JRAP (1998) 28, 1, 60-71

# A simultaneous multinomial logit model of indirect internal migration and earnings

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**Abstract.** We investigate internal migration in the United States in a human capital context, adding to the literature on repeat migration. Our study is the first to model direct and indirect internal migration which, until now, has been studied only in the context of international migration. We model direct and indirect migration, constructing a multinomial logit migration equation that we estimate simultaneously with a system of earnings equations for individuals by migration status. We find that earnings estimates differ significantly by migration status and that the propensity to migrate, both directly and indirectly, is correlated with the earning power of individuals.

## 1. Introduction

Numerous studies have established the importance of internal human migration both as a means to redistribute labor to its most productive location and as an investment in human capital for individuals to increase their productivity and earnings. We investigate the process of internal migration in the United States in a human capital context, adding to the literature on repeat migration.

Previous studies have modeled repeat migration within countries. Our study is the first, however, to model direct and indirect internal migration that until now has been studied only in the context of international migration. We begin with a descriptive analysis of individuals by migration status. First, we disaggregate migrants (those who change county of residence) into two groups depending on whether they move directly to a new location (direct migration), or make at least one intermediary move (indirect migration). We find that indirect migrants are more likely to be highly educated, professional, and white than are direct migrants or nonmigrants. Moreover, indirect migrants are found to differ from direct migrants and nonmigrants, not only in terms of migration behavior, but also with respect to the returns they receive from other characteristics and earning power overall. This trend is possibly due to unob-

served heterogeneity exemplified by these migrants' willingness to make such additional investments in human capital. The extent to which direct and indirect migrants differ in these ways illustrates the importance of disaggregation by migration classification (direct versus indirect). Modeling migrants in the aggregate masks these differences.

We further investigate direct and indirect migration with the construction of a multinomial logit migration equation that we estimate simultaneously with earnings equations for individuals by migration status: (1) direct migrants, (2) indirect migrants, and (3) nonmigrants. This system of four simultaneous estimations allows us to use information from the error terms of each equation for a more efficient estimation of the model. In addition, we correct for the self-selection bias that we find to be present. Our results indicate that earnings estimates are not independent of migration status. In addition, we find that variables causing direct migration do not necessarily cause indirect migration. Our tests of migration self-selection provide strong evidence that those who choose to invest in human capital through indirect migration also tend to have higher earnings due to unobserved heterogeneity.

## 1.1 Conceptual Framework

Individuals will choose to migrate if their discounted marginal benefits exceed their perceived marginal costs. Individuals' objective functions, therefore, will reflect the following:

$$PV(t) = \int_0^T [E_{it} - E_{jt}]e^{-pt}\,dt - C_{ij} \qquad (1)$$

where:

E = Earnings in regions i and j respectively at time t;
T = The time for which individuals will remain in the labor force;
C = The cost of moving from area i to j;
P = The discount rate.

This properly reflects direct migration where, in relocating, workers incur pecuniary and psychic costs of a move in order to reside in a location where their labor can be better utilized, more productive and reap higher earnings.

In recent years both theoretical and empirical studies of internal human migration have disaggregated migration flows into various subgroups in an effort to reduce specification bias (DaVanzo 1983; Grant and Vanderkamp 1985; Morrison and DaVanzo 1986). Much of the focus of such studies has been on repeat migration.

Studies of both internal migration and immigration have recognized the importance of prior moves when modeling migration behavior. Many focus on the amount of labor market information possessed by various migrant types. Differences in the way potential migrants respond to personal as well as loca-

tion-specific characteristics are affected by information gathered from previous moves (Michalowski 1991). In studies of internal human migration, it is often argued that those making multiple moves receive different levels of information influencing the way they make subsequent labor market decisions such as job search, further migration, and earnings.

