The Effect of Business Cycle Fluctuations on Migration Decisions*

Tyler Ransom†

Duke University

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Abstract

I examine mechanisms that differentially influence migration behavior in response to labor market shocks between employed and unemployed workers in the US. Over the period of the Great Recession, overall migration rates in the US remained close to their respective long-term trends. However, migration evolved differently by employment status with unemployed workers being more likely to migrate during the recession and employed workers less likely. I estimate a dynamic non-stationary search model of migration, focusing on the role of employment frictions, earnings, and amenities on migration decisions. My results show that employed workers are faced with a large job queuing penalty when moving locations, which results in differing migration incentives for the two groups when faced with adverse labor market shocks. I also find that migration rates were muted because of the national scope of the Great Recession. I show that moving subsidies aimed at mitigating local unemployment are greatly hindered by workers' preferences for amenities.

JEL Classification: E32, J22, J61, J64, R23

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†Contact: Social Science Research Institute, Duke University, Box 90989, Durham, NC 27708-0989. E-mail: *tyler.ransom@duke.edu*

1 Introduction

In the US and in other developed countries, unemployed workers are more likely than employed workers to migrate to a different location within the country. This result holds across all migration distances and worker ages.[1] This fact indicates that migration rates should increase during recessions, when unemployment rates increase. However, overall migration rates in the US remained close to their respective long-term trends during the period of the Great Recession.[2] Taken together, these facts are consistent only if migration rates trended differently by employment status over the Great Recession period. Indeed, data show that migration rates for the unemployed increased, while migration rates for the employed fell. Overall migration rates followed the long-run trend.[3]

Understanding how migration incentives differ for employed and unemployed workers is important because migration is the primary way in which local labor markets adjust to shocks (Topel, 1986; Blanchard and Katz, 1992). Knowledge about the factors that affect migration is useful both in predicting migratory response to labor market shocks, and in informing policy that seeks to encourage migration.

In this paper, I examine mechanisms through which migration behavior differs between the employed and unemployed when each group is faced with a variety of labor market shocks. I also investigate the effect of a moving subsidy offered to unemployed workers (e.g. Moretti, 2012). Specifically, I estimate a dynamic search model of migration and labor supply where locations (US cities) are characterized in three dimensions: (*i*) amenities, (*ii*) earnings prospects, and (*iii*) employment prospects. This paper is the first to jointly model locational choice and labor supply while allowing labor market shocks to influence the decision separately for employed, unemployed, and non-participating individuals.[4]

[1] Schmutz and Sidibé (2015) show evidence of these trends in France. Schlottmann and Herzog (1981) document this in the United States.

[2] Molloy and Wozniak (2011) show that migration is actually *countercyclical* in the US since 1950, noting that the Great Recession period is an exception. This stands in even starker contrast to the observed differences in migration behavior between the employed and unemployed, and emphasizes the importance of understanding this behavior.

[3] See Figures 1 and 2 which show these trends using US data from the Current Population Survey (CPS).

[4] There is a large literature on migratory response to labor market shocks (Notowidigdo, 2011; Monras, 2014; Yagan, 2014; Foote, Grosz, and Stevens, 2015). There is also a growing literature estimating individ-

Characterizing locations in these three dimensions captures the main complementarities that workers take into account when choosing where to live. Each period, an individual chooses whether or not to enter the labor force in a particular location. If he chooses to enter the labor force, he enters a lottery and becomes employed (or continues to be employed) with some probability. The model is dynamic in the sense that individuals take into account the evolution of both earnings and job prospects when choosing a location.[5] Crucial to the dynamics is the fact that individuals face costs in moving locations or changing the labor supply decision.

In order to estimate such a complex model, I utilize recent developments in the estimation of large state-space dynamic discrete choice models. By making use of conditional choice probabilities (CCPs) and the property of finite dependence, I tractably estimate a model that includes many alternative locations and unemployment risk that is both stochastic and time-varying.[6]

I estimate the model using confidential panel data on white males from the Survey of Income and Program Participation (SIPP) covering the years 2004-2013. This allows me to focus on the time period leading up to and covering the Great Recession, when local labor market shocks have been most salient. The large coverage of the SIPP also allows me to observe many moves and to estimate location-specific model parameters.

I find that the observed differential in migration rates by employment status is primarily due to asymmetry in how job offer and job destruction rates evolved over the Great Recession. In particular, job offer rates decreased by about five times more than job destruction rates increased. Furthermore, employed workers face a steep job queu-

ual models of migration that allow for forward-looking behavior (Gould, 2007; Gemici, 2011; Kennan and Walker, 2011; Baum-Snow and Pavan, 2012; Bishop, 2012; Coate, 2013; Adda, Dustmann, and Görlach, 2014; Mangum, 2015; Schmutz and Sidibé, 2015). The canonical migration model that incorporates unemployment risk is Harris and Todaro (1970).

[5]Thus, the term "earnings prospects" actually encompass the following four features of a location: earnings levels, variance of earnings shocks (or earnings volatility), persistence of earnings shocks, and earnings trends. The same four features are also encompassed in the term "employment prospects," except time series data on the local unemployment rate is used instead. Amenities are both individual- and location-specific, but do not vary over time.

[6]The literature on estimation of dynamic models using CCPs originated with Hotz and Miller (1993). Altuğ and Miller (1998) expanded the set of models that can be estimated in this fashion by introducing the concept of finite dependence. I employ methods from both of these papers while showing how finite dependence can be achieved even in the presence of a stochastic choice set (Arcidiacono and Miller, 2014).

ing penalty when moving locations, whereas unemployed workers face no such penalty. These two factors together give employed workers an incentive to stay in their current location and keep their jobs, in contrast with unemployed workers who are more likely to migrate in order to avoid search costs.

I also find evidence that the national scope of the Great Recession muted the migration rates of unemployed workers. Using estimates of the model, I simulate out-migration rates from various locations under a scenario where the current location receives either a purely localized unemployment shock or a shock that is correlated across locations. For unemployed workers, the simulated migration rate is 8-12 times larger in the purely localized case than in the correlated case. The response is largest in areas with low amenities and low job-finding rates.

I also use the estimates of the structural model to analyze the effectiveness of a spatial unemployment insurance policy by simulating the effect of a move subsidy. I find that recipients of the subsidy most strongly prefer locations with higher amenities and locations that are near their birth location. Workers also prefer locations with greater employment certainty relative to locations with higher earnings, primarily because job search is costly. Subsidy recipients also prefer to stay close to their origin location because moving costs increase with distance.

These results have strong implications for policy that seeks to increase out-migration from shocked areas. Because workers are influenced roughly equally by amenities and employment certainty, my findings underscore the difficulty in implementing migration policy that would have the intended consequence of inducing migration from high-unemployment areas to low-unemployment areas.

In the next section, I present a structural model of migration and labor supply that incorporates non-stationary earnings and unemployment risk at the local level. In the following section, I detail the data used in the analysis and examine descriptive patterns that form the basis of the research questions at hand.

The remainder of the paper is outlined as follows: Section 4 discusses estimation and identification, Section 5 discusses the empirical estimates, Section 6 discusses counterfactual simulations of the model, and Section 7 concludes.

2 A Model of Labor Supply and Locational Choice

2.1 Overview

I now introduce the model that I will estimate and use to examine counterfactual scenarios that will shed light on why migration behavior differs by employment status in response to local labor market shocks. In each period, individuals choose a location of residence and whether or not to supply labor. The choice set is exhaustive in that in covers every possible location in the United States, and every possible labor market status. A key element of the model is that, while an individual may control his labor supply decision, he cannot control his employment *outcome*. That is, an unemployed worker may exogenously receive a job offer and an employed worker may exogenously be laid off. Furthermore, these job offer and destruction rates vary by location and calendar time, thus capturing heterogeneity in local business cycles. Modeling labor supply as an explicit choice is essential to the model, because the employment probabilities are conditional on labor force participation.

Individuals are forward-looking and in each period choose the alternative that maximizes the present discounted value of utility. Thus, individuals take into account local labor market conditions when choosing where to locate—in addition to amenities and earnings prospects, which have been traditionally modeled in the migration literature. Individuals also understand that there are costs associated with changing locations or labor force status. These costs motivate individuals to be forward-looking when considering their decision in each period.

The model is the first to jointly specify locational choice and labor supply in a dynamic setting while also allowing for a rich set of local labor market conditions to separately influence the migration decision by employment status. While the model is rich in terms of dynamics and local labor market heterogeneity, it has three primary restrictions: (i) it is a partial equilibrium analysis; (ii) it abstracts from asset accumulation; and (iii) it ignores the effect of idiosyncratic earnings shocks on preferences—that is, choices are influenced by the deterministic component of earnings and not actual earnings realizations because the earnings shocks are relayed only after the decision is made.[7]

The partial equilibrium analysis implemented here is admittedly restrictive but comes at the advantage of estimating a dynamic model. Other migration models have focused on general equilibrium across space, but at the cost of ignoring dynamics (Roback, 1982; Piyapromdee, 2014; Diamond, 2016).[8] There are only two dynamic spatial equilibrium analyses (Mangum, 2015; Schmutz and Sidibé, 2015). Estimating such models is much more difficult and requires a different set of restrictive assumptions in order to be computationally feasible.[9]

The other two restrictions are made for purposes of estimation tractability. While assets and idiosyncratic earnings shocks are important state variables in migration and labor supply decisions, abstracting from them allows me to make use of a much more computationally tractable estimation algorithm. This algorithm is described in more detail in the following section.

I now present each feature of the model in more detail, beginning with earnings and flow utilities for each alternative.[10]

2.2 Earnings

Monthly earnings for individual i in location ℓ and calendar year t are a function of location-year fixed effects $\psi_{0\ell t}$, work experience x_{it}, and idiosyncratic shocks $\eta_{i\ell t}$. The log earnings equation is

$$\ln w_{i\ell t} = \psi_{0\ell t} + \psi_1 G\left(x_{it}\right) + \eta_{i\ell t} \tag{2.1}$$

where $G\left(\cdot\right)$ is a quadratic polynomial. Human capital accumulation is accounted for by including work experience as a determinant of earnings. Heterogeneity and nonstation-

[7]Kennan and Walker (2011) and Bishop (2012) face this same set of restrictions.

[8]Gaubert (2015) analyzes a spatial equilibrium model of firm migration, but also abstracts from dynamics.

[9]For instance, neither of these models allows for human capital accumulation. Mangum (2015) does not allow for employment rates to differ by employment status. Schmutz and Sidibé (2015) do not allow for the possibility of non-employed workers to move locations.

[10]A cross-referenced notation glossary for all Greek symbols is available in Table B.10.

arity in earnings is accounted for by the location-year dummies, which allow for business cycle effects to be different across locations. Importantly, individuals observe the time dummies in calendar year t but must form expectations about their evolution in future periods. The idiosyncratic shocks $\eta_{\ell t}$ are assumed to be distributed $N\left(0, \sigma_\eta^2\right)$ and are independent over time and locations and independent of all other state variables.

2.2.1 Forecasting earnings

Individuals are uncertain about future realizations of the $\psi_{0\ell t}$'s and the $\eta_{i\ell t}$'s. They forecast future earnings according to an AR(1) process (with drift) on the $\psi_{0\ell t}$'s:

$$\psi_{0\ell t} = \rho_{0\ell} + \rho_1 \psi_{0\ell t-1} + \zeta_{\ell t} \tag{2.2}$$

where $\zeta_{\ell t}$ is distributed $N\left(0, \sigma_{\zeta_\ell}^2\right)$. In other words, individuals know the drift and autocorrelation coefficients ($\rho_{0\ell}$ and ρ_1) and shock variances ($\sigma_{\zeta_\ell}^2$) for each location, and integrate over future realizations of $\zeta_{\ell t}$ using information about the distribution from which $\zeta_{\ell t}$ is drawn.

Individuals also forecast future earnings shocks $\eta_{i\ell t}$ but do not need to integrate over any distribution because the $\eta_{i\ell t}$'s are assumed to be mean-zero and independent over time, and because they are assumed to not enter the flow utility equations below.

2.3 Employment probabilities

Individuals who choose to supply labor obtain employment with probability $\pi_{i\ell t}$, which depends on their level of work experience x_{it}, their current location ℓ, their previous location and employment status, and the previous unemployment rate in each location.

$$\pi_{i\ell t}\left(x_{it}\right) = \begin{cases} (1-\delta_{i\ell t}) & \text{if employed in } \ell \text{ in } t-1 \\ \lambda_{i\ell t} & \text{if not employed in } \ell \text{ in } t-1 \\ \lambda_{i\ell t}^e & \text{if employed in } \ell' \neq \ell \text{ in } t-1 \\ \lambda_{i\ell t}^u & \text{if not employed in } \ell' \neq \ell \text{ in } t-1 \end{cases} \tag{2.3}$$

Equation (2.3) operates as follows. Individuals arrive in a location and, if choosing to supply labor, are entered into a lottery that assigns them employment with probability $\pi_{i\ell t}$. Individuals pre-commit to working if they are assigned to employment.[11] Employed individuals are thus laid off with probability $\delta_{i\ell t}$ and unemployed individuals receive a job offer with probability $\lambda_{i\ell t}$. Individuals coming from employment in another location receive an offer with probability $\lambda^{e}_{i\ell t}$. Individuals coming from non-employment in another location receive an offer with probability $\lambda^{u}_{i\ell t}$. In particular, these employment probability parameters are indexed by location and time, which allows for heterogeneous business cycle effects across locations — a trend seen in the data. As with other non-stationary parameters in the model, individuals observe these probabilities in calendar year t but must form expectations about their evolution in future periods.

In practice, each of the employment probabilities is parameterized as a predicted logistic probability, where the logistic regression has right hand side variables as follows: location fixed effects, lagged unemployment rate, and a mover dummy. Non-stationarity enters the employment probabilities through movements in the lagged unemployment rate.

2.3.1 Forecasting employment probabilities

Individuals forecast future employment probabilities according to an AR(1) process (with drift) on the local unemployment rate $\mathrm{UR}_{\ell t}$:

$$\mathrm{UR}_{\ell t} = \phi_{0\ell} + \phi_{1\ell}\mathrm{UR}_{\ell t-1} + \xi_{\ell t} \tag{2.4}$$

where, again, individuals know the shock variance and autocorrelation of the $\mathrm{UR}_{\ell t-1}$'s in each location, but integrate over possible realizations of the $\xi_{\ell t}$'s given realizations of $\mathrm{UR}_{\ell t-1}$. $\xi_{\ell t}$ is assumed to be drawn from a distribution that is $N\left(0, \sigma^2_{\xi_\ell}\right)$.

[11] In this sense, individuals choose locations not by the availability of job offers, but by the likelihood of finding a job once in the destination location. Thus, workers search for a job in the location upon arrival. This motivates the sample selection discussed in the next section, since this group of people are more likely to move before finding a job (Basker, 2003).

This implies that, for each t, the time-t forecasted future employment probability is

$$\mathbb{E}_t \pi_{i\ell t+1} = \int_{\xi_\ell} \Pr\left(\mu_2\left(\phi_{0\ell} + \phi_{1\ell}\mathrm{UR}_{\ell t} + \xi_{\ell t+1}\right) + z_{i\ell}\mu\right) dF\left(\xi_{\ell t+1}\right) \tag{2.5}$$

where μ_2 is a parameter governing the relationship between the lagged unemployment rate in location ℓ and the employment probability, and $z_{i\ell}\mu$ represents other right-hand side variables and parameters in the probability that are stationary (e.g. location, work experience). In practice, μ_2 is allowed to vary by employment status to capture the fact that unemployed workers are more vulnerable to economic downturns. More details on the form and estimation of these probabilities are given in section 4.2.

2.4 State variables, flow utilities, and stochastic employment

Denote by $d_{it} = (j, \ell)$ the choice for individual i in calendar year t, where $j \in \{0, 1\}$ indexes labor force status, $\ell \in \{1, \ldots, L\}$ indexes locations, and $\mathcal{J} = \{0, 1\} \times \{1, \ldots, L\}$ denotes the entire choice set. Labor force participation is denoted by $j = 1$ while $j = 0$ indicates out of the labor force. As mentioned before, individuals control their labor supply decision, but not their employment outcome. To differentiate between the two, let $y_{it} \in \{e, u, n\} \times \{1, \ldots, L\}$ be the choice outcome, where e denotes employment, u unemployment, and n non-participation. The set $\{1, \ldots, L\}$ covers all possible locations in the United States. A complete list of these locations can be found in Table B.4.

Let Z_{it} denote the state variables for individual i in calendar year t. Z_{it} contains work experience, age, calendar time t, previous decision d_{it-1}, and previous employment outcome y_{it-1}. The flow utility associated with making choice (j, ℓ) is

$$U_{ij\ell t}\left(Z_{it}, \varepsilon_{ij\ell t}\right) = u_{ij\ell t}\left(Z_{it}\right) + \varepsilon_{ij\ell t} \tag{2.6}$$

The flow payoffs associated with choices j and ℓ are an expectation of the employment outcomes:

$$u_{i1\ell t}\left(Z_{it}\right) = \pi_{i\ell t}\left(Z_{it}\right) u^{e}_{i\ell t}\left(Z_{it}\right) + \left(1 - \pi_{i\ell t}\left(Z_{it}\right)\right) u^{u}_{i\ell t}\left(Z_{it}\right) \tag{2.7}$$

$$u_{i0\ell t}\left(Z_{it}\right) = u^{n}_{i\ell t}\left(Z_{it}\right) \tag{2.8}$$

The flow utility corresponding to each employment outcome is given by

$$u^{e}_{i\ell t}\left(Z_{it}\right) = \alpha_\ell + \Delta_\ell\left(Z_{it}\right) + \Xi_1\left(Z_{it}\right) + \gamma_3 b^{ST}_{i\ell} + \gamma_4 b^{DIV}_{i\ell} + \gamma_0 \ln \widetilde{w}_{i\ell t}\left(Z_{it}\right) \tag{2.9}$$

$$u^{u}_{i\ell t}\left(Z_{it}\right) = \alpha_\ell + \Delta_\ell\left(Z_{it}\right) + \Xi_1\left(Z_{it}\right) + \gamma_3 b^{ST}_{i\ell} + \gamma_4 b^{DIV}_{i\ell} + \gamma_1 + \gamma_2 \tag{2.10}$$

$$u^{n}_{i\ell t}\left(Z_{it}\right) = \alpha_\ell + \Delta_\ell\left(Z_{it}\right) + \Xi_0\left(Z_{it}\right) + \gamma_3 b^{ST}_{i\ell} + \gamma_4 b^{DIV}_{i\ell} + \gamma_1 \tag{2.11}$$

The first term α_ℓ is a location fixed effect measuring the net value of all amenities in location ℓ. The variables $b^{ST}_{i\ell}$ and $b^{DIV}_{i\ell}$ are dummies that are true if the individual was born in any of the states (ST) or Census divisons (DIV) contained in location ℓ.[12] $\ln \widetilde{w}_{i\ell t}\left(Z_{it}\right)$ is the deterministic component of log earnings for an individual in location ℓ with states Z_{it}, γ_1 is a home production benefit, and γ_2 is a cost of searching for employment.[13] Home production benefits and search costs are constant across locations. $\Delta_\ell\left(Z_{it}\right)$ are costs of moving to ℓ which are incurred if the previous location is different from ℓ. Likewise, $\Xi\left(Z_{it}\right)$ are labor supply switching costs which are incurred whenever a person enters or exits the labor force. The unobserved part of the flow utility $\varepsilon_{ij\ell t}$ is a preference shock, but can equivalently be thought of as a shock to moving costs or switching costs. These preference shocks are assumed to be drawn from a standard Type I extreme value distribution, independently across i, j, ℓ, and t. The $\varepsilon_{ij\ell t}$'s are also independent of the other variables in the model.

