A_{t+1}(\epsilon,\mu) &= e^A_t(\epsilon,\mu) - \delta e^A_t(\epsilon,\mu) \\ &\quad +p\left(\theta^A_l\right)\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} + u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right) \\ &\quad +p\left(\theta^A_d\right)\left(1-p\left(\theta^B_l\right)\right) \\ &\quad \times\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} - u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right) \end{aligned} \tag{14}$$

$$\begin{aligned} u^B_{t+1}(\epsilon,\mu) &= u^B_t(\epsilon,\mu) + \delta e^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} - u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}} \\ &\quad -p\left(\theta^B_l\right)\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} - u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right) \\ &\quad -p\left(\theta^A_d\right)\left(1-p\left(\theta^B_l\right)\right) \\ &\quad \times\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} - u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right)\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_d(\mu)\right\}} \end{aligned} \tag{15}$$

$$\begin{aligned} e^B_{t+1}(\epsilon,\mu) &= e^B_t(\epsilon,\mu) - \delta e^B_t(\epsilon,\mu) \\ &\quad +p\left(\theta^B_l\right)\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} - u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right) \\ &\quad +p\left(\theta^B_d\right)\left(1-p\left(\theta^A_l\right)\right) \\ &\quad \times\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\le\epsilon^A_l(\mu)\right\}} + u^B_t(\epsilon,\mu)\,\mathbb{I}_{\left\{\epsilon\ge\epsilon^B_l(\mu)\right\}}\right), \end{aligned} \tag{16}$$

Aggregate unemployment in location j is simply the integral of the type-specific unemployment $u^j_t(\epsilon,\mu)$ over the distribution of (ϵ,μ) in that location. For a case where$\epsilon^B_d < \epsilon^A_l < \epsilon^B_l < \epsilon^A_d$, we derive the steady state measure of workers of each types are defined as follow.

Unemployment for other possible cases can be derived in similar way.

1. $\epsilon > \epsilon_d^A$: $mo^A = mo^B = u_B = e_B = 0$ and

$$\begin{aligned} u_A &= \frac{\delta f(\epsilon,\mu)}{p(\theta_l^A)+\delta} \\ e_A &= \frac{p(\theta_l^A)\delta f(\epsilon,\mu)}{\delta\{p(\theta_l^A)+\delta\}} \end{aligned}$$

   in steady state.

2. $\epsilon \in [\epsilon_l^B, \epsilon_d^A]$: $mo^A = 0$ because $\epsilon \geq \epsilon_l^B > \epsilon_l^A$. All the unemployed in B moves to A in migration stage because $\epsilon \geq e_l^B$. Thus $mo_t^B = u_t^B$.

$$\begin{aligned} e^A &= \frac{p_l^A f(\epsilon,\mu)}{\delta + \{p_l^A + p_d^B(1-p_l^A)\}} \\ e^B &= \frac{p_d^B\left(1-p_l^A\right) f(\epsilon,\mu)}{\delta + \{p_l^A + p_d^B(1-p_l^A)\}} \\ u^A &= \frac{\delta f(\epsilon,\mu)\left\{1-p_d^B\left(1-p_l^A\right)\right\}}{\delta + \{p_l^A + p_d^B(1-p_l^A)\}} \\ u^B &= \frac{\delta p_d^B\left(1-p_l^A\right) f(\epsilon,\mu)}{\delta + \{p_l^A + p_d^B(1-p_l^A)\}} \end{aligned}$$

   in steady state.

3. $\epsilon \in [\epsilon_l^A, \epsilon_l^B]$: Whenever they are unemployed, they stay the place. Therefore, $mo^A = mo^B = 0$.

