Published in final edited form as:
J Econom. 2010 May 1; 156(1): 229–238. doi:10.1016/j.jeconom.2009.09.019.

Wages, Welfare Benefits and Migration

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Abstract

Differences in economic opportunities give rise to strong migration incentives, across regions within countries, and across countries. In this paper we focus on responses to differences in welfare benefits across States. We apply the model developed in Kennan and Walker (2008), which emphasizes that migration decisions are often reversed, and that many alternative locations must be considered. We model individual decisions to migrate as a job search problem. A worker starts the life-cycle in some home location and must determine the optimal sequence of moves before settling down. The model is sparsely parameterized. We estimate the model using data from the National Longitudinal Survey of Youth (1979). Our main finding is that income differences do help explain the migration decisions of young welfare-eligible women, but large differences in benefit levels provide surprisingly weak migration incentives.

1. Introduction

Differences in economic opportunities give rise to strong migration incentives, across regions within countries, and across countries. Despite the extensive literature on migration (see Greenwood [1997] and Lucas [1997] for example), not much is known about how income differences affect migration choices. In this paper we focus on responses to differences in welfare benefits across States. We apply the model developed in Kennan and Walker (2008), which emphasizes that migration decisions are often reversed, and that many alternative locations must be considered. We analyze the migration decisions of women who are eligible to receive Aid to Families with Dependent Children (AFDC).

Interest in welfare-induced migration dates from at least the early nineteenth century and the reform of England's Poor Laws. In the United States, the issue has been part of the public discussion surrounding welfare policy since 1969 when the U.S. Supreme Court struck down residency requirements for AFDC receipt. The recent literature on welfare-induced migration is summarized by Meyer (2000). While the consensus view from earlier work reviewed by Moffitt (1992) was that differences in welfare benefits across states had a significant effect on migration decisions, subsequent studies by Levine and Zimmerman (1999) and by Walker (1994) found little or no effect. Meyer argued that by paying careful attention to the determinants of welfare participation, the ambiguity in these results can be resolved in favor of a significant (but small) effect of welfare on migration.[2] Gelbach (2004)

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[2]Recognizing the dependency across behavior is important. Kaestner et al. (2001) results indicate the importance of incorporating employment in studies of welfare migration. Liu et al. (this volume) show the importance of controlling for residential choice in their analysis of school quality on child development outcomes.

also found a significant effect, arguing that previous studies had failed to properly account for dynamic selection effects. None of these studies contains a fully specified dynamic choice model, however, and we believe that our model can provide a more systematic analysis. We use the framework to consider the effects of alternative welfare policies, such as a policy of national standardized benefits.

We model individual decisions to migrate as a job search problem. A worker can draw a wage only by visiting a location, thereby incurring a moving cost. Locations are distinguished by known differences in wage distributions, amenity values and alternative income sources. A worker starts the life-cycle in some home location and must determine the optimal sequence of moves before settling down. There is a two-dimensional ranking of locations, *ex ante*: some places have high wages, while others have high welfare benefits which provide an attractive fallback option.

The model is sparsely parameterized. In addition to expected income, migration decisions are influenced by age, climate amenities, moving costs, including a fixed cost, a reduced cost of moving to a previous location, and a cost that is proportional to distance, and by differences in location size, measured by the population in origin and destination locations. We also allow for a bias in favor of the home location.

Our main finding is that income differences do help explain the migration decisions of young welfare-eligible women, but large differences in benefit levels provide surprisingly weak migration incentives. Indeed, our counterfactual simulations we recover modest supply elasticities of about 0.1 to 0.15. Responses, however, are not symmetric with flows somewhat more responsive to wage declines than wage increases, and there are noticeable differences across States. Moreover, the adjustment process is slow and there is a tendency for individuals in low-income areas to move to higher income locations but the influence of countervailing forces is strong. In our second set of counterfactual simulations we use the model estimates to investigate migration responses to uniform benefit levels and wages for all States. Interestingly, we find minuscule responses from these experiments.

2. Descriptive Evidence on Migration Behavior

We use migration histories from the 1979 Cohort of the National Longitudinal Survey of Youth (NLSY79) to provide descriptive evidence on interstate migration behavior among young women. (We present a detailed analysis of a subset of these data later in the paper.) The NLSY79 is nationally representative of American youth living in the United States at the start of 1979. We use data from the 1979-1994 waves.[3] In order to obtain a relatively homogeneous sample, we consider only women with no college education, using only the years after schooling is completed. Respondents are tracked from age 19 through the 1994 interview (the maximum age is 36 years old). For this introductory descriptive analysis, we impose no restrictions on marital status or the presence of children.

We drop respondents who served in the armed forces and observations with missing information on education, marital status, children in the household and those that could not be geocoded. The descriptive sample includes 2,899 women and 33,552 person-years. The average annual interstate migration rate is 4.2 percent. Figure 1 plots the annual interstate migration rates for single and married women, and for women with children (regardless of marital status). Since Ravenstein (1885, 1889), migration has been recognized as an activity

[3]Residential location is point-sampled as of the date of the interview. In the initial survey, limited information on birth place and residence at age 14 were collected. And in 1982, all residences since the start of the survey were recorded. Location as of the date of the interview is the only locational measure available for all rounds of the survey. We use only information through the 1994 interview, as the 1994 interview marks the move from an annual to biennial interview schedule.

of the young.[4] Indeed, migration rates among these three groups exhibit a strong age gradient. Married women have slightly higher annual migration rates; neither marriage nor children in the household seem to be barriers to movement.

In our econometric analysis we concentrate on single women with dependent children - those who are nominally eligible for AFDC benefits. Figure 2 presents the annual migration rate of welfare eligibles and a natural comparison group, married women with children. Annual migration rates are clearly lower for the welfare-eligible group.

Within the descriptive sample, about a quarter of all women make at least one interstate move and among those who move, more than 59 percent move more than once and 22.5 percent move three times or more. Fully three-quarters of all moves are repeat. And "home" is a common destination for repeat moves:[5] about half of all repeat moves are a return to the home location. Again, welfare-eligible women exhibit the same dynamic behavior. Restricting attention to women who are ever-welfare eligible, 60 percent of the moves are repeat moves, and home is the destination of a repeat move 54 percent of the time. The prevalence of repeat and return migration indicates the need for a dynamic analysis of migration.