[12] For example, an individual born in Indiana would have this dummy turned on for the following locations: Indianapolis, Chicago, and the two East North Central Census division synthetic locations. There are two cities in the model that straddle Census divisions: New York City and St. Louis, MO.

[13] While γ_1 is labeled as a benefit and γ_2 a cost, the sign of each is freely estimated.

2.5 Moving costs and switching costs

2.5.1 Moving costs

Let h indicate the previous location, which is embedded in Z_{it}, and define $D(\ell, h)$ as the great circle distance between the two locations. The moving costs are a function of a fixed cost, distance, age, and previous employment status, and are specified as

$$\Delta_\ell (Z_{it}) = \Big(\theta_0 + \theta_1 D(\ell, h) + \theta_2 D^2 (\ell, h) + \theta_3 \text{age}_{it} + \theta_4 \text{age}_{it}^2 + \theta_5 \text{employed}_{it-1} + \theta_6 \text{unemployed}_{it-1}\Big) 1\{\ell \neq h\} \tag{2.12}$$

where $1\{A\}$ is an indicator meaning that A is true. Moving costs are specified in a reduced-form manner to flexibly capture trends in the data. This specification is in line with Kennan and Walker (2011) and Bishop (2012).[14] Additionally, I allow the moving cost to differ by previous employment status to capture heterogeneous responses to preference shocks by previous employment status. This dimension of moving costs has not been explored previously in the literature.

The intercept θ_0 corresponds to the fixed cost of moving, while θ_1 and θ_2 capture the fact that moving costs increase with distance, but at a potentially decreasing rate. θ_3 and θ_4 capture a similar idea with age. θ_5 and θ_6 are included to capture differences in psychic costs and financial costs for those who were previously employed compared with those who were previously unemployed.[15] The signs on the θ's are written here as being positive but are allowed to be freely estimated. The fixed cost and linear terms of distance and age are expected to have a negative sign, while the signs on the two quadratic terms are expected to be positive. The expected sign of the previous employment status dummies is ambiguous because, for example, while employed individuals might have more financial capital to facilitate moving, they also might face steeper psychic costs to moving locations relative to unemployed persons due to their greater attachment to the current location.

[14] Davies, Greenwood, and Li (2001) also include moving costs in a conditional logit analysis of migration.

[15] Those who were previously out of the labor force serve as the reference group.

2.5.2 Switching costs

Switching costs are modeled in a similar way as moving costs. Let k index the previous labor supply choice (0 for out of the labor force, 1 for in the labor force), which is embedded in Z_{it}. The labor force switching costs are allowed to vary by entry or exit and have the following form for each:

$$\Xi_1 (Z_{it}) = \left(\theta_7 + \theta_8 \text{age}_{it} + \theta_9 \text{age}_{it}^2\right) 1\{k = 0\} \tag{2.13}$$

$$\Xi_0 (Z_{it}) = \left(\theta_{10} + \theta_{11} \text{age}_{it} + \theta_{12} \text{age}_{it}^2\right) 1\{k = 1\} \tag{2.14}$$

As with the moving costs, the intercepts θ_7 and θ_{10} are fixed costs of switching employment status, while the other parameters capture the fact that switching costs increase with age, but at a decreasing rate. As with the moving costs, the signs of the θ's are freely estimated. The fixed costs and linear age terms are expected to have a negative sign, while the θ's associated with the quadratic age terms are expected to be positive.[16]

2.6 The optimization problem

Individuals sequentially choose d_{it} to maximize the sum of their present discounted utility according to the following expression:

$$\max_{d_{it}} \mathbb{E} \left[\sum_{t=0}^{T} \beta^t \sum_j \sum_\ell \left(u_{ij\ell t} (Z_{it}) + \varepsilon_{ij\ell t} \right) 1\{d_{it} = (j, \ell)\} \right] \tag{2.15}$$

with discount factor β. Individuals observe current-period preference shocks before making a decision, but do not observe future shocks and must take expectations accordingly.

Define by $V_{it} (Z_{it})$ the ex ante value function for individual i in period t just before ε_{it} is revealed.

$$V_{it} (Z_{it}) = \mathbb{E}_\varepsilon \max_{j,\ell} \left\{ u_{ij\ell t} (Z_{it}) + \varepsilon_{ij\ell t} + \beta \int V_{it+1} (Z_{it+1}) \, dF (Z_{it+1} | Z_{it}) \right\} \tag{2.16}$$

[16] Previous employment status is not included in the switching costs so as to maintain clear interpretation of the search cost parameter γ_2 in (2.10).

Under mild regularity conditions, (2.16) follows Bellman's optimality principle.[17] Now define the choice-specific value function $v_{ij\ell t}$ as the flow payoff of choosing (j, ℓ) minus $\varepsilon_{ij\ell t}$ plus future utility assuming the optimal decision is made in every period from $t+1$ on. This notation is helpful in empirically representing the dynamic programming problem.

$$v_{ij\ell t}(Z_{it}) = u_{ij\ell t}(Z_{it}) + \beta \int V_{it+1}(Z_{it+1})\, dF(Z_{it+1}|Z_{it}) \tag{2.17}$$

$$= u_{ij\ell t}(Z_{it}) + \beta \int \mathbb{E}_{\varepsilon} \max_{k,m} \{v_{ikmt+1}(Z_{it+1}) + \varepsilon_{ikmt+1}\}\, dF(Z_{it+1}|Z_{it}) \tag{2.18}$$

Expressing the value functions as choice-specific value functions simplifies the connection between the theory and empirics, as will be shown in greater length later on.

In summary, equations (2.15)-(2.18) establish the mathematical framework through which individuals make forward-looking decisions. Specifically, individuals integrate over unknown future preference shock realizations $\varepsilon_{ij\ell t}$ using the value function.

3 Trends in Migration, Unemployment, and Earnings

3.1 Data

This section describes the data used to estimate the model. The main data source is the Survey of Income and Program Participation (SIPP), 2004 and 2008 panels. This dataset is supplemented with data on location characteristics and local labor market conditions.

The SIPP is a longitudinal survey of a stratified random sample of residents of the United States, administered by the United States Census Bureau. Respondents are interviewed every four months over a four- or five-year span. Survey respondents are asked questions regarding their living arrangements, labor force participation, earnings, assets, government program participation, migration, and education, among many other topics. In order to preserve confidentiality, the data used here — which make use of detailed residence location and earnings that are not top-coded — are not released publicly by

[17] These conditions include additive separability of the flow utility covariates and preference shocks, and conditional independence of the state variables and preference shocks.

the SIPP and are only available through the Census Research Data Center (RDC) Network.[18] Furthermore, the confidential version of the SIPP is linked via the respondent's social security number to Internal Revenue Service (IRS) and Social Security Administration (SSA) administrative data on annual earnings, employment history, government program participation, and social security benefits receipts. I make use of this link to create work experience profiles based on the administrative data that are less vulnerable to survey recall error.

The SIPP is essential to studying migration and labor supply behavior during the Great Recession. It is the only national panel survey that covers the time period of the Great Recession on a multi-cohort basis.[19] Furthermore, the SIPP is a survey and thus can separately measure unemployment and labor force attachment, two effects that are conflated in studies that use administrative data such as tax records.[20] Separating employment from labor force participation is crucial when studying these dynamics during the Great Recession when unemployment intensely fluctuated. Finally, the SIPP is a much larger sample than any other longitudinal surveys that have primarily been used in the literature (e.g. the National Longitudinal Survey of Youth (NLSY) cohorts or the Panel Study of Income and Dynamics (PSID)). This feature allows me to estimate location-specific parameters with greater precision.[21]

The main disadvantages of the SIPP are two-fold. First, its panels are relatively short — four to five years in length. Second, attrition rates in the SIPP are higher than in other longitudinal surveys. However, while attrition rates are high, there is evidence that they do not bias labor market outcomes even though these outcomes are different for attriters versus non-attriters (Zabel, 1998).[22]

With the data in hand, I now introduce the outcome and explanatory variables used in the analysis. As discussed in section 2, individuals choose a location and labor force

[18]For more information regarding the SIPP, see *http://www.census.gov/sipp/*. For more information about conducting research using confidential data in an RDC, see *http://www.census.gov/ces/rdcresearch/*.

[19]In contrast, the National Longitudinal Survey of Youth (NLSY) cohorts, which are heavily used in the literature, only follow a certain age group of individuals during the Great Recession.

[20]See Yagan (2014) and Schmutz and Sidibé (2015).

[21]For example, Kennan and Walker (2011) and Bishop (2012) are both required to estimate location specific earnings effects in the CPS because there is not enough power in the NLSY79.

[22]Zabel compares the attrition behavior of the SIPP and PSID.

participation status. Their outcomes are employment or unemployment (if participating in the labor force), and monthly earnings if employed.

Labor force participation and unemployment are defined as follows:

labor force participants are those who have a full-time job or are seeking a full-time job. Those who are self-employed or who voluntarily work part-time are excluded from the labor force.

unemployment closely resembles the U-6 unemployment definition reported by the BLS.[23] Unemployment is defined here as labor force participation that is not full-time employment. Full-time employment is defined as working 35 or more hours per week for all weeks in the survey month.

Locations are defined as cities. In order to maintain tractability, I restrict to the 35 cities that are most frequently observed in the SIPP. There are also 20 residual synthetic locations to ensure that the locational choice set is exhaustive. These synthetic locations are grouped into two population bins (small and medium). Table B.4 on page 69 contains a complete list of all 55 locations. A map of the 35 cities can be found in Figure B.7 on page 70.

Finally, monthly earnings are defined as the sum of earnings across all jobs in the survey month. I deflate earnings by cost of living in the location as described at the end of this section. All monetary figures throughout this paper are expressed in constant 2000 dollars unless otherwise noted.

The explanatory variables used in the analysis are work experience and age, along with education level, gender and race which determine the selection of the estimation sample. Work experience is generated from administrative records as an annualized measure of the sum of all quarters worked. Age is generated from the SSA data by comparing the calendar year and month with the birth year and month.

I focus on full-time employment for three reasons. First, full-time employees are most likely to be employed throughout the year, which more closely matches the time horizon

[23] U-6 is defined as total unemployed, plus all marginally attached workers, plus total involuntary part-time workers, as a percent of the civilian labor force plus all marginally attached workers.

of the model. Second, the SIPP does not measure hours worked at the monthly level — only at the wave level. Thus, measuring earnings at the hourly level is more difficult. I focus on full-time jobs because these jobs are most likely to be salaried, and an hourly earnings measure does not appropriately capture marginal labor productivity for salaried workers. Finally, there is evidence that part-time employment and unemployment are highly correlated, making it innocuous to consider involuntary part-time workers as unemployed workers.[24]

Modeling a large number of locations is essential to capturing the actual locational choice alternatives that individuals face. I focus on cities rather than states because business cycle effects are heterogeneous across cities, even within the same state. Furthermore, because many cities cross state boundaries, focusing on cities more closely characterizes the actual local labor market. Modeling the largest cities is a parsimonious way of categorizing the choice set, as 43% of the US population resides in the 30 largest cities. Finally, the residual locations are divided into population categories because there is evidence in the urban economics literature that a variety of labor market outcomes differ systematically by city size due to agglomeration economies, thick market effects, and human capital externalities (Glaeser and Maré, 2001; Wheeler, 2006; Yankow, 2006; Gould, 2007; Baum-Snow and Pavan, 2012; Bleakley and Lin, 2012). Dividing the residual categories by city size is a parsimonious way of capturing these effects.

I estimate the model using non-Hispanic white men of prime working age (i.e. ages 18-55 at the beginning of the survey) who have completed school and do not have a bachelor's degree. Along with the variables discussed above, I also use the characteristics of the county of residence in the analysis. I use four annual observations for the 2004 panel — the interview month of waves 2, 5, 8, and 11 — to measure location, labor market outcomes, and individual characteristics. The 2008 Panel is slightly longer, so I use the same waves in addition to wave 14. The entire dataset spans the years 2004-2013, but any given individual can only appear in at most five of those years. The average individual is observed for between two and three years, but over half the sample has at least three

[24] For instance, the trend in the overall ratio of part-time workers to full-time workers closely follows the trend in the unemployment rate. Figure B.8 on page 71 shows this relationship.

observations. For more details on sample selection and construction of key variables, see Appendix B.

My definition of city is the Core Based Statistical Area (CBSA) as defined in 2009 by the U.S. Office of Management and Budget (OMB). CBSAs include one or more counties and are defined according to commuting ties. As such, they are a reasonable measure of whether or not a county belongs to a city.[25] Using the 2009 definition, there are a total of 942 CBSAs — 366 Metropolitan Statistical Areas (MSAs) and 576 Micropolitan Statistical Areas (μSAs). Because it is infeasible to estimate this many locations, the choice set is aggregated as discussed above.

The geographical variables of interest are the population, unemployment rate, and price level of the worker's city. Population is defined as the 2000 Census population level in the county of residence, aggregated to the CBSA level. It is used to divide locations that are smaller than the top 35 cities. The unemployment rate is taken at the county level from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics data series and aggregated to the CBSA level, weighting by county population.[26] This variable is used in the model to inform individuals about their employment prospects in each location. I merge these city characteristics using a crosswalk that maps counties to CBSAs. Further details on data sources can be found in Table B.3 on page 68.

Following a number of papers in the literature, I spatially deflate earnings using the American Chamber of Commerce Research Association's Cost of Living Index (ACCRA-COLI).[27] I calculate the index in a like manner as Baum-Snow and Pavan (2012), who use a utility indifference condition to derive the price index at location j relative to base location 0 as a share-weighted geometric mean of prices in the consumer's basket of goods. For housing prices, I follow Winters (2009) and use quality-adjusted gross rents instead of the

[25] Most CBSAs are composed of less than 5 counties. Notable exceptions are Atlanta (28 counties), New York City (22 counties), Washington, D.C. (22 counties), Richmond, VA (20 counties), and St. Louis (16 counties). Commuting Zones (CZs), another popular definition of local labor markets, have slightly different boundaries than CBSAs for the largest 30 cities. Both CBSAs and CZs capture the essence of metropolitan areas by classifying the geographical space surrounding a centroid such that all participants within the space have at least some level of interaction. The definitions differ on the definition of the threshold of interaction.

[26] For the 20 residual locations, unemployment is aggregated to the location level.

[27] Studies using this data include: Glaeser and Maré (2001); Yankow (2006); Kennan and Walker (2011); and Baum-Snow and Pavan (2012), among others.

housing prices listed in ACCRA. Winters finds that spatially deflating earnings in this way yields an elasticity of 1 between nominal earnings and nominal prices, as predicted by economic theory. Further details on the construction of this index can be found in Appendix B.2.

3.2 Descriptive Findings

This section explains descriptive evidence in the evolution of migration, employment prospects, and earnings by location over the past 10-20 years. First, I show that migration rates changed very little during the Great Recession, but that the migration rate for the unemployed increased while the migration rate for the employed decreased slightly.

Figure 1 on page 46 shows how migration has changed over the time period of 2002-2013 by move distance. Consistent with the migration literature, migration rates decline with distance. There does not appear to be a significant deviation in these migration rates over the period of the Great Recession, relative to the general downward trend that has been well documented by Molloy, Smith, and Wozniak (2011).[28]

Figure 2 on page 47 shows that, in all years, migration rates for the unemployed are higher than for the employed.[29] Of particular interest is the fact that the migration rate for the unemployed increases during the Great Recession, while the migration rate for the employed decreases slightly.

I now compare the evolution of migration with the evolution of unemployment. Figure 3 on page 48 plots unemployment rates for select cities over the period of 1990-2014 with recessions indicated by gray boxes. Unemployment rates increase during and after

[28] Kaplan and Schulhofer-Wohl (2013) discuss reasons for why this is, focusing on the fact that occupations have become less geographically dependent, and that technological innovations have improved individuals' ability to learn about distant locations, removing the need to experience them through migration. Molloy and Wozniak (2011) show that migration has been pro-cyclical in the postwar era, and more so for national than local business cycle fluctuations. However, they focus mainly on the cyclicality of wages and moving costs without considering unemployment risk. The story changes when incorporating unemployment risk, which fluctuates more than wages. Additionally, they note that the HP filter they use to de-trend their migration data shows little cyclicality in migration since 2005, consistent with the findings presented here.

[29] Because the figure is based on CPS data, the data are stratified by *current* employment status rather than *previous* employment status, which is how the model treats migration differentials. However, because there is strong persistence in employment, these trends are unlikely to be significantly affected by this discrepancy between the descriptive evidence and the model.

recessions for all cities, highlighting the fact that the recessions tend to have national influence. However, there is also marked heterogeneity in how much city unemployment rates change as a result of recessions. To visualize this heterogeneity, Figure 4 plots the evolution in the unemployment *ranking* and shows that there is extensive variation over time in relative unemployment rates. Such fluctuations in local labor market conditions motivate modeling employment prospects specific to location and time period.

While unemployment rates are informative of the strength of labor markets, they alone do not explain why migration rates increased for the unemployed during the Great Recession, but not for the employed. The model introduced in the previous section is required, because it allows for differential effects of local unemployment on the respective job prospects of employed and unemployed workers. This is because the differential impact of the Great Recession on job finding rates turns out to be a key explanation for the observed migration trends.

3.3 Estimation subsample

I estimate the model on non-Hispanic white males aged 18-55 who have completed schooling by the time of the first SIPP interview, and who do not hold a bachelor's degree. I focus on males of a particular education level, race, and ethnicity in order to form a homogenous sample. The sample selection here is very similar to that of Kennan and Walker (2011). The final estimation subsample comprises 16,648 males each averaging 3.03 annual observations. For complete details on sample selection, see Appendix B.1 and Table B.1.

Tables 1 and 2 list descriptive statistics for the estimation subsample. The average individual in the sample is 42 years old and has 23 years of work experience. Living in the same location of birth is common, with almost 75% of the sample residing in their state of birth. Table 2 lists the migration statistics in the sample, which contains 568 movers who make 653 moves. While the observed rate of repeat and return migration is lower than in other studies, this is primarily due to the short panel of the SIPP. While not the focus of the current analysis, I emphasize that the dynamic model introduced in the previous section allows for repeat and return migration.

In the next section, I detail the procedures used to estimate the structural model that was previously introduced.

