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 start by documenting that an increase in the share of workers older than 40 in the working age population in one state causes i) a reduction in the inflow rate into that state, and ii) a reduction in the outflow rate from that state for workers at all ages. To understand these facts, we proceed by developing a simple equilibrium search model consisting of two locations populated by two types of workers who differ in moving costs. Firms prefer hiring local workers who have higher moving costs and thus a lower outside option. An increase in the fraction of high-moving-cost workers causes firms to recruit more from the local labor market This increase in the local job-finding rate reduces the migration rate of all workers, a phenomenon that we label as "migration spillovers". When calibrated, our model successfully explains the cross-sectional facts on population flows and the aging population. Finally, we use the model to quantify the contribution of the aging population to the decline in migration since the mid-1980s. We find that aging population 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.

JEL Codes: D83, J11, J24, J61, R12, R23
Keywords: Interstate migration, labor mobility, population aging

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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 by 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]

In this paper, 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 at most 0.3 percentage points 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). They find that the direct effect of compositional changes in the population is too small to explain much of the decline and that most of the decline is accounted for by a declining trend common across all age 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] 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 ground, that in addition to the direct compositonal effect on migration, an increase in the fraction of older workers in the pop-

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

ulation reduces migration by inducing a lower equilibrium migration rate for *all* workers (*migration spillovers*).

To illustrate these migration spillovers, we analyze a simple economy consisting of two locations. Each location is populated by two types of workers whose moving costs differ. Workers can look for jobs in both locations. Low-moving-cost workers search for jobs in all locations, whereas high-moving-cost workers search only in their current location. Similarly, firms can create jobs for local residents or for out-of-towners. Workers can observe local jobs as well as jobs advertised for out-of-towners by the firms in the other location. High-moving-cost workers are more attractive to firms, because their lower outside option allows firms to hire them at lower wages.

Our main theoretical result is that there is a positive composition externality of high-moving-cost workers on the local labor market: An increase in the fraction of high-moving-cost workers causes firms to create more jobs for local residents and thus decreases the migration rate of all workers. This result is intuitive. When the fraction of high-moving-cost workers increases in the economy, jobs for local residents are more likely to be taken by high-moving-cost workers. In contrast, jobs created for out-of-towners are always taken by workers with low moving costs. Thus, firms find it relatively more profitable to create jobs for local workers and less profitable to create jobs for out-of-towners. Consequently, jobs in the local market become more abundant and jobs for out-of-towners become scarcer. This increase in the local job-finding rate coupled with the decrease in the distant job-finding rate lowers the equilibrium migration rate for all workers. We label this effect as "migration spillovers."

We enrich the simple model to quantify the importance of the aging population for interstate migration. We calibrate this model by targeting several labor market and migration-related moments in the 1980s. The model is quantitatively consistent with two non-targeted cross-sectional facts: i) the negative correlation between the fraction of "older" population (defined as aged 40 and over) and the inflow rate and ii) the negative correlation between the fraction of older population and the fraction of local hires. We then change the share of each age group to that of 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, 78 percent is due to migration spillovers and just 22 percent is due to the direct effect of compositional change. Consistent with the data, our model generates sizable declines in migration rates through the migration spillovers for *all* age groups. Thus, our results suggest that accounting for the migration spillovers is important in evaluating the effect of compositional changes in the population.

Not only is the general equilibrium effect important to correctly measure the effect of the aging population on migration, but it is also important to understanting several interesting cross-sectional facts across states. We document that an increase in the share of workers older than 40 in the working age population in one state, relative to other states, is associated with i) a substantial reduction in the inflow rate into that state and ii) a reduction in the outflow rate from that state for workers at all ages. These facts are robust to various state-level controls as well as to the use of an instrumental variables strategy as in Shimer (2001). The model explains these facts through the general equilibrium effect: Firms in a location with an older population recruit a larger share of their workers in the local market. This increase in the local job finding rate reduces the outmigration propensities of local workers at all ages as well as the inflow rate to that location. The model generated elasticities are remarkably similar to those in the data.

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 concern about this issue may be misplaced. We find that the sharp decline in migration causes only a slight increase in the aggregate unemployment rate. 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.[5]

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.[6]

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

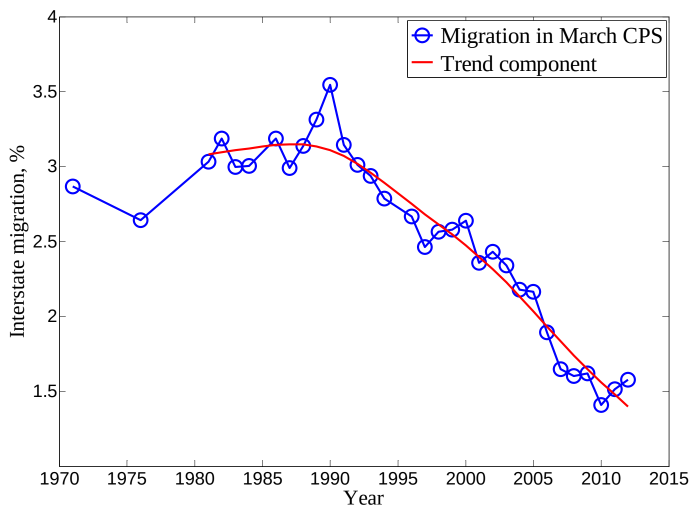
[6]Lutgen and Van der Linden (2013) study the efficiency implications of job search opportunities in multiple

The rest of the paper is organized as follows. Section 2 documents the stylized facts on the decline in interstate migration. Section 3 describes a simple model and presents the main proposition regarding the existence of the spillover effect. Section 4 presents the quantitative model, our calibration, and the results. Finally, section 5 concludes.

2 Stylized Facts

We start this section by documenting the long-run decline in interstate migration in the United States. The blue line in figure 1 plots the evolution of interstate gross migration rates from the March Supplement of the Current Population Survey (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. The decline is substantial: The migration rate in 2010 is only 50 percent of what it was during the 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.

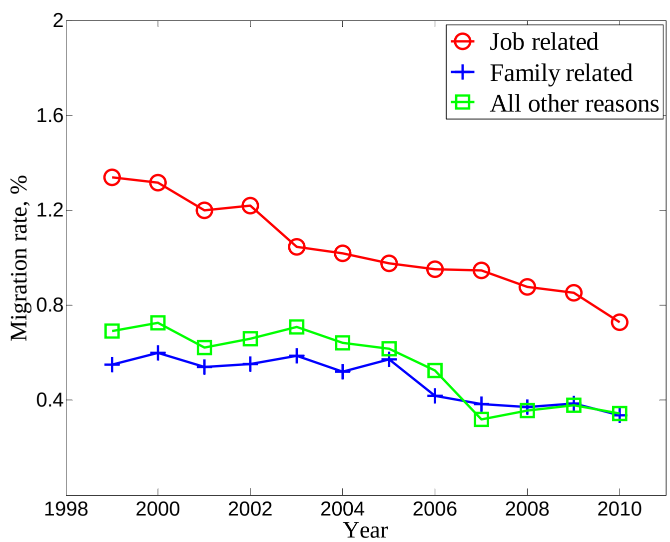
To better understand the nature of the decline in migration, figure 2 shows the fraction of the working-age population that moved across states for different reasons. Of the variety of reasons

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.

to move,[7] 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 for all categories of moves.

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 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. People between the ages of 25 and 29 are almost four times more likely to move across states than those aged 50 to 54. These differences, coupled with population aging in the United States, call for the possibility that aging might be an important factor behind the declining migration rates.

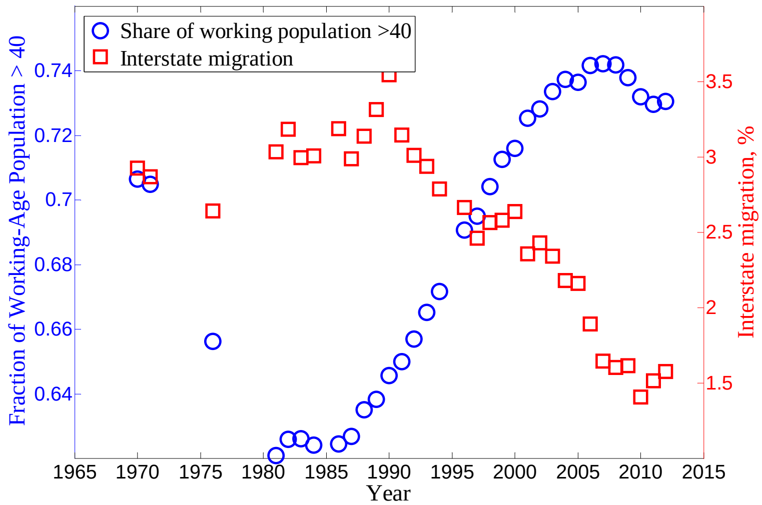
FIGURE 2
REASONS TO MOVE IN THE UNITED STATES



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.

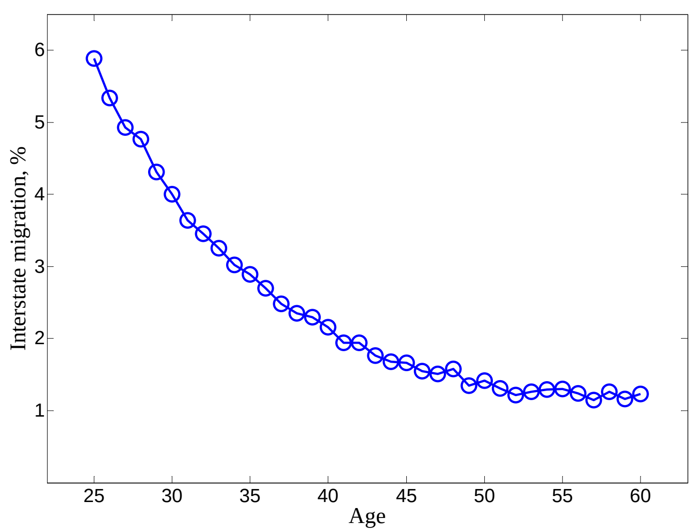
[7]These reasons include job-related factors (e.g., for a new job, job-transfer, job search, easier commute, etc.), family-related factors (e.g., changes in marital status, to establish one's own household, etc.), housing-related factors (e.g., to own, better housing, better neighborhood, etc.), and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

Figure 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 non-imputed observations. The interstate migration rate decreases sharply over the working life and most of the decline occurs before age 40.