A number of studies have examined internal repeat migration (Morrison and DaVanzo 1986; Grant and Vanderkamp 1985; Schlottmann and Herzog 1982). Some researchers have developed theories of repeat migration. Yezer and Thurston (1976), Allen (1979) and DaVanzo (1981) are proponents of the *disappointment hypothesis*. According to this theory, misinformation about wages in destination regions may be a source of disappointment to migrants. Disappointed migrants have a tendency to have lower wages and are more likely to migrate again. Some studies also explore the *information effect*. This term refers to a tendency for the quality of labor market information to be influenced by distance. It is argued that longer initial moves mean poorer information and, consequently, increases the probability of an additional migration. Studies of internal migration have not, to our knowledge, investigated direct versus indirect migration.

Although the literature is not extensive, some work has been done investigating indirect moves in terms of international migration (Barrett 1976; Gould 1979). Greenwood and Trabka (1991) contend that indirect immigration is important for the U.S., showing that indirect migrants differ significantly from direct migrants in terms of age and level of skills. More recently Greenwood and Young (1995) go further, finding that indirect immigrants to Canada are better educated and more likely to speak French or English than are direct migrants.

In our study, we investigate indirect and direct migration within the United States. An indirect move by migrants signals that a previous move has been made in the lifetime of the migrant. In the context of human capital theory we would view the prior move as an investment in human capital. Because a primary function of migration is to redistribute labor to its most productive location, we would expect those making a previous move to have more effectively used their existing human capital and/or to have acquired additional human capital, setting them apart from direct movers and nonmigrants. Indirect migrants are expected to be more informed due to experience or failure in a previous move. In addition, indirect migrants have the opportunity to accumulate human capital during their stay in their first destination (of course, some moves may be due to misinformation). In contrast, many direct moves may be short exploratory moves or moves simply to get away from a depressed area or situation. For these reasons we expect that earning power of individuals will differ by migration status.

## 2. Data and Descriptive Analysis
### 2.1 Data

Data used in our study are a subset of the *Panel Study of Income Dynamics* sample of United States residents. Our data exclude students and those who do not report any earnings. This data set is ideal for our study because it contains microdata on county of residence, earnings, and various personal characteristics. The total number of observations used in the estimations is 4,187.

Our study utilizes data from 1983 through 1987. The multinomial logit migration equation models migration that occurs during both 1984 and 1985. A two-year duration is used to better balance the data set, as there are a limited number of migrants in a given year. Thus, those who change county of residence during 1984 and 1985 are considered migrants. Individuals are classified as direct migrants if they move from their county of birth. Those who have moved from their county of birth prior to a move are considered indirect migrants. Explanatory variables used to predict migration are taken from the 1983 survey and are defined in Table 1. Earnings are estimated using the 1987 survey of 1986 annual earnings. Annual earnings are divided by hours worked during the year. Variables used to explain earnings are from the 1986 data and are presented in Table 2.

It is our contention that direct and indirect migration differ in important ways. Mean values for characteristics of direct migrants, indirect migrants, and nonmigrants given in Table 2 indicate that indirect migrants tend to be the most highly educated group, followed by direct migrants, and trailed by nonmigrants (13.85, 13.63, and 12.89 years, respectively). This is not surprising as those who invest in one form of human capital may possess characteristics that make them predisposed to make other human capital investments. It is not surprising that indirect migrants have less work experience due to possible job change often associated with migration (17.29 years as compared to 21.2 years for direct migrants and 22.82 years for nonmigrants). Labor mobility may involve a change of residence with no change of job status, a change of job status with no change of residence or a change of both residence and job status. Krieg (1979) examines the relationship of job change and geographic mobility in depth. Migrants are less likely to be married because family ties discourage migration (Mincer 1978). In addition, indirect migrants are represented by a relatively larger proportion of professionals, whites, and males. Our data illustrate a large difference in the percentage of indirect migrants who are professionals (43.3 percent) as compared to direct migrants (39.6 percent) and nonmigrants (29.5 percent). This trend may be due to specialization in occupations that are often associated with professional employment.