It is instructive to focus on the group of women who have been seen as most responsive to State differences in welfare -- never-married high school dropouts with dependent children.[6] Our descriptive sample from the NLSY has 11,023 person years (age 19 and older) of female dropouts. Their annual migration rate is only slightly below the sample average at 4.14 percent. Consistent with the difference in migration rates between women with and without children, the annual migration rate for dropouts with children is 3.88 percent while the rate for those without children is 4.93 percent. Yet the migration rate for these low-skill single mothers varies substantially by their entry into single-motherhood - for those who never married (prior to 1994) the annual migration rate is 1.70 percent while dropouts who entered single motherhood following marriage have an annual migration rate of 4.71 percent. This suggests that the women with the greatest incentive to migrate to States with higher welfare benefits may also have relatively high moving costs. We discuss this further below in the context of our model estimates.

This brief descriptive analysis of interstate migration by high-school educated women within the NLSY shows that annual migration rates decline with age, and that women with dependent children move at about the same frequency as do other women at these ages. And for all groups of women repeat and return migration are important.

3. An Optimal Search Model of Migration

We use a modified version of the search model of migration developed in Kennan and Walker (2008). The basic assumption is that wages[7] are local prices of individual skill bundles. The individual knows the wage in the current location, but not in other locations, and in order to determine the wage at each location, it is necessary to move there. For computational reasons, the state space is restricted so as to include information on wage realizations in at most two locations, these being the current location and the previous location (if any). In each location welfare acts as a fallback option, and the value of this is known.

[4]See also Long (1988).

[5]"Home" is defined as the State of residence at age 14.

[6]See Meyer (2000) and Gelbach (2004), for example.

[7]We use "wage" and "earnings" interchangeably since there is no hours of work choice in the model.

The model aims to describe the migration decisions of young workers in a stationary environment. The wage offer in each location may be interpreted as the best offer available in that location. It may be that wage differentials across locations equalize amenity differences, but a stationary equilibrium with heterogeneous worker preferences and skills still requires migration to redistribute workers from where they happen to be born to their equilibrium location. Alternatively, it may be that wage differentials are slow to adjust to location-specific shocks, because gradual adjustment is less costly for workers and employers. In that case, our model can be viewed as an approximation in which workers take current wage levels as a rough estimate of the wages they will face for the foreseeable future. In any case, the model is intended to describe the partial equilibrium response of labor supply to wage differences across locations; from the worker's point of view the source of these differences is immaterial, provided that the differences are permanent. A complete equilibrium analysis would of course be much more difficult, but our model can be viewed as a building-block toward such an analysis.

Suppose there are J locations, and individual i's wage W_{ij} in location j is a random variable with a known distribution. The fallback option is B_j, and thus income in location j is $Y_{ij} = \max [W_{ij}, B_j]$. Migration decisions are made so as to maximize the expected discounted value of lifetime utility, subject to budget constraints. In general, the level of assets is an important state variable for this problem, but we focus on a special case in which assets do not affect migration decisions. Suppose the marginal utility of income is constant, and individuals can borrow and lend without restriction at a given interest rate. Then expected utility maximization reduces to maximization of expected lifetime income, net of moving costs, with the understanding that the value of amenities is included in income, and that both amenity values and moving costs are measured in consumption units. This is a natural benchmark model, although of course it imposes strong assumptions.

a. Earnings and Expected Income

The wage of individual i at age a in location j in period t is specified as

$$w_{ij}(a)=\mu_j+\upsilon_{ij}+G(a)+\eta_i+\varepsilon_{ij}(a) \tag{1}$$

where μ_j is the mean wage in location j, υ is a permanent location match effect, G(a) represents the age-earnings profile, η is an individual effect that is fixed across locations, and ε is a transient effect. We assume that η, υ and ε are independent random variables that are identically distributed across individuals and locations. We also assume that the realizations of η and υ are seen by the individual.

The realization of the transient wage component ε affects income in the current period, but it has no implications for future wage draws in any location, so it has no bearing on migration decisions. On the other hand the individual effect η_i is permanent, and the location match effect υ_{ij} is permanent for location j, so both of these components affect migration decisions, and must therefore be treated as state variables. Since it is not feasible to compute the value function for more than a small number of possible realizations of these variables, we model both η and υ as discrete random variables. The size of the state space grows quickly as the number of possible realizations of υ increases, since it is necessary to compute the continuation value for every possible combination of location match realizations in every pair of current and previous locations. The best n-point approximation of any distribution F puts equal weight on support points s_k determined by $nF(s_k) = k - ½$. If F is symmetric around zero, the three-point approximation involves just one free parameter, determined by $F(s_1) = 1/6$ (See Kennan [2006]). In practice, we use a three-point distribution for υ and a five-point distribution for η, both symmetric around zero. For the transient component ε we need a continuous distribution that is flexible enough to account for the observed variability of earnings. We assume that ε is drawn from a normal distribution with zero mean for each person, but we allow the variance to vary across people. Specifically, person i initially draws $\sigma_\varepsilon(i)$ from some distribution, and subsequently draws ε_{it} from a normal distribution with mean zero and standard deviation $\sigma_\varepsilon(i)$, with ε_{it} drawn independently in each period. The distribution from which σ_ε is drawn is specified as a (uniform) discrete distribution with two support points, where these support points are parameters to be estimated.

Expected income for a woman who is eligible for welfare in location j is given by

$$E \max\left(w_{ij}(a), B_j\right) = B_j + \sigma_\varepsilon\left(\phi\left(z_{ij}\right) + z_{ij}\Phi\left(z_{ij}\right)\right) \tag{2}$$

where ϕ and Φ are the standard normal density and distribution functions, B_j is the welfare benefit in location j, and

$$z_{ij} = \frac{B_j - \left(\mu_j + \upsilon_{ij} + G(a_i) + \eta_i\right)}{\sigma_\varepsilon} \tag{3}$$

b. The Value Function

Let x be the state vector. The utility flow in the current period if location j is chosen is specified as

$$\tilde{u}(x, j) = u(x, j) + \zeta_j \tag{4}$$

where ζ_j represents influences on migration decisions that are not included in the model. We assume that ζ_j is drawn from a Type I extreme value distribution, and that the draws from this distribution are independent over locations, and over periods. Let $p(x'|x,j)$ be the transition probability from state x to state x'. The probability that a person in state x will choose location j can then be written as

$$\rho(x, j) = \exp\left(v(x, j) - \bar{v}(x)\right) \tag{5}$$

where v and $\bar{V}$ are defined as the functions that solve the following pair of equations

$$v(x, j) = u(x, j) + \beta \sum_{x'} p(x'|x, j)\bar{v}(x') \tag{6}$$

$$\exp\left(\bar{v}(x)\right) = \sum_{k=1}^{n} \exp\left(v(x, k)\right) \tag{7}$$

Consider a person with "home" location h, who is in location ℓ this period and in location j next period. The flow of utility in the current period for such a person is specified as

$$u(x,j)=\alpha_0\,y(\ell^0,\omega)+\alpha^H\chi\left(\ell^0=h\right)+\sum_{k=1}^{K}\alpha_k Y_k\left(\ell^0\right)-\Delta_\tau(x,j) \quad (8)$$

The notation is as follows. Income in the current period is denoted by $y(\ell^0,\omega)$, where ℓ^0 is the current location, and ω represents the individual fixed effect and the location match draw, as described more fully below. The parameter α_0 is the marginal utility of income. There is a premium α^H that allows each individual to have a preference for their home location (χ_A is used as an indicator meaning that A is true). Amenity values in the current location are denoted by $Y_k(\ell^0)$, and $\Delta_\tau(x,j)$ is the cost of moving from ℓ^0 to j.