To evaluate the direct effect of compositional change, we conduct the following 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:

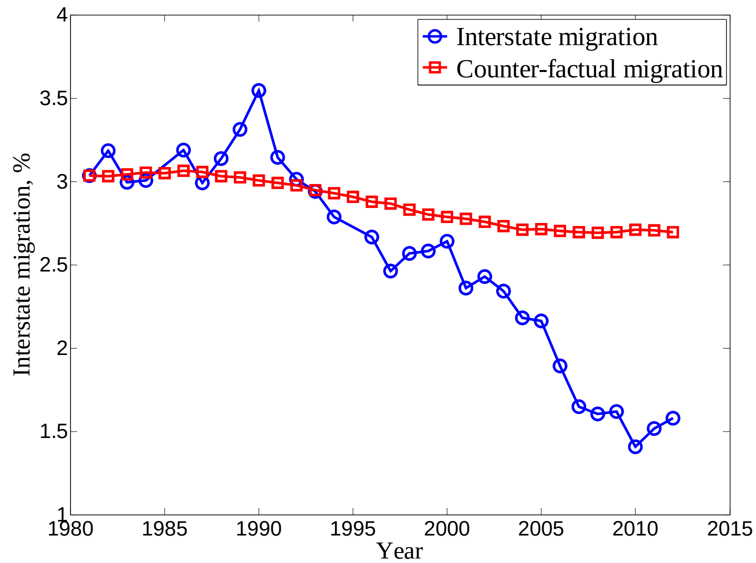
$$\hat{m}_t = \sum_i s_{i,t} \times \overline{m}_{i,t}.$$

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,

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

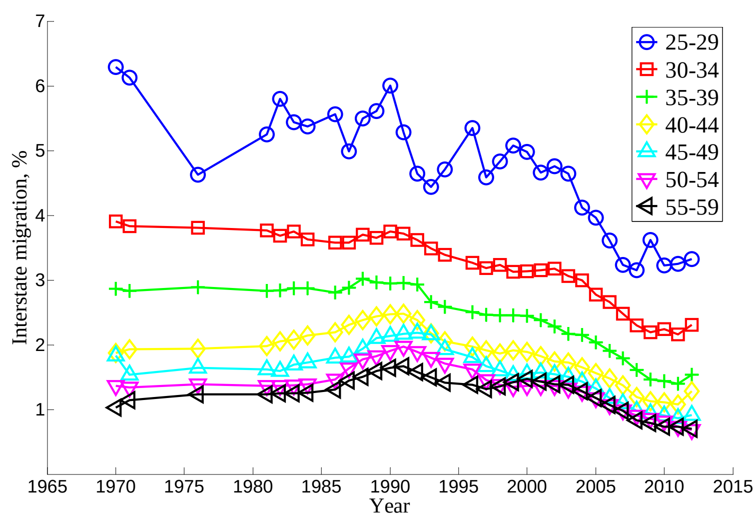
The red line in figure 5 plots the resulting counterfactual migration rates. The result suggests that the aging population is not significant enough to explain a sizable portion of the decline in migration. Based on this finding, we investigate how the life-cycle pattern of migration has evolved. Figure 6 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 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 5-year moving average of interstate migration rates for each age group.

Section 3 presents our mechanism through which compositional changes affect migration rates. This mechanism is an indirect general equilibrium effect that operates through a change in the labor market and lowers the equilibrium migration rate for *all* individuals (migration spillovers). As we argue later through the lens of this simple model, the accounting exercise in figure 5 captures only the direct effect of compositional change, and hence it provides only a lower bound on the effect of aging on migration.

3 Theoretical Insights from a Simplified Model

To illustrate the indirect effect of compositional change through general equilibrium, we analyze an economy with two locations populated by two types of workers whose moving costs differ. The model combines the island framework in Lucas and Prescott (1974) and the local labor market with search frictions in Mortensen and Pissarides (1994).

3.1 Environment

The model economy consists of two symmetric locations, A and B, populated by a measure one of infinitely lived, risk-neutral individuals who can be of two types. The first type, which we label "*settlers*," faces very large moving costs, and thus they never move. Individuals of the second type, labeled "*nomads*," do not face any moving costs and are perfectly mobile. 2ϕ measure of individuals are settlers and are distributed evenly across A and B. The goal of this section is to show that an increase in ϕ may result in a lower migration rate even for nomads.

Within a period, unemployed individuals look for a job. Settlers search only within their current location, whereas nomads are allowed to search for jobs in both locations. For tractability, we assume that the job search is sequential: workers first look for a job in their current location. In the case of an unsuccessful local search, they may look for a job in the other location.

Firms advertise for vacant positions by paying a fixed cost, κ, to attract workers. They may advertise for a given position in their own location or in the other location.

Workers can see only the jobs advertised in their own location. These advertisements can belong to local firms as well as to firms in the other location.[8] As a result, there are two distinct labor markets in each location. The first market is the "*local market*," where workers look for local jobs and meet local firms. In the other market, the "*distant market*," workers look for jobs created by firms in the other location and advertised in the workers' location.

[8] For example, unemployed workers in Philadelphia can acquire information on job postings from local newspapers. These job postings can be advertised by firms already located in Philadelphia or by firms located in another city.

Both the local and the distant labor markets are subject to search frictions. Matches are determined by the matching function $m(v,u)$, where v and u indicate the number of job postings and the number of unemployed workers in a labor market, respectively. Assuming a constant-returns-to-scale matching function, job- and worker-finding probabilities for workers and firms are determined by four market tightnesses. Let θ_l^i and θ_d^i denote the market tightnesses in location i in the local and distant labor markets, respectively. $q(\theta)$ is the worker-finding rate for a firm, whereas $p(\theta)$ is the job-finding probability for an unemployed worker.[9] In what follows, we will simplify the notation for the sake of brevity and drop the location superscript i.[10]

3.2 The Problem of Workers and Firms

The following equations show the value of being unemployed for both types of workers. A superscript of s denotes a settler, whereas n refers to a nomad:

$$\begin{aligned} U^s &= b + \beta \left\{ p(\theta_l) W^s(w^s) + (1 - p(\theta_l)) U^s \right\} \\ U^n &= b + \beta \left\{ p(\theta_l) W^n(w_l^n) + (1 - p(\theta_l)) \Delta^n \right\}, \end{aligned}$$

where

$$\Delta^n = \max \left\{ p(\theta_d) W^n(w_d^n) + (1 - p(\theta_d)) U^n, U^n \right\}.$$

Once employed, the match dissolves with probability δ regardless of the type of worker. The value of employment for type i worker is given by the following equations:

$$W^i(w) = w + \beta \left\{ (1-\delta) W^i(w) + \delta U^i \right\}.$$

Firms matched with a worker collect $y - w$ until the match is dissolved. Thus, the value of a matched firm is given by

$$J(w) = y - w + \beta (1-\delta) J(w).$$

[9] $q(\cdot)$ is decreasing and $p(\cdot)$ is increasing with respect to θ: $q'(\theta) < 0$ and $p'(\theta) > 0$.

[10] As the measure of settlers is the same across locations, the equilibrium, provided that it exists, will be symmetric.

3.3 Wage Determination

Wages are determined by Nash bargaining between a firm and a worker. The following equations define the wage-determination problem in the worker-firm pair:

$$\begin{aligned} w^s &= \arg\max \{W^s(w) - U^s\}^\eta J(w)^{1-\eta} \\ w_l^n &= \arg\max \{W^n(w) - \Delta^n\}^\eta J(w)^{1-\eta} \\ w_d^n &= \arg\max \{W^n(w) - U^n\}^\eta J(w)^{1-\eta}. \end{aligned}$$

Note that the outside option for nomads in the local market Δ^n contains the additional option value of search in the distant market.

3.4 Steady-State Equilibrium

We assume free entry of firms. This ensures that, in equilibrium, the value of creating a vacancy will be zero in each market. Equations (1) and (2) describe the free-entry conditions in the distant and local markets, respectively:

$$\kappa = q(\theta_d) J(w_d^n) \tag{1}$$

$$\kappa = q(\theta_l) \left\{ \frac{u^s}{u^n + u^s} J(w^s) + \frac{u^n}{u^n + u^s} J(w_l^n) \right\}, \tag{2}$$

where u^j is the steady-state measure of unemployed individuals of type j. Both conditions equate the cost of posting a vacancy to the expected value of creating a vacancy. Note that in the local labor market, there are two types of workers. Thus, the expected value of a vacancy is a weighted average of the profits of employing each type, where the weights are given by the share of each type in the unemployment pool.

As shown in Diamond (1982) and Mortensen (1982), Nash bargaining splits the surplus of a match between the worker and the firm according to their bargaining power. In particular, the worker gets η share of the surplus, and the firm gets the remainder. Using the value functions of workers and firms, we show that the surplus generated by a firm and a settler is given by

$$S^s(\theta_l, \theta_d) \equiv J(w) + W^s(w) - U^s = \frac{y - b}{1 - \beta\{(1-\delta) - \eta p(\theta_l)\}}. \tag{3}$$

The surplus of a match between a firm and a nomad from the other location is given by

$$\begin{aligned} S_d^n(\theta_l, \theta_d) &\equiv J(w) + W^n(w) - U^n \\ &= \frac{y - b}{1 - \beta\left[(1-\delta) - \{\eta p(\theta_l) + (1 - \eta p(\theta_l))\,\eta p(\theta_d)\}\right]}. \end{aligned} \tag{4}$$

Similarly, the surplus of a match between a firm and a nomad in the local market is as follows:

$$\begin{aligned} S_l^n(\theta_l, \theta_d) &\equiv J(w) + W^n(w) - \Delta^n \\ &= \frac{(1 - \eta p(\theta_d))(y - b)}{1 - \beta\left[(1-\delta) - \{\eta p(\theta_l) + (1 - \eta p(\theta_l))\,\eta p(\theta_d)\}\right]}. \end{aligned} \tag{5}$$

The effective discount factor in the match with a settler is $\beta\{1 - \delta - \eta p(\theta_l)\}$. Note that the effective discount factor for a nomad differs from that of the settler by $(1 - \eta p(\theta_l))\,\eta p(\theta_d)$. This difference is due to the additional job search opportunity of nomads, which arises from the option of searching in the distant labor market. Consequently, the surplus of a match with a settler is larger than that with a nomad: $S^s(\theta_l, \theta_d) > S_d^n(\theta_l, \theta_d) > S_l^n(\theta_l, \theta_d)$ for all positive θ_l and θ_d. Using the Nash bargaining solution that $J^i = (1 - \eta) S^i$, we now rewrite the free-entry conditions in equations (1) and (2) as functions of match surplus functions.