Estimation of earnings is the next phase of our study. The fact that indirect migrants tend to be educated professionals underscores the economic impor-

**Table 1.** The variable definitions

| Variables | Definition |
|---|---|
| HOME | =1 if home owner, = 0 otherwise |
| EDU | Number of schooling years |
| AGE | Age |
| CHILD | Number of children |
| PROF | =1 if professional, = 0 otherwise |
| MALE | =1 if male, =0 otherwise |
| WHITE | =1 if white, =0 otherwise |
| TENURE | Number of months on current job |
| EMP | =1 if employed, =0 otherwise |
| SELF | =1 if self employed, =0 otherwise |
| MARITAL | =1 if married, =0 otherwise |
| EXPER | Years of experience; AGE-EDU-5 |
| SOUTH | =1 if from south, =0 otherwise |
| WEST | =1 if from west, =0 otherwise |
| WAGE | Annual earnings divided by annual hours worked |

tance of such migration. Differences in individual characteristics, both measured and unmeasured, along with significant differences in characteristics found in the above mentioned studies of international indirect migration lead us to believe that earnings estimation of these two migrant groups (direct and indirect migrants) may differ significantly.

To our knowledge, this is the first study to examine indirect versus direct migration in the context of internal migration. We contribute to the literature in another way. Studies of international indirect migration have not estimated earnings by migration status due to data limitations. We are able to do this in our study of internal migration. One focus of our econometrics approach involves the correction for selectivity bias. It is often argued that those who migrate may, on average, have relatively better earnings opportunities at potential destinations and relatively less opportunity at the original location. This self-selection may bias comparisons of earnings for migrants versus nonmigrants.

Studies of self-selection in migration traditionally involve a two-step procedure. In the two-stage approach, a migration equation is first estimated from which a correction factor is obtained. The correction factor is then included in a subsequent earnings estimation to allow efficient estimates of earnings. Corresponding earnings estimates are then used to estimate the parameters of the migration equation. (See Shaw 1991, Alaris 1989, Robinson and Tomes 1982, and Nakosteen and Zimmer 1980.) More specifically, the first stage of the basic two-stage procedure entails estimating the earnings equation, enabling us to obtain the Mill's ratio. The coefficient on the Mill's ratio provides information for the correlation between the migration and the earnings equation. This ratio is

**Table 2.** Descriptive statistics

| Variables | Mean Values | | |
|---|---|---|---|
| | Nonmigrants | Direct Migrants | Indirect Migrants |
| EDU | 12.89 | 13.63 | 13.85 |
| EXPER | 22.82 | 21.2 | 17.29 |
| PROF | 0.295 | 0.396 | 0.433 |
| SOUTH | 0.463 | 0.415 | 0.496 |
| WEST | 0.159 | 0.171 | 0.192 |
| MALE | 0.790 | 0.780 | 0.854 |
| WHITE | 0.637 | 0.762 | 0.788 |
| SELF | 0.107 | 0.067 | 0.102 |
| MARITAL | 0.653 | 0.561 | 0.645 |
| HOME | 0.607 | 0.555 | 0.338 |
| CHILD | 0.119 | 0.096 | 0.097 |
| EMP | 0.904 | 0.854 | 0.866 |
| AGE | 37.72 | 36.83 | 33.13 |
| TENURE | 84.13 | 80.58 | 44.54 |
| WAGE | 9.337 | 10.135 | 9.412 |

then used on the right side equation of the migration equation. The second stage estimation involves estimating the migration equation with the Mill's ratio.

Rather than using a two-stage process, our study estimates a system of migration and earnings equations together in a simultaneous fashion, utilizing information contained in the error term of each equation. We also correct for self-selection bias, i.e., the possibility that unobserved determinants of migration are correlated with unobserved determinants of earning power.

The simultaneous estimation procedure that we use estimates both sets of equations (migration and earnings) as a multivariate system (normally distributed). Such a joint system includes correlation parameters, which will be estimated directly when we optimize the full information maximum likelihood function. This is all done in one stage. The two-step procedure may have a generated regressor bias problem, because the second stage involves the Mill's ratio variable that is generated using the estimated coefficients. The direct full information maximum likelihood estimation procedure does not have such a problem, because it estimates the model in one stage.