4 Identification and Estimation

This section discusses informal identification and details of the estimation procedure. Because of the assumption that the idiosyncratic shocks are independent of one another and independent across time, each section of the model can be consistently estimated in separate stages. The resulting procedure happens in two stages: (i) estimation of the earnings parameters and employment probabilities; and (ii) estimation of the flow utility parameters. Of particular importance is the assumption that the idiosyncratic earnings shocks do not affect the flow utility of employment in (2.9) because they are relayed too slowly.

4.1 Identification

This section informally discusses identification of various parameters of the model.[30] As in all dynamic discrete choice models, only differences in utility are identified. I choose to normalize all parameters relative to labor force participation in the first location ($d_{it} = (1, 1)$). The scale of utility is normalized by assuming payoff shocks are drawn from a Type I extreme value distribution. As is common practice, I do not estimate the discount factor β and instead set it equal to 0.9.

I now present a more detailed discussion of the identification of each of the model's parameters: the parameters of the earnings equation, employment probabilities, and flow utilities.

The vector of earnings parameters is identified from variation in earnings across locations, time, and levels of work experience. These parameters are consistently estimated using OLS because I assume that there is no selection on unobservables in the model. This is a restrictive assumption that is addressed at the end of this section.

[30] See Magnac and Thesmar (2002) for a formal discussion of identification in dynamic discrete choice models.

Job destruction and job offer probabilities ($\pi_{i\ell t}$) are identified non-parametrically from transitions between employment states. This is possible because of the assumption that employment happens according to a lottery with pre-commitment. An implication of this assumption is that individuals transition between employment states as soon as an offer is received.

Identification of the expected earnings coefficient in the flow utility of employment requires variation in earnings that is excluded from the flow utility equation. I make use of two such exclusion restrictions. The first is variation in work experience, and the second is variation in mean earnings across time periods within each location. These exclusion restrictions allow me to distinguish between expected earnings differences and amenity differences.

I now discuss the implications of the exclusion restrictions for identification of the expected earnings coefficient. The work experience exclusion restriction hinges on the assumption that work experience is uncorrelated with time-varying amenities. This is a reasonable assumption because most time-varying amenities in a given location are indeed uncorrelated with work experience (e.g. crime, air pollution). The time dummy exclusion restriction implies that amenities are fixed over time. In the short run, this is likely to hold, as amenities that vary over time within a location (e.g. crime or economic development) are much less volatile than local labor market conditions.[31] Given that this model focuses on a 10-year period, this is a reasonable exclusion restriction.

The search cost parameter γ_2 is identified from the share of labor force participants that are unemployed. This share is in turn identified through the search friction parameters $\pi_{i\ell t}$, which are identified from transitions between employment states.

Parameters in the moving cost equation (Δ_ℓ) are identified from variation between the observed characteristics of movers and the probability of moving, along with the assumption that moving costs are symmetric (i.e. a move from Boston to Chicago has the same cost as a move from Chicago to Boston). Specifically, variation in the origin and destination of moves identifies the distance parameters, and variation in the ages of movers

[31] For instance, over the 11-year period from 2000-2010, annual crime rates in Washington, D.C. for a variety of crimes remained mostly stable. See http://www.dccrimepolicy.org/Briefs/images/Volatility-Brief-3-10-11_1.pdf for more details.

identifies the age parameters. Variation in the previous employment status of movers identifies the employment parameters.

Switching cost parameters Ξ_j are identified from the observed characteristics of those who enter or exit the labor force. However, these switching costs cannot be separately identified from home production benefits and local amenities because the set of all three is linearly dependent. Thus, identification is only possible under either a symmetry assumption or by taking the difference in the costs. I choose the latter because there is no theoretical reason for why the entry and exit costs should be symmetric. The results presented hereafter represent the cost of labor force exit subtracted from the cost of labor force entry, because the utility of labor force participation is the baseline alternative.

4.2 Estimation of earnings parameters and employment probabilities

As discussed in the preceding section, the earnings equation parameters are consistently estimated by OLS. The employment probabilities are estimated using transitions between employment and unemployment. While they could in principle be estimated non-parametrically, I estimate them as predicted probabilities from a pair of logit regressions in order to allow for a common effect of moving from a different location in each employment state.

Each of the estimated employment probabilities can be summarized in words. $\hat{\lambda}_{i\ell t}$ measures the probability that an individual was not employed in the previous period and is employed in the current period in the same location. Likewise, $\hat{\delta}_{i\ell t}$ measures job destruction, i.e. the probability that an individual is not employed in the current period but was employed in the current location in the previous period. Finally, $\hat{\lambda}^{e}_{i\ell t}$ and $\hat{\lambda}^{u}_{i\ell t}$ measure the probability of employment in a new location given previous employment status e or u.

The logit equation for $\hat{\delta}_{i\ell t}$ and $\hat{\lambda}^{e}_{i\ell t}$ is estimated conditional on choosing to supply labor and having been employed in the previous period.

$$\Pr\left(y_{it} = (e, \ell) \middle| d_{it} = (1, \ell), y_{it-1} = (e, \cdot)\right) = \frac{\exp\left(\Theta_1\right)}{1 + \exp\left(\Theta_1\right)} \tag{4.1}$$

where

$$\Theta_1 = \mu_{1\ell}^e + \mu_2^e \mathrm{UR}_{\ell t-1} + \mu_3^e G\left(x_{it}\right) + \mu_4^e 1\left\{y_{it-1} = \left(e, \ell'\right)\right\}$$

and where $\mathrm{UR}_{\ell t-1}$ is the lagged unemployment rate in location ℓ and $G\left(\cdot\right)$ is a quadratic polynomial. The excluded category is $1\left\{y_{it-1} = \left(e, \ell\right)\right\}$. A similar regression can be estimated conditional on non-employment in the previous period.

$$\Pr\left(y_{it} = \left(e, \ell\right) \middle| d_{it} = \left(1, \ell\right), y_{it-1} = \left(\left\{u, n\right\}, \cdot\right)\right) = \frac{\exp\left(\Theta_2\right)}{1 + \exp\left(\Theta_2\right)} \tag{4.2}$$

where

$$\Theta_2 = \mu_{1\ell}^u + \mu_2^u \mathrm{UR}_{\ell t-1} + \mu_3^u G\left(x_{it}\right) + \mu_4^u 1\left\{y_{it-1} = \left(\left\{u, n\right\}, \ell'\right)\right\}$$

The excluded category in (4.2) is $1\left\{y_{it-1} = \left(\left\{u, n\right\}, \ell\right)\right\}$. Non-stationarity in the $\pi_{i\ell t}$'s is accounted for through the evolution of the local unemployment rate.

Conditioning (4.1) and (4.2) on labor force participants is crucial, because in the model individuals do not exogenously transition between labor force participation states—they only exogenously transition between employment states (conditional on participating in the labor force).

It then follows that

$$1 - \hat{\delta}_{i\ell t} = \frac{\exp\left(\hat{\mu}_{1\ell}^e + \hat{\mu}_2^e \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^e G\left(x_{it}\right)\right)}{1 + \exp\left(\hat{\mu}_{1\ell}^e + \hat{\mu}_2^e \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^e G\left(x_{it}\right)\right)} \tag{4.3}$$

$$\hat{\lambda}_{i\ell t}^e = \frac{\exp\left(\hat{\mu}_{1\ell}^e + \hat{\mu}_2^e \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^e G\left(x_{it}\right) + \hat{\mu}_4^e\right)}{1 + \exp\left(\hat{\mu}_{1\ell}^e + \hat{\mu}_2^e \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^e G\left(x_{it}\right) + \hat{\mu}_4^e\right)} \tag{4.4}$$

$$\hat{\lambda}_{i\ell t} = \frac{\exp\left(\hat{\mu}_{1\ell}^u + \hat{\mu}_2^u \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^u G\left(x_{it}\right)\right)}{1 + \exp\left(\hat{\mu}_{1\ell}^u + \hat{\mu}_2^u \mathrm{UR}_{\ell t-1}\right) + \hat{\mu}_3^u G\left(x_{it}\right)} \tag{4.5}$$

$$\hat{\lambda}_{i\ell t}^u = \frac{\exp\left(\hat{\mu}_{1\ell}^u + \hat{\mu}_2^u \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^u G\left(x_{it}\right) + \hat{\mu}_4^u\right)}{1 + \exp\left(\hat{\mu}_{1\ell}^u + \hat{\mu}_2^u \mathrm{UR}_{\ell t-1} + \hat{\mu}_3^u G\left(x_{it}\right) + \hat{\mu}_4^u\right)} \tag{4.6}$$

4.3 Estimation of flow utility parameters

Estimation of the flow utility parameters follows Hotz and Miller (1993) and Arcidiacono and Miller (2011) by making use of two separate estimation methods that are closely related: (i) conditional choice probabilities (CCPs); and (ii) finite dependence. CCPs make use of a function mapping future value terms from the individual's dynamic programming problem into the probability of making a discrete choice. These probabilities are called CCPs and are found in the data. Finite dependence allows the researcher to formulate the future value terms into a finite sequence of future payoffs. Together, the two strategies yield substantial computational savings by eliminating the need to solve the dynamic programming problem using backwards recursion.

4.3.1 Conditional choice probabilities

To show how this is done, recall equations (2.17) and (2.18), which show that, by definition, the value function $V_{it+1}(Z_{it+1})$ is equivalent to the $\mathbb{E}\max$ of the conditional value functions in period $t+1$ plus the ε_{t+1}'s.

When the ε's are assumed to be Type I extreme value, equation (2.18) simplifies to

$$v_{ij\ell t}(Z_{it}) = u_{ij\ell t}(Z_{it}) + \beta \int \ln\left(\sum_k \sum_m \exp\left(v_{ikmt+1}(Z_{it+1})\right)\right) dF\left(Z_{it+1}|Z_{it}\right) + \beta\overline{\gamma} \quad (4.7)$$

where $\overline{\gamma}$ is Euler's constant, the mean of a standard Type I extreme value distribution (McFadden, 1974; Rust, 1987). Thus, the $\mathbb{E}\max$ is the natural log of the sum of the exponentiated conditional value functions, plus Euler's constant.[32]

I will now show how (4.7) can be manipulated to admit CCPs. First, multiply and divide by the exponentiated conditional value function associated with a given choice

[32] This follows from the fact that the Type I extreme value distribution has a closed-form CDF. The mean of the distribution is Euler's constant. If the ε_t's were assumed to be normally distributed, the $\mathbb{E}\max$ term would not have a closed form, for the same reason that the Normal CDF does not have a closed form. The CCP method works for any distribution of ε, but requires numerical integration or simulation methods for distributions that are outside of the Generalized Extreme Value family.

alternative (e.g. (j', ℓ')), $\exp\left(v_{ij'\ell' t+1}\left(Z_{it+1}\right)\right)$, to get

$$\begin{aligned}
\int V_{it+1}\left(Z_{it+1}\right) dF\left(Z_{it+1}|Z_{it}\right) &= \int \ln\left(\frac{\exp\left(v_{ij'\ell' t+1}\left(Z_{it+1}\right)\right)}{\exp\left(v_{ij'\ell' t+1}\left(Z_{it+1}\right)\right)}\right.\\
&\qquad \left.\times \sum_k \sum_m \exp\left(v_{ikmt+1}\left(Z_{it+1}\right)\right)\right) dF\left(Z_{it+1}|Z_{it}\right) + \overline{\gamma} \qquad (4.8)\\
&= \int \left[v_{ij'\ell' t+1}\left(Z_{it+1}\right)\right.\\
&\qquad \left. + \ln\left(\frac{\sum_k \sum_m \exp\left(v_{ikmt+1}\left(Z_{it+1}\right)\right)}{\exp\left(v_{ij'\ell' t+1}\left(Z_{it+1}\right)\right)}\right)\right] dF\left(Z_{it+1}|Z_{it}\right) + \overline{\gamma}\\
&\qquad\qquad (4.9)\\
&= \int \left[v_{ij'\ell' t+1}\left(Z_{it+1}\right) - \ln p_{ij'\ell' t+1}\left(Z_{it+1}\right)\right] dF\left(Z_{it+1}|Z_{it}\right) + \overline{\gamma}\\
&\qquad\qquad (4.10)
\end{aligned}$$

Comparing (2.17) with (4.10) shows that, for any choice alternative (j', ℓ'), the future value function is equal to the conditional value function $v_{ij'\ell' t+1}$ minus the log probability of choosing (j', ℓ'). This log probability is the conditional choice probability, and can in principle be recovered non-parametrically from the data. The CCP method pares down the number of future-period conditional value functions from $2L$ to 1.

While it is helpful that the number of conditional value functions has decreased, the value function as currently expressed still has a recursive structure. In mathematical terms, $v_{ij'\ell' t+1}\left(Z_{it+1}\right)$ in (4.10) is a function of V_{it+2}, which is a function of V_{it+3}, etc. In order to eliminate this recursive structure and the need to use backward recursion to solve the model, I make use of the property of finite dependence.

4.3.2 Finite dependence

Finite dependence is based on the fact that in discrete choice models only differences in utility (or, in dynamic models, differences in the present value of utility) matter in estimation, e.g. $v_{ij'\ell' t} - v_{i0\ell t}$. Hence, it is possible to express the value function for choosing (j', ℓ') in period t in terms of a sequence of decisions up to τ periods ahead, then create a corresponding sequence of decisions for choosing the base alternative $(0, \ell)$ in period t such that after τ periods the value functions are the same and can cancel out. The key insight is that this sequence of decisions need not be optimal.[33]

In the case where the choice outcomes correspond to the choice alternatives, the following sequences could be used for all (j', ℓ') to create a cancellation in period $t+3$:

- $v_{ij'\ell't}$ path: choose $d_{it} = (j', \ell')$; $d_{it+1} = (0, \ell')$; $d_{it+2} = (0, \ell)$
- $v_{i0\ell t}$ path: choose $d_{it} = (0, \ell)$; $d_{it+1} = (j', \ell)$; $d_{it+2} = (0, \ell)$

where ℓ is the location in period $t-1$. In both cases, the states in period $t+3$ are one additional year of work experience, three additional years of age, and previous decision equal to non-participation in location ℓ. The value function $V_{it+3}(Z_{it+3})$ is thus the same for both and vanishes when the standard utility normalization is applied.

In the case where labor market outcomes are stochastic, however, inducing the cancellation of the future value terms is not as straightforward. To illustrate how the setup proceeds in this case, recall equation (4.10), rewritten below in conserved notation:

$$\mathbb{E}_t V_{it+1}(Z_{it+1}) = \mathbb{E}_t \left[v_{ij'\ell't+1}(Z_{it+1}) - \ln \left(p_{ij'\ell't+1}(Z_{it+1}) \right) \right] + \overline{\gamma}$$

The key idea is that this equality holds for a weighted sum of $v_{ij'\ell't+1}$'s such that the weights add up to unity:

$$\begin{aligned}
\mathbb{E}_t V_{it+1}(Z_{it+1}) &= \mathbb{E}_t \left[v_{ij'\ell't+1}(Z_{it+1}) - \ln \left(p_{ij'\ell't+1}(Z_{it+1}) \right) \right] + \overline{\gamma} \\
&= \sum_{(k,m)\in\mathcal{J}} \omega_{(k,m)} \left\{ \mathbb{E}_t \left[v_{ikmt+1}(Z_{it+1}) - \ln \left(p_{ikmt+1}(Z_{it+1}) \right) \right] + \overline{\gamma} \right\} \qquad (4.11) \\
&\text{s.t.} \sum_{(k,m)\in\mathcal{J}} \omega_{(k,m)} = 1
\end{aligned}$$

In the application below, the $\omega_{(k,m)}$'s are functions of the current and future employment probabilities.

[33] For other studies using finite dependence to aid estimation, see Altuğ and Miller, 1998; Arcidiacono and Miller, 2011; Bishop, 2012; Coate, 2013; Gayle, 2013; Arcidiacono and Miller, 2014; Arcidiacono, Aucejo, Maurel, and Ransom, 2016.

Figure 5 shows how the finite dependence structure works in the case of stochastic choice outcomes. It depicts the choice sequences for $v_{ij'\ell' t}$ and $v_{i0\ell t}$ conditional on the previous choice outcome y_{it-1}. Because of the random nature of employment outcomes, the individual must take expectations over all possible outcomes. Thus, each period of labor force participation induces two outcomes, which are depicted in tree form in Figure 5 (recall that $\pi_{i\ell t} = 0$ for the non-participation decision). Decisions are depicted by boxes, and outcomes are depicted by nodes. Probabilities are written next to edges connecting the nodes.

The top branches of each sub-tree in the diagram have the same state variables in $t+3$. However, because the individual must take expectations over the future employment outcomes, cancellation of these terms is not possible except for the case of degenerate employment probabilities or the case where $\pi_{i\ell' t} = \pi_{i\ell t+1}$. This equality does not hold in general.

In order to induce the cancellation, I make use of the insights provided by equation (4.11). The diagram for this case is provided in Figure 6. The difference is that now the $t+1$ decision in the expression for $v_{i0\ell t}$ is a weighted sum of $d_{it+1} = (1, \ell)$ and $d_{it+1} = (0, \ell)$. The ω's are pushed through to the $t+3$ states as with the other probabilities in the tree.

Cancellation is possible by solving for the ω's that make the top branches of each tree equal:

$$\pi_{i\ell' t} V_{t+3} = \omega_{(1,\ell)} \pi_{i\ell t+1} V_{t+3} \tag{4.12}$$

Solving (4.12) for ω gives

$$\omega_{(1,\ell)} = \frac{\pi_{i\ell' t}}{\pi_{i\ell t+1}} \tag{4.13}$$

A similar solution strategy can be used for the bottom branches of each tree, with the same value of ω being true for both cases.

While derived algebraically using the structure of the $\mathbb{E}\max$ term, the value of ω has an intuitive interpretation. Individuals weigh the relative employment probabilities across time in each candidate location when deciding how much weight to place on their next-period decision d_{it+1}.