Remark 1. *(Equilibrium Wages) In equilibrium, the wage of settlers is lower than that of nomads:*

$$w^s < w_d^n < w_l^n.$$

The result is straightforward given the relative sizes of the surpluses of these matches. The details of the derivation can be found in appendix B.1. The fact that firms pay lower wages to settlers than to nomads indicates that the job creation of firms may change when the composition of the population changes. In the next proposition, we study the effect of a higher share of settlers on the equilibrium tightnesses of the different labor markets.

Proposition 1. *(Share of immobile workers and labor market tightnesses) If the elasticity of the worker-finding rate with respect to the market tightness is high enough compared to the bargaining share of workers η,*

1. *The local labor market tightness increases with the measure of immobile workers:*

$$\frac{d\theta_l}{d\phi} > 0.$$

2. The distant labor market tightness is inversely related to the measure of immobile workers:

$$\frac{d\theta_d}{d\phi} < 0.$$

The details of the proof of the proposition can be found in appendix B. As we have noted before, remark 1 shows that firms make a higher profit from a match with a settler. Fixing market tightnesses, the share of settlers among the unemployed pool, $\frac{u^s}{u^n+u^s}$, increases with ϕ, thereby increasing the expected profit from a vacancy in the local market (see equation (18)). In equilibrium, θ_l must become higher for the free-entry condition in equation (18) to hold. The increase in local opportunities in turn reduces the surplus of a match with a nomad, S_d^n. As a result, firms expect less profit in the distant labor market. For the free-entry condition in this market to hold, θ_d must decrease.

We now turn to the implications of proposition 1 for the equilibrium migration rate and unemployment. Recall that in our model, only the nomads move in the event of an unsuccessful local search and a successful distant job search. Thus, their migration rate depends crucially on the local and distant job-finding rates. The next corollary shows that the migration rate of nomads is decreasing in the share of settlers, ϕ.

Corollary 2. *(Share of settlers and the equilibrium migration rate of nomads) As the measure of settlers increases, the migration rate (mr) of nomads decreases:*

$$\frac{dmr}{d\phi} < 0.$$

Proposition 1 implies that an increase in the share of settlers increases the local job-finding probability, but decreases the job finding rate in the distant market. The migration rate of an unemployed nomad is given by $(1 - p(\theta_l))\, p(\theta_d)$ and is clearly decreasing in ϕ. Moreover, the overall migration rate of nomads, measured as $\frac{(1-p(\theta_l))p(\theta_d)u^n}{0.5-\phi}$, also decreases with ϕ. We label this general equilibrium effect *migration spillover*s.

Now, we use our model to study the implication of changes in population composition for equilibrium unemployment.

Corollary 3. *(Share of settlers and the equilibrium aggregate unemployment rate)*

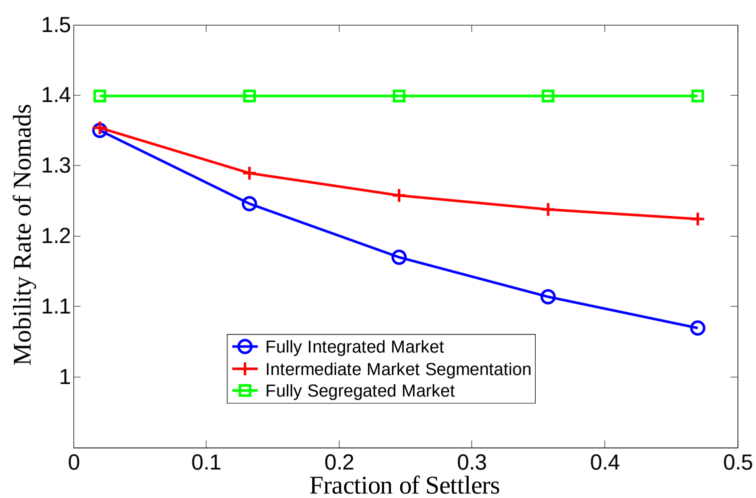
1. *The conditional unemployment rates (ur^j) decrease for all types:*

$$\frac{dur^s}{d\phi} < 0 \quad \textit{and} \quad \frac{dur^n}{d\phi} < 0.$$

2. *The effect on the aggregate unemployment rate is ambiguous; and it is positive if the compositional effect (larger share of settlers) is greater than the general equilibrium effect.*

In this model, there are two effects in the increase of share of settlers, ϕ, on unemployment. The first is a general equilibrium effect. This effect arises because firms, in response to an increase in ϕ, post more vacancies in the local labor market and fewer vacancies in the distant market. Meanwhile, there is also a compositional effect at work that is captured by the first term: an increase in settlers with a higher unemployment rate because of their limited job search capabilities puts an upward pressure on aggregate unemployment. To sum up, the effect on aggregate unemployment is ambiguous and depends on the relative sizes of the two effects.

FIGURE 7
MARKET SEGMENTATION AND THE MIGRATION SPILLOVERS



Note: Figure 7 shows the importance of the market structure for the existence of the spillover effect. In solid blue line, we plot the relationship between the fraction of immobile workers and the equilibrium migration rate of mobile workers. The dashed red line shows the same relationship for a model with complete market segmentation in the local labor market ($\rho = 1$). Finally, the dashed-dotted green line shows an intermediate case, where $\rho = 0.5$. This figure clearly shows that the migration spillover effect does not exist in a model with perfect market segmentation. The degree of the spillovers, as measured by the slope of the line, is decreasing in the extent of market segmentation.

In this section, we have developed a simple model of migration and used it to demonstrate how the equilibrium migration rate of perfectly mobile nomads is affected by changes in the population composition. The key to this result is that in the local market, there is no market segmentation by type. To illustrate the role of this labor market structure in generating the results, we now turn to an alternative search process and introduce a market segmentation parameter, ρ. With probability $1-\rho$, we assume that nomads search along with settlers in the local labor market. With probability ρ, however, nomads participate in a segregated local labor market. If $\rho = 0$, this environment is identical to the model we already presented. As ρ approaches 1, the local market becomes completely segregated.

All the equations pertaining to this model and the related derivations are presented in appendix B.6. Figure 7 shows that if the local labor market is perfectly segregated by type, the change in population composition does not affect the migration rate of nomads. Thus, there is no migration spillover. The extent of the migration spillover is measured by the slope of the line, and it is decreasing in ρ.

4 Quantifying the Importance of Migration Spillovers

In this section, we extend the model in section 3 and evaluate quantitatively the effect of an aging population on interstate migration. First, we allow for multiple types of workers with finite moving costs. Each type corresponds to a specific age group in the data. Second, we introduce heterogeneity in the permanent preferences for locations. This results in variation in the age composition across locations. The rest of the quantitative model builds on the structure of the labor market presented in section 3.

4.1 Model

4.1.1 Environment

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

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

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.

4.1.2 Value Functions and Decision Rules

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

$$
\begin{aligned}
W^{A}(w,\epsilon,\mu) &= w+\epsilon+\beta\left[(1-\delta)W^{A}(w,\epsilon,\mu)+\delta U^{A}(\epsilon,\mu)\right] \\
W^{B}(w,\epsilon,\mu) &= w-\epsilon+\beta\left[(1-\delta)W^{B}(w,\epsilon,\mu)+\delta U^{B}(\epsilon,\mu)\right] \\
U^{A}(\epsilon,\mu) &= b+\epsilon+\beta\left[\max\left\{\Sigma^{A}(\epsilon,\mu),\Sigma^{B}(\epsilon,\mu)-\mu\right\}\right] \\
U^{B}(\epsilon,\mu) &= b-\epsilon+\beta\left[\max\left\{\Sigma^{A}(\epsilon,\mu)-\mu,\Sigma^{B}(\epsilon,\mu)\right\}\right],
\end{aligned} \tag{6}
$$

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

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

Here, $w_d^{-j}(\epsilon,\mu)$ 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

$$
J(w)=y-w+\beta(1-\delta)J(w). \tag{7}
$$

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: $\epsilon_{A,l}(\mu), \epsilon_{B,l}(\mu), \epsilon_{A,d}(\mu)$, and $\epsilon_{B,d}(\mu)$.[11] The cutoff $\epsilon_{A,l}$ governs the migration decision for a worker residing in A at the beginning of the period. Workers with $\epsilon \geq \epsilon_{A,l}(\mu)$ decide to stay in A and engage in a local job search there. Workers with $\epsilon < \epsilon_{A,l}(\mu)$ move to B before a local job search begins. This cutoff is defined

[11] 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.

by the following equation:

$$\Sigma^{A}\left(\epsilon_{A,l}\left(\mu\right),\mu\right)=\Sigma^{B}\left(\epsilon_{A,l}\left(\mu\right),\mu\right)-\mu. \tag{8}$$

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

$$\Sigma^{A}\left(\epsilon_{B,l}\left(\mu\right),\mu\right)-\mu=\Sigma^{B}\left(\epsilon_{B,l}\left(\mu\right),\mu\right). \tag{9}$$

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 market, and they are defined by the following equations:

$$U^{A}\left(\epsilon_{A,d}\left(\mu\right),\mu\right) = W^{B}\left(w,\epsilon_{A,d}\left(\mu\right),\mu\right)-\mu \tag{10}$$

$$U^{B}\left(\epsilon_{B,d}\left(\mu\right),\mu\right) = W^{A}\left(w,\epsilon_{B,d}\left(\mu\right),\mu\right)-\mu. \tag{11}$$

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.