## 3. The Model

The earnings function is represented as

$$\mathrm{Ln}W_i^s = X_i^s \beta^s + u_i^s \tag{2}$$

where:

$LnW_i$ = The natural log of the hourly wage for each of i individuals;
$X_i$ = The vector of explanatory variables;
$\beta$ = The vector of coefficients; and
s = Indices of three types of migration: nonmigrant, direct, and indirect (s = 1, 2, 3).

The corresponding utility function is given as

$$U_i^s = Z_i^s \gamma^s + v_i^s \tag{3}$$

where:

Z = The vector of explanatory variables; and
$\gamma$ = The vector of coefficients.

The ith individual is assumed to choose the sth migration choice if

$$U_i^s > \max U_i^j \; j = 1,2,3 \; j \neq s \tag{4}$$

Equations (3) and (4) comprise a standard random utility models resulting in a multinomial logit model (McFadden 1973). The subscript i is omitted for simplicity.

$$\text{Prob}[e^s < Z^s\gamma^s] = F^s(Z^{s\text{gamma}^s}) = \frac{\exp(Z^s\gamma^s)}{\exp(Z^s\gamma^s) + \sum_{j=1, j\neq s}^{3} \exp(Z^j\gamma^s)} \tag{5}$$

In order to estimate the earnings equations (2) and the choice equations (5), we follow Lee's (1983) approach and convert $e^s$ into a standard random variable $e^{*s} = J(e^s) = \Phi^{-1}F(e^s)$ where $\Phi^{-1}$ is the inverse standard normal CDF. (See Maddala 1983, p. 276.) F is the cumulative density function for the logistic model. The two systems result in a bivariate normal distribution. The migration and the earnings equations are estimated jointly using the full information maximum likelihood method (FIML). That is, the rho parameters in equation (5) are treated just like any other unknown parameters and estimated jointly with the beta vectors using the FIML. The BFGS algorithm in Gauss is used to optimize the likelihood function. The joint density for the sth choice and the earnings equation is

$$P_s = (1/\sqrt{(2\pi\sigma_s^2)}) \exp(-.5(\ln W^s - X^s\beta^s)^2/\sigma_s^2)\, \Phi\left[\frac{J^s(Z^s\gamma^s) - \rho_s/\sigma_s(LnW^s - X^s\beta^s)}{\sqrt{(1-(\rho_s)^2)}}\right] \tag{6}$$

where:

$\rho_s$ = The correlation coefficient between the earnings and migration equations for different types of migrants; and
$\sigma_s$ = The standard deviation of the wage equations.

The joint likelihood function is

$$LnL = \prod_{i=1}^{n} \prod_{j=1}^{3} [P_j]^{C_j} \tag{7}$$

There are three migration choices and $C_j = 1$ if an individual chooses the jth choice. The coefficients associated with the nonmigrants in the choice function in (3) are normalized to be zero. The unconditional expected earnings is

$$E(\ln W^s) = X^s\beta^s - \sigma_s\rho_s\phi[J^s(Z^s\gamma^s)]/F^s(Z^s\gamma^s) \quad (8)$$

where:

$\phi$ = Normal probability function; and

F = Cumulative density function (Maddala 1983, p. 276).

The sign of $\rho_s$ indicates the direction of selectivity bias. For example, a negative value of $\rho_s$ implies positive selectivity: $\rho_s < 0$ means that the individuals choosing sth migration type tend to earn more than the population at large.

## 3.1 Empirical Model

The empirical model estimated is given by:

$$MIG_t = f(HOME, EDU, AGE, CHILD, PROF, MALE, WHITE, TENURE, EMP, SELF, MARITAL, CONSTANT) \quad (9)$$

$$EARN = F(EDU, EXPER, EXPER^2, PROF, SOUTH, WEST, MALE, WHITE, SELF, MARITAL, CONSTANT) \quad (10)$$

where:

$MIG_t$ = Migration type for each individual.