Putting everything together, the final equation for the differenced conditional value function expression is then (suppressing i subscripts and assuming $j' = 1$):[34]

$$
\begin{aligned}
v_{j'\ell' t} - v_{0\ell t} = \; & \pi_{\ell' t} u^e_{\ell' t}(Z_t) + (1-\pi_{\ell' t})\, u^u_{\ell' t}(Z_t) - u^n_{\ell t}(Z_t) \\
& + \beta \Big[\pi_{\ell' t} u^n_{\ell t+1}\left(Z^1_{t+1}\right) - \pi_{\ell' t} \ln p_{0\ell' t+1}\left(Z^1_{t+1}\right) \\
& + (1-\pi_{\ell' t})\, u^n_{\ell t+1}\left(Z^2_{t+1}\right) - (1-\pi_{\ell' t}) \ln p_{0\ell' t+1}\left(Z^2_{t+1}\right) \\
& - \pi_{\ell' t} u^e_{\ell t+1}\left(Z^3_{t+1}\right) \\
& - \left(\frac{\pi_{\ell' t}(1-\pi_{\ell t+1})}{\pi_{\ell t+1}}\right) u^u_{\ell t+1}\left(Z^3_{t+1}\right) - \left(1 - \frac{\pi_{\ell' t}}{\pi_{\ell t+1}}\right) u^n_{\ell t+1}\left(Z^3_{t+1}\right) \\
& + \left(\frac{\pi_{\ell' t}}{\pi_{\ell t+1}}\right) \ln p_{1\ell t+1}\left(Z^3_{t+1}\right) + \left(1 - \frac{\pi_{\ell' t}}{\pi_{\ell t+1}}\right) \ln p_{0\ell t+1}\left(Z^3_{t+1}\right) \Big] \\
& + \beta^2 \Big[\pi_{\ell' t} u^n_{\ell t+2}\left(Z^4_{t+2}\right) - \pi_{\ell' t} \ln p_{0\ell t+2}\left(Z^4_{t+2}\right) \\
& + (1-\pi_{\ell' t})\, u^n_{\ell t+2}\left(Z^5_{t+2}\right) - (1-\pi_{\ell' t}) \ln p_{0\ell t+2}\left(Z^5_{t+2}\right) \\
& - \pi_{\ell' t} u^n_{\ell t+2}\left(Z^6_{t+2}\right) + \pi_{\ell' t} \ln p_{0\ell t+2}\left(Z^6_{t+2}\right) \\
& - \left(\frac{\pi_{\ell' t}(1-\pi_{\ell t+1})}{\pi_{\ell t+1}}\right) u^n_{\ell t+2}\left(Z^7_{t+2}\right) + \left(\frac{\pi_{\ell' t}(1-\pi_{\ell t+1})}{\pi_{\ell t+1}}\right) \ln p_{0\ell t+2}\left(Z^7_{t+2}\right) \\
& - \left(1 - \frac{\pi_{\ell' t}}{\pi_{\ell t+1}}\right) u^n_{\ell t+2}\left(Z^8_{t+2}\right) + \left(1 - \frac{\pi_{\ell' t}}{\pi_{\ell t+1}}\right) \ln p_{0\ell t+2}\left(Z^8_{t+2}\right) \Big]
\end{aligned}
\tag{4.14}
$$

where the integrals over the future state variables have been suppressed for notational simplicity. Superscripts on the state variables Z denote different sets of states.[35]

Equation (4.14) is a complex formula that includes employment probabilities, flow utility parameters, and log CCPs. However, it is a linear function of all structural parameters which greatly simplifies the estimation. Most importantly, there is no need to use backward recursion in the estimation procedure.

Figures 5 and 6 have illustrated how finite dependence can be used even in models

[34] For the case $j' = 0$, the formula is much simpler because $\pi_{\ell' t} = 0$ for all ℓ'. Equation (A.3) in Appendix A.2 details this case.

[35] Additionally, the state dependence of the employment probabilities $\pi_{\ell' t}$ and $\pi_{\ell t+1}$ is also suppressed for simplicity. $\pi_{\ell' t}$ is always evaluated at Z_t while $\pi_{\ell t+1}$ is always evaluated at Z^3_{t+1}.

where choice outcomes are not included in the choice set. This method can be used in a variety of other discrete choice applications where stochastic choice outcomes might not be aligned with deterministic choices.

Using CCPs and finite dependence, the optimization problem has been reduced from a backward recursion problem to a simple multi-stage static estimation problem with an adjustment term comprised of CCPs, current and future flow utilities, and employment probabilities, resulting in impressive computational gains that make possible the estimation of the model.

4.3.3 Integrating out local labor market shocks

When making decisions about the future, agents need to form expectations over the evolution of the labor market conditions in each location. This is outlined in equations (2.2) and (2.4). However, the evolution of these labor market conditions also enters the future value term associated with each alternative. Because this future value term is non-linear, the future labor market shocks need to be integrated out of the value function. Furthermore, because the shock in *each* location enters the choice probability associated with any given location, the dimension of this integral is on the order of double the number of locations.[36] With many locations, the only way to compute the integral is using Monte Carlo techniques.

The structure of the forecasting problem further underscores the advantages in using CCPs and finite dependence to estimate the flow utility parameters. If estimating the parameters using the full solution (backwards recursion) method, the researcher would be required to evaluate the value function at each realization of the labor market shocks and integrate accordingly. To make the backwards recursion tractable, interpolation methods (Keane and Wolpin, 1994) or simplification of the state space (Kennan and Walker, 2011) would have to be used.

In my case, I can use the finite dependence assumption to exactly rewrite the value function in terms of one- and two-period ahead CCPs and flow payoffs. This only requires

[36] L of the $2L$ dimensions correspond to the earnings AR(1) shocks ζ_t and the other L dimensions correspond to the unemployment rate shocks ξ_t.

integration of the relevant CCPs and employment probabilities, of which there are only nine for each choice alternative (see equation 4.14).

Formally, an example of the time-t expectation of one of the log CCPs (choosing alternative $(0, \ell')$) is written as follows:

$$E_t \left[\ln \left(p_{0\ell' t+1} \left(\xi_{t+1}, \zeta_{t+1} \right) \right) \middle| Z_{it} \right] = \int \ln p_{0\ell' t+1} \left(\xi_{t+1}, \zeta_{t+1} \right) f \left(\xi, \zeta \right) d\xi d\zeta \tag{4.15}$$

where ξ_{t+1} and ζ_{t+1} are respectively L-dimensional vectors of earnings and employment shocks in period $t+1$. f is the density of a multivariate normal distribution with mean 0 and covariance Ψ.[37]

The integral in (4.15) is of dimension $2L$ and thus needs to be estimated using Monte Carlo methods. This is done by drawing D draws from the $N(0, \Psi)$ density, plugging them into the CCPs, and averaging over the draws as written below:

$$\int \ln p_{0\ell' t+1} \left(\xi_{t+1}, \zeta_{t+1} \right) f \left(\xi, \zeta \right) d\xi d\zeta \approx \frac{1}{D} \sum_{d=1}^{D} \ln p_{0\ell' t+1} \left(\xi_d, \zeta_d \right) \tag{4.16}$$

where (ξ_d, ζ_d) is the dth draw from f.[38]

For integration of the two-period-ahead CCPs, the variance of f is modified to account for uncertainty in the one-period-ahead outcomes. In this case, the variance matrix of f is

$$\Psi + \Psi \odot RR' \tag{4.17}$$

where $\odot$ is the element-wise (Hadamard) product and R is a $2L \times 1$ vector of autocorrelation parameters corresponding to earnings or employment forecasting (ρ_1 or $\phi_{1\ell}$). The result in (4.17) comes about because the forecasting shocks are assumed to be normally distributed and independent over time.

[37] Ψ is estimated by computing the covariance of the AR(1) residuals for all equations in both AR(1) systems.

[38] In practice, the value of D is set to 20 for computational reasons. Larger values of D give very similar results.

4.4 Summary of the algorithm

To summarize, the estimation algorithm for the structural model proceeds in the following steps:

1. Estimate the earnings parameters and employment probabilities by OLS and a binary logit, respectively.

2. Use OLS to estimate the autocorrelation parameters associated with the time series of local earnings and unemployment. Calculate the covariance matrix Ψ of the residuals from these estimates, which is a $2L \times 2L$ matrix.

3. Draw a total of D local labor market shocks from a multivariate normal distribution with mean 0 and covariance Ψ.

4. Using parameter estimates from a flexible conditional logit model, calculate the CCPs at relevant values of the state variables and at each of the D market shock realizations.[39]

5. Calculate the expected future value terms along each of the finite dependence paths using the estimated earnings parameters, employment probabilities, and CCPs as inputs. Integrate out market shocks by averaging across the D shock realizations drawn in Step 3.

6. Estimate the flow utility parameters of the structural choice model. This amounts to estimating a conditional logit with an offset term containing the future value terms computed in Step 5.

[39] The specification of the flexible conditional logit model used has $2L$ alternatives which include the following as covariates for all alternatives: location-specific intercepts (amenities); an intercept for labor force participation; birth state and region dummies; and the moving cost and switching cost covariates in the structural model. Additionally, the labor force participation alternatives include the following: expected log earnings (conditional on working); employment probability multiplied by a dummy indicating previously employed (to proxy for on-the-job search); and employment probability multiplied by a dummy indicating not previously employed (to proxy for job search).

5 Empirical Results

This section discusses in detail each of the empirical results of the model. The primary findings are as follows: (i) employed workers are more heavily shielded from adverse labor market shocks and face a heavier job queuing penalty when switching locations, the combination of which turns out to be an important factor in explaining the differential migration response to labor market shocks between the two groups; (ii) workers face large costs in searching for a job and moving locations; and (iii) there is substantial heterogeneity in amenities and labor market conditions across locations.

Results from the model estimation are found in Tables 3 through 8. These results comprise estimates from each section of the model. I also discuss post-estimation results contained in Tables 9 through 10 in this section.

5.1 Model estimates

I begin by discussing the estimated employment probabilities at different points of the business cycle as reported in Tables 3 through 5 (see equations (2.4), (4.1), and (4.2)). Table 3 lists the estimates of separate binary logistic regressions that predict the probability of being employed conditional on previous employment status. Workers who were previously employed have steeper experience profiles and are less affected by the unemployment rate in the location. The coefficient on the mover dummy is large, negative, and significant for employed workers, but positive and insignificant for unemployed workers.

Table 4 lists moments of the predicted values of these regressions for workers with no experience, at the location level. I emphasize two results from this table. First, employed workers are more insulated from the recession. From 2007 to 2011, the employment probability for the employed only dropped by one to two percentage points. In contrast, unemployed workers were hit harder, as they saw their probabilities drop by almost 10 percentage points over the same time period. Second, the job queuing penalty for changing locations is large for employed workers but non-existent for the unemployed. These two differentials have important impacts on migration behavior, as will be shown in Section 6.2. Table 4 reports moments of the distribution of employment probabilities from each of the 55 locations in the years 2007 (right before the Great Recession) and 2011 (at the start of the recovery). Table 5 indicates that there is also a large amount of variation in the local autocorrelation processes.

Tables 6 and 7 present earnings equation estimates, as well as estimates from the earnings forecasting equation (2.2). The main result from these estimates is that shocks to local earnings are substantially heterogeneous across locations. Also interesting is the large dispersion across locations in the variance of these local earnings shocks. The distribution of location-specific shock standard deviations has a mean of 0.09 and a standard deviation of 0.045, indicating that some cities are much more vulnerable to shocks than others. The earnings equation estimates in Table 6 are sensible, with returns to experience that increase, but at a decreasing rate.

Table 8 presents the flow utility parameter estimates. The positive coefficient on expected log earnings indicates that differences in earnings matter in migration decisions. The search cost parameter is large with a magnitude slightly larger than the earnings elasticity. Individuals value locations that are close to their state of birth, but have no differential preferences for locations in their Census division of birth. The fixed labor force switching cost indicates that labor force exit is costlier than labor force entry. However, the sign flips when consider the age profile of this cost, indicating that the cost of entering the labor force is greater than the cost of exiting as individuals get older. The parameters in the moving cost equation have the expected signs and match up with other estimates in the literature. Fixed costs of moving are substantial, but also steeply increase with distance. It is also more costly for older individuals to move. Interestingly, employed workers have lower costs of moving than both unemployed workers and non-participants. This indicates that financial resources may be more important in migration decisions than psychological attachment to a location.

5.2 Moving costs, amenity values, and location-specific parameters

With estimates on the elasticity of income and moving costs in Table 8, I can calculate moving costs and amenity values. The expected earnings parameter converts utility to money and can be thus used to express the structural parameter estimates in monetary units. It is also important to note that these moving cost estimates represent the moving costs faced by the *average* individual, not the *marginal* individual (i.e. the person who is just indifferent between staying and moving). Table 9 displays sample moving costs by previous employment status. The fixed cost of moving is calculated to be -\$153,537 for an employed person and -\$175,745 for an unemployed person. The moving costs for the average mover are -\$419,147 and -\$445,751, respectively. These figures are similar in magnitude to those reported in Kennan and Walker (2011) and Bishop (2012).[40] Importantly, the monetary value of the moving cost reflects psychological costs of moving (e.g. acclimating to a new location or leaving behind friends and family) in addition to monetary costs (e.g. paying for a moving truck or mortgage closing costs). For more details on the computation of the moving costs, see Appendix A.1.

As discussed in Kennan and Walker (2011) and Bishop (2012), the moving cost represents the cost faced to the average individual if he were forced to move to an arbitrary location in an arbitrary time period. Allowing the individual to choose the best available location would substantially reduce this cost. Kennan and Walker also show that the moving cost for actual moves is much lower than for the average mover. A similar line of logic applies to the current model.

I also find that amenity values are economically significant, but not nearly as large as moving costs. This is not surprising given that amenities are consumed in each period, whereas moving costs are incurred in only one period for each move. To put the amenity values in perspective, a one-standard-deviation increase in local amenities is valued at just under \$4,000, while moving from the bottom to the top of the amenity distribution would be worth about \$17,000 per period. Such a move would compensate for the average fixed cost of moving in just over nine years. Preferences for birth state proximity are in between these two values at \$11,000. This value explains why such a high fraction of individuals in the data are observed to be living in a market that contains his birth state.

Due to disclosure concerns, I am unable to present location-specific parameter estimates. In order to gauge the plausibility of my parameter estimates, I regress various

[40] Bishop (2012) calculates the fixed cost of moving to be -\$277,857.

location-specific parameters from the model on a set of location characteristics.[41] The results are reported in Table 10. The main takeaway is that these parameters can be quite different by region, and that a simple vector of locational characteristics can explain between one-fifth and two-thirds of the variation across locations in these parameters. I regress the model estimates (35 CBSAs only) of amenities, earnings, job destruction, job offers, and the unemployment and earnings time series parameters on the log population of the location and a vector of Census division dummies. The results are enlightening and also provide an intuition check for the model estimates. Amenities do not systematically vary with population, but are substantially lower in the Rust Belt and the South (Tennessee to Texas) and highest in New England, the Northern Midwest, the Mountain West, and the Pacific. Earnings levels (adjusted for cost of living) do not strongly correlate with city size, but are persistently different across regions. Estimates of the employment probabilities indicate that larger markets appear to have more churning, but that there is also substantial variation across regions. This is consistent with evidence on thick-market effects in the labor market (Bleakley and Lin, 2012). Finally, the standard deviation of the AR(1) shock to earnings is lower in larger cities. This could be due to the fact that larger cities are more industrially diversified, so when faced with industry-specific shocks, the impact of the shock is (mechanically) lessened. Such evidence is found in Malizia and Ke (1993). The drift and shock persistence parameters do not show any systematic patterns across geography.

6 Model Fit and Counterfactual Simulations

In this section, I verify that the structural model fits the data well, and then discuss the results obtained from counterfactual simulations of the model, which constitute the substantive empirical conclusions regarding the mechanisms through which migration behavior differs between the employed and the unemployed.

[41] Schmutz and Sidibé (2015) conduct a similar analysis using the parameters of their model with 200 locations.

6.1 Model Fit

Tables 11 and 12 show migration probabilities and employment transitions in the model and in the data. Panel (a) of Table 11 shows how migration varies by previous employment status. The model exactly matches these differences. Migration probabilities over age and distance are shown in panels (b) and (c) of this table. The model and data also match up well along these dimensions.

Table 12 compares employment transitions in the data and model conditional on migrating or staying. Panels (a) and (b) compare employment transition rates conditional on migration. These match up very closely with the exception of transitions out of labor force non-participation. This is likely due to the fact that, in the data, the cell sizes associated with transitions out of non-participation are relatively small. Panels (c) and (d) compare these transitions conditional on staying in a location. Again, the data and model match up well.

6.2 Counterfactual Simulations

Now that I have established that the model fits the data well, I discuss counterfactual simulations of the model that provide my primary empirical results. Specifically, I simulate six different counterfactual policies, separately by employment status for six different locations and two different calendar years. The six locations correspond to three pairs of artificial cities, each possessing characteristics at specific points in the respective distribution of city characteristics for local amenities, earnings, and employment probabilities. For example, I calculate the difference in the probability of out-migration with and without the policy in a city at the 75th percentile of the amenities distribution versus a city at the 25th percentile of the amenities distribution. All other city characteristics are identical across the two cities.[42] This process is repeated for earnings and employment probabilities. Constructing the counterfactuals in this way allows me to hold fixed city characteristics, which turn out to be strong predictors of migration behavior.

There are four principle findings in this section:

[42] In all cases, the artificial city is set to be in the same geographical location. The exact geographical location of the artificial city makes little difference to the final results.

1. Correlated labor market shocks dampen out-migration from impacted areas. This result is strongest for unemployed workers facing a local unemployment shock, where out-migration is anywhere from 8-12 times larger for this group in response to a local unemployment shock. This result is driven in part by the fact that employed workers face steep job queuing penalties (compared to the unemployed) when changing locations. As the business cycle worsens, this dampening effect amplifies.

2. City characteristics significantly affect migration response. For example, out-migration response to a moving subsidy is strongest in a low-amenity city. Similarly, out-migration response to an adverse unemployment shock is strongest in a high-unemployment city.

3. Unemployed workers who have been given a moving subsidy favor locations closer to their place of birth, locations with higher amenities, and locations with higher employment certainty — they do not favor locations with higher earnings once accounting for these other attributes. Workers favor employment certainty over higher earnings because job search is costly.

4. Migration response depends on current aggregate business cycle conditions. Examining the same set of counterfactual shocks in the economic environment of 2007 vs. 2011 shows that, for some shocks, the magnitude of out-migration response is smaller in 2011 when the labor market everywhere was already weak. However, for other shocks, and for the two subsidies, out-migration response is larger in 2011 than in 2007.

Each counterfactual policy is purely temporary. That is, each policy is in effect for only one calendar year. This is because analyzing policy innovations with a longer time horizon would require conditional choice probabilities (CCPs) derived from the new policy, and generating these counterfactual CCPs would require solving the full model via backwards recursion. This is infeasible given the size of the model's state space. By restricting the policy horizon to a short term, I can calculate the appropriate CCPs without solving the model by making use of the finite dependence structure outlined in Section 4.3.2. I emphasize that, because of the autocorrelated structure of some components of the model, the *effect* of a counterfactual policy may not be temporary. However, each policy innovation is purely transitory.

I focus my discussion on the impact of the policies on out-migration of young unemployed workers who were not born in the impacted location because these are the workers who respond the most to such policies. The results of the simulations are reported in Tables 13 and 14. Corresponding tables for unemployment and labor force participation rates can be found in Tables B.6 through B.9 in the appendix.

The bottom row of Tables 13 and 14 shows the predicted out-migration rates for each artificial city, by employment status for years 2007 and 2011. These migration rates are heterogeneous across cities, employment status, and the business cycle. In particular, predicted out-migration is highest for the city with the lowest amenities. In contrast, out-migration is smallest for the city with high amenities. These results point to the importance of considering amenities when forming policy that is intended to affect migration behavior. The baseline migration rates also differ markedly by employment status. The rate of out-migration for unemployed workers is 1.2 to 1.5 times the rate for employed workers. Furthermore, in more adverse business cycle conditions, this ratio widens.