4.1.3 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.[12] The bargaining problem in the local labor market is given by

$$w_l^j(\epsilon, \mu) = \arg\max \left[W^j(w, \epsilon, \mu) - \Delta^j(w, \epsilon, \mu)\right]^\eta J(w)^{1-\eta}. \tag{12}$$

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

$$w_d^j(\epsilon, \mu) = \arg\max \left[W^j(w, \epsilon, \mu) - \mu - U^{-j}(w, \epsilon, \mu)\right]^\eta J(w)^{1-\eta}. \tag{13}$$

4.1.4 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.[13] 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 (14)−(16) describe the zero profit conditions in the distant and local markets of A and B:

$$\kappa = q\left(\theta_l^j\right)\sum_{i=1}^{N}\frac{\int u^j(\mu_i, \epsilon)\, J\left(w_l^j(\mu_i, \epsilon)\right)}{\sum_{i=1}^{N}\int u^j(\mu_i, \epsilon)}, \quad j \in \{A, B\} \tag{14}$$

$$\kappa = q\left(\theta_d^A\right)\sum_{i=1}^{N}\frac{\int u^B(\mu_i, \epsilon)\, J\left(w_d^A(\mu_i, \epsilon)\right)\mathbb{I}_{\{\epsilon>\epsilon_{B,d}(\mu_i)\}}}{\sum_{j=1}^{N}\left(1-p_l^B\right)\int u^B(\mu_j, \epsilon)\,\mathbb{I}_{\{\epsilon>\epsilon_{B,d}(\mu_i)\}}} \tag{15}$$

$$\kappa = q\left(\theta_d^B\right)\sum_{i=1}^{N}\frac{\int u^A(\mu_i, \epsilon)\, J\left(w_d^B(\mu_i, \epsilon)\right)\mathbb{I}_{\{\epsilon<\epsilon_{A,d}(\mu_i)\}}}{\sum_{j=1}^{N}\left(1-p_l^A\right)\int u^A(\mu_j, \epsilon)\,\mathbb{I}_{\{\epsilon<\epsilon_{A,d}(\mu_i)\}}} \tag{16}$$

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

[13] Derivation of these steady-state unemployment measures are in appendix D.

Definition 4. A steady-state equilibrium consists of value functions $\left\{W^j, U^j, J\right\}_{j\in\{A,B\}}$, 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 $\left\{u^j\right\}_{j\in\{A,B\}}$, and a set of market tightnesses $\left\{\theta_l^j, \theta_d^j\right\}_{j\in\{A,B\}}$, such that:

1. The value functions satisfy equations in (6) and (7),
2. The cutoff values solve (8)−(11),
3. Wages solve the Nash bargaining problems in (12) and (13),
4. Steady-state unemployment measures satisfy the law of for labor market,
5. Market tightnesses satisfy the free-entry conditions in (14)−(16).

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 D.4.

4.2 Calibration

We have presented a quantitative model to study the effect of compositional changes in the population on migration.[14] 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.

4.2.1 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.

[14]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 1.

TABLE 1
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 1 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.[15] 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.

[15] 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 2
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 2 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, $\{\mu_i\}_{i=1}^N$.[16] 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 2.

4.2.2 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 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

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

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 3
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 3 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 3 summarizes the moments used in the estimation and provides the fit of the model to the targeted moments.

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

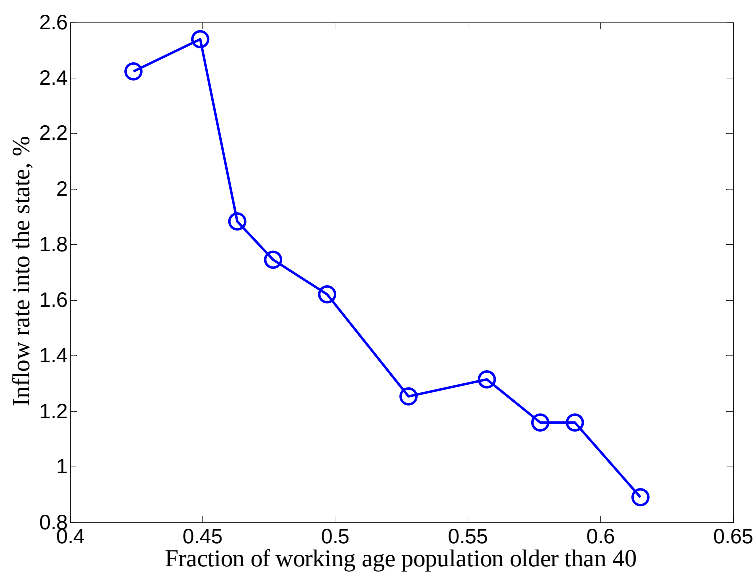
Before turning to the implications of an aging population for the time series of migration, we assess the model's performance on several nontargeted moments. We study the relationship between the age composition and population flows across states and document two new cross-sectional facts.

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.[17] We use these facts to evaluate our estimated model and find it to be quantitatively consistent with both of these facts.

4.3.1 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.

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 11 and 12 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

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

is robust to controlling for various state-level variables and fixed effects.[18] 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 4. The calibrated model is quantitatively consistent with the cross-sectional relationship.

Table 4
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)	

4.3.2 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 5
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)	

[18] 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 9 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 10 shows that these relationships are robust to controlling for fixed effects.

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 5 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.

4.3.3 Migration Spillovers and the Cross-Sectional Facts

How does the model explain the cross-sectional correlations between age composition and population flows? Recall that in the model of section 3, an increase in the share of settlers, that is the share of low-mobility workers, makes it profitable for firms to hire more from the local market. The intuition behind the model's success in explaining the cross-sectional facts is based on the same mechanism. 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 4.4, but also important to understanding key cross-sectional facts.

4.4 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.

4.4.1 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 1. We solve for the equilibrium of the estimated model and report equilibrium migration rates. Table 6 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.

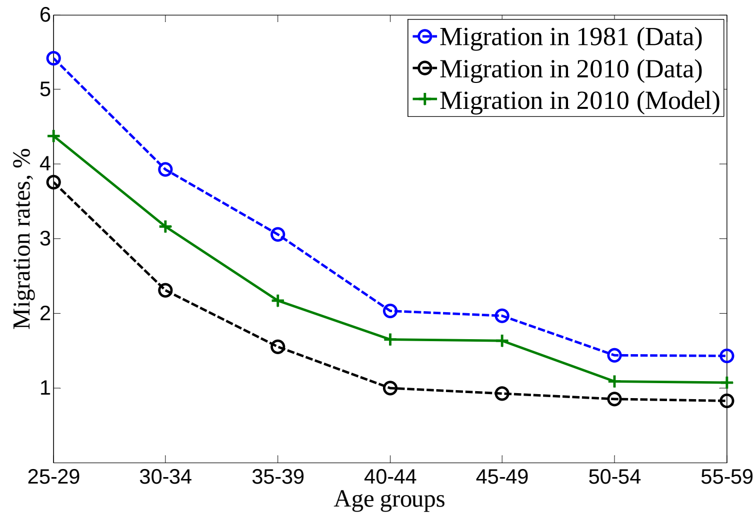
TABLE 6
MIGRATION: DATA VS. MODEL

		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 6 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



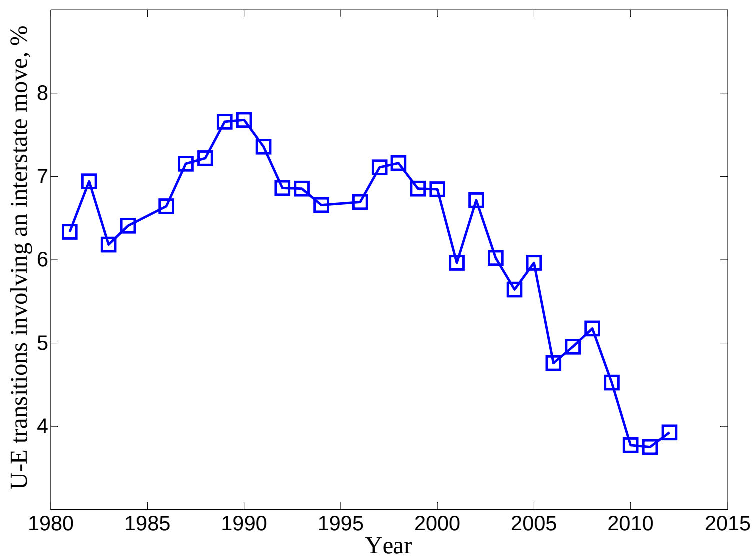
Note: Figure 9 shows the migration rates of different age groups from the data and compare the model counterparts. The x-axis is the seven age groups used in our estimation. The y-axis is the migration rate. The blue dashed line is the migration rate of each age group in 1980 and the black dashed line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

4.4.2 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 7, 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 7 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 7
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 7 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.

4.4.3 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 8
Aging Population and Unemployment

	1980	2010	Change
Aggregate unemployment rate, %	8.16	8.37	0.21

Note: Table 8 shows the implications of the aging population for the aggregate unemployment rate in the model.

Table 8 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.

5 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 9
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 9 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 10

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 9 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 11

Cross-sectional regressions: state demographics and inflow rates

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Log(inflow rate)	Log(inflow rate)	Log(inflow rate)	Log(inflow rate)	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 11 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.