All other variables are individual characteristics defined in Table 1.

## 4. Results

Of primary importance is whether earnings estimations differ by migration classification. It has been our contention that indirect migrants differ from direct migrants in important ways. The statistical significance of the differences is discerned using a likelihood ratio test. Earnings are estimated simultaneously with the migration decision. Earnings estimates are given in Table 3. In the maximum likelihood ratio test, the equality of the estimated coefficients of the earnings equations is tested across the groups ($\beta^{nonmig} = \beta^{direct\ mig} = \beta^{indirect\ mig}$). The calculated Chi-squared value of 40.15 is found to be statistically significant at the 1 percent level for 22 degrees of freedom, rejecting the equality of coefficients across different earnings functions. The statistical significance of the results highlights the need to study these migrant classes as distinct groups rather than as an aggregate.

Due to self-selection in the migration process, there may be an inherent bias in the effect of migration on earnings. The statistically significant t-statistics on all three rho-coefficients indicate strong sample selectivity. For example, the direction of selectivity for nonmigrants is negative ($\hat{\rho}^{nonmig} = 0.729$, t = 19.302), which means that after controlling for all other observed characteristics, the individuals who choose not to migrate earn lower wages than the individuals with the similar characteristics drawn randomly from the population of migrants and nonmigrants. Both the direct and indirect migrants, on the other hand, have

**Table 3.** The full information maximum likelihood estimation of model (7)

| Panel A: Choice equations<br>Explanatory variables | Direct migration | Indirect migration |
|---|---|---|
| HOME | .377[b] (2.449) | -1.204[a] (-9.685) |
| EDU | -0.298 (-0.994) | 0.761[a] (2.659) |
| AGE | -0.071 (-0.914) | -0.070 (-1.093) |
| CHILD | -1.221[b] (-2.133) | 0.007 (0.014) |
| PROF | -0.124 (-0.828) | 0.038 (0.277) |
| MALE | -0.233 (-0.984) | 0.470[a] (2.822) |
| WHITE | 0.661[a] (3.346) | 0.806[a] (5.994) |
| TENURE | -0.080 (-1.175) | -0.556[a] (-5.381) |
| EMP | -0.334[c] (-1.715) | -0.323[b] (-1.993) |
| SELF | -0.260 (-1.121) | -0.482[c] (-1.948) |
| MARITAL | 0.201 (1.121) | 0.145 (1.110) |
| CONSTANT | -2.081[a] (3.814) | -2.696[a] (-5.519) |

| Panel B: Earnings equations<br>Explanatory variables | Nonmigrants | Direct migrants | Indirect migrants |
|---|---|---|---|
| EDU | 0.687[a] (13.130) | 0.430[b] (2.023) | 0.865[a] (5.591) |
| EXPER | 0.103[a] (2.735) | 0.002 (0.010) | 0.043 (0.375) |
| $EXPER^2$ | -0.147[b] (-2.031) | -0.045 (-0.137) | -0.168 (-0.752) |
| PROF | 0.251[a] (10.029) | 0.276[a] (2.932) | 0.230[a] (3.612) |
| SOUTH | -0.087[a] (-4.050) | -0.041 (-0.412) | -0.133[b] (-2.139) |
| WEST | 0.041 (1.495) | 0.064 (0.487) | 0.025 (0.322) |
| MALE | 0.209[a] (6.313) | 0.012 (0.069) | 0.405[a] (4.310) |
| WHITE | 0.174[a] (7.800) | 0.483[a] (3.471) | 0.226[a] (2.682) |
| SELF | -0.316[a] (7.421) | -0.197 (-1.047) | -0.281[b] (-2.215) |
| MARITAL | 0.132[a] (4.687) | 0.181 (1.581) | 0.001 (0.016) |
| CONSTANT | 0.942[a] (10.781) | -1.220[b] (-2.370) | 0.069 (0.254) |
| SIGMA | 0.597[a] (57.420) | 1.201[a] (6.392) | 0.611[a] (14.083) |
| RHO | 0.729[a] (19.311) | -0.940[a] (-26.026) | -0.453[a] (-3.559) |