The moving cost is specified as.

$$\Delta_x(x,j)=\left(\gamma_{0x}+\gamma_1 D(\ell^0,j)-\gamma_2\chi\left(j\in A\left(\ell^0\right)\right)-\gamma_3\chi(j=\ell^1)+\gamma_4\alpha-\gamma_5 n_j\right)\chi(j\neq\ell^0) \quad (9)$$

We allow for unobserved heterogeneity in the cost of moving: there may be several types, indexed by τ, with differing values of the intercept γ_0. In particular, there may be a "stayer" type, for whom the cost of moving is prohibitive. The moving cost is an affine function of distance, $D(\ell^0,j)$. The set of locations adjacent to location ℓ is denoted by $A(\ell)$; moves to an adjacent location may be less costly, because it is possible to change States while remaining in the same general area. The previous location is denoted by ℓ^1; a move to a previous location may be less costly, relative to moving to a new location. The cost of moving is also allowed to depend on age, a. Finally, we allow for the possibility that it is cheaper to move to a large location, as measured by population size n_j. The point of this is to control for the obvious asymmetries between locations like Montana and Texas.

c. Welfare Eligibility, Marriage and Human Capital

Women are eligible for welfare benefits only if they are single, with dependent children, and if their earnings are low. Thus a complete specification of the value function would require a model of marriage and divorce, including a theory of how the marital surplus is divided, and of how likely it is that the surplus disappears, so that the marriage breaks up. This is a tall order. In addition, a woman who is out of the labor force (either because she is collecting welfare or because she is married and doing non-market work) forgoes the human capital accumulation associated with labor market experience. Thus a fully specified model should encompass the relationship between current work and future wages, as in Shaw (1989) and Imai and Keane (2004). In particular, the opportunity cost of being on welfare may be considerably higher than the current wage. Thus a more complete model would require a much larger state space than that used here, with marital status, number of children, and accumulated market work experience treated as state variables.

Our model can be viewed as a simplification based on two approximations. First, when a welfare-eligible woman marries, she receives no surplus, either because the surplus is negligible, or because her share is negligible. Second, the experience associated with non-market work yields the same increment of human capital as the same amount of market work experience.[8]

[8]Card and Hyslop (2005) analyzed the effects of the Canadian Self-Sufficiency Project, which provided subsidies for long-term welfare recipients who found full-time jobs. They found that the program had a strong effect on welfare participation, but they found no evidence that the increased work experience of program participants led to higher wages in subsequent years.

4. Empirical Implementation

4.1 Welfare Benefits

Benefits correspond to the combined AFDC and Food Stamp benefit for a family of 3 in 1989. We use the benefit structure as of 1989 to facilitate comparison with the 1990 Census data that we use to calculate State-specific wages.[9] Table 5 in the appendix shows that the differences in benefits across states are large: for example the highest annual benefit among the 48 continental states is $7,568 in California and the lowest is $3,426 in Alabama (in 1983 dollars). In the second column of the table, these differences are adjusted for differences in the cost of living across States, using the ACCRA cost of living index (http://www.coli.org). Even after this adjustment, the differences remain large. The last column of the table shows the wage percentile in the 1990 PUMS data corresponding to the benefit level by State. The typical situation is that less than 50 percent of single women with children earn more than the benefit level.

4.2 Locations

Ideally, locations would be defined as local labor markets. We obviously cannot let J be the number of counties, since there are over 3,100 counties in the U.S. Indeed, even restricting J to the number of States still far exceeds current computational capabilities. To aggregate locations beyond the state level (e.g. Census Regions) is unattractive, because benefit levels are set at the State level, and there are large differences across States, even within the same region. Consequently, we define locations as States, but restrict the information available to each individual to include only the wage realizations in the current and previous locations.

5. The Likelihood Function

Consider an individual who visits N_i locations. We index these locations in the order in which they appear, and we use the notation K_{it}^0 and K_{it}^1 to represent the position of $\ell^0(i,t)$ and $\ell^1(i,t)$ in this index. Thus $K_{it}=\left(K_{it}^0, K_{it}^1\right)$ is a pair of integers between 1 and N_i.

In each location there is a draw from the distribution of location match wage components, which is modeled as a uniform distribution over the finite set $Y=\{\upsilon(1), \upsilon(2), \cdots, \upsilon(n_\upsilon)\}$. We index this set by ω_υ, with $\omega_\upsilon(j)$ representing the match component in location j, where $1 \le \omega_\upsilon(j) \le n_\upsilon$. Similarly, in each location there is a draw from the location match preference distribution, which is modeled as a uniform distribution over the finite set $\Xi = \{\xi(1), \xi(2), \cdots, \xi(n_\xi)\}$, indexed by ω_ξ. Each individual also draws from the distribution of fixed effects, which is modeled as a uniform distribution over the finite set $H=\{\eta(1), \eta(2), \cdots, \eta(n_\eta)\}$, and we use ω_η to represent the outcome of this. And each individual draws a transient variance, from a uniform distribution over the set $\varsigma = \{\sigma_\varepsilon(1), \sigma_\varepsilon(2), \cdots, \sigma_\varepsilon(n_\varepsilon)\}$ with the outcome indexed by ω_ε.

The unobserved components for individual i are then represented by a vector ω^i with $N_i + 3$ elements: $\omega^i=\left(\omega_\xi^i, \omega_\eta^i, \omega_\tau^i, \omega_\nu^i(1), \omega_\nu^i(2), \cdots, \omega_\nu^i(N_i)\right)$, where N_i is the number of locations visited by this individual. The set of possible realizations of ω^i is denoted by $\Omega(N_i)$; there are $n_\xi n_\eta n_\tau (n_\nu)^{N_i}$ points in this set, and the discrete approximation result in Kennan (2006) implies that they are equally likely.