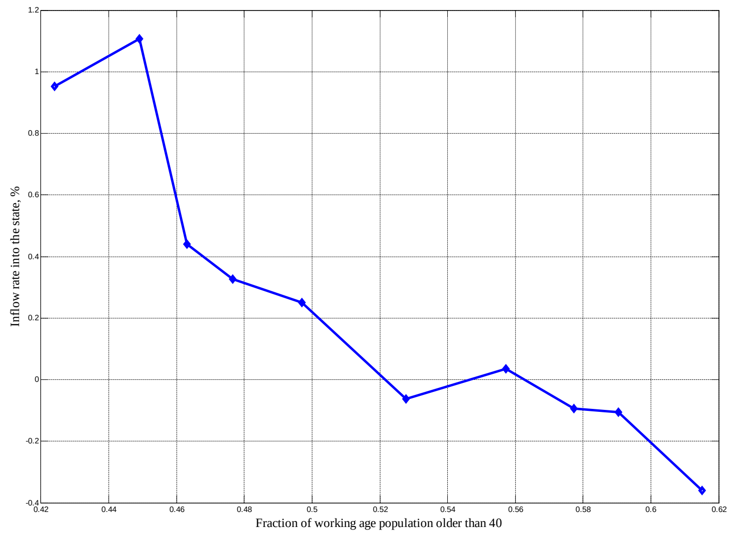
TABLE 12

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 12 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 Proofs of Propositions in Section 3

B.1 Proof of Remark 1

From the value of a firm with an employee,

$$\begin{aligned} J(w) &= y - w + \beta(1-\delta) J(w) \\ J(w) &= \frac{y-w}{1-\beta(1-\delta)}. \end{aligned}$$

Under the Nash bargaining, the equilibrium wage satisfies

$$J\left(w^j\right) = (1-\eta) S^j,$$

where j indicates the type of worker. Combining the above two equations,

$$\begin{aligned} w^s &= y - \{1-\beta(1-\delta)\}(1-\eta) S^s \\ w_l^n &= y - \{1-\beta(1-\delta)\}(1-\eta) S_l^s \\ w_d^n &= y - \{1-\beta(1-\delta)\}(1-\eta) S_d^n, \end{aligned}$$

or

$$
\begin{aligned}
w^s &= \eta y\left[\frac{1-\beta\{(1-\delta)-p(\theta_l)\}}{1-\beta\{(1-\delta)-\eta p(\theta_l)\}}\right]+(1-\eta)\,b\left[\frac{1-\beta(1-\delta)}{1-\beta\{(1-\delta)-\eta p(\theta_l)\}}\right]\\
w_l^n &= \eta y\left[\frac{1-\beta\{(1-\delta)-p(\theta_l)-(1-\eta p(\theta_l))\,p(\theta_d)\}+\{1-\beta(1-\delta)\}(1-\eta)\,p(\theta_d)}{1-\beta\{(1-\delta)-\eta p(\theta_l)-(1-\eta p(\theta_l))\,\eta p(\theta_d)\}}\right]\\
&\quad+(1-\eta)\,b\left[\frac{\{1-\beta(1-\delta)\}(1-\eta p(\theta_d))}{1-\beta\{(1-\delta)-\eta p(\theta_l)-(1-\eta p(\theta_l))\,\eta p(\theta_d)\}}\right]\\
w_d^n &= \eta y\left[\frac{1-\beta\{(1-\delta)-p(\theta_l)-(1-\eta p(\theta_l))\,p(\theta_d)\}}{1-\beta\{(1-\delta)-\eta p(\theta_l)-(1-\eta p(\theta_l))\,\eta p(\theta_d)\}}\right]\\
&\quad+(1-\eta)\,b\left[\frac{1-\beta(1-\delta)}{1-\beta\{(1-\delta)-\eta p(\theta_l)-(1-\eta p(\theta_l))\,\eta p(\theta_d)\}}\right].
\end{aligned}
$$

B.2 Proof of Proposition 1

Using the Nash bargaining solution, we can rewrite the free-entry conditions as follows:

$$
\kappa = q(\theta_d)(1-\eta)\,S_d^s(\theta_l,\theta_d) \tag{17}
$$

$$
\kappa = q(\theta_l)(1-\eta)\left\{\frac{u^s}{u^n+u^s}S^s(\theta_l,\theta_d)+\frac{u^n}{u^n+u^s}S_l^n(\theta_l,\theta_d)\right\}. \tag{18}
$$

The steady state measure of type j unemployed workers in location i, u_i^j, is determined by imposing the steady state condition on the following law of motions:

$$
\begin{aligned}
u_{i,t+1}^s &= \left(1-p\left(\theta_l^i\right)\right)u_{i,t}^s+\delta\left(\phi-u_{i,t}^s\right)\\
u_{i,t+1}^n &= \left\{1-p\left(\theta_l^i\right)-\left(1-p\left(\theta_l^i\right)\right)p\left(\theta_d^j\right)\right\}u_{i,t}^n+\delta e_{i.t}^n\\
e_{i,t+1}^n &= (1-\delta)\,e_{i,t}^n+p\left(\theta_l^i\right)u_i^n+\left(1-p\left(\theta_l^j\right)\right)p\left(\theta_d^j\right)u_j^n.
\end{aligned}
$$

From the symmetric equilibrium condition,

$$
\begin{aligned}
u^s &= \frac{\delta\phi}{\delta+p(\theta_l)}\\
e^n &= \frac{\{p(\theta_l)+(1-p(\theta_l))\,p(\theta_d)\}(0.5-\phi)}{\delta+p(\theta_l)+(1-p(\theta_l))\,p(\theta_d)}\\
u^n &= \frac{\delta(0.5-\phi)}{\delta+p(\theta_l)+(1-p(\theta_l))\,p(\theta_d)}
\end{aligned}
$$

and the ratio of unemployed workers between two types at the steady state is

$$\frac{u^s}{u^s+u^n} = \frac{\phi\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}}{\left(0.5-\phi\right)\left(p\left(\theta_l\right)+\delta\right)+\phi\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}}.$$

This expression completes the two free-entry conditions as a set of two equations with two unknowns, (θ_l, θ_d). We can rewrite the free-entry condition for the distant labor market such that

$$\begin{aligned} F\left(\theta_l,\theta_d\right) &= \kappa\left[1-\beta\left\{(1-\delta)-\eta p\left(\theta_l\right)-\left(1-\eta p\left(\theta_l\right)\right)\eta p\left(\theta_d\right)\right\}\right] \\ &\quad -q\left(\theta_d\right)(1-\eta)(y-b)=0. \end{aligned} \tag{19}$$

By applying the implicit function theorem on the equation (19),

$$\frac{d\theta_d}{d\theta_l} = -\frac{\frac{dF}{d\theta_d}}{\frac{dF}{d\theta_l}} = \frac{\kappa\beta\eta p'\left(\theta_l\right)\left(1-p\left(\theta_d\right)\right)}{q'\left(\theta_d\right)(1-\eta)(y-b)-\kappa\beta\eta\left(1-p\left(\theta_l\right)\right)p'\left(\theta_d\right)} < 0. \tag{20}$$

Now we know $\theta_d\left(\theta_l\right)$ and $\theta_d'\left(\theta_l\right) < 0$. For the local labor market,

$$\begin{aligned} G\left(\phi,\theta_l\right) &= \kappa-q\left(\theta_l\right)(1-\eta)\left\{\frac{u^s}{u^n+u^s}S^s+\frac{u^n}{u^1+u^s}S_l^n\right\} \\ &= \kappa-q(\theta_l)(1-\eta)\left\{\tfrac{u^s}{u^n+u^s}\left(S^s-S_l^n\right)+S_l^n\right\}=0. \end{aligned} \tag{21}$$

In the same way, we apply the implicit function theorem on the equation (21). First,

$$\frac{\partial G}{\partial \phi} = -\frac{0.5\left(p\left(\theta_l\right)+\delta\right)\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}}{\left\{0.5\left(p\left(\theta_l\right)+\delta\right)+f\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2} < 0 \tag{22}$$

because

$$\frac{\partial}{\partial\phi}\left(\frac{u^s}{u^n+u^s}\right) = \frac{0.5\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}\left(p\left(\theta_l\right)+\delta\right)}{\left\{0.5\left(p\left(\theta_l\right)+\delta\right)+\phi\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2} > 0$$

and $S^s - S_l^n > 0$. From the definition of match surplus,

$$\begin{aligned} S_l^n &= \frac{(y-b)\left(1-\eta p\left(\theta_d\right)\right)}{1-\beta\left\{(1-\delta)-\eta p\left(\theta_l\right)-\left(1-\eta p\left(\theta_l\right)\right)\eta p\left(\theta_d\right)\right\}} \\ &= \left(1-\eta p\left(\theta_d\right)\right)S_d^n. \end{aligned}$$

Note that

$$\frac{\partial S_d^n}{\partial \theta_l} = \frac{\beta (y-b) \eta p'(\theta_l)(1-\eta p(\theta_d))}{[1-\beta\{1-\delta-\eta p(\theta_l)-(1-\eta p(\theta_l))\eta p(\theta_d)\}]^2} \times \frac{q'(\theta_d)(1-\eta)(y-b)}{\kappa\beta(1-\eta p(\theta_l))\eta p'(\theta_d) - q'(\theta_d)(1-\eta)(y-b)} < 0.$$

Therefore,

$$\begin{aligned}
& \frac{\partial S_l^n}{\partial \theta_l} \\
= \; & \frac{\partial}{\partial \theta_l}\left((1-\eta p(\theta_d)) S_d^n\right) \\
= \; & -\eta p'(\theta_d) \frac{\partial \theta_d}{\partial \theta_l} S_d^n + (1-\eta p(\theta_d)) \frac{\partial S_d^n}{\partial \theta_l} \\
= \; & \frac{\beta \eta p'(\theta_l)(1-\eta p(\theta_d))(y-b)}{\Gamma(\theta_l,\theta_d)} \\
& \times \left[\eta\kappa p'(\theta_d) + q'(\theta_d)(1-\eta)\frac{(1-\eta p(\theta_d))(y-b)}{1-\beta\{1-\delta-\eta p(\theta_l)-(1-\eta p(\theta_l))\eta p(\theta_d)\}}\right] \\
= \; & \frac{\beta \eta p'(\theta_l)(1-\eta p(\theta_d))(y-b)}{\Gamma(\theta_l,\theta_d)} \times \left[\eta p'(\theta_d) q(\theta_d) + q'(\theta_d)(1-\eta p(\theta_d))\right](1-\eta) S_d^n
\end{aligned}$$

where

$$\Gamma(\theta_l,\theta_d) = [1-\beta\{1-\delta-\eta p(\theta_l)-(1-\eta p(\theta_l))\eta p(\theta_d)\}] \times \left[\kappa\beta(1-\eta p(\theta_l))\eta p'(\theta_d) - q'(\theta_d)(1-\eta)(y-b)\right].$$