In order to weigh the mechanisms influencing migration, I compare adverse earnings and unemployment shocks that are either completely localized, or correlated across all locations (but originating in the current location). The first four rows of each panel of Tables 13 and 14 report simulated independent and correlated adverse shocks to earnings and employment in each location. The earnings shock corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the 2008-2009 increase in the local unemployment rate for the average location in the data.

The key result from this exercise is the difference in behavior between employed and unemployed workers when faced with unemployment shocks. This difference stems from the difference in job queuing penalties that these groups face. Employed workers are more likely to stay in their current location when faced with either a localized or correlated shock, whereas the opposite is true for unemployed workers. What is interesting is that, when the unemployment shock is correlated across locations, the employed workers become more likely to stay, while the unemployed workers become less likely to leave. Comparing the third and fourth rows of each panel of the table shows that unemployed workers would have been anywhere from 8 to 12 times more likely to out-migrate in response to a localized unemployment shock. The staying propensity for the employed ranges from 1.5 to 1.8 larger in the presence of a correlated shock relative to a localized shock. The fact that the Great Recession was national in scope is one reason why migration for the employed decreased over the period. This result also potentially explains results in Yagan (2014), who finds that migration insurance was lower in the Great Recession because migrants who left heavily-shocked areas were not successful in finding employment relative to migrants during the 2001 recession.

I also study the role of moving costs and search costs in explaining migration behavior. The fifth and sixth rows of each panel of Tables 13 and 14 simulate scenarios with a complete search cost subsidy, and a moving cost subsidy equal to 10% of the fixed cost of moving. For all cities and employment statuses, out-migration rates increase. The increase in migration rates under a moving subsidy is largest in areas with low amenities and job-finding rates. Unemployed workers are more responsive to each subsidy.

I now use the model to analyze what happens when workers are given a moving subsidy. A similar policy has been proposed by Moretti (2012), among others.[43] Because the moving subsidy is not tied to a particular destination location, I analyze where workers who accept the subsidy would choose to relocate. Table 15 shows estimates of a regression of the net migration probability (multiplied by 100) on a vector of location characteristics (amenities, earnings, job offer probability, and birth location proximity). The origin location is excluded from this regression. These regressions are run separately for each of the three origin cities and each pair of calendar years discussed above.

Table 15 predicts that, all else equal, migrants will choose locations that are near their

[43]These proposed policies focus on the fact that unemployment is an externality that should be internalized through subsidized migration. The model presented here does not include such externalities. However, such proposals abstract from preferences for amenities, which my model shows are important determinants of migration.

birth location, close to their origin location, and that have higher employment certainty and higher amenities.[44] This finding is consistent with Monras (2014), who finds that out-migration from heavily shocked areas was constant during the Great Recession, but that in-migration into heavily shocked areas decreased markedly. Interestingly, migrants value employment certainty much more than earnings, regardless of the origin city. The reason for this is that unemployment risk enters the flow utility of labor force participation twice (multiplied by the earnings and multiplied by the search cost and home production benefit), but earnings enters the flow utility once (multiplied by the unemployment risk). Hence, workers are more sensitive to unemployment uncertainty because it is costly to find a job.

In summary, I emphasize that the response to each counterfactual shock is heterogeneous across locations. Specifically, cities with low amenities and low job-finding rates see the largest out-migration response to adverse shocks and favorable subsidies. Furthermore, areas with higher amenities and higher job-finding rates are the prime destinations for out-migrants. This heterogeneity underscores the difficulty in implementing migration policy that would have the intended consequence of inducing migration from high-unemployment areas to low-unemployment areas, because workers value amenities about the same as employment certainty and much more strongly than earnings.

7 Conclusion

This paper studies why migration trends over the business cycle differ for employed and unemployed workers, and how migration for each group responds to various labor market shocks and migration subsidies. To answer these questions, I develop and tractably estimate a rich dynamic model of labor supply and migration that allows for non-stationarity in both earnings and unemployment. I estimate the model using two

[44] These results echo findings by Deryugina, Kawano, and Levitt (2014) who conclude that individuals displaced by Hurricane Katrina migrated to areas offering better economic opportunities, resulting in immediate wage gains. However, they also conclude that these wage gains were likely nominal (i.e. there were no utility gains), because housing prices for these people also increased by the same amount. My results show that migrants tend to choose places with higher amenities and that are closer to family (as proxied by birth location). This suggests that there can, in fact, be utility gains for displaced workers provided these workers are not native to the shocked location.

panels of the Survey of Income and Program Participation (SIPP) covering the period before, during, and after the Great Recession (years 2004-2013).

I find that, the divergence of job offer and job destruction rates over the Great Recession explains much of the observed differences in behavior between the employed and unemployed. The divergence was caused by two factors: (i) employed workers are much more insulated from recessions than unemployed workers; and (ii) employed workers face a steep job queuing penalty when moving locations, whereas unemployed workers face no such penalty.

I use the model to simulate the effect of a correlated adverse labor market shock (such as the Great Recession) and contrast its migratory response with the case of a purely localized shock. I find that, if the Great Recession shock had been purely localized, out-migration of the unemployed would have been 8-12 times larger. Similarly, employed workers would have been less likely to stay in their current location.

I also use the model to simulate the effect of a moving cost subsidy offered to unemployed workers. I find that the response to the subsidy is heterogeneous across locations. Specifically, cities with low amenities and low job-finding rates see the largest out-migration response to the subsidy. In contrast, a location's ranking in the earnings distribution matters very little in terms of out-migration response.

When examining the destination locations of subsidy recipients, I find that areas with higher amenities and higher job-finding rates are the prime destinations. The complexity of migration response to the subsidy underscores the difficulty in implementing migration policy that would have the intended consequence of inducing migration from high-unemployment areas to low-unemployment areas, because workers value amenities about the same as employment certainty and much more than earnings. Furthermore, it is difficult to distinguish between individuals who are marginally and inframarginally attached to a location. This is evidenced by the nearly equal proportion of employed workers who would take up a migration subsidy if offered to them.

References

Adda, Jérôme, Christian Dustmann, and Joseph-Simon Görlach. 2014. "Migrant Wages, Human Capital Accumulation and Return Migration." Working paper, Bocconi University.

Altuğ, Sumru and Robert A. Miller. 1998. "The Effect of Work Experience on Female Wages and Labour Supply." *Review of Economic Studies* 65 (1):45–85.

Arcidiacono, Peter, Esteban Aucejo, Arnaud Maurel, and Tyler Ransom. 2016. "College Attrition and the Dynamics of Information Revelation." Working paper, Duke University.

Arcidiacono, Peter and Robert A. Miller. 2011. "Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity." *Econometrica* 79 (6):1823–1867.

———. 2014. "Nonstationary Dynamic Models with Finite Dependence." Working paper, Duke University and Carnegie Mellon University.

Basker, Emek. 2003. "Education, Job Search and Migration." Working Paper 02-16, University of Missouri Department of Economics.

Baum-Snow, Nathaniel and Ronni Pavan. 2012. "Understanding the City Size Wage Gap." *Review of Economic Studies* 79 (1):88–127.

Bishop, Kelly. 2012. "A Dynamic Model of Location Choice and Hedonic Valuation." Working paper, Washington University in St. Louis.

Blanchard, Olivier and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1992 (1):1–75.

Bleakley, Hoyt and Jeffrey Lin. 2012. "Thick-Market Effects and Churning in the Labor Market: Evidence from US Cities." *Journal of Urban Economics* 72 (2):87–103.

Coate, Patrick. 2013. "Parental Influence on Labor Market Outcomes and Location Decisions of Young Workers." Working paper, Duke Univeristy.

Davies, Paul S., Michael J. Greenwood, and Haizheng Li. 2001. "A Conditional Logit Approach to U.S. State-to-State Migration." *Journal of Regional Science* 41 (2):337–360.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt. 2014. "The Economic Impact of Hurricane Katrina on its Victims: Evidence from Individual Tax Returns." Working Paper 20713, National Bureau of Economic Research.

Diamond, Rebecca. 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000." *American Economic Review* Forthcoming.

DuMond, J. Michael, Barry T. Hirsch, and David A. Macpherson. 1999. "Wage Differentials across Labor Markets and Workers: Does Cost of Living Matter?" *Economic Inquiry* 37 (4):577–598.

Foote, Andrew, Michel Grosz, and Ann Huff Stevens. 2015. "Locate Your Nearest Exit: Mass Layoffs and Local Labor Market Response." Working Paper 21618, National Bureau of Economic Research.

Gaubert, Cecile. 2015. "Firm Sorting and Agglomeration." Working paper, UC Berkeley.

Gayle, Wayne-Roy. 2013. "CCP Estimation of Dynamic Discrete/Continuous Choice Models with Generalized Finite Dependence and Correlated Unobserved Heterogeneity." Working paper, University of Virginia.

Gemici, Ahu. 2011. "Family Migration and Labor Market Outcomes." Working paper, Royal Holloway, University of London.

Glaeser, Edward and David Maré. 2001. "Cities and Skills." *Journal of Labor Economics* 19 (2):316–342.

Gould, Eric. 2007. "Cities, Workers and Wages: A Structural Analysis of the Urban Wage Premium." *Review of Economic Studies* 74 (2):477–506.

Harris, John R. and Michael P. Todaro. 1970. "Migration, Unemployment and Development: a Two-Sector Analysis." *American Economic Review* :126–142.

Hotz, V. Joseph and Robert A. Miller. 1993. "Conditional Choice Probabilities and the Estimation of Dynamic Models." *Review of Economic Studies* 60 (3):497–529.

Kaplan, Greg and Sam Schulhofer-Wohl. 2013. "Understanding the Long-Run Decline in Interstate Migration." Working Paper 697, Federal Reserve Bank of Minneapolis.

Keane, Michael P. and Kenneth I. Wolpin. 1994. "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence." *Review of Economics and Statistics* :648–672.

Kennan, John and James R. Walker. 2011. "The Effect of Expected Income on Individual Migration Decisions." *Econometrica* 79 (1):211–251.

Magnac, Thierry and David Thesmar. 2002. "Identifying Dynamic Discrete Decision Processes." *Econometrica* 70 (2):801–816.

Malizia, Emil E. and Shanzi Ke. 1993. "The Influence of Economic Diversity on Unemployment and Stability." *Journal of Regional Science* 33 (2):221–235.

Mangum, Kyle. 2015. "Cities and Labor Market Dynamics." Working Paper 2015-2-3, Georgia State University.

McFadden, Daniel. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, edited by Paul Zarembka. Academic Press, New York, 105–142.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2011. "Internal Migration in the United States." *Journal of Economic Perspectives* 25 (3):173–96.

Molloy, Raven S. and Abigail Wozniak. 2011. "Labor Reallocation over the Business Cycle: New Evidence from Internal Migration." *Journal of Labor Economics* 29 (4):697–739.

Monras, Joan. 2014. "Economic Shocks and Internal Migration." Working paper, Sciences Po.

Moretti, Enrico. 2012. *The New Geography of Jobs*. New York: Houghton Mifflin Harcourt.

Notowidigdo, Matthew J. 2011. "The Incidence of Local Labor Demand Shocks." Working Paper 17167, National Bureau of Economic Research.

Piyapromdee, Suphanit. 2014. "The Impact of Immigration on Wages, Internal Migration and Welfare." Working paper, University of Wisconsin-Madison.

Roback, Jennifer. 1982. "Wages, Rents, and the Quality of Life." *Journal of Political Economy* 90 (6):1257–1278.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]*. Minneapolis: University of Minnesota.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica* 55 (5):999–1033.

Schlottmann, Alan M. and Henry W. Herzog, Jr. 1981. "Employment Status and the Decision to Migrate." *Review of Economics and Statistics* 63 (4):590–598.

Schmutz, Benoît and Modibo Sidibé. 2015. "Job Search and Migration in a System of Cities." ERID Working Paper 181, Duke University.

Topel, Robert H. 1986. "Local Labor Markets." *Journal of Political Economy* 94 (3):S111–S143.

Wheeler, Christopher H. 2006. "Cities and the Growth of Wages Among Young Workers: Evidence from the NLSY." *Journal of Urban Economics* 60 (2):162–184.

Winters, John V. 2009. "Wages and Prices: Are Workers Fully Compensated for Cost of Living Differences?" *Regional Science and Urban Economics* 39 (5):632–643.

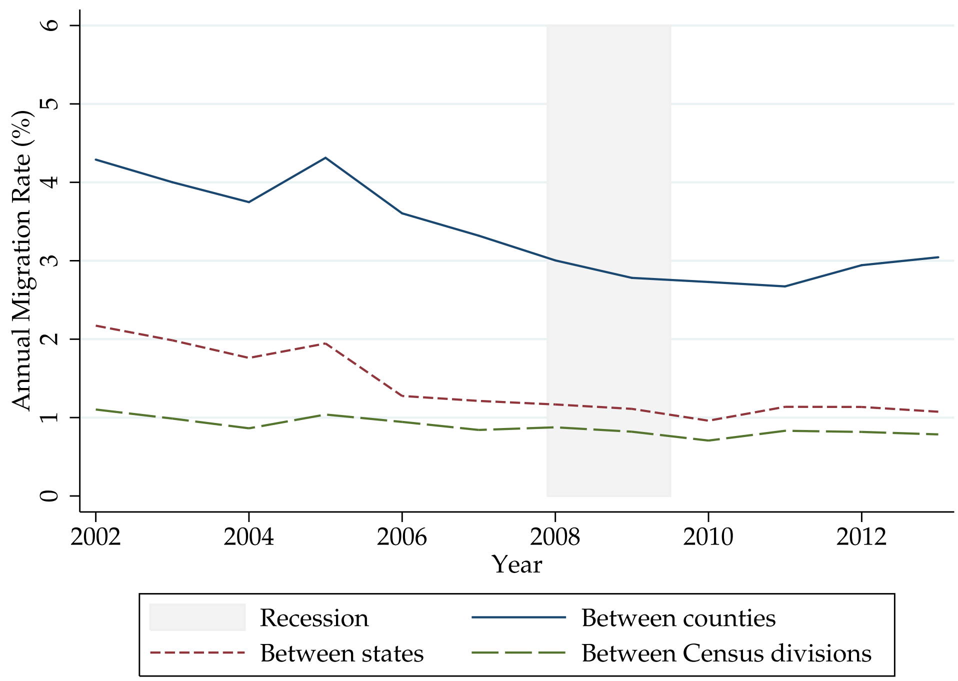
Yagan, Danny. 2014. "Moving to Opportunity? Migratory Insurance over the Great Recession." Working paper, UC Berkeley.

Yankow, Jeffrey J. 2006. "Why Do Cities Pay More? An Empirical Examination of Some Competing Theories of the Urban Wage Premium." *Journal of Urban Economics* 60 (2):139–161.

Zabel, Jeffrey E. 1998. "An Analysis of Attrition in the Panel Study of Income Dynamics and the Survey of Income and Program Participation with an Application to a Model of Labor Market Behavior." *Journal of Human Resources* 33 (2):479–506.

Figures and Tables

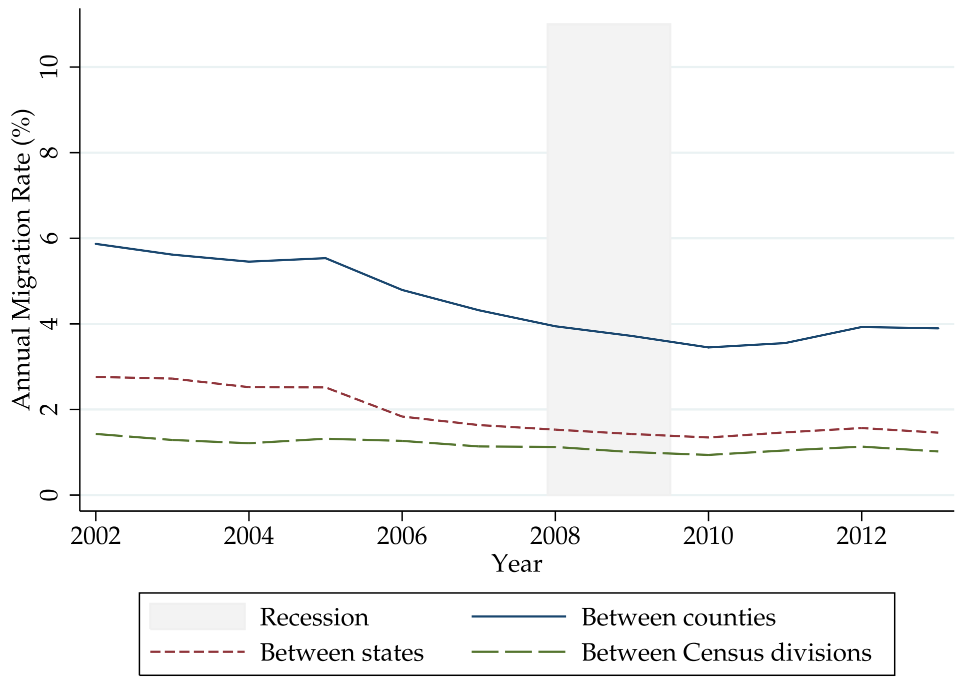
Figure 1: Annual migration rates by distance, non-college-graduate whites



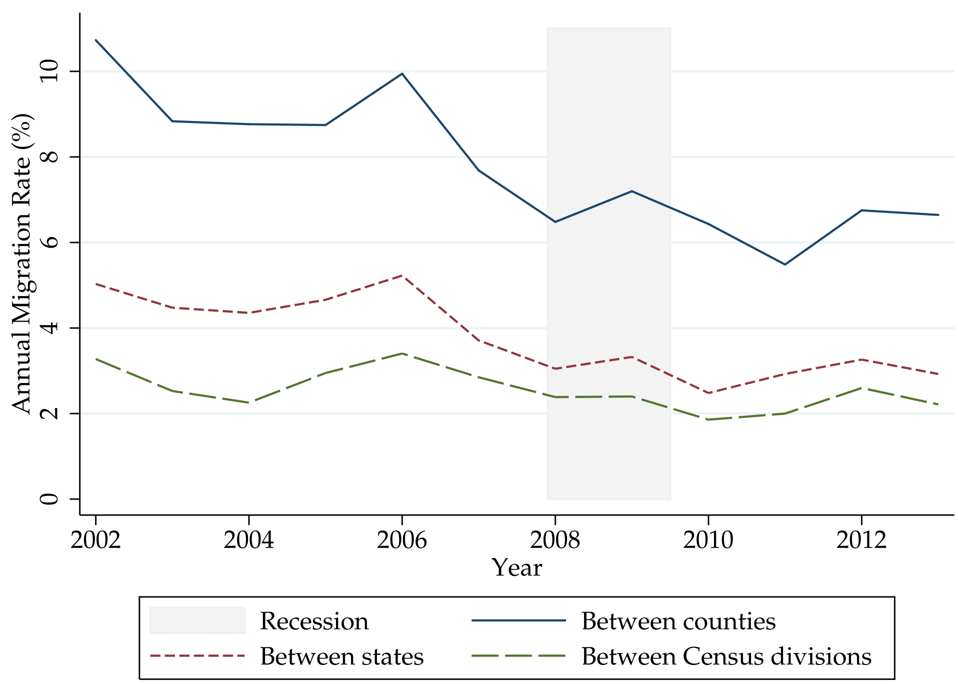
Source: Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC)