[9] Benefits varied from year to year, as documented by Robert Moffitt's database on State welfare benefits (http://www.econ.jhu.edu/people/moffitt/datasets.html). However the relative generosity of benefits across States is constant over time. Moreover, to incorporate the temporal change in benefits requires a significant extension to our model - we must model the women's subjective beliefs about future benefits. For a discussion and an application of such forward-looking behavior that does not consider migration see Keane and Wolpin (2002a,b).

The likelihood of an individual history is a mixture over the possible realizations listed in $\Omega(N_i)$. For each period in the history, two pieces of information contribute to the likelihood: the observed income, and the location choice. We describe these in turn.

We assume that each person takes a draw from the wage distribution in each period, and accepts a job at this wage if and only if the wage exceeds the benefit B_j. Observed income can then be written as $y_i(t) = d_{it}B_j + (1\text{-}d_{it})w_i(t)$, where d_{it} is an indicator of whether $y_i(t)$ is left-censored.

Let $\psi_{it}(\omega^i)$ be the likelihood of the observed income for person i in period t. Then

$$\psi_{it}(\omega^i)=(\Phi(z_{it}))^{d_{it}}\left(\frac{\phi(z_{it})}{\sigma_\varepsilon\left(\omega_\varepsilon^i\right)}\right)^{1-d_{it}} \tag{19}$$

where ϕ and Φ are the standard normal density and distribution functions, and where

$$z_{it}(\omega^i)=\frac{\max(B_{it},w_{it})-\mu_j-G(a_{it})-\upsilon\left(\omega_\upsilon^i\left(\kappa_{it}^0\right)\right)-\eta\left(\omega_\eta^i\right)}{\sigma_\varepsilon\left(\omega_\varepsilon^i\right)} \tag{20}$$

The second piece of information relevant for the likelihood is the location choice. Let $\lambda_{it}(\omega^i,\theta_\tau)$ be the likelihood of the destination chosen by person i in period t, where θ_τ is the parameter vector, for someone of type τ:

$$\lambda_{it}\left(\omega^i,\theta_\tau\right)=\rho_{h(i)}\left(\ell(i,t),\omega_\upsilon^i\left(\kappa_{it}^0\right),\omega_\upsilon^i\left(\kappa_{it}^1\right),a_{it},\omega_\eta^i,\omega_\varepsilon^i,j_i(t),\theta_\tau\right) \tag{21}$$

The choice probabilities depend on the home location, the individual fixed effect, the variance of the transient component, the current and previous locations, the current and previous draws from the location match distribution, the destination, and the current age.

The likelihood of an individual history, for a person of type τ, can be written as

$$L_i(\theta_\tau)=\sum_{\omega^i\in\Omega(N_i)}p_\Omega(\omega^i)\prod_{t=1}^{T_i}\psi_{it}(\omega^i,\theta)\lambda_{it}(\omega^i,\theta_\tau) \tag{22}$$

The loglikelihood of the whole sample is a mixture over heterogeneous types, given by

$$\Lambda(\theta)=\sum_{i=1}^{N}\log\left(\sum_{\tau=1}^{K}\pi_\tau L_i(\theta_\tau)\right) \tag{23}$$

where π_τ is the probability of type τ.

6. Empirical Results

Our primary data source is the NLSY79; we also use data from the 1990 Census. To form the estimation sample we restrict the descriptive sample from the NLSY79 to person-year observations for welfare-eligible women. Specifically, we restrict the estimation sample to welfare-eligible women with no more than twelve years of education, observed over the period 1979-1994. We consider only women who never enrolled in college, using only the years after schooling is completed. We exclude those who ever served in the military. We follow each person from age 20 to the 1994 interview, including only those years in which the woman was single, with children under age eighteen in the household.

a. Maximum Likelihood Estimates

First we use the 1990 PUMS to estimate the State specific means of the wage offer distributions. We need the large sample size of the PUMS to estimate mean wages for less populous States. Then we jointly estimate the utility and cost parameters of the migration choice process and the remaining parameters of the wage offer distributions. We fix the discount factor (β) to 0.95, and the decision making horizon (T) to 40.

i. High School Graduates

Table 1 shows that differences in expected income are a significant determinant of migration decisions for welfare-eligible high school graduates. There are 3,466 person-years in the data, with 88 interstate moves.[10] This is an annual migration rate of 2.54%, and the first model in Table 1 simply matches this rate by setting the probability of moving to each of J-1 locations to a constant value, namely $\frac{1}{J-1}\frac{88}{3466}$, with J = 51.[11] The next model estimates the parameters of the earnings process using only the information on earnings. This is followed by maximum likelihood estimates of the joint loglikelihood function for migration and earnings, in a specification in which earnings do not influence migration choices (α_0=0); in this case the joint likelihood factors into separate components for migration and earnings. Next income is introduced with no unobserved heterogeneity in moving costs. The last set of estimates includes both unobserved heterogeneity and the effect of income, and the likelihood ratio test indicates that the income coefficient is significantly different from zero, with a p-value of .021.

These estimates show that population size, distance, climate (represented by total heating degree days), home, adjacent, and previous locations all have significant effects on migration. Somewhat surprisingly, the model can account for the relationship between age and migration rates without allowing age to directly affect moving costs.[12] Joint estimation of the earnings and migration parameters makes little difference: the migration data are not informative about the wage process.

ii. High School Dropouts

Table 2 shows estimates for a sample of high school dropouts. It might seem that the influence of differences in welfare benefits would be more important for dropouts than for high school graduates, since their labor market options are more limited. Indeed, Gelbach (2004) analyzes the effects of welfare benefits by using dropouts as the “treatment group,” and uses high school graduates as a control group. The problem with this is that it does not allow for differences in migration costs. For instance, it may well be that high school graduates are better equipped to deal with the problems of setting up a household in a new location. The estimates for

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[10] Table 6 in the appendix shows how we reached this sample.

[11] In other words the estimate of γ_0 solves the equation ; the solution is γ_0 = log(168900) - log(88).

[12] This contrasts with the results in Kennan and Walker (2008), where it was found that age increases the migration cost for high school men in the NLSY.

dropouts in Table 2 are noisier than the high school estimates, but there is certainly no indication that welfare has a stronger effect for those with less education. Moreover, the migration rate for dropouts is considerably lower than the rate for high school graduates, suggesting that moving costs are indeed higher for dropouts.[13]

b. Goodness of Fit

Our model specification is parsimonious with only fourteen parameters to fit the dynamic migration process and earnings. It is natural to ask how well this simple model fits the data. In particular, since the model pays little attention to individual histories, it is reasonable to suppose it will have difficulty tracking panel data.