Thus,

$$\frac{\partial S_l^n}{\partial \theta_l} < 0$$

if $\eta p'(\theta_d) q(\theta_d) + q'(\theta_d)(1-\eta p(\theta_d)) > 0$, or

$$\eta < -\frac{q'(\theta_d)}{q(\theta_d)^2} = \frac{1-\theta_d p'(\theta_d)}{p(\theta_d)}.$$

For Cobb-Douglas matching function, the above condition can be written as follows:

$$p(\theta) < \frac{1-\alpha}{\eta}.$$

This conditions always holds if $1-\alpha>\eta$ because $p(\theta)\in[0,1]$. In this case,

$$\begin{aligned}\frac{\partial G}{\partial\theta_l} &= -q'(\theta_l)(1-\eta)\left\{\frac{u^s}{u^n+u^s}S^s+\frac{u^n}{u^n+u^s}S_l^n\right\}\\ &\quad -q(\theta_l)(1-\eta)\left\{\frac{\partial}{\partial\theta_l}\left(\frac{u^s}{u^n+u^s}\right)(S^s-S_l^n)+\frac{u^s}{u^n+u^s}\frac{\partial S^s}{\partial\theta_l}+\frac{u^n}{u^n+u^s}\frac{\partial S^n}{\partial\theta_l}\right\}>0,\end{aligned}$$

because

$$\begin{aligned}&\frac{\partial}{\partial\theta_l}\left(\frac{u^s}{u^n+u^s}\right)\\ =\ &\phi(0.5-\phi)\\ &\times\frac{(p(\theta_l)+\delta)(1-p(\theta_l))p'(\theta_d)\frac{d\theta_d}{d\theta_l}-p'(\theta_l)\{(p(\theta_l)+\delta)p(\theta_d)+(1-p(\theta_l))p(\theta_d)\}}{\{0.5(p(\theta_l)+\delta)+\phi(1-p(\theta_l))p(\theta_d)\}^2}<0\end{aligned}$$

and

$$\frac{\partial S^s}{\partial\theta_l}=-\frac{(y-b)\beta\eta p'(\theta_l)}{\{1-\beta(1-\delta)+\beta\eta p(\theta_l)\}^2}<0.$$

Thus

$$\frac{d\theta_l}{d\phi}=-\frac{\frac{\partial G}{\partial\phi}}{\frac{\partial G}{\partial\theta_l}}>0.$$

Combining the above result with (20),

$$\frac{d\theta_d}{d\phi}<0.$$

B.3 Proof of Corollary 2

The migration rate of mobile workers is defined as the share of workers moved out of total number of mobile households. At the steady state, the population flow between the two places is equal to $2(1-p(\theta_l))p(\theta_d)u^1$. Therefore,

$$\begin{aligned}mr(\theta_l,\theta_d)&=\frac{2(1-p(\theta_l))p(\theta_d)u^1}{2(e^1+u^1)}\\ &=\frac{(1-p(\theta_l))p(\theta_d)}{0.5-\phi}\times\frac{\delta(0.5-\phi)}{\delta+p(\theta_l)+(1-p(\theta_l))p(\theta_d)} \qquad (23)\\ &=\frac{\delta(1-p(\theta_l))p(\theta_d)}{\delta+p(\theta_l)+(1-p(\theta_l))p(\theta_d)}\\ &=\frac{\delta}{\frac{\delta+p(\theta_l)}{(1-p(\theta_l))p(\theta_d)}+1} \qquad (24)\end{aligned}$$

In proposition (1), we prove that $\frac{d\theta_d}{d\phi} < 0$ and $\frac{d\theta_l}{d\phi} > 0$ and the job finding rate is positively correlated with the market tightness θ: $p'(\theta) > 0$. Thus the increase in immobile households increases the denominator of the steady state migration rate of mobile households (24), resulting lower migration rate.

$$\frac{dmr}{d\phi} < 0$$

B.4 Proof of Corollary 3

The unemployment rate of settlers is

$$ur^s(\theta_l) = \frac{2u^s}{2\phi} = \frac{\frac{\delta\phi}{\delta + p(\theta_l)}}{\phi} = \frac{\delta}{\delta + p(\theta_l)}.$$

It is straight forward to show that the unemployment rate of immobile households decreases as the local job finding rate $p(\theta_l)$ is increasing function of ϕ. For nomads, the conditional unemployment rate is

$$ur^n(\theta_l, \theta_d) = \frac{2u^n}{2(0.5 - \phi)} = \frac{\frac{\delta(0.5-\phi)}{\delta + p(\theta_l) + (1-p(\theta_l))p(\theta_d)}}{0.5 - \phi} = \frac{\delta}{\delta + p(\theta_l) + (1 - p(\theta_l))\, p(\theta_d)}.$$

Using the equation (20) and $\Phi(\theta_d, \theta_l) \equiv q'(\theta_d)(1-\eta)(y-b) - \kappa\beta\eta(1-p(\theta_l))\, p'(\theta_d)$,

$$\begin{aligned}
&\frac{dur^n}{d\phi} \\
&= -\frac{p'(\theta_l)\frac{d\theta_l}{d\phi}(1 - p(\theta_d)) + (1 - p(\theta_l))\, p'(\theta_d)\frac{d\theta_d}{d\theta_l}\frac{d\theta_l}{d\phi}}{\{\delta + p(\theta_l) + (1 - p(\theta_l))\, p(\theta_d)\}^2} \\
&= -\left(\frac{d\theta_l}{d\phi}\right) \times \frac{p'(\theta_l)(1 - p(\theta_d)) + (1 - p(\theta_l))\, p'(\theta_d)\frac{d\theta_d}{d\theta_l}}{\{\delta + p(\theta_l) + (1 - p(\theta_l))\, p(\theta_d)\}^2} \\
&= -\left(\frac{d\theta_l}{d\phi}\right) \times \frac{1}{\{\delta + p(\theta_l) + (1 - p(\theta_l))\, p(\theta_d)\}^2} \\
&\qquad \times \left[p'(\theta_l)(1 - p(\theta_d)) + (1 - p(\theta_l))\, p'(\theta_d) \times \frac{\kappa\beta\eta p'(\theta_l)(1 - p(\theta_d))}{\Phi(\theta_d, \theta_l)}\right] \\
&= -\left(\frac{d\theta_l}{d\phi}\right) \times \frac{1}{\{\delta + p(\theta_l) + (1 - p(\theta_l))\, p(\theta_d)\}^2} \times \frac{p'(\theta_l)(1 - p(\theta_d))\, q'(\theta_d)(1-\eta)(y-b)}{\Phi(\theta_d, \theta_l)} < 0,
\end{aligned}$$

because of the properties of the matching function, $q'(\theta) < 0$ and $p'(\theta) > 0$. In summary,

$$\frac{dur^0}{d\phi} < 0 \quad \text{and} \quad \frac{dur^1}{d\phi} < 0.$$

Now we turn to the aggregate unemployment rate. In aggregate level, the total number of unemployed households is

$$2\left(u^0+u^1\right)=2\left[\frac{\delta\phi}{p\left(\theta_l\right)+\delta}+\frac{\delta\left(0.5-\phi\right)}{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)}\right]$$

By taking the derivative with respect to the fraction of settlers, we can characterize two distinct factors affecting the unemployment rates.

$$\begin{aligned}\frac{d\left(u^0+u^1\right)}{d\phi}=&\frac{\delta}{\delta+p\left(\theta_l\right)}-\frac{\delta}{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)}\\&-p'\left(\theta_l\right)\frac{d\theta_l}{d\phi}\left[\frac{\delta\phi}{\left\{p\left(\theta_l\right)+\delta\right\}^2}+\frac{\delta\left(0.5-\phi\right)\left(1-p\left(\theta_d\right)\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right]\\&-p'\left(\theta_d\right)\left(1-p\left(\theta_l\right)\right)\frac{d\theta_d}{d\theta_l}\frac{d\theta_l}{d\phi}\left[\frac{\delta\left(0.5-\phi\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right].\end{aligned}\tag{25}$$

The first line of the equation captures the direct effect from the change in composition of household types, and the bottom two lines captures the general equilibrium effect in both local and distant labor markets. It is obvious to show that the composition effect is positive:

$$\frac{\delta}{\delta+p\left(\theta_l\right)}-\frac{\delta}{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)}>0.\tag{26}$$

We can verify that the general equilibrium effect, represented by the last two terms in the above equation (25), is negative:

$$\begin{aligned}&-p'\left(\theta_l\right)\frac{d\theta_l}{d\phi}\left[\frac{\delta\phi}{\left\{\delta+p\left(\theta_l\right)\right\}^2}+\frac{\delta\left(0.5-\phi\right)\left(1-p\left(\theta_d\right)\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right]\\&\qquad-p'\left(\theta_d\right)\left(1-p\left(\theta_l\right)\right)\frac{d\theta_d}{d\theta_l}\frac{d\theta_l}{d\phi}\left[\frac{\delta\left(0.5-\phi\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right]<0\end{aligned}\tag{27}$$

because

$$\begin{aligned}&-p'\left(\theta_l\right)\frac{d\theta_l}{d\phi}\left[\frac{\delta\phi}{\left\{\delta+p\left(\theta_l\right)\right\}^2}+\frac{\delta\left(0.5-\phi\right)\left(1-p\left(\theta_d\right)\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right]\\&-p'\left(\theta_d\right)\left(1-p\left(\theta_l\right)\right)\frac{d\theta_d}{d\theta_l}\frac{d\theta_l}{d\phi}\left[\frac{\delta\left(0.5-\phi\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\right]\\=&-\delta p'\left(\theta_l\right)\frac{d\theta_l}{d\phi}\\&\times\left[\frac{\phi}{\left\{\delta+p\left(\theta_l\right)\right\}^2}+\frac{\left(0.5-\phi\right)\left(1-p\left(\theta_d\right)\right)}{\left\{\delta+p\left(\theta_l\right)+\left(1-p\left(\theta_l\right)\right)p\left(\theta_d\right)\right\}^2}\times\frac{q'\left(\theta_d\right)\left(1-\eta\right)\left(y-b\right)}{\Phi\left(\theta_d,\theta_l\right)}\right].\end{aligned}$$

The aggregate unemployment increases if the composition effect dominates the general equilibrium effect.