$$\begin{aligned} u_A &= \frac{\delta p_d^A\left(1-p_l^B\right) f(\epsilon,\mu)}{p_d^A(1-p_l^B)(\delta+p_l^A) + p_d^B(1-p_l^A)(\delta+p_l^B) + 2p_d^A(1-p_l^B)p_d^B(1-p_l^A)} \\ u_B &= \frac{\delta p_d^B\left(1-p_l^A\right) f(\epsilon,\mu)}{p_d^A(1-p_l^B)(\delta+p_l^A) + p_d^B(1-p_l^A)(\delta+p_l^B) + 2p_d^A(1-p_l^B)p_d^B(1-p_l^A)} \\ e_A &= \frac{\left\{p_l^A + p_d^B\left(1-p_l^A\right)\right\} p_d^A\left(1-p_l^B\right) f(\epsilon,\mu)}{p_d^A(1-p_l^B)(\delta+p_l^A) + p_d^B(1-p_l^A)(\delta+p_l^B) + 2p_d^A(1-p_l^B)p_d^B(1-p_l^A)} \\ e_B &= \frac{\left\{p_l^B + p_d^A\left(1-p_l^B\right)\right\} p_d^B\left(1-p_l^A\right) f(\epsilon,\mu)}{p_d^A(1-p_l^B)(\delta+p_l^A) + p_d^B(1-p_l^A)(\delta+p_l^B) + 2p_d^A(1-p_l^B)p_d^B(1-p_l^A)}. \end{aligned}$$

4. $\epsilon \in \left[\epsilon_B^d, \epsilon_A^l\right]$: $mo^A = u_t^A$and $mo^B = 0$.

$$\begin{aligned}
e_A &= \frac{p_d^A \left(1-p_l^B\right) f\left(\epsilon,\mu\right)}{\delta + \{p_l^B + p_d^A\left(1-p_l^B\right)\}} \\
e_B &= \frac{p_l^B f\left(\epsilon,\mu\right)}{\delta + \{p_l^B + p_d^A\left(1-p_l^B\right)\}} \\
u_A &= \frac{\delta p_d^A \left(1-p_l^B\right) f\left(\epsilon,\mu\right)}{\delta + \{p_l^B + p_d^A\left(1-p_l^B\right)\}} \\
u_B &= \frac{\delta f\left(\epsilon,\mu\right)\left\{1-p_d^A\left(1-p_l^B\right)\right\}}{\delta + \{p_l^B + p_d^A\left(1-p_l^B\right)\}}.
\end{aligned}$$

5. $\epsilon < \epsilon_d^B$: $mo^A = mo^B = u_A = e_A = 0$ and

$$\begin{aligned}
u_B &= \frac{\delta f\left(\epsilon,\mu\right)}{p\left(\theta_l^B\right) + \delta} \\
e_B &= \frac{p\left(\theta_l^B\right)\delta f\left(\epsilon,\mu\right)}{\delta\left\{p\left(\theta_l^B\right) + \delta\right\}}.
\end{aligned}$$

C.3 Match Surplus Functions for Each Migration Patterns

For each possible ordering of cutoff values, we analytically find the match surplus functions (or a system of equations of them) and use the derivation for computation. In this section we derive the match surplus functions for the first order ($\epsilon_{B,d}^n < \epsilon_{A,l}^n < \epsilon_{B,l}^n < \epsilon_{A,d}^n$). Surplus functions for other possible cases can be derived in similar way.

1. $\epsilon > \epsilon_d^A$

   (a) $S_l^A = \frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^A\right)}$

   (b) $S_l^B = \frac{y-2\beta\epsilon-b+(1-\beta)\beta\mu-\beta p\left(\theta_l^A\right)\eta S_l^A}{1-\beta(1-\delta)} - p\left(\theta_d^A\right)\eta S_d^A$

   (c) $S_d^A = 2\epsilon - \left(1-\beta\right)\mu + \frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^A\right)}$

   (d) $S_d^B = \frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^A\right)} - \mu - \frac{2\epsilon(1+\beta\delta)+\beta^2\delta\mu}{1-\beta(1-\delta)}$

   (e) $\Sigma_A = \frac{1}{1-\beta}\left[b + \epsilon + \frac{p\left(\theta_l^A\right)\eta(y-b)}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^A\right)}\right]$

   (f) $\Sigma_B = b - \epsilon + \beta\left(\Sigma_A - \mu\right) + p\left(\theta_d^A\right)\eta S_d^A + p\left(\theta_l^B\right)\eta S_l^B$

2. $\epsilon \in [\epsilon_{B,l}, \epsilon_{A,d}]$

   (a) $S_l^A = \frac{y-b-(1+\beta\delta)p\left(\theta_d^B\right)\eta S_d^B}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^A\right)}$