A simple test is to compare the distribution of moves in the sample with the prediction of the model. Using estimates from the full model in Table 1 we simulate individual migration histories in the NLSY. We start individuals in their first observed location and simulate 1000 histories for each replica, continuing each simulated history for the number periods observed in the sample for that individual. As a benchmark we present the distribution of moves generated by a binomial random variable with an annual migration probability equal to 2.54 percent.[14] Table 3 presents the results. The homogeneous binomial substantially underestimates the incidence of repeat migration; the model fits this reasonably well.[15]

7. The Effects of Wage and Welfare Differences on Migration Decisions

We use the estimated model to analyze labor supply responses to changes in benefit levels and in mean wages for selected States. We are interested in the magnitudes of the migration flows in response to local wage changes, local benefit changes and nationwide changes in benefits and in the timing of these responses. First we do a baseline simulation, starting people in given locations, and allowing them to make migration decisions in response to the 1989 benefits and to the wage distributions estimated from the NLSY data. Then we do counterfactual simulations, starting people in the same locations, facing different benefits and wage distributions.

We take a set of 100,000 people, with 200 replicas of each person, distributed over States according to the 1990 Census data for single female high school graduates aged 20 to 36 with children. We assume that each person is initially in the home State, at age 23 (the mean first age of welfare eligibility within the NLSY79), and simulate 10-year histories for women who expect to always be eligible to receive welfare. We consider separately responses to 20 percent increases and decreases in wages and benefits for California, Illinois, and Wisconsin. California and Illinois are large states; California's benefits were the highest among 48 continental states, while Illinois's benefits place it near the median. Wisconsin offered high benefits relative to its neighbors (particularly Illinois) and the problem of welfare-induced migration was the subject of legislative debates.[16]

The second set of counterfactual experiments investigates migration responses to uniform benefit levels for all States. We use our structural model estimates to simulate what the migration flows would have been if these differences had been absent. In the public discussion prior to the passage of TANF one argument in support of a national welfare standard was that within a decentralized system competition between States following

[13]For women who never married (prior to 1994) the migration rate is extremely low: 6 moves in 690 observations (0.87%). The rate is higher for high school graduates who never married: 21 moves in 1,092 observations (1.92%).

[14]Since we have an unbalanced panel, the binomial probabilities are weighted by the distribution of years per person.

"beggar-thy-neighbor" policies would result in a minimum national benefit level.[17] We find that equalizing welfare benefits would have had a negligible effect on migration, regardless of whether the national benefit is set at either the lowest or the highest State benefit level. This finding might help explain why the race to the bottom did not in fact occur.

a. Results for California, Illinois, and Wisconsin

We simulate baseline migration decisions using the estimated wage distributions described previously. Then we increase or decrease benefits or mean wage in a single target State by 20%, and compare the migration decisions induced by these changes. Supply elasticities are measured relative to the supply of labor in the baseline simulation. For example, the elasticity of the response to a wage increase in California after 5 years is computed as (ΔL/L)/(Δw/w), where L is the number

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[15]It is notable that the migration rate in the simulated data does not match the rate in the actual data. It might seem that the maximum likelihood estimate should automatically get this right, since the migration rate can be adjusted by varying the fixed cost of moving. But although it is certainly feasible to choose parameter values that match the observed migration rate, this generally does not maximize the likelihood. To illustrate, consider a simple version of the model in which there are just two parameters: a fixed cost of moving for the mover type, and a mixture probability for the two types. The loglikelihood for this model can be written as

$$\Lambda(\theta)=\sum_{i=1}^{S}\log\left(\sigma+(1-\sigma)(1-q)^{n_i}\right)+(N-S)(1-\sigma)+M\log(q)+(K_m-M)\log(1-q) \quad (25)$$

where the data are ordered so that the first S people never moved, σ is the probability of the stayer type, N is the total number of people, M is the number of moves, K_m is the number of person-years for people who moved at least once, n_i is the number of observations and m_i is the number of moves for person i, and q is the probability of a move (for the mover type).
The gradient of the loglikelihood in this model is given by

$$g_q=-\sum_{i=1}^{S}\frac{n_i(1-\sigma)(1-q)^{n_i-1}}{\sigma+(1-\sigma)(1-q)^{n_i}}+\frac{M}{q}-\frac{K_m-M}{1-q} \quad (26)$$

$$(1-\sigma)g_\Gamma=\sum_{i=1}^{S}\frac{1}{\sigma+(1-\sigma)(1-q)^{n_i}}-N \quad (27)$$

Setting σ = 0 gives

$$\begin{aligned} g_\sigma &= \sum_{i=1}^{S}\frac{1}{(1-q)^{n_i}}-N \\ g_q &= \frac{M}{q}-\frac{K-M}{1-q} \end{aligned} \quad (28)$$

where K is the total number of person-years. If q = M/K then g_q is zero, but g_σ is not zero except in special cases. In the case of a balanced sample, the gradient is given by

$$(1-q)g_q=\frac{n_1 S\sigma}{\sigma+(1-\sigma)(1-q)^{n_1}}+\frac{M}{q}-K \quad (29)$$

$$(1-\sigma)g_\sigma=\frac{S}{\sigma+(1-\sigma)(1-q)^{n_1}}-N \quad (30)$$

Setting g_σ = 0 and substituting in the equation for g_q gives

$$(1-q)g_q=K\sigma+\frac{M}{q}-K \quad (31)$$

Setting g_q = 0 then gives q(1-σ) = M/K, meaning that the expected migration rate at the ML parameter estimates matches the average migration rate in the data.

[16]See Corbett (1991) and the Wisconsin Expenditure Survey (1986).

[17]See Peterson and Rom (1990) and Corbett (1991), for example.

of welfare eligible women in California after 5 years in the baseline simulation, and ΔL is the difference between this and the number of welfare eligible women in California after 5 years in the counterfactual simulation.

Figure 3 shows the results obtained for wages for the three target States. The supply elasticities are modest: about 0.1 to 0.15. Interestingly, the responses are not symmetric, with flows somewhat more responsive to wage declines than wage increases, and there are noticeable differences across States. Figure 4 shows that the response to benefit changes is smaller than the response to wages: after ten years the accumulated response to a 20 percent increase in benefits is between 1 to 2 percent. The adjustment process is slow - individuals do not adjust immediately to a new opportunity. Rather the timing of moves is strongly influenced by the sequence of preference or payoff shocks, only in the absence of preference shocks would respondents adjustment immediately. There is a tendency for individuals in low-income areas to move to higher income locations but the influence of countervailing forces is strong. The somewhat larger responsiveness to wage versus benefit changes is evidence that everyone is affected by the wages, but high-wage women are not much affected by welfare benefits. In particular, women with favorable individual fixed effects are unlikely to be on benefits.

b. National Welfare Benefits and National Wage Offer Distributions

The second set of counterfactual experiments investigates migration responses to uniform benefit levels for all states. Investigation of a national benefit level is also interesting because the result is *a priori* ambiguous - implementing a national welfare benefit may serve to increase or decrease migration rates. Since the level of the National benefit may influence migration rates we consider three regimes: (a) “minimum”- uniform benefits set equal to Mississippi’s 1989 benefits, (b) “average”- uniform benefits equal to population weighted mean benefits in 1989, and c) “maximum” - benefits set equal to California’s benefits in 1989. We follow the same experiment for wages and remove State differences in mean wages. We consider a National wage offer distribution set at the population weighted mean of the State means. We shift the National mean wage separately by plus and minus 20 percent.