Figure 2: Annual migration rates by current employment status and distance

(a) Employed, age 25+

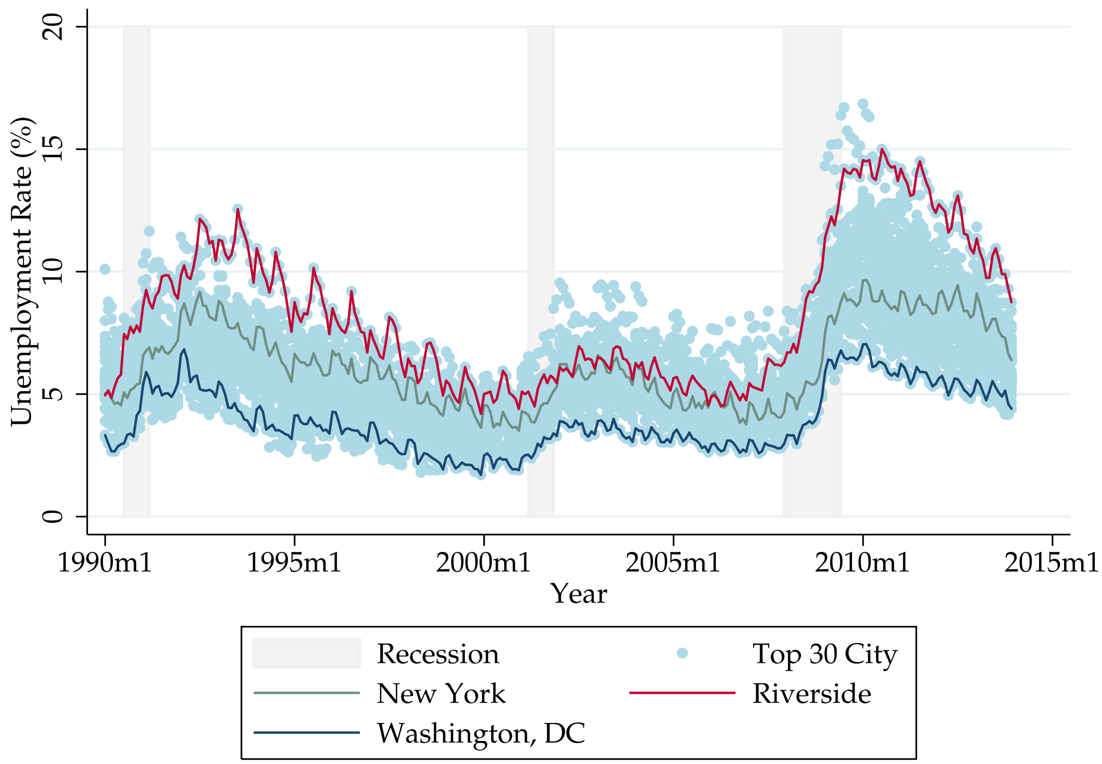


(b) Unemployed, age 25+



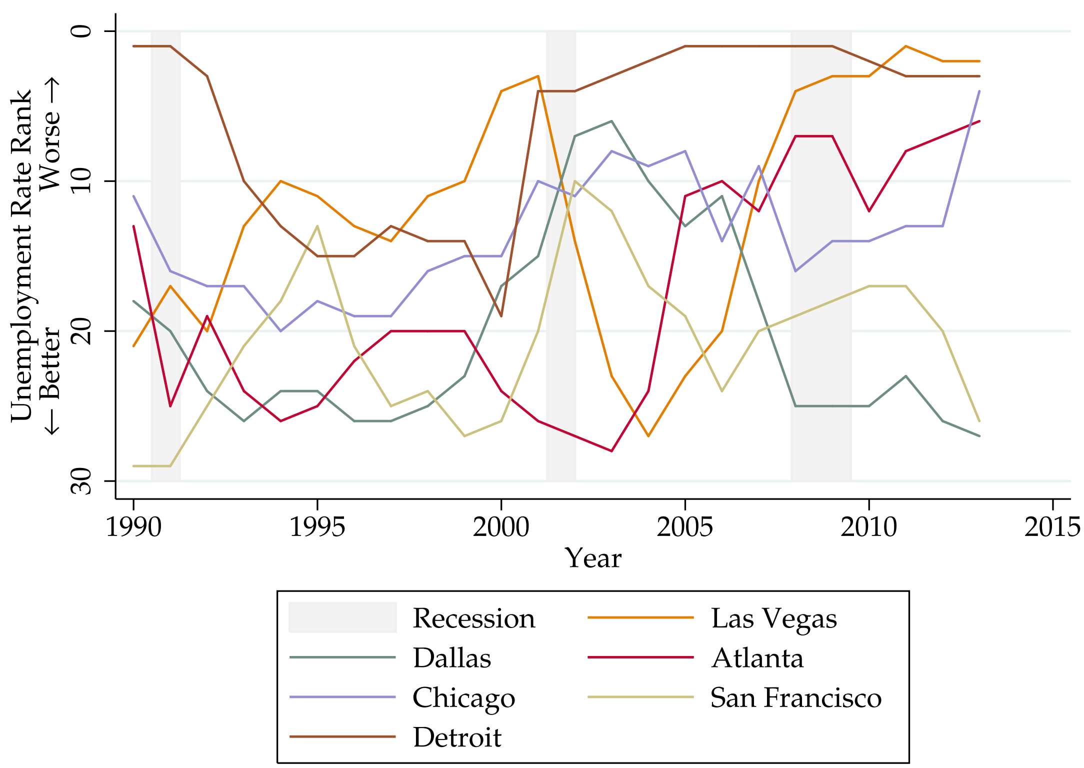
Source: Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC)

Figure 3: Unemployment rates, select cities



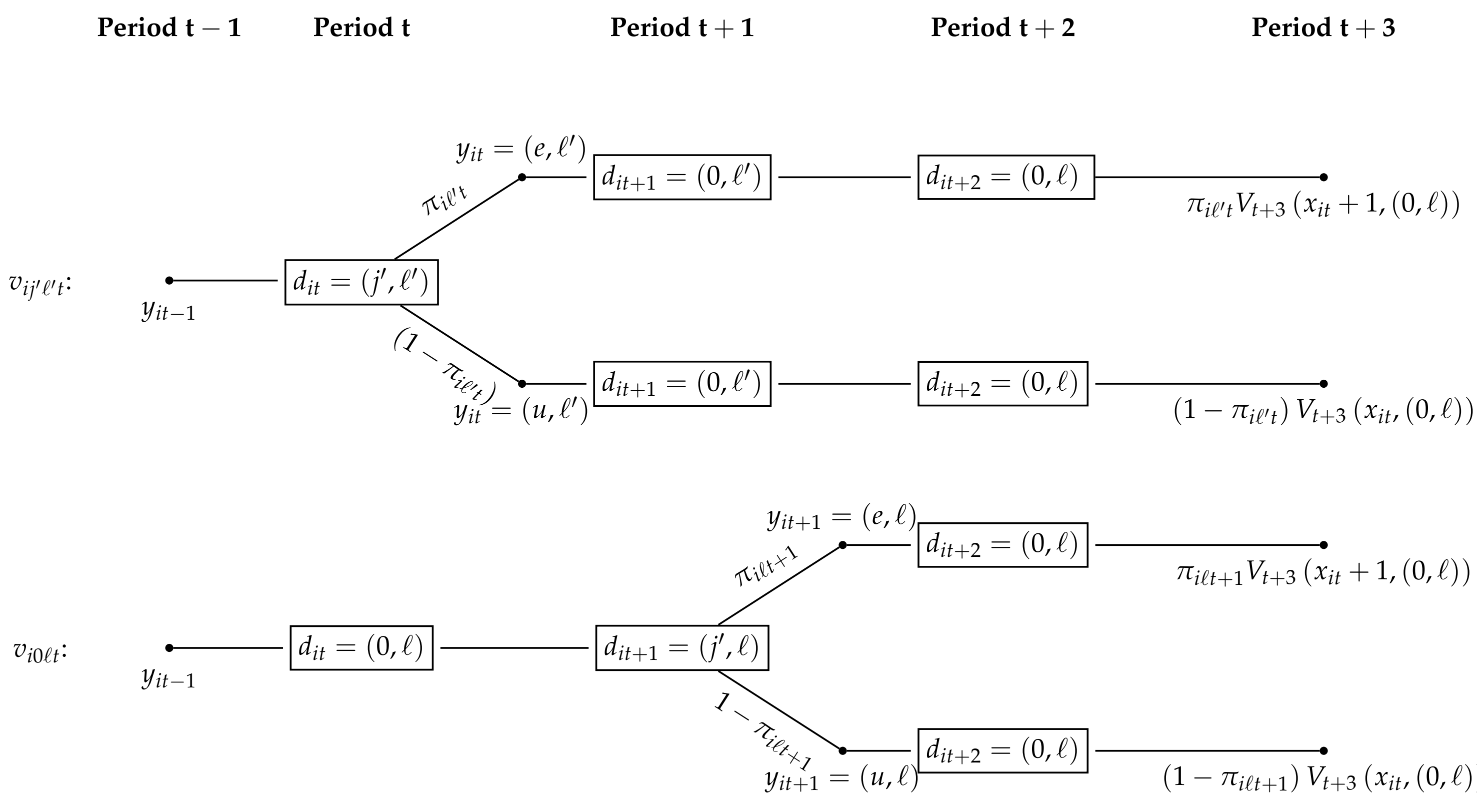
Source: Bureau of Labor Statistics, Local Area Unemployment Statistics

Figure 4: Unemployment rankings, select cities



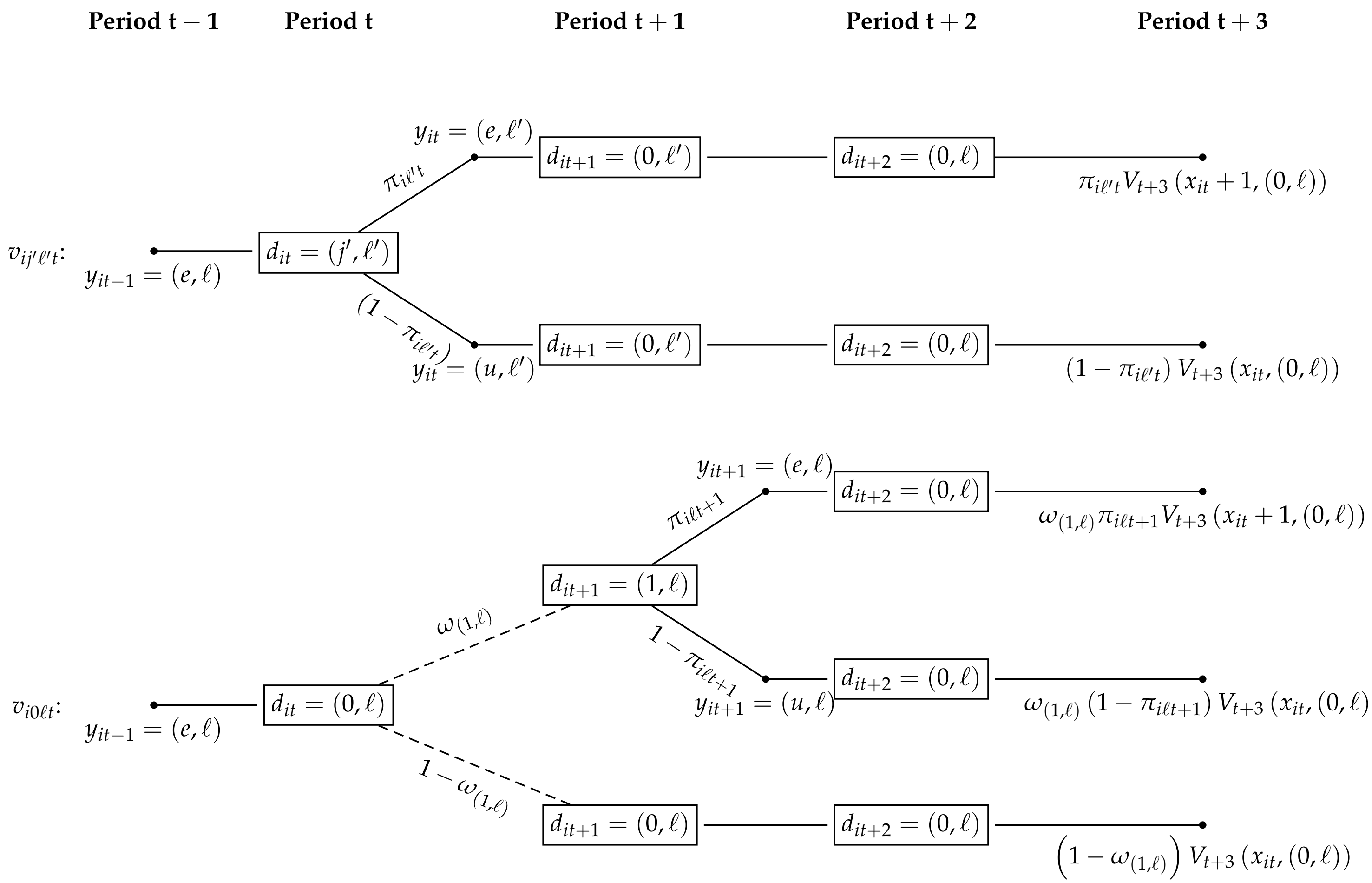
Source: Bureau of Labor Statistics, Local Area Unemployment Statistics

Figure 5: Finite dependence paths conditional on y_{it-1}



Note: This figure depicts the evolution of the state space given the finite dependence paths described in Section 4.3.2. Cancellation of the future value terms does not occur unless $\pi_{i\ell' t} = \pi_{i\ell t+1}$. This equality does not hold in general.

Figure 6: Expanded finite dependence paths conditional on y_{it-1}



Note: This figure depicts the evolution of the state space given the finite dependence paths described in Section 4.3.2. Cancellation of the future value terms occurs when $\omega_{(1,\ell)} = \frac{\pi_{i\ell't}}{\pi_{i\ell t+1}}$, as described in Equations (4.12) and (4.13).

Table 1: Descriptive statistics of the estimation subsample of the SIPP, 2004-2013

Variable	Mean	Std Dev
Log monthly earnings (2000 dollars)[a]	7.96	0.52
Work experience (years)	22.60	9.49
Age (years)	42.29	9.76
Lives in location in birth state	0.74	0.44
Lives in location in birth Census division	0.75	0.43
Number of persons	16,648	
Number of observations	50,415	

Notes: For complete sample selection rules, see Table B.1.

[a] Conditional on being employed full-time with monthly earnings between $400 and $22,000. This variable has 29,238 person-year observations. The earnings variable is spatially deflated to account for differences in cost of living according to the procedure outlined in Appendix B.2

Table 2: Migration in the SIPP, 2004-2013

Number of persons (age 18-55)	16,648
Movers	568
Movers (%)	3.41
Moves	653
Moves per mover	1.15
Repeat moves (% of all moves)	13.38
Return moves (% of all moves)	8.98

Note: Moves are defined as changing locations as defined in the model.

Table 3: Structural employment probability equation estimates

Variable	Previously employed Coeff	Previously employed Std Err	Previously non-employed Coeff	Previously non-employed Std Err
Constant	1.3056***	0.2220	0.2566	0.2237
Experience	0.0858***	0.0091	0.0359***	0.0086
$\text{Experience}^2/100$	-0.1228***	0.0208	-0.0285	0.0219
Lagged local unempl. rate	-0.0314***	0.0104	-0.0922***	0.0110
Mover dummy	-0.9257***	0.1280	0.1929	0.1557
Location fixed effects	✓		✓	
Log likelihood	-10,046.57		-6,672.55	
Observations	30,898		9,949	
Persons	12,013		6,087	

Notes: Reported numbers are coefficients from logit regressions conditional on previous employment status. *** p<0.01; ** p<0.05; * p<0.10.

Table 4: Estimated employment probabilities over time

Previous status	Symbol	2007	2011	Δ
Employed	$(1-\delta_t)$	0.9001	0.8901	-0.0100
		(0.0182)	(0.0210)	
Employed & move	(λ_t^e)	0.7603	0.7405	-0.0198
		(0.0371)	(0.0413)	
Non-employed	(λ_t)	0.4801	0.3868	-0.0933
		(0.0735)	(0.0743)	
Non-employed & move	(λ_t^u)	0.5016	0.4074	-0.0942
		(0.0732)	(0.0752)	

Notes: Reported numbers are mean of estimated parameters (evaluated at 0 years of work experience) from L separate locations. Standard deviations in parentheses.

Table 5: Estimates of unemployment rate forecasting equations

Parameter	Symbol	Mean	Std Dev
Drift	(ϕ_0)	0.0171	0.0052
Autocorrelation	(ϕ_1)	0.7670	0.0840
SD of shock	(σ_ξ)	0.0137	0.0035

Notes: Reported numbers are distributional moments of parameters from L separate AR(1) regressions.

Table 6: Structural earnings equation estimates

Parameter	Coeff	Std Err
constant	7.5708***	0.0673
experience	0.0432***	0.0015
$\text{experience}^2/100$	-0.0595***	0.0033
Location-time fixed effects	✓	
R^2	0.1628	
Observations	11,404	
persons	29,238	

Notes: Reported numbers are coefficients from an OLS log earnings regression conditional on full-time employment and observing earnings. See footnote (a) of Table 1 for complete details on this subsample. *** p<0.01; ** p<0.05; * p<0.10

Table 7: Earnings forecasting estimates

Parameter	Symbol	Mean	Std Dev
Earnings			
Drift	(ρ_0)	-0.1043	0.0388
Autocorrelation	(ρ_1)	0.7080	—
SD of shock	(σ_ζ)	0.0934	0.0448

Notes: Reported numbers are distributional moments of parameters from a pooled AR(1) regression with location-specific drift and shock variance, but common autocorrelation coefficient. The standard error of ρ_1 is 0.0397, which both rejects that the process is a unit root, and rejects that the process is white noise.