N = 4174
McFadden's R-squared = .14
LnL = -5,257.74

The variables in choice equations are for 1983
Values in parentheses are the t-statistics
SIGMA represents three standard errors of estimates for the three earnings equations
The three RHO values are the residual correlation coefficients between the three choice and earnings equations, indicating the extent and the direction of the selectivity bias; a positive value indicates the negative selectivity
The variables in earnings equations are for 1986
Statistical significance at the 1 percent, 5 percent, and 10 percent are represented by a, b, and c, respectively

positive selectivity ($\hat{\rho}^{dirmig}$ = -0.940, t = -26.026; $\hat{\rho}^{indmig}$ = -0.453, t = -3.559), showing that the migrants tend to earn more than the rest of the population drawn randomly.

Furthermore, a likelihood ratio test is also performed to test the joint significance test of all three rho coefficients. This tests the extent to which earning power and the migration decision are jointly determined. The calculated $\chi^2$ is 91.33 which is highly statistically significant as compared to the 5 percent critical value for three degrees of freedom (7.82). Hence, the null hypothesis of the rho coefficients being equal to zero (no selectivity) is rejected. Thus, we may conclude that there is a statistically significant relationship between earning power and the migration decision.

The full information maximum likelihood joint estimates of choice and earnings equations are presented in Table 3. The most striking result is that while the estimated coefficient of years of education is negative and insignificant in determining direct migration, it is highly statistically significant and positive in explaining indirect migration. Those who accumulate human capital in the form of education also tend to accumulate human capital through indirect migration.

Other explanatory variables that are not statistically significant determinants of direct migration, but do significantly influence indirect migration are MALE, TENURE, and SELF. Men are more likely to invest in indirect migration, as are those with less months of tenure with employer and self-employed individuals. Conversely, number of children has a negative effect on direct migration, but does not significantly influence direct migration.

Variables found to be statistically significant in both direct and indirect estimations include HOME, WHITE, and EMP. Whites are more likely to undertake both varieties of moves. Homeowners are less likely to be indirect movers, but more likely to undertake direct moves. Those who are employed are less likely to engage in either form of migration.

Statistical significance of work experience differs for migrants and nonmigrants. It appears that migration nullifies the impact of work experience, possibly due to a loss of location-specific human capital, and loss of local labor market knowledge.

## 5. Conclusion

Our findings center around two major areas of interest. First, we examine migration behavior and earning power for individuals controlling for direct versus indirect migration behavior. We estimate a system of migration and earnings equations in a simultaneous fashion, allowing the use of information contained in the error term of each equation to be used in the joint estimation. While education was found to increase one's proclivity to make indirect moves

significantly, it has a negative but insignificant effect on the propensity to make direct moves. Gender differences are also found, with men being more likely to make indirect moves. Self-employed individuals as well as those with less accumulated time with their present employer are more likely to be indirect migrants.

Our second area of interest is the difference in earning power by migration status. Results indicate that earnings estimations differ significantly by migration status, implying that direct and indirect migrants should not be pooled together as migrants when estimating earnings. In addition, we found that the propensity to migrate is correlated with earning power of individuals. More specifically, nonmigrants exhibit negative selectivity, tending to receive lower wages than the population at large. Conversely, both direct and indirect migrants tend to earn higher wages than the general population when considering self-selection bias.

Taken as a whole, our results indicate that it is important to disaggregate migrants according to whether they have previously accumulated human capital through migration (indirect migrants) or have not (direct migrants) when estimating earnings or the returns to migration. To our knowledge this is the first study to estimate earnings functions for indirect internal migration, extending the literature on repeat migration. The significance of our results lead us to believe that more research in the area of indirect migration is warranted, both at the international and national levels.

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