Table 4 presents results for the counterfactual national benefit and wage offer distributions. Migration responses are summarized by the annual migration rate and the proportion of women who ever move. The first row of the table reports the values for the baseline simulation. Rows two through four report the benefit experiments while rows five through seven report the wage experiments. The striking feature of the experiments is their minuscule effects.

We find that uniform benefits *increase* migration (compare the migration rate in row 1 versus rows 2-4). A natural intuition is that State-variation in benefit levels (as in the baseline) should increase migration versus a uniform benefit. The intuition is correct if the State benefit levels are independent of other influences on migration. However, benefits are in fact negatively correlated with these other influences, and thus serve to dampen migration flows. As confirmation, if we reflect State benefits about the population weighted mean (so that States with higher than average benefits become lower than average and vice versa) the annual migration rate increases to 2.224 percent.

8. Conclusion

We have used a structural econometric model of sequential migration decisions to analyze responses to differences in income opportunities across States, for women eligible for welfare benefits. The model allows for a large number of alternative choices. Migration decisions are made so as to maximize the expected present value of lifetime income. The interaction of wages and welfare benefits is modeled by using a simple error-components model for wages, allowing for permanent unobserved ability differences across people, as well as quasi-permanent differences in matches between people and locations.

Our model controls for noneconomic factors affecting migration (such as differences in population size across States) and it accounts for various influences on migration costs, including distances between States. Each individual is associated with a particular home location, which acts as a powerful magnet. The estimated version of the model gives a plausible description of the main migration patterns seen in the data, including the high incidence of return migration (despite the large number of untried alternatives) and the negative relationship between age and migration rates.

Our empirical results show a significant effect of income differences on interstate migration, for unskilled single women with dependent children in the NLSY. At the same time we find that the tendency to migrate toward higher welfare benefits is weak. Even though the observed benefit differences are large, these differences apparently play only a small part in expected income calculations for most welfare-eligible women.

Acknowledgments

The National Science Foundation and the National Institutes of Child Health and Human Development provided research support. We thank Taisuke Otsu for outstanding research assistance. We are grateful to Kate Antonovics, Peter Arcidiacono, Zvi Eckstein, Phil Haile, Mike Keane, Derek Neal, Karl Scholz, Ken Wolpin, Jim Ziliak and seminar and conference participants at Duke, Iowa, North Carolina, Ohio State, Rochester, the Upjohn Institute, Wisconsin, and Yale for helpful comments.

Appendix

The appendix reports additional information on wage and benefit levels and our sample selection rules defining the sample. Table 5 reports wages, benefits, and the percentile of the wage distribution corresponding to the State's benefit level, as estimated using the 1990 Public Use Micro Sample. Table 6 lists our sample selection rules and the corresponding number of women and person-years eliminated by each rule. The second half of Table 6 reports the distribution of person years of the estimation sample.

Table 5

Wages and Benefits, by State Single Women with Children, 1989

	Benefits	Adjusted Benefits	Wage Percentiles (PUMS)
Alabama	3,426	3,604	60.6
Alaska	9,765	7,232	32.0
Arizona	5,061	4,894	56.7
Arkansas	4,258	4,517	57.8
California	**7,568**	**6,877**	46.1
Colorado	5,497	5,667	56.4
Connecticut	7,297	5,948	52.5
Delaware	5,332	4,972	60.1
DC	5,739	4,625	63.7
Florida	5,023	4,954	61.4

	Benefits	Adjusted Benefits	Wage Percentiles (PUMS)
Georgia	4,897	5,036	56.9
Hawaii	8,381	6,325	48.6
Idaho	5,139	5,291	53.3
Illinois	5,448	5,316	54.5
Indiana	5,032	5,228	62.5
Iowa	5,748	5,879	48.2
Kansas	6,126	6,353	48.7
Kentucky	4,394	4,665	53.9
Louisiana	4,123	4,136	46.1
Maine	6,048	6,307	44.5
Maryland	5,806	5,729	63.2
Massachusetts	6,735	5,874	46.6
Michigan	6,774	6,485	39.4
Minnesota	6,687	6,643	48.4
Mississippi	**3,445**	**3,601**	53.4
Missouri	5,013	5,365	57.8
Montana	5,516	5,524	46.9
Nebraska	5,545	5,921	56.7
Nevada	5,313	4,910	62.2
New Hampshire	6,445	5,313	68.2
New Jersey	6,029	5,178	57.7
New Mexico	4,839	4,807	48.6
New York	6,890	6,342	47.1
North Carolina	4,858	4,918	62.7
North Dakota	5,700	5,840	39.3
Ohio	5,294	5,343	50.5
Oklahoma	5,284	5,331	50.8
Oregon	6,271	6,092	46.2
Pennsylvania	5,806	5,705	50.1
Rhode Island	6,629	5,988	43.8
South Carolina	4,277	4,405	62.2
South Dakota	5,565	5,803	49.7
Tennessee	3,958	4,196	63.0
Texas	4,065	4,113	60.0
Utah	5,632	5,807	55.2
Vermont	7,345	6,768	42.8
Virginia	5,477	5,553	61.7
Washington	6,552	6,554	47.4
West Virginia	4,694	4,788	43.2
Wisconsin	6,581	6,860	50.9
Wyoming	5,516	5,491	51.4

Table 6

Sample Selection

	Respondents		Person-Years	
Women in cross section and supplemental samples		5,827		87,405
Restrictions applied to respondents				
Ever in Military	-88			
Never a single mother	-3,335			
High school dropouts and ever attended College	-1,390			
Single mother only before age 20	-18			
Residence at age 14 not reported	-23			
Subtotal	-4,854	973		14,595
Restrictions applied to periods				
Delete periods before age 20			-2,106	
Delete periods with missing current or next location	-5		-1,233	
Delete periods in school			-51	
Delete periods of change in marital/cohab status	-2		-2,455	
Restrict to periods of single motherhood	-167		-4,535	
Delete periods if youngest child older than age 17			-10	
Delete periods living with partner	-90		-647	
Delete if ever in jail	-15		-92	
Subtotal	-279		-11,129	
Analysis Sample		694		3,466
Years per Person				
1		130		130
2		107		214
3		76		228
4		51		204
5		60		300
6		45		270
7		42		294
8		39		312
9		47		423
10		41		410
11		20		220
12		18		216
13		9		117
14		7		98
15		2		30
		694		3,466