B.5 Efficiency of Decentralized Equilibrium

So far, we have studied how the market equilibrium varies when there is change in composition of settlers. In this section, we define and solve a social planner's problem and compare the solution to the decentralized economy to understand the relation between the allocation efficiency of the market outcome and the population composition. The social planner optimally chooses the market tightness functions for two distinct markets. In the local labor market, social planner is not able to distinct two different types of households ex-ante as the firms in the decentralized economy.

$$
\begin{aligned}
& W\left(u^s, u^n\right) \\
= & \max_{\theta_l, \theta_d} b\left(u^s+u^n\right)+y\left(0.5-u^s-u^n\right)+\beta\left\{-\kappa \theta_l\left(u^s+u^n\right)-\kappa \theta_d\left(1-p\left(\theta_l\right)\right) u^n+W\left(\hat{u}^s, \hat{u}^n\right)\right\}
\end{aligned}
$$

where

$$
\begin{aligned}
\hat{u}^s & =\left(1-p\left(\theta_l\right)\right) u^s+\delta\left(\phi-u^s\right) \\
\hat{u}^n & =\left(1-p\left(\theta_l\right)\right)\left(1-p\left(\theta_d\right)\right) u^n+\delta\left(0.5-\phi-u^n\right).
\end{aligned}
$$

The market tightness in the local labor market affects the both groups of households, but the distant labor market tightness affects only the mobile households who didn't find jobs in the first labor market. From the law of motion of unemployed workers for both types,

$$
\begin{aligned}
\kappa & = -p^{\prime}\left(\theta_l\right)\left[\frac{u^s}{\left\{u^s+\left(1-\theta_d p^{\prime}\left(\theta_l\right)\right) u^n\right\}} \frac{\partial W}{\partial u^s}+\frac{u^n\left(1-p\left(\theta_d\right)\right)}{\left\{u^s+\left(1-\theta_d p^{\prime}\left(\theta_l\right)\right) u^n\right\}} \frac{\partial W}{\partial u^n}\right] \\
\kappa & = -p^{\prime}\left(\theta_d\right) \frac{\partial W}{\partial u^n}.
\end{aligned}
$$

In the local market, the expected gain from increasing a job finding rate by $p'(\theta_l)$ is the weighted average of gains from having additional workers by types. Since $p(\theta_d)$ fraction of unemployed nomads become employed in the distant job search, the effective number of additional nomad workers matched in the local labor market is is $(1-p(\theta_d))\,u^n$, not u^n. Furthermore, considering the fact that there is a distant market for nomads in the second stage, the social planner acts as if there are less unemployed nomads in the local market $((1-\theta_d p'(\theta_l))\,u^n)$, as opposed to the firms in the decentralized market (u^n). Applying the Envelope Theorem, we can analytically solve the value of each additional match as the following:

$$\begin{aligned} R_n \equiv -\frac{\partial W}{\partial u^n} =& \frac{y-b+\beta\kappa\theta_l+\beta\kappa\theta_d\left(1-p\left(\theta_l\right)\right)}{1-\beta\left\{\left(1-p\left(\theta_l\right)\right)\left(1-p\left(\theta_d\right)\right)-\delta\right\}} \\ R_s \equiv -\frac{\partial W}{\partial u^s} =& \frac{y-b+\beta\kappa\theta_l}{1-\beta\left\{\left(1-p\left(\theta_l\right)\right)-\delta\right\}}. \end{aligned}$$

We first set $\phi = 0$ and study how the efficiency of equilibrium changes with remote-job search. In this case, the first-order conditions of the social planner's problem at the steady state are simplified as following:

$$\begin{aligned} \kappa &= -p'\left(\theta_l\right)\left(\frac{1-p\left(\theta_d\right)}{1-\theta_d p'\left(\theta_l\right)}\right)\frac{\partial W}{\partial u^n} \\ \kappa &= -p'\left(\theta_d\right)\frac{\partial W}{\partial u^n}. \end{aligned}$$

The optimality condition can be rewritten as

$$\frac{p'\left(\theta_d\right)}{p'\left(\theta_l\right)\left(1-p\left(\theta_d\right)\right)} = \frac{1}{1-\theta_d p'\left(\theta_l\right)}.$$

Now we compare the solution of the social planner's problem to the equilibrium of decentralized market. Define

$$\omega \equiv \frac{1-p\left(\theta_d\right)}{1-\theta_d p'\left(\theta_l\right)} = \frac{p'\left(\theta_d\right)}{p'\left(\theta_l\right)}.$$

$$\begin{aligned} \kappa &= \frac{p'\left(\theta_d^{SP}\right)(y-b)}{1-\beta\left[(1-\delta)-\left(1-\frac{p'\left(\theta_d^{SP}\right)}{q\left(\theta_l^{SP}\right)}\right)p\left(\theta_l^{SP}\right)-\left(1-p\left(\theta_l^{SP}\right)\right)\left(1-\frac{p'\left(\theta_d^{SP}\right)}{q\left(\theta_d^{SP}\right)}\right)p\left(\theta_d^{SP}\right)\right]} \\ \kappa &= \frac{\omega p'\left(\theta_l^{SP}\right)(y-b)}{1-\beta\left[(1-\delta)-\left(1-\frac{\omega p'\left(\theta_l^{SP}\right)}{q\left(\theta_l^{SP}\right)}\right)p\left(\theta_l^{SP}\right)-\left(1-p\left(\theta_l^{SP}\right)\right)\left(1-\frac{\omega p'\left(\theta_l^{SP}\right)}{q\left(\theta_d^{SP}\right)}\right)p\left(\theta_d^{SP}\right)\right]} \end{aligned}$$

Recall the free entry conditions in the decentralized market with $\phi = 0$ are

$$\begin{aligned} \kappa =& \frac{q\left(\theta_d\right)(1-\eta)(y-b)}{1-\beta\left[(1-\delta)-\eta p\left(\theta_l\right)-\left(1-\eta p\left(\theta_l\right)\right)\eta p\left(\theta_d\right)\right]} \\ \kappa =& \frac{q\left(\theta_l\right)(1-\eta)\left(1-\eta p\left(\theta_d\right)\right)(y-b)}{1-\beta\left[(1-\delta)-\eta p\left(\theta_l\right)-\left(1-\eta p\left(\theta_l\right)\right)\eta p\left(\theta_d\right)\right]}. \end{aligned}$$

It is straightforward that the Hosios condition does not apply in this economy. When the bargaining power is set equal to $p'(\theta_d) = q(\theta_d)(1-\eta)$ or

$$1 - \frac{p'(\theta_d)}{q(\theta_d)} = \eta,$$

the optimality condition of the planner's problem in distant market becomes

$$\begin{aligned}
\kappa &= \frac{q\left(\theta_d^{SP}\right)(1-\eta)(y-b)}{1-\beta\left[(1-\delta) - \eta p\left(\theta_l^{SP}\right) - \left(1-p\left(\theta_l^{SP}\right)\right)\eta p\left(\theta_d^{SP}\right)\right]} \\
&\neq \frac{q\left(\theta_d^{SP}\right)(1-\eta)(y-b)}{1-\beta\left[(1-\delta) - \eta p\left(\theta_l^{SP}\right) - \left(1-\eta p\left(\theta_l^{SP}\right)\right)\eta p\left(\theta_d^{SP}\right)\right]}.
\end{aligned}$$

Similarly, if $\omega p'(\theta_l) = q(\theta_l)(1-\eta)$ or

$$1 - \frac{\omega p'(\theta_l)}{q(\theta_l)} = 1 - \frac{p'(\theta_d)}{q(\theta_l)} = \eta,$$

$$\begin{aligned}
\kappa &= \frac{q\left(\theta_l^{SP}\right)(1-\eta)(y-b)}{1-\beta\left[(1-\delta) - \eta\left(\theta_l^{SP}\right) - \left(1-p\left(\theta_l^{SP}\right)\right)\eta p\left(\theta_d^{SP}\right)\right]} \\
&\neq \frac{q\left(\theta_l^{SP}\right)(1-\eta)\left(1-\eta p\left(\theta_d^{SP}\right)\right)(y-b)}{1-\beta\left[(1-\delta) - \eta p\left(\theta_l^{SP}\right) - \left(1-\eta p\left(\theta_l^{SP}\right)\right)\eta p\left(\theta_d^{SP}\right)\right]}.
\end{aligned}$$

Even after correcting the search externality by setting the bargaining share of each parties to be consistent with their externality in each labor market, the optimal outcome cannot be implemented in decentralized economy. Workers use the existence of additional search opportunity in the other location when they negotiate their wages, and it makes the match surplus functions be dependent to $1-\eta p(\theta_l)$ and $1-\eta p(\theta_d)$.

B.6 A Model with Alternative Labor Market Structure

We introduce two distinct local labor markets, local market 1 and local market 2. All the immobile workers participate in the local labor market 1 whereas mobile individuals split into two local labor markets. $1-\rho$ fraction of mobile workers search along with immobile workers in the local labor market 1 and the otherρ fraction of mobile workers search in a segregated local labor market 2. For simplicity, ρ is assumed to be i.i.d.

Under this modified labor market structure, the value functions of each type are given by:

$$\begin{aligned}
U^s &= b+\beta\left\{p(\theta_l^1)W^s(w^s)+\left(1-p\left(\theta_l^1\right)\right)U^s\right\} \\
U^n &= b+\beta[(1-\rho)\,p\left(\theta_l^1\right)W^n\left(w^n\right)+\rho p\left(\theta_l^2\right)W^n\left(w^n\right) \\
&\quad +\left(1-(1-\rho)\,p\left(\theta_l^1\right)-\rho p\left(\theta_l^2\right)\right)\left\{p\left(\theta_d\right)W^n\left(w^n\right)+\left(1-p\left(\theta_d\right)\right)U^n\right\}] \\
W^s\left(w\right) &= w+\beta\left\{(1-\delta)\,W^s\left(w^s\right)+\delta U^s\right\} \\
W^n\left(w\right) &= w+\beta\left\{(1-\delta)\,W^n\left(w^n\right)+\delta U^n\right\}
\end{aligned}$$

The value of a firm with a matched worker at wage w collects $y-w$ every period until the match dissolves with exogenous probability δ.