Table 8: Structural choice equation estimates

Parameter	Symbol	Coeff	Std. Err
Expected log earnings	(γ_0)	0.916**	0.397
Home production benefit	(γ_1)	-0.902	3.477
Search cost	(γ_2)	-1.195***	0.069
Birth state bonus	(γ_3)	0.207***	0.072
Birth division bonus	(γ_4)	-0.002	0.073
Switching costs			
Fixed cost	$(\theta_{10} - \theta_7)$	0.335**	0.127
Age	$(\theta_{11} - \theta_8)$	-0.095***	0.006
$\text{Age}^2/100$	$(\theta_{12} - \theta_9)$	0.109***	0.008
Moving costs			
Fixed cost	(θ_0)	-3.148***	0.361
Distance (1000 miles)	(θ_1)	-2.063***	0.078
Distance^2	(θ_2)	0.369***	0.025
Age	(θ_3)	-0.094***	0.018
$\text{Age}^2/100$	(θ_4)	0.056**	0.023
Employed_{t-1}	(θ_5)	0.197*	0.110
Unemployed_{t-1}	(θ_6)	-0.230*	0.128
Log likelihood		-18,478	
Observations		50,415	
Persons		16,648	
Discount factor	(β)	0.9	

Notes: Reported numbers are flow utility parameter estimates from the dynamic choice model described in Sections 2 and 4. *** p<0.01; ** p<0.05; * p<0.10

Table 9: Sample moving costs and amenity values (2014 dollars)

Utility component	Monetary value Employed	Unemployed
Moving costs		
Fixed cost of moving	-\$153,537	-\$175,745
Average mover, 500-mile move	-\$419,147	-\$445,751
Average mover, NY to LA	-\$537,589	-\$564,193
Young mover, NY to LA	-\$319,073	-\$336,530
Amenities		
Std. Dev. of local amenities	\$3,907	
Range of local amenities	\$16,661	
Birth state bonus	\$10,764	

Notes: Values are evaluated at the parameter estimates in Table 8 and at the sample average of monthly earnings (log earnings equal to 7.96). The average mover is age 39, and a young mover is age 25. The great-circle distance from New York to Los Angeles is 2,446 miles. For more details on how these values are calculated, see Section A.1.

Table 10: Determinants of local labor market attributes

(a) Amenities, earnings, and employment levels

Variable	Amenities (α_ℓ) Coeff	Std Err	Earnings (w_ℓ) Coeff	Std Err	Job destruction (δ_ℓ) Coeff	Std Err	Job offer (λ_ℓ) Coeff	Std Err
constant	-0.0530	0.3091	7.6440***	0.2088	0.5898***	0.0371	-0.0010	0.1071
ln(population)	0.0093	0.0208	-0.0266	0.0141	0.0146***	0.0025	0.0243***	0.0072
New England	0.0098	0.0496	-0.1659***	0.0335	-0.0129***	0.0060	-0.0249	0.0172
Mid Atlantic	-0.0352	0.0484	-0.0098	0.0327	0.0250***	0.0058	-0.0171	0.0168
E N Central	-0.0778**	0.0338	0.1215***	0.0228	0.0162***	0.0041	-0.0265***	0.0117
W N Central	0.0057	0.0465	0.0840***	0.0314	0.0427***	0.0056	-0.0529***	0.0161
S Atlantic	-0.0388	0.0349	0.0503***	0.0236	0.0269***	0.0042	0.0127	0.0121
E S Central	-0.0591	0.0577	0.0548	0.0390	-0.0160***	0.0069	0.1251***	0.0200
W S Central	-0.1233**	0.0482	0.2393***	0.0326	0.0539***	0.0058	0.0244	0.0167
Mountain	0.0198	0.0563	0.0982***	0.0380	0.0020	0.0068	0.0802***	0.0195
R^2	0.3848		0.3368		0.4507		0.2230	

Notes: Each column is a separate regression with 350 observations (35 cities, 10 time periods) of the corresponding model parameter on the log population of the location and Census division dummies. Amenities and AR(1) shock standard deviations do not vary over time, so these regressions have 35 observations. *** p<0.01; ** p<0.05; * p<0.10

(b) Earnings and unemployment drift, persistence, and volatility

Variable	Earnings drift ($\rho_{0\ell}$) Coeff	Std Err	UR drift ($\phi_{0\ell}$) Coeff	Std Err	UR persistence ($\phi_{1\ell}$) Coeff	Std Err	Earnings volatility (σ_{ζ_ℓ}) Coeff	Std Err	UR volatility (σ_{ξ_ℓ}) Coeff	Std Err
constant	-0.0346	0.1466	0.0190	0.0197	0.4310	0.2896	0.5331***	0.1667	-0.0091	0.0137
ln(population)	-0.0057	0.0099	-0.0001	0.0013	0.0237	0.0195	-0.0266***	0.0112	0.0018*	0.0009
New England	-0.0563***	0.0235	-0.0015	0.0032	-0.0132	0.0464	-0.0185	0.0267	-0.0034	0.0022
Mid Atlantic	-0.0134	0.0230	-0.0051*	0.0031	0.0505	0.0453	0.0025	0.0261	-0.0052***	0.0021
E N Central	0.0477***	0.0160	0.0028	0.0022	-0.0454	0.0317	-0.0317*	0.0182	-0.0019	0.0015
W N Central	0.0123	0.0220	0.0011	0.0030	-0.0660	0.0436	-0.0366	0.0251	-0.0027	0.0021
S Atlantic	0.0098	0.0165	-0.0047***	0.0022	0.0394	0.0327	-0.0160	0.0188	-0.0024	0.0015
E S Central	0.0234	0.0274	-0.0002	0.0037	-0.0163	0.0541	-0.0313	0.0311	-0.0006	0.0026
W S Central	0.0613***	0.0229	0.0010	0.0031	-0.1074***	0.0452	-0.0277	0.0260	-0.0060***	0.0021
Mountain	0.0184	0.0267	-0.0026	0.0036	-0.0043	0.0527	-0.0545*	0.0304	-0.0011	0.0025
R^2	0.5989		0.4347		0.5004		0.3534		0.3953	

Notes: "UR" denotes unemployment rate. Each column is a separate regression with 350 observations (35 cities, 10 time periods) of the corresponding model parameter on the log population of the location and Census division dummies. Amenities and AR(1) shock standard deviations do not vary over time, so these regressions have 35 observations. *** p<0.01; ** p<0.05; * p<0.10

Table 11: Model fit: observed vs. predicted migration probabilities

(a) Migration probabilities by $t-1$ employment status

$t-1$ Employment status	Data	Model
Employed	1.29%	1.29%
Unemployed	1.19%	1.19%
Out of labor force	1.69%	1.70%
Overall	1.25%	1.25%

(b) Migration probabilities by age

Age range	Data	Model
18-25	2.52%	2.86%
26-35	2.00%	1.84%
36-45	1.13%	1.26%
46-55	0.86%	0.83%

(c) Migration probabilities by distance migrated

Distance (miles)	Data	Model
0-500	0.72%	0.70%
501-1,000	0.31%	0.35%
1,001-1,500	0.13%	0.13%
1,501-2,000	0.07%	0.05%
2,001+	0.06%	0.05%

Notes: All numbers in this table correspond to migration probabilities (multiplied by 100 and expressed as percentages). Data probabilities consist of conditional means of an indicator for migration. Model probabilities consist of conditional means of the predicted probability of leaving the current location.

Table 12: Model fit: employment transitions by migration status

(a) Employment transitions conditional on migrating (Data)

	Period t		
Period $t-1$	E	U	N
Employed (E)	70.98%	22.69%	6.33%
Unemployed (U)	41.40%	46.50%	12.10%
Out of labor force (N)	16.52%	17.39%	66.09%

(b) Employment transitions conditional on migrating (Model)

	Period t		
Period $t-1$	E	U	N
Employed (E)	74.00%	20.93%	5.08%
Unemployed (U)	44.15%	45.11%	10.74%
Out of labor force (N)	12.94%	12.61%	74.45%

(c) Employment transitions conditional on staying (Data)

	Period t		
Period $t-1$	E	U	N
Employed (E)	86.92%	9.86%	3.23%
Unemployed (U)	36.33%	49.75%	13.93%
Out of labor force (N)	10.81%	10.41%	78.78%

(d) Employment transitions conditional on staying (Model)

	Period t		
Period $t-1$	E	U	N
Employed (E)	86.51%	9.86%	3.63%
Unemployed (U)	38.25%	49.13%	12.63%
Out of labor force (N)	10.19%	12.18%	77.63%

Notes: All numbers in this table correspond to employment transition probabilities (multiplied by 100 and expressed as percentages). Data probabilities consist of conditional means of employment transition by migration status. Model probabilities consist of conditional means (by employment status) of the predicted conditional probability of making an employment transition (conditional on leaving or staying).

Table 13: Counterfactual change in out-migration rate by employment status for origin cities of various characteristics, year 2007

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory ↓ w shock in current location	0.0026	0.0044	0.0046	0.0073
correlated transitory ↓ w shock in current location	-0.0016	0.0045	-0.0025	0.0074
independent transitory ↑ UR shock in current location	-0.0054	0.0269	-0.0092	0.0434
correlated transitory ↑ UR shock in current location	-0.0090	0.0027	-0.0155	0.0044
one period no search costs	0.0124	0.0159	0.0209	0.0258
one period moving subsidy (10% of fixed cost of moving)	0.0231	0.0282	0.0384	0.0453
baseline migration probability	0.0687	0.0862	0.1239	0.1528

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory ↓ w shock in current location	0.0035	0.0058	0.0038	0.0061
correlated transitory ↓ w shock in current location	-0.0021	0.0059	-0.0021	0.0062
independent transitory ↑ UR shock in current location	-0.0072	0.0351	-0.0076	0.0364
correlated transitory ↑ UR shock in current location	-0.0119	0.0039	-0.0130	0.0029
one period no search costs	0.0163	0.0207	0.0177	0.0218
one period moving subsidy (10% of fixed cost of moving)	0.0302	0.0368	0.0325	0.0381
baseline migration probability	0.0933	0.1175	0.1014	0.1227

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory ↓ w shock in current location	0.0034	0.0052	0.0035	0.0069
correlated transitory ↓ w shock in current location	-0.0020	0.0052	-0.0023	0.0073
independent transitory ↑ UR shock in current location	-0.0081	0.0270	-0.0070	0.0491
correlated transitory ↑ UR shock in current location	-0.0120	0.0028	-0.0129	0.0048
one period no search costs	0.0189	0.0215	0.0152	0.0226
one period moving subsidy (10% of fixed cost of moving)	0.0297	0.0336	0.0309	0.0420
baseline migration probability	0.0914	0.1055	0.0955	0.1385

Notes: Numbers refer to the change in the out-migration rate from the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock (↓ w) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table 14: Counterfactual change in out-migration rate by employment status for origin cities of various characteristics, year 2011

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory ↓ w shock in current location	0.0023	0.0036	0.0041	0.0059
correlated transitory ↓ w shock in current location	-0.0026	0.0038	-0.0040	0.0063
independent transitory ↑ UR shock in current location	-0.0080	0.0303	-0.0136	0.0482
correlated transitory ↑ UR shock in current location	-0.0131	0.0002	-0.0225	0.0004
one period no search costs	0.0146	0.0188	0.0242	0.0301
one period moving subsidy (10% of fixed cost of moving)	0.0245	0.0304	0.0404	0.0481
baseline migration probability	0.0734	0.0938	0.1318	0.1654

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory ↓ w shock in current location	0.0031	0.0047	0.0034	0.0049
correlated transitory ↓ w shock in current location	-0.0033	0.0051	-0.0034	0.0052
independent transitory ↑ UR shock in current location	-0.0105	0.0393	-0.0112	0.0403
correlated transitory ↑ UR shock in current location	-0.0172	0.0007	-0.0187	-0.0003
one period no search costs	0.0189	0.0243	0.0204	0.0253
one period moving subsidy (10% of fixed cost of moving)	0.0317	0.0393	0.0340	0.0404
baseline migration probability	0.0986	0.1276	0.1070	0.1318

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory ↓ w shock in current location	0.0032	0.0040	0.0030	0.0061
correlated transitory ↓ w shock in current location	-0.0031	0.0040	-0.0037	0.0072
independent transitory ↑ UR shock in current location	-0.0119	0.0272	-0.0101	0.0629
correlated transitory ↑ UR shock in current location	-0.0172	0.0003	-0.0187	0.0004
one period no search costs	0.0228	0.0246	0.0167	0.0278
one period moving subsidy (10% of fixed cost of moving)	0.0316	0.0347	0.0322	0.0472
baseline migration probability	0.0981	0.1098	0.1003	0.1613

Notes: Numbers refer to the change in the out-migration rate from the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock (↓ w) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table 15: Characteristics of destination location given moving cost subsidy to unemployed workers in various origin cities, year 2007

(a) Amenities

	high amenity city		low amenity city	
	Coeff	Std Err	Coeff	Std Err
constant	0.2217	0.1610	0.2824	0.2591
amenities	0.0274*	0.0090	0.0440*	0.0145
earnings (conditional on working)	-0.0001	0.0060	-0.0001	0.0096
employment probability	0.0187*	0.0070	0.0302*	0.0112
ln(distance)	-0.0351*	0.0132	-0.0562*	0.0211
state of birth	0.2418*	0.0261	0.3885*	0.0419
region of birth	0.0173	0.0214	0.0279	0.0345

(b) Earnings level

	high earnings city		low earnings city	
	Coeff	Std Err	Coeff	Std Err
constant	0.2580	0.2092	0.2654	0.2181
amenities	0.0354*	0.0117	0.0369*	0.0122
earnings (conditional on working)	-0.0001	0.0077	-0.0001	0.0081
employment probability	0.0243*	0.0090	0.0257*	0.0094
ln(distance)	-0.0457*	0.0171	-0.0472*	0.0178
state of birth	0.3153*	0.0339	0.3256*	0.0353
region of birth	0.0225	0.0279	0.0236	0.0291

(c) Employment probability level

	high emp. prob. city		low emp. prob. city	
	Coeff	Std Err	Coeff	Std Err
constant	0.2399	0.1886	0.2864	0.2445
amenities	0.0319*	0.0105	0.0413*	0.0136
earnings (conditional on working)	-0.0001	0.0070	0.0000	0.0090
employment probability	0.0211*	0.0082	0.0300*	0.0106
ln(distance)	-0.0420*	0.0154	-0.0517*	0.0200
state of birth	0.2906*	0.0306	0.3555*	0.0396
region of birth	0.0201	0.0251	0.0268	0.0326

Notes: Dependent variable is predicted migration rate to location ℓ (in percentage points). Covariates are locational characteristics of the candidate destination locations. The amenities, earnings, and employment probability variables are each standardized to have mean-zero, unit variance. All locations (including synthetic locations) are included in the regression. Controls also included for local earnings drift, earnings volatility, unemployment drift, unemployment persistence, and unemployment volatility. * $p<0.05$

A Model Appendix

A.1 Calculating moving costs and amenity values

With expected earnings included in the utility function, I can use the parameter γ_0 in equation (2.9) to convert from units of utility to money and assign a monetary value to the cost of moving and to the amenities. Because earnings do not enter linearly, however, the moving cost needs to be evaluated at some value (e.g. the average earnings in the data). The fixed cost of moving for a previously employed person $(\theta_0 + \theta_5)$ given in equation (2.13) is calculated as follows:

$$\begin{aligned}
\text{Moving Cost} &= \frac{\theta_0 + \theta_5}{\gamma_0} \left(\frac{12 \exp\left(\overline{w}\right) \text{ dollars}}{\text{year}} \right) && \text{(A.1)} \\
&= \frac{12\theta_0 \exp\left(\overline{w}\right)}{\gamma_0} \text{ dollars} && \text{(A.2)} \\
&= \frac{12\left(-3.148 + 0.197\right) \exp\left(7.96\right)}{0.916} \\
&= -\$153,537 \text{ in 2014 dollars}
\end{aligned}$$

where I multiply by 12 in order to convert monthly earnings to an annual measure and inflate by the CPI to convert from 2000 to 2014 dollars.

The other moving costs (e.g. moving costs at a particular age or between two particular locations) are obtained by calculating the predicted value from the moving cost equation at the relevant characteristics of the mover and origin and destination locations. This predicted value is then substituted for $\theta_0 + \theta_5$. A similar method is used to calculate amenity values.

A.2 Finite dependence for non-employment alternatives

The finite dependence formula written in equation (4.14) is rewritten below for the case of a non-employment alternative (i.e. corresponding to $j' = 0$).

$$
\begin{aligned}
v_{j'\ell' t}\left(Z_t\right) - v_{0\ell t}\left(Z_t\right) = & u^n_{\ell' t}\left(Z_t\right) - u^n_{\ell t}\left(Z_t\right) + \\
& \beta\left[\left(u^n_{\ell' t+1}\left(\left\{0, \ell'\right\}, x_t\right) - \ln p_{0\ell' t+1}\left(\left\{0, \ell'\right\}, x_t\right)\right)\right. \\
& \left. - u^n_{\ell t+1}\left(\left\{0, \ell\right\}, x_t\right) + \ln p_{0\ell t+1}\left(\left\{0, \ell\right\}, x_t\right)\right] + \\
& \beta^2\left[u^n_{\ell t+2}\left(\left\{0, \ell'\right\}, x_t\right) - \ln p_{0\ell t+2}\left(\left\{0, \ell'\right\}, x_t\right)\right. \\
& \left. - u^n_{\ell t+2}\left(\left\{0, \ell\right\}, x_t\right) + \ln p_{0\ell t+2}\left(\left\{0, \ell\right\}, x_t\right)\right]
\end{aligned}
\tag{A.3}
$$

B Data Appendix

B.1 Estimation subsample

The estimation subsample is restricted to non-Hispanic white males aged 18-55 who have completed schooling by the time of the first SIPP interview and who do not hold a bachelor's degree. The final estimation subsample comprises 16,648 males each averaging 3.03 annual observations. Earnings are computed as total monthly earnings across all jobs in the interview month. Observations with monthly earnings higher than $22,000 or lower than $400 are excluded from earnings estimates. The small percentage of workers with survey data containing missing or imputed monthly earnings are assigned a monthly estimate of annual earnings reported on their W-2 tax form. For complete details on sample selection, see Table B.1.

B.2 Population and Prices

I gather locational characteristics from a variety of sources. Using the Missouri Census Data Center's MABLE/Geocorr12 program, I form a crosswalk that maps every county to its Core Based Statistical Area (CBSA) as of 2009. The locational characteristics used in this analysis are population (in 2000) and prices (varying by year). Population is calculated by summing the population of each component county. If the individual does not live in a CBSA, his county population is used instead.

Locational prices come from the ACCRA-COLI data. This data, generously provided by Christopher Timmins, contains quarterly information from 1990-2008 on six different categories of goods (groceries, housing, utilities, medical, transportation and miscellaneous) across a wide range of surveyed locations, both metropolitan and rural. I average prices over quarters and CBSA (since some large CBSAs have multiple price listings) to form an annual price index for each CBSA. For locations that are not included in a particular year, I assign each location to one of five population categories and then impute the price by assigning the average price of all other locations in the same state and population category. If the location still has no price information, I repeat the process but aggregate at the level of census region instead of state.

Multiple studies have found that housing prices listed in ACCRA are not good measures of true housing costs (e.g. Baum-Snow and Pavan 2012, DuMond, Hirsch, and Macpherson 1999, Winters 2009). As a result, I follow Winters (2009) and use quality-adjusted gross rents from the 2005 American Community Survey (ACS) compiled by Ruggles et al. (2010). This consists of regressing log gross rents on a vector of housing characteristics and CBSA fixed effects. The housing price level of a given city is then the predicted average gross rents for that city evaluated at the mean housing characteristics for the entire sample. This price level is then included in place of the ACCRA housing price level when forming the price index in (B.1) below. For more details regarding the specific housing characteristics included in the analysis, see p. 636 of Winters. It is also important to note that the ACS does not include location information for low populated areas. For locations that are not identifiable in the ACS, I use states instead of CBSAs. I exclude houses that are in an identifiable CBSA and repeat the process outlined above, assigning rural housing prices as state fixed effects plus average sample characteristics.