   (b) $S_l^B = \frac{1}{1-\beta(1-\delta)}$
   $\times \left[y - 2\epsilon\beta + (1-\beta)\beta\mu - b - \beta p\left(\theta_l^A\right)\eta S_l^A - \beta p\left(\theta_d^B\right)\eta S_d^B - \{1-\beta(1-\delta)\}p\left(\theta_d^A\right)\eta S_d^A\right]$

   (c) $S_d^A = 2\epsilon - (1-\beta)\mu + \frac{y-b-\beta p\left(\theta_l^A\right)\eta S_l^A - \beta p\left(\theta_d^B\right)\eta S_d^B}{1-\beta(1-\delta)}$

   (d) $S_d^B = \frac{y-2(1+\beta\delta)\epsilon-\{1-\beta(1-\delta-\beta\delta)\}\mu-b-\beta p\left(\theta_l^A\right)\eta S_l^A}{1-\beta(1-\delta)+\beta\eta p\left(\theta_d^B\right)}$

   (e) $\Sigma_A = \frac{b+\epsilon+p\left(\theta_d^B\right)\eta S_d^B+p\left(\theta_l^A\right)\eta S_l^A}{1-\beta}$

   (f) $\Sigma_B = b - \epsilon + \beta(\Sigma_A - \mu) + p\left(\theta_d^A\right)\eta S_d^A + p\left(\theta_l^B\right)\eta S_l^B$

3. $\epsilon \in [\epsilon_{A,l}, \epsilon_{B,l}]$

   (a) $S_l^A = \frac{y-b-(1+\beta\delta)p\left(\theta_d^B\right)\eta S_d^B}{1-\beta(1-\delta)+\beta\eta p\left(\theta_A^l\right)}$

   (b) $S_l^B = \frac{y-b-(1+\beta\delta)p\left(\theta_d^A\right)\eta S_d^A}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}$

   (c) $S_d^A = \frac{y+2\epsilon-b-\{1-\beta(1-\delta)\}\mu+\beta\delta\left\{U^A-U^B\right\}-\beta p\left(\theta_l^B\right)\eta S_l^B}{1-\beta(1-\delta)+\beta\eta p\left(\theta_d^A\right)}$

   (d) $S_d^B = \frac{y-2\epsilon-b-\{1-\beta(1-\delta)\}\mu-\beta\delta\left\{U^A-U^B\right\}-\beta p\left(\theta_l^A\right)\eta S_l^A}{1-\beta(1-\delta)+\beta\eta p\left(\theta_d^B\right)}$

   (e) $\Sigma_A = \frac{b+\epsilon+p\left(\theta_d^B\right)\eta S_d^B+p\left(\theta_l^A\right)\eta S_l^A}{1-\beta}$

   (f) $\Sigma_B = \frac{b-\epsilon+p\left(\theta_d^A\right)\eta S_d^A+p\left(\theta_l^B\right)\eta S_l^B}{1-\beta}$

4. $\epsilon \in [\epsilon_{B,d}, \epsilon_{A,l}]$

   (a) $S_l^A = \frac{y-b+\beta\mu(1-\beta)+2\beta\epsilon-\beta p\left(\theta_l^B\right)\eta S_l^B-\beta p\left(\theta_d^A\right)\eta S_d^A}{1-\beta(1-\delta)} - p\left(\theta_d^B\right)\eta S_d^B$

   (b) $S_l^B = \frac{y-b-(1+\beta\delta)p\left(\theta_d^A\right)\eta S_d^A}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}$

   (c) $S_d^A = \frac{y+2(1+\beta\delta)\epsilon-\{1-\beta(1-\delta-\beta\delta)\}\mu-b-\beta p\left(\theta_l^B\right)\eta S_l^B}{1-\beta(1-\delta)+\beta\eta p\left(\theta_d^A\right)}$

   (d) $S_d^B = -2\epsilon - (1-\beta)\mu + \frac{y-b-\beta p\left(\theta_l^B\right)\eta S_l^B-\beta p\left(\theta_d^A\right)\eta S_d^A}{1-\beta(1-\delta)}$