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

The wage of a match is determined by Nash Bargaining after the labor market searches are done.

$$w^i=argmax\left\{W^i\left(w\right)-U^i\right\}^{\eta}J\left(w\right)^{1-\eta}.$$

Under the Nash bargaining assumption, a firm and a worker split the match surplus proportional to their bargaining power. The match surplus of settler is given by:

$$\begin{aligned}
S^s\left(\theta_l^1,\theta_l^2,\theta_d\right) &\equiv J\left(w\right)+W^s\left(w\right)-U^s \\
&= \frac{y-b}{1-\beta\left\{(1-\delta)-\eta p\left(\theta_l^1\right)\right\}}.
\end{aligned}$$

Similarly, the surplus of a match with a nomad is as follows:

$$\begin{aligned}
& S^n\left(\theta_l^1,\theta_l^2,\theta_d\right) \\
\equiv\;& J\left(w\right)+W^n\left(w\right)-U^n \\
=\;& \frac{y-b}{1-\beta\left[(1-\delta)-\eta\left\{(1-\rho)\,p\left(\theta_l^1\right)+\rho p\left(\theta_l^2\right)+\left(1-(1-\rho)\,p\left(\theta_l^1\right)-\rho p\left(\theta_l^2\right)\right)p\left(\theta_d\right)\right\}\right]}.
\end{aligned}$$

Under the modified market structure, there are three labor markets in each location. We define θ_l^1 and θ_l^2 as the market tightness of local labor market 1 and 2, respectively. The market tightness for a distant labor market is denoted by θ_d. For each labor market, we assume the free entry condition holds. Therefore, in equilibrium the expected return of posting a vacancy is equal to the posting cost, κ.

$$\begin{aligned}
\kappa &= q\left(\theta_d\right) J\left(w^n\right) \\
\kappa &= q\left(\theta_l^2\right) J\left(w^n\right) \\
\kappa &= q\left(\theta_l^1\right)\left\{\frac{u^s}{(1-\rho)\,u^n+u^s} J\left(w^s\right)+\frac{(1-\rho)\,u^n}{(1-\rho)\,u^n+u^s} J\left(w^n\right)\right\}.
\end{aligned}$$

C Data

This sections 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)).[19] After 1996, we exclude observations with imputed migration data to avoid complications arising due to changes in CPS imputation procedures.[20]

Table 13
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.[21] SIPP is a large representative sample of households interviewed every four months (a "wave") for

[19] The data can be obtained on https://cps.ipums.org/cps/.
[20] See Kaplan and Schulhofer-Wohl (2012) for a detailed explanation.
[21] Two exceptions we are aware of are Aaronson and Davis (2011) and Guler and Taskin (2012).

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 C. 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.[22]

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.[23] We use personal exemptions. Census Bureau provides annual homeownership rates and population estimates.[24] 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.[25]

D Additional Results: The Quantitative Model

D.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. $\epsilon_{B,d} < \epsilon_{B,l}^B$

5. $\epsilon_l^A < \epsilon_l^B$

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

[23]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 used county-county population flows to construct MSA-MSA population flows.

[24]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.

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

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

D.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:

$$\begin{aligned} u^A_{t+1}(\epsilon,\mu) \quad = \quad & u^A_t(\epsilon,\mu) + \delta e^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} + u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}} \\ & -p\left(\theta^A_l\right)\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} + u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right) \\ & -p\left(\theta^B_d\right)\left(1-p\left(\theta^A_l\right)\right) \\ & \times\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} + u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right)\mathbb{I}_{\{\epsilon\leq\epsilon^A_d(\mu)\}} \end{aligned} \tag{28}$$

$$\begin{aligned} e^A_{t+1}(\epsilon,\mu) \quad = \quad & e^A_t(\epsilon,\mu) - \delta e^A_t(\epsilon,\mu) \\ & +p\left(\theta^A_l\right)\left(u^A_t(\epsilon,\mu) - u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} + u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right) \\ & +p\left(\theta^A_d\right)\left(1-p\left(\theta^B_l\right)\right) \\ & \times\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} - u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right) \end{aligned} \tag{29}$$

$$\begin{aligned} u^B_{t+1}(\epsilon,\mu) \quad = \quad & u^B_t(\epsilon,\mu) + \delta e^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} - u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}} \\ & -p\left(\theta^B_l\right)\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} - u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right) \\ & -p\left(\theta^A_d\right)\left(1-p\left(\theta^B_l\right)\right) \\ & \times\left(u^B_t(\epsilon,\mu) + u^A_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\leq\epsilon^A_l(\mu)\}} - u^B_t(\epsilon,\mu)\mathbb{I}_{\{\epsilon\geq\epsilon^B_l(\mu)\}}\right)\mathbb{I}_{\{\epsilon\geq\epsilon^B_d(\mu)\}} \end{aligned} \tag{30}$$

$$
\begin{aligned}
e_{t+1}^{B}(\epsilon,\mu) &= e_t^B(\epsilon,\mu) - \delta e_t^B(\epsilon,\mu) \\
&+ p\left(\theta_l^B\right)\left(u_t^B(\epsilon,\mu) + u_t^A(\epsilon,\mu)\,\mathbb{I}_{\{\epsilon \le \epsilon_l^A(\mu)\}} - u_t^B(\epsilon,\mu)\,\mathbb{I}_{\{\epsilon \ge \epsilon_l^B(\mu)\}}\right) \\
&+ p\left(\theta_d^B\right)\left(1 - p\left(\theta_l^A\right)\right) \\
&\times \left(u_t^A(\epsilon,\mu) - u_t^A(\epsilon,\mu)\,\mathbb{I}_{\{\epsilon \le \epsilon_l^A(\mu)\}} + u_t^B(\epsilon,\mu)\,\mathbb{I}_{\{\epsilon \ge \epsilon_l^B(\mu)\}}\right),
\end{aligned}
\tag{31}
$$

Aggregate unemployment in location j is simply the integral of the type-specific unemployment $u_t^j(\epsilon,\mu)$ over the distribution of (ϵ,μ) in that location. For a case where$\epsilon_d^B < \epsilon_l^A < \epsilon_l^B < \epsilon_d^A$, 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

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

   in steady state.

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

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

   in steady state.

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

0.

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

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

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

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

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

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

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

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

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

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

D.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 D.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 D.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.

D.5 Comparing our Hypothesis with Alternative Explanations

In this section we assess the relative importance of our mechanism compared to two alternative explanations. Molloy et al. (2013) document that the decline in downward trend in labor market transitions occurred over the same period and suggest possible linkage of the decline in migration rate and labor turnover rates. To evaluate relative importance of our own mechanism compared to the decline in labor turnover, we reduce the job destruction rate δ to 2.9 percent to be consistent with the average separation between 2000 and 2005, instead of using the average delta over the sample period.

In Kaplan and Schulhofer-Wohl (2013) authors argue that people can acquire information regarding their true locational preference without actual migration thanks to the development of information technology and transportation. We implement their mechanism by injecting new-born to the economy who do not know their preference at the beginning of their life. By shorten the time required to learn their location preference, we quantify the importance of reduced repeat-migration.

TABLE 14
SUMMARY OF COUNTER-FACTUAL ANALYSIS

	Benchmark (1980)	Counter-Factual (2006)
Migration Spillovers	Population share =1980	Increase the share of older population
	Job destruction rate=1980	Job destruction rate=1980
	No learning delay	No learning delay
Labor Market Turnover	Population share =1980	Population share =1980
	Job destruction rate=1980	Reduced the job destruction rate
	No learning delay	No learning delay
Information	Population share =1980	Population share =1980
	Job destruction rate=1980	Job destruction rate=1980
	learn location preference after T periods	No learning delay

We recalibrate the generalized version of our model and decompose three distinct mechanisms. Generalized version of our model has an additional parameter to calibrate, the share of new-born, d. As the share of new-born who are randomly assigned to their locations increase, the quantitative importance of learning is increasing as well. We discipline this parameter by matching the non-labor market related migration be 70% of the total migration. We define the non-labor market related migration as the move without an offer from the distant labor market. Tables 14 and 15 summarize the counter-factual exercise. It shows that with the presence of alternative explanations, the migration spillovers still accounts at least half of the decline in migration.

Table 15
Comparison of Alternative Mechanisms

		Data		Counter factual Analysis		
		1980	2006	Spillovers	Lower δ	Information
		(Data=Counter factual)	(Change)	(Change)	(Change)	(Change)
Aggregate migration rate		3.0%	1.6% (1.4%)	2.3% (0.7%)	2.5% (0.5%)	2.7% (0.3%)
By age group	25 − 29	5.4%	3.3% (2.1%)	4.4% (1.0%)	4.5% (0.9%)	4.8% (0.6%)
	30 − 34	3.9%	2.3% (1.6%)	3.3% (0.6%)	3.0% (0.9%)	3.5% (0.4%)
	35 − 39	3.1%	1.8% (1.3%)	2.9% (0.2%)	2.4% (0.7%)	2.9% (0.2%)
	40 − 45	2.0%	1.5% (0.5%)	1.8% (0.2%)	1.6% (0.4%)	1.8% (0.2%)
	45 − 49	2.0%	1.0% (1.0%)	1.7% (0.3%)	1.6% (0.4%)	1.8% (0.2%)
	50 − 54	1.4%	0.9% (0.5%)	1.0% (0.4%)	1.3% (0.1%)	1.3% (0.1%)
	55 − 59	1.4%	1.1% (0.3%)	1.0% (0.4%)	1.3% (0.1%)	1.3% (0.1%)

Note: Table compares the counteractual migration rates of the model to the data. The first row shows aggregate migration rate and the other rows show the migration rate for each group. The first two columns show the actual migration rates in the data. The third column shows what happens to migration rates with the aging of population. The fourth colum shows what happens to migration rates if the separation rate declines to 2.6% without the change in population composition. The fifth colum reports what happens to migration rates if the learning of location preference type is immediate.