With location-specific prices in hand, I compute the price index according to Baum-Snow and Pavan (2012):

$$\text{INDEX}_j = \prod_g \left(\frac{p_g^j}{p_g^0} \right)^{s_g} \tag{B.1}$$

where g indexes goods in the consumer's basket, p_g^j is the price of good g in location j, and s_g is the share of income on good g. In practice, g corresponds to the six categories of goods included in the ACCRA data: groceries, housing, utilities, transportation, health care and all other goods. I use the income shares provided by ACCRA which were computed using the Consumer Expenditure Survey (CEX).

Once this is accomplished, I temporally deflate the indices using the CPI-U in 2000 and spatially deflate using the population-weighted average location in 2000. I then deflate earnings by dividing monthly earnings by this index.

Equation (B.1) is derived from an indifference relationship for identical workers in location j with utility function U over a vector of goods z (which is allowed to differ in price across locations) is given by

$$\overline{v} = \max_{z} U(z) + \lambda \left[w_j - \sum_g p_g^j z_g \right]. \tag{B.2}$$

Log-linearizing (B.2) around a mean location (indexed by 0) yields an equilibrium relationship in earnings adjusted for cost of living between locations j and 0, with s_g indicating the share of income spent on good z_g:

$$\ln(w_0) = \ln(w_j) - \sum_g s_g \left[\ln\left(p_g^j\right) - \ln\left(p_g^0\right) \right] \tag{B.3}$$

Taking the exponential of both sides and rearranging terms yields equation (B.1).

B.3 SIPP Sample Design

The SIPP is a two-stage stratified random sample. The sampling frame is the Master Address File (MAF), which is a database maintained by the Census Bureau and used in other surveys such as the American Community Survey (ACS) and Decennial Censuses. The primary sampling unit (PSU) is one or more bordering counties. Within the PSU, addresses are divided into two groups: those with lower incomes and those with higher incomes. Addresses in the lower-income group are sampled at a higher rate.

Table B.1: Sample selection

	Remaining Persons	Remaining Person-years
Non-Hispanic, non-college graduate white males in wave 1 of 2004 or 2008 SIPP panel	37,499	124,719
Drop those enrolled in school at any point of survey	30,410	102,740
Drop those outside of 18-55 age range at start of survey	20,153	65,836
Drop those who attrited from survey	20,148	58,320
Drop those missing link to administrative data	16,648	50,415
Final estimation sample	16,648	50,415

Table B.2: Distribution of person-years

Years per person	Persons	Person-years
1	3,576	3,576
2	2,117	4,234
3	4,641	13,923
4	2,888	11,552
5	3,426	17,130
Final estimation sample	16,648	50,415

Table B.3: Data sources

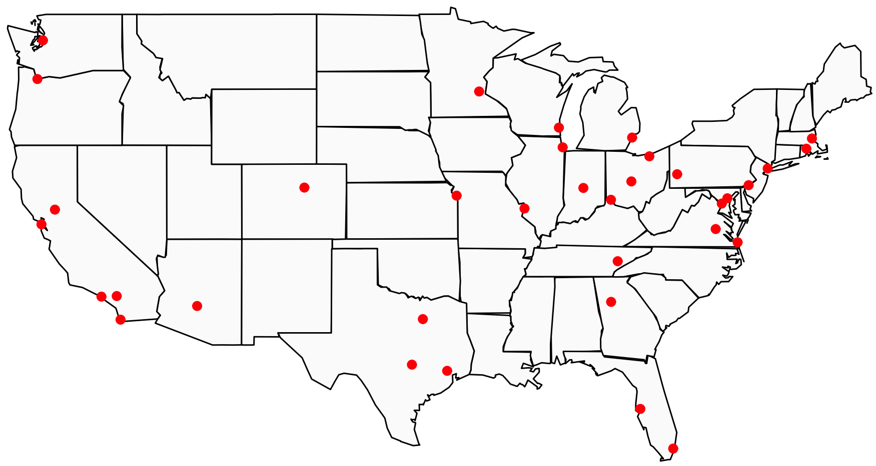
Data	Source	Years
Earnings and location & employment transitions	SIPP, 2004 and 2008 Panels	2004-2013
CBSA population	Census Bureau	2000
County unemployment rate	Bureau of Labor Statistics (BLS)	1990-2013

Table B.4: Locations in the model

Location	Location
Atlanta , GA	San Diego , CA
Austin , TX	San Francisco , CA
Baltimore , MD	Seattle , WA
Boston , MA	St. Louis , MO
Chicago , IL	Tampa , FL
Cincinnati , OH	Virginia Beach, VA
Cleveland , OH	Washington , DC
Columbus , OH	New England Division small
Dallas , TX	New England Division medium
Denver , CO	Mid Atlantic Division small
Detroit , MI	Mid Atlantic Division medium
Houston , TX	E N Central Division small
Indianapolis , IN	E N Central Division medium
Kansas City , MO	W N Central Division small
Knoxville , TN	W N Central Division medium
Los Angeles , CA	S Atlantic Division small
Miami , FL	S Atlantic Division medium
Milwaukee , WI	E S Central Division small
Minneapolis , MN	E S Central Division medium
New York , NY	W S Central Division small
Philadelphia , PA	W S Central Division medium
Phoenix , AZ	Mountain Division small
Pittsburgh , PA	Mountain Division medium
Portland , OR	Pacific Division small
Providence , RI	Pacific Division medium
Richmond , VA	Alaska
Riverside , CA	Hawaii
Sacramento , CA	

Notes: The cutoff between small and medium is defined by CBSA population of 193,000. This number corresponds to the first tercile of the observed city population distribution in the SIPP. Rural areas (i.e. areas not in any CBSA) are included with small CBSAs.

Figure B.7: Map of cities in the model

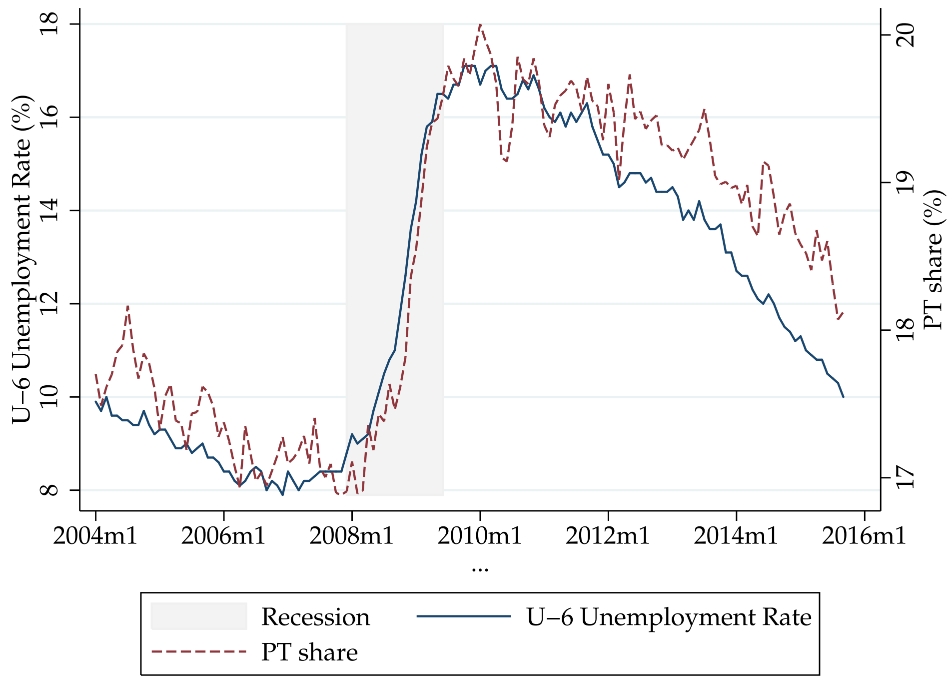


Note: Dots correspond to CBSA centroids of cities that are included in the model.

Table B.5: Census divisions and their component states

Census Division Name	States Included
New England	CT, RI, MA, VT, NH, ME
Middle Atlantic	NY, NJ, PA
South Atlantic	DE, MD, DC, VA, WV, NC, SC, GA, FL
East South Central	KY, TN, MS, AL
East North Central	OH, IN, IL, WI, MI
West North Central	MN, IA, MO, KS, NE, SD, ND
West South Central	AR, LA, OK, TX
Mountain	MT, WY, CO, NM, AZ, UT, NV, ID
Pacific	CA, OR, WA, AK, HI

Figure B.8: Trends in U-6 Unemployment Rate and Part-time Employment Share



Source: FRED Economic Data, Federal Reserve Bank of St. Louis.
Note: PT share corresponds to the fraction of employed persons who work part-time.

Table B.6: Counterfactual change in unemployment rate by employment status for origin cities of various characteristics, year 2007

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory $\downarrow w$ shock in current location	-0.0002	-0.0025	-0.0006	-0.0037
correlated transitory $\downarrow w$ shock in current location	0.0012	-0.0017	0.0012	-0.0032
independent transitory $\uparrow$ UR shock in current location	0.0184	0.0384	0.0181	0.0249
correlated transitory $\uparrow$ UR shock in current location	0.0186	0.0472	0.0188	0.0429
one period no search costs	-0.0009	0.0051	-0.0024	-0.0011
one period moving subsidy (10% of fixed cost of moving)	-0.0038	-0.0145	-0.0063	-0.0232
baseline migration probability	0.1531	0.4683	0.1440	0.4341

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory $\downarrow w$ shock in current location	-0.0004	-0.0031	-0.0004	-0.0032
correlated transitory $\downarrow w$ shock in current location	0.0012	-0.0024	0.0012	-0.0026
independent transitory $\uparrow$ UR shock in current location	0.0183	0.0318	0.0183	0.0309
correlated transitory $\uparrow$ UR shock in current location	0.0186	0.0449	0.0188	0.0453
one period no search costs	-0.0016	0.0020	-0.0018	0.0015
one period moving subsidy (10% of fixed cost of moving)	-0.0050	-0.0188	-0.0053	-0.0195
baseline migration probability	0.1491	0.4525	0.1476	0.4491

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory $\downarrow w$ shock in current location	-0.0003	-0.0027	-0.0004	-0.0038
correlated transitory $\downarrow w$ shock in current location	0.0010	-0.0021	0.0013	-0.0031
independent transitory $\uparrow$ UR shock in current location	0.0159	0.0408	0.0194	0.0171
correlated transitory $\uparrow$ UR shock in current location	0.0161	0.0496	0.0201	0.0387
one period no search costs	-0.0017	-0.0003	-0.0017	0.0023
one period moving subsidy (10% of fixed cost of moving)	-0.0041	-0.0161	-0.0056	-0.0231
baseline migration probability	0.1243	0.4271	0.1637	0.4741

Notes: Numbers refer to the change in the unemployment rate in the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock ($\downarrow w$) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table B.7: Counterfactual change in unemployment rate by employment status for origin cities of various characteristics, year 2011

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory ↓ w shock in current location	-0.0002	-0.0022	-0.0006	-0.0033
correlated transitory ↓ w shock in current location	0.0014	-0.0012	0.0016	-0.0026
independent transitory ↑ UR shock in current location	0.0204	0.0251	0.0204	0.0101
correlated transitory ↑ UR shock in current location	0.0210	0.0379	0.0218	0.0350
one period no search costs	-0.0018	0.0074	-0.0037	-0.0009
one period moving subsidy (10% of fixed cost of moving)	-0.0046	-0.0177	-0.0076	-0.0280
baseline migration probability	0.1736	0.5274	0.1627	0.4858

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory ↓ w shock in current location	-0.0004	-0.0027	-0.0004	-0.0028
correlated transitory ↓ w shock in current location	0.0015	-0.0018	0.0015	-0.0020
independent transitory ↑ UR shock in current location	0.0204	0.0176	0.0204	0.0169
correlated transitory ↑ UR shock in current location	0.0213	0.0362	0.0216	0.0369
one period no search costs	-0.0026	0.0033	-0.0029	0.0027
one period moving subsidy (10% of fixed cost of moving)	-0.0059	-0.0229	-0.0064	-0.0235
baseline migration probability	0.1689	0.5080	0.1672	0.5051

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory ↓ w shock in current location	-0.0003	-0.0023	-0.0004	-0.0036
correlated transitory ↓ w shock in current location	0.0012	-0.0014	0.0016	-0.0031
independent transitory ↑ UR shock in current location	0.0179	0.0326	0.0214	-0.0074
correlated transitory ↑ UR shock in current location	0.0184	0.0434	0.0231	0.0281
one period no search costs	-0.0027	0.0002	-0.0028	0.0031
one period moving subsidy (10% of fixed cost of moving)	-0.0048	-0.0188	-0.0068	-0.0295
baseline migration probability	0.1381	0.4805	0.1894	0.5238

Notes: Numbers refer to the change in the unemployment rate in the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock (↓ w) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table B.8: Counterfactual change in labor force participation rate by employment status for origin cities of various characteristics, year 2007

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory ↓ w shock in current location	0.0014	-0.0005	0.0012	0.0000
correlated transitory ↓ w shock in current location	0.0057	0.0010	0.0053	0.0013
independent transitory ↑ UR shock in current location	0.0180	-0.0050	0.0180	-0.0053
correlated transitory ↑ UR shock in current location	0.0149	-0.0133	0.0150	-0.0129
one period no search costs	0.0072	0.0244	0.0072	0.0244
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9598	0.8491	0.9599	0.8491

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory ↓ w shock in current location	0.0013	-0.0002	0.0013	-0.0003
correlated transitory ↓ w shock in current location	0.0055	0.0012	0.0056	0.0011
independent transitory ↑ UR shock in current location	0.0178	-0.0053	0.0184	-0.0049
correlated transitory ↑ UR shock in current location	0.0148	-0.0132	0.0153	-0.0128
one period no search costs	0.0071	0.0243	0.0073	0.0245
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9602	0.8495	0.9591	0.8482

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory ↓ w shock in current location	0.0011	-0.0005	0.0014	0.0000
correlated transitory ↓ w shock in current location	0.0054	0.0008	0.0053	0.0016
independent transitory ↑ UR shock in current location	0.0186	-0.0052	0.0162	-0.0052
correlated transitory ↑ UR shock in current location	0.0154	-0.0126	0.0136	-0.0136
one period no search costs	0.0069	0.0204	0.0062	0.0269
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9544	0.8516	0.9681	0.8459

Notes: Numbers refer to the change in the labor force participation rate in the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock (↓ w) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table B.9: Counterfactual change in labor force participation rate by employment status for origin cities of various characteristics, year 2011

(a) Amenities

Counterfactual scenario	high amenity city emp	high amenity city unemp	low amenity city emp	low amenity city unemp
independent transitory ↓ w shock in current location	0.0014	-0.0002	0.0012	0.0003
correlated transitory ↓ w shock in current location	0.0052	0.0017	0.0049	0.0019
independent transitory ↑ UR shock in current location	0.0153	-0.0046	0.0153	-0.0049
correlated transitory ↑ UR shock in current location	0.0130	-0.0135	0.0130	-0.0131
one period no search costs	0.0055	0.0296	0.0055	0.0296
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9727	0.8333	0.9728	0.8333

(b) Earnings level

Counterfactual scenario	high earnings city emp	high earnings city unemp	low earnings city emp	low earnings city unemp
independent transitory ↓ w shock in current location	0.0013	0.0001	0.0013	0.0000
correlated transitory ↓ w shock in current location	0.0050	0.0018	0.0051	0.0018
independent transitory ↑ UR shock in current location	0.0151	-0.0049	0.0155	-0.0045
correlated transitory ↑ UR shock in current location	0.0129	-0.0135	0.0132	-0.0131
one period no search costs	0.0054	0.0295	0.0055	0.0296
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9730	0.8336	0.9724	0.8328

(c) Employment probability level

Counterfactual scenario	high emp. prob. city emp	high emp. prob. city unemp	low emp. prob. city emp	low emp. prob. city unemp
independent transitory ↓ w shock in current location	0.0013	-0.0002	0.0012	0.0003
correlated transitory ↓ w shock in current location	0.0054	0.0013	0.0040	0.0023
independent transitory ↑ UR shock in current location	0.0176	-0.0047	0.0112	-0.0048
correlated transitory ↑ UR shock in current location	0.0149	-0.0128	0.0097	-0.0138
one period no search costs	0.0059	0.0242	0.0039	0.0334
one period moving subsidy (10% of fixed cost of moving)	0.0000	0.0000	0.0000	0.0000
baseline migration probability	0.9647	0.8374	0.9825	0.8281

Notes: Numbers refer to the change in the labor force participation rate in the specified location in response to the listed counterfactual. All figures are for 25-year-olds who were not born in the origin location. "high" refers to a location in the 75th percentile of the given distribution; "low" refers to the 25th percentile. All characteristics not set to "high" or "low" are set to the median. The earnings shock (↓ w) corresponds to the 70th percentile of the cross-location distribution in earnings AR(1) shock deviations. The unemployment shock corresponds to the jump from 2008 to 2009 for the average location in the data. To focus the results, each candidate location has median AR(1) parameters for both earnings and employment. Individuals are assigned the same geographical birth location and the same geographical origin location in all counterfactuals. Individual characteristics in each of the simulations are evaluated at the average of the population conditional on the given employment status.

Table B.10: Greek symbol notation glossary

Greek symbol	Equation of first reference	Description
α	(2.9)	Local amenities
β	(2.15)	Discount factor
γ	(2.9)	Flow utility parameters
$\overline{\gamma}$	(4.7)	Euler's constant
δ	(2.3)	Job destruction probability
ε	(2.6)	Preference shocks
ζ	(2.2)	Shocks to evolution of earnings parameters
η	(2.1)	Earnings shocks
θ	(2.13)	Moving and switching cost parameters
λ	(2.3)	Job offer probability
μ	(4.1)	Parameters in estimation of emp. prob.
ξ	(2.4)	Shocks to evolution of unemployment rate
π	(2.7)	Employment probabilities
ρ	(2.2)	Parameters governing evolution of earnings parameters
σ_ζ	(2.2)	Std deviation of shocks to evolution of earnings parameters
σ_η	(2.1)	Std deviation of earnings shocks
σ_ξ	(2.4)	Std deviation of shocks to evolution of unemployment rate
ϕ	(2.4)	Parameters governing evolution of employment probabilities
ψ	(2.1)	Earnings parameters
ω	(4.11)	Value function weights
Δ	(2.9)	Moving cost
Θ	(4.1)	Employment probability determinants
Ξ	(2.9)	Switching cost
Ψ	(4.15)	Covariance of local labor market shocks