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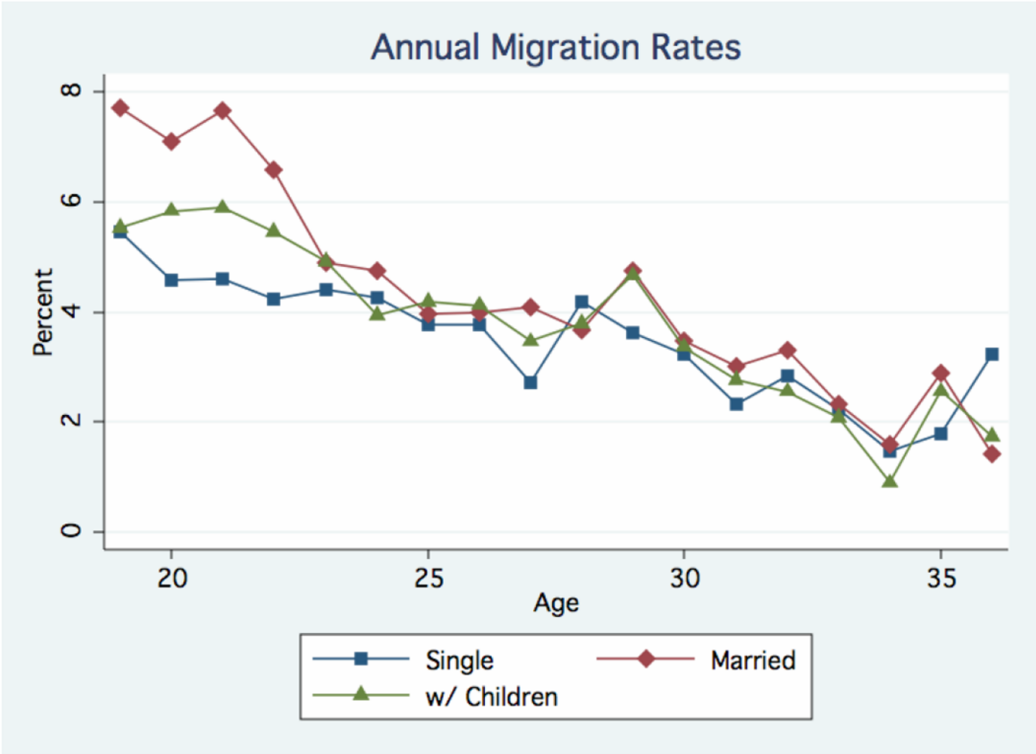