   (e) $\Sigma_A = b + \epsilon + \beta(\Sigma_B - \mu) + p\left(\theta_d^B\right)\eta S_d^B(\epsilon,\mu) + p\left(\theta_l^A\right)\eta S_l^A(\epsilon,\mu)$

   (f) $\Sigma_B = \frac{b-\epsilon+p\left(\theta_d^A\right)\eta S_d^A(\epsilon,\mu)+p\left(\theta_l^B\right)\eta S_l^B(\epsilon,\mu)}{1-\beta}$

5. $\epsilon < \epsilon_{B,d}$

   (a) $S_l^A = \frac{y-b+2\beta\epsilon+(1-\beta)\beta\mu-\beta p\left(\theta_l^B\right)\eta S_l^B}{1-\beta(1-\delta)} - p\left(\theta_d^B\right)\eta S_d^B$

   (b) $S_l^B = \frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}$

   (c) $S_d^A = \frac{1}{1-\beta(1-\delta)}\left[y + 2\left(1+\beta\delta\right)\epsilon - \left\{1-\beta\left(1-\delta-\beta\delta\right)\right\}\mu - \frac{\beta p\left(\theta_l^B\right)\eta(y-b)}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}\right]$

   (d) $S_d^B = -2\epsilon - (1-\beta)\mu + \frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}$

   (e) $\Sigma_A = b + \epsilon + \beta\left(\Sigma_B - \mu\right) + p\left(\theta_d^B\right)\eta S_d^B + p\left(\theta_l^A\right)\eta S_l^A$

   (f) $\Sigma_B = \frac{b-\epsilon}{1-\beta} + \frac{p\left(\theta_l^B\right)\eta}{1-\beta}\left[\frac{y-b}{1-\beta(1-\delta)+\beta\eta p\left(\theta_l^B\right)}\right]$

C.4 Overview of the Computational Algorithm

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

1. **Loop 1**: Guess a vector of the structural parameters Θ.

   (a) **Loop 2**: Start with initial guess of market tightnesses, $\left\{\theta_l^j, \theta_d^j\right\}_{j\in\{A,B\}}$.

      i. For each type of workers ($i = 1, 2, .., N$), assume a possible order of cutoffs and derive the match surplus functions $\left\{S_{A,l}^{i,o}, S_{B,l}^{i,o}, S_{A,d}^{i,o}, S_{B,d}^{i,o}, \Sigma_A^{i,o}, \Sigma_B^{i,o}\right\}_{i=1,2,..N}^{o=1,2,..5}$ for each case based on C.3.

      ii. Find the correct ordering of cutoffs, $\left\{\epsilon_{A,l}^i, \epsilon_{B,l}^i, \epsilon_{A,d}^i, \epsilon_{B,d}^i\right\}_{i\in\{1,2,...,N\}}$:

         A. For all five possible orderings, compute the exact cutoff values implied by the match surplus functions.

$$\begin{aligned}
\Sigma_B^{i,o}\left(\epsilon_{A,l}^{i,o}, \mu_i\right) - \Sigma_A^{i,o}\left(\epsilon_{A,l}^{i,o}, \mu_i\right) &= \mu_i \\
\Sigma_A^{i,o}\left(\epsilon_{B,l}^{i,o}, \mu_i\right) - \Sigma_B^{i,o}\left(\epsilon_{B,l}^{i,o}, \mu_i\right) &= \mu_i \\
\eta S_{B,d}^{i,o}\left(\epsilon_{A,d}^{i,o}, \mu_i\right) &= 0 \\
\eta S_{A,d}^{i,o}\left(\epsilon_{B,d}^{i,o}, \mu_i\right) &= 0.
\end{aligned}$$

         B. Check if the computed cutoff values are consistent with the assumption of the ordering.

iii. Using the cutoff values and job finding probabilities, we compute the steady-state unemployment of each type in each location using C.2.

iv. Compute the distance from the free-entry condition of four labor markets.

v. Repeat **Loop 2** with different initial guess until the free-entry conditions are satisfied.

(b) Simulate the economy and obtain long-run averages of model generated moments M_i^{model}.

(c) Compute $\sum \left(\frac{M_i^{model} - M_i^{data}}{M_i^{data}} \right)^2$ and end the **Loop 1** if it satisfies the convergence criterion. Otherwise, return to 1.