Figure 1.
Annual Migration Rates

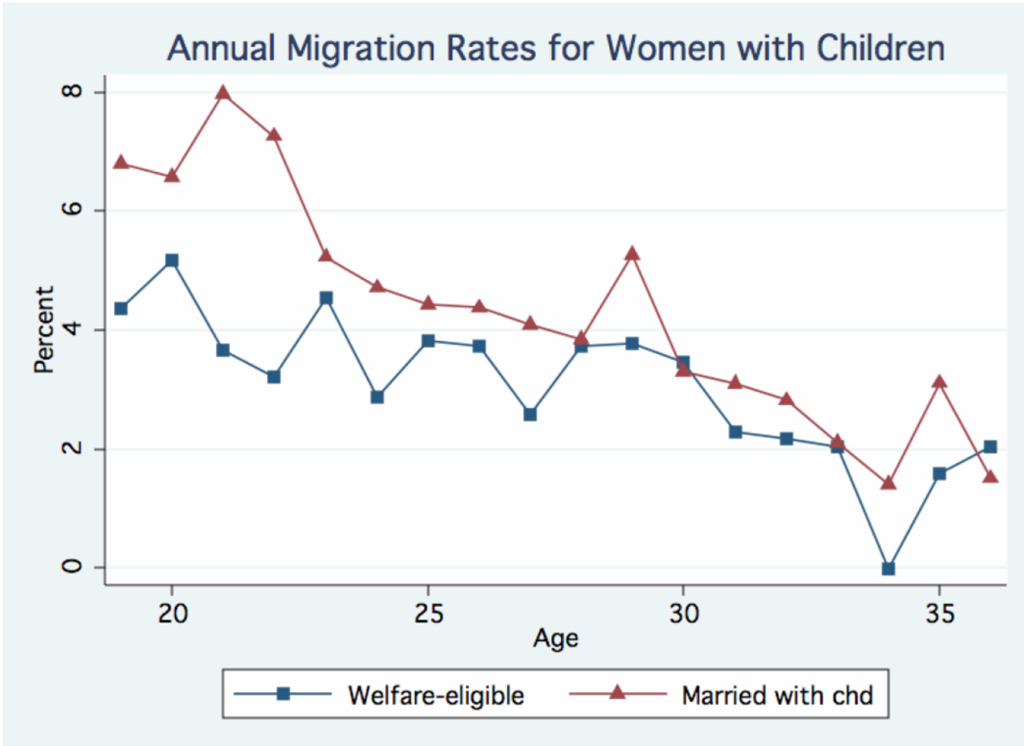

Figure 2.
Annual Migration Rates for Women with Children

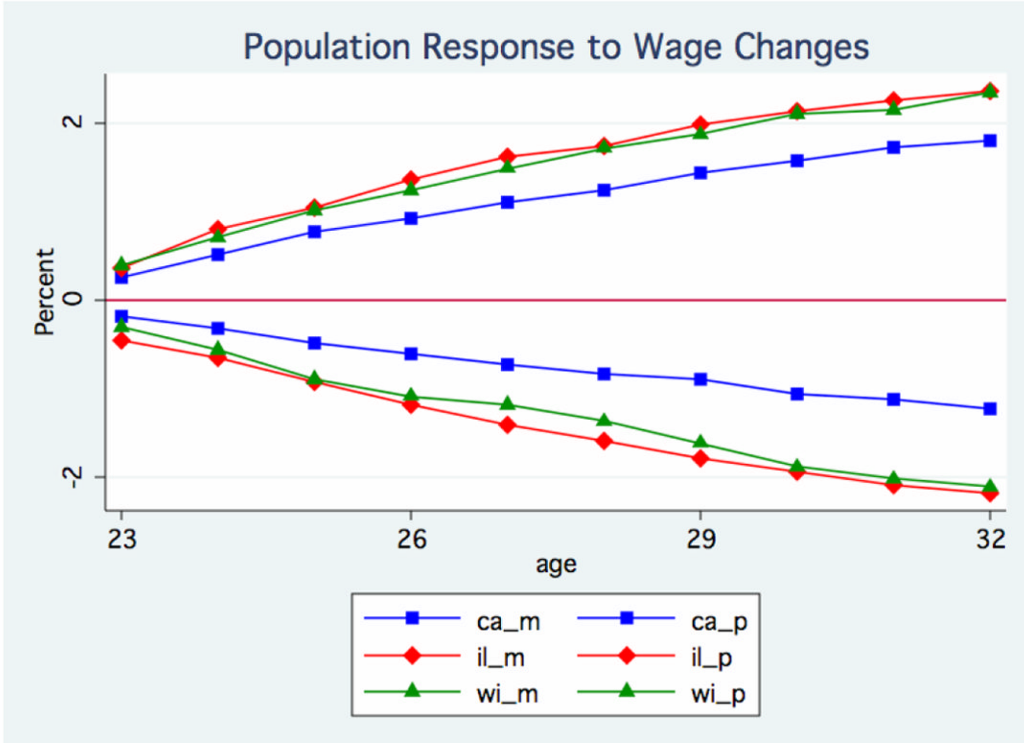

Figure 3.
Population Response to Wage Changes

Figure 4.
Population Response to Benefit Changes

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Table 1

Interstate Migration, Young Welfare-Eligible Women High School Graduates

	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$
Utility and Cost										
Disutility of Moving (γ_0)	7.560	0.108	----	----	5.895	0.674	6.635	0.701	5.960	0.704
Distance (γ_1) (1K miles)	----	----	----	----	0.449	0.191	0.480	0.212	0.447	0.195
Adjacent Location (γ_2)	----	----	----	----	0.326	0.162	0.404	0.187	0.331	0.165
Home Premium (α^H)	----	----	----	----	0.278	0.037	0.170	0.020	0.293	0.038
Previous Location (γ_3)	----	----	----	----	3.710	0.274	3.831	0.265	3.780	0.287
Age (γ_4)	----	----	----	----	0.332	0.455	0.425	0.476	0.306	0.466
Population (γ_5) (10 mill.)	----	----	----	----	0.518	0.178	0.543	0.199	0.476	0.186
Stayer Probability	----	----	----	----	0.523	0.086	0	----	0.530	0.086
Heating (1000 deg-days)	----	----	----	----	-0.026	0.009	-0.018	0.006	-0.032	0.009
Income (α_0) ($10,000)	----	----	----	----	----	----	0.226	0.130	0.396	0.211
Wages										
Wage intercept			-3.092	0.287	-3.092	0.287	-3.143	0.289	-3.110	0.287
Age effect (linear)			3.051	0.419	3.051	0.419	3.128	0.421	3.087	0.420
Age effect (quadratic)			-0.721	0.152	-0.721	0.152	-0.754	0.153	-0.737	0.152
Transient component 1 (σ)			0.213	0.006	0.213	0.006	0.212	0.006	0.213	0.006
Transient component 2 (σ)			0.594	0.011	0.594	0.011	0.595	0.011	0.594	0.011
Fixed Effect 1			0.488	0.027	0.488	0.027	0.493	0.028	0.488	0.027
Fixed Effect 2			1.016	0.033	1.016	0.033	1.016	0.033	1.015	0.033
Loc Match component			0.337	0.017	0.337	0.017	0.337	0.018	0.334	0.018
Loglikelihood	-754.392		-1850.988		-2426.708		-2435.322		-2424.046	
Exclude Income: $\chi^2(1)$					5.32					

Notes:

There are 3466 (person-year) observations, and 694 individuals. There are 88 moves.

Table 2

Interstate Migration, Young Welfare-Eligible Women

	High School Graduates		High School Dropouts	
	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$
Utility and Cost				
Disutility of Moving (γ_0)	5.960	0.704	4.807	1.393
Distance (γ_1) (1000 miles)	0.447	0.195	0.984	0.471
Adjacent Location (γ_2)	0.331	0.165	2.980	0.550
Home Premium (α^H)	0.293	0.038	-0.484	0.408
Previous Location (γ_3)	3.780	0.287	0.319	1.118
Age (γ_4)	0.306	0.466	0.450	0.072
Population (γ_5) (10 million)	0.476	0.186	0.821	0.400
Stayer Probability	0.530	0.086	0.717	0.096
Heating (1,000 degree-days)	-0.032	0.009	-0.045	0.026
Income (α_0) ($10,000)	0.396	0.211	0.276	0.405
Wages				
Wage intercept	-3.110	0.287	-3.419	0.640
Age effect (linear)	3.087	0.420	2.334	0.912
Age effect (quadratic)	-0.737	0.152	-0.451	0.328
Transient component 1 (s.d)	0.213	0.006	0.226	0.024
Transient component 2 (s.d)	0.594	0.011	0.594	0.029
Fixed Effect 1	0.488	0.027	0.665	0.130
Fixed Effect 2	1.015	0.033	0.931	0.125
Location Match component	0.334	0.018	0.495	0.064
Loglikelihood	-2424.046		-841.795	
Observations	3,466		2,012	
Moves	88		41	
Migration Rate	2.54%		2.04%	

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Table 3

Goodness of Fit Frequency Distribution of Moves per Person

Moves	Binomial		NLSY		Model	
	Count	**Percent**	**Count**	**Percent**	**Count**	**Percent**
None	616.7	88.9%	627	90.3%	632,832	91.2%
One	71.3	10.3%	50	7.2%	37,536	5.4%
More	6.0	0.9%	17	2.5%	23,632	3.4%
Proportion of movers with more than one move		7.8%		25.4%		38.6%
Total observations	694		694		694,000	
Migration rate	2.539%		2.539%		2.633%	

Table 4

Counterfactual Experiments National Welfare Benefit and National Wage Offer Distribution

Experiment	Annual Migration Rate (%)	Movers (%)
Baseline	2.145	11.84
No Income	2.016	11.29
National benefit eq Mississippi	2.199	13.18
National benefit eq population weighted mean benefit 1989	2.173	12.04
National benefit eq California	2.153	11.94
Reflection	2.224	
National Wage eq population weighted mean wage	2.105	12.83
-reduce mean wage 20%	2.085	11.71
-increase mean wage 20%	2.128	11.97