Canadian International Labour Network

Labour Market Outcomes:

A Cross-National Study

CILN is a collaberative research venture between the Social Sciences and Humanities Research Council (SSHRC) and McMaster University. Additional funding is provided by the University of British Columbia, the University of Toronto, Queen's University, York University and Human Resources Development Canada (HRDC).

McMaster University

DEPARTMENT OF ECONOMICS

The Value of a Fresh Start: Earnings Persistence and the Migration of Single Mothers

Isaac C. Rischall[1]
Department of Economics
McMaster University
1280 Main St. West
Hamilton, Ontario, Canada L8S 4M4
(905)-525-9140 ext. 23211
fax: (905)-521-8232
rischall@mcmaster.ca
March 12, 1999

[1] I would like to thank the Canadian International Labour Network (CILN) for financial support. CILN is a major research initiative of the Social Sciences and Humanities Research Council of Canada (SSHRCC) and McMaster University. I would also like to thank John Kennan, Jim Walker, Mahmoud El-Gamal, Glen Cain, Peter Kuhn and participants of the University of Wisconsin-Madison Labor Economics, McMaster University and Bureau of Labor Statistics Workshops for all of their valuable comments. All errors are my own.

The Value of a Fresh Start: Earnings Persistence and the Migration of Single Mothers

ABSTRACT

This paper considers the possibility that migration provides individuals with a "fresh start." In other words, I consider a model where the temporary component of earnings is correlated over time and migration causes this correlation to change. Results for single mothers suggest that migration causes the correlation of the temporary components to decline significantly. Furthermore, if one does not control this effect of migration one finds that single mothers decrease their earnings and income by migrating. However, if one considers migration as a fresh start then, on average, a single mother migrants increase their expected earnings and income ten percent by moving. JEL(J61)

The Value of a Fresh Start: Earnings Persistence and the Migration of Single Mothers

I. Introduction

Economists generally consider migration to be a human capital investment. Individuals increase their earnings by migrating, but will only make the investment if the benefits exceed the costs. Another popular view of migration is that it is a means to provide an individual with a “fresh start.” This romantic vision of migration suggests that people who are dissatisfied with their current life can solve some of their problems by moving to a new area. The goals of this paper are to determine whether there is any evidence of a fresh start with respect to earnings and ascertain how estimates of the effects of migration change when one accounts for the possibility of the fresh start.

If migration provides individuals with a fresh start with respect to earnings then one would expect individuals who have faced recent declines in earnings to move. This is consistent with the finding in the human capital literature that shows individuals invest in human capital when their opportunity costs are low. For instance, Ashenfelter (1978) shows that the mean earnings of participants in government training programs decline in the year prior to program entry. Mincer (1978) shows that the migration rates are higher for the unemployed.

However, typical models of migration do not account for the possibility that the earnings decline would persist if they did not migrate. In other words, there is something intrinsic about moving to a new location that changes outcomes. For instance, an individual’s social networks may be such that this person associates with individuals who abuse drugs or alcohol. This might lower one’s own productivity. Migrating and leaving this social network might improve the individual’s productivity. I model the intrinsic change in outcomes by suggesting that there is an unobserved temporary component of earnings that is persistent over time. Migration causes the persistence to decline. Ignoring this change in persistence might understate the true effect of migration on earnings.

For this paper I analyze single mothers. Typical analysis of the effects of migration focuses on men. Mincer (1978) finds that male heads of household increase earnings by migrating. However, I show that the estimates from simple models suggest migration decreases earnings of single mothers.[2] I use my analysis to show that the effects of migration on earnings are positive for single mothers once one accounts for the possibility of the fresh start. The fact that there is a change in sign when considering the two approaches implies that examining single mothers stresses the importance of considering migration as a fresh start.

When considering single mother migration the literature typically examines the welfare magnet hypothesis to see whether these women move to higher benefit regions. Moffitt (1992) reviews the welfare magnet literature and shows that the more recent studies have found a high correlation between state benefit levels and migration. Most of this literature examines moves across highly aggregated regions. Included in this review is Blank (1988) which finds that the typical low-income female-headed household is more likely to move from a low-wage, low-benefit region than from a high-wage, high benefit region. Although single mothers move to higher benefit regions, they are also moving to higher wage regions. Furthermore, Walker (1994) finds no evidence supporting the welfare magnet hypothesis when analyzing migration across contiguous counties. Thus, there is evidence of single mothers migrating for benefits. However, there is also evidence that single mothers move for other reasons such as wages. With this paper I show that there significant group of single mothers who improve earnings by migrating.

The paper is organized in the following manner: Section II describes the National Longitudinal Survey of Youth (NLSY) data set used for the empirical analysis, and compares individual outcomes conditional on migrating to those conditional on staying using exogenous selection and fixed-effects

[2] Rischall (1998) estimates these simple models for males and found that migration increases earnings.

assumptions. These identifying assumptions indicate that migration causes single mothers to have lower earnings and income, and makes them more likely to receive welfare. However, these traditional assumptions do not account for persistent negative earnings shocks. The data reveal that the earnings of migrants decline sharply relative to the wages of stayers in the years before they migrate. Section III presents an earnings equation with correlated error terms over time, where the correlation changes if an individual moves. Section III also provides the empirical methodology used to estimate the parameters of the earnings equation. Specifically, the Estimation/Classification (EC)-algorithm is used to classify individuals into different types to account for selection into migration, and to estimate the parameters for each of these types. This estimator can account for unobserved individual heterogeneity which is important when considering migration. It can also allow for error terms to be correlated across observations. Section IV presents the estimates of the parameters of the model of Section III. The results from these estimates indicate that there is a significant decline in the persistence of temporary component of earnings if an individual migrates. Furthermore, estimating the effects of migration using traditional identification assumptions understates the returns to migration. The EC-algorithm divides the single mothers into two types which I label wage earners and benefit receivers. On average, the wage earner migrants increase their expected earnings and income ten percent by migrating. Furthermore, the migration behavior of these women is not sensitive to an overall change in benefit level. Of the women who primarily receive benefits, most change their earnings and income outcomes little by migrating. However, a small portion increase income by moving to states with much higher benefit levels than their initial location. Section V provides concluding remarks.

II. Data

The data for this paper come from the geo-coded National Longitudinal Survey of Youth (NLSY) for the years 1979-1992. Since I am interested in the outcomes of those who are eligible to receive benefits, I have restricted my sample to single mothers. This is the group most likely to receive Aid to Families with Dependent Children (AFDC).[3] The subsample consists of mothers who have never been married.[4] I have omitted 1,593 observations where respondents receive neither earnings nor AFDC benefits in either the current year or the previous year, because I want to restrict my sample to those that need income from earnings or benefits.

Furthermore, I have partitioned the NLSY panel into annual cross-sections from 1980 to 1991. These separate cross-sections are pooled into one large data set. This leaves me with a sample of 829 single mothers who have never been married whom I observe a total of 4,213 times. Variable definitions are contained in Table 1. Summary statistics of the resulting data set are contained in Table 2. Three variable descriptions regarding migration and three variable descriptions regarding income and earnings deserve special attention.

Move is defined as a migration across counties, unless that migration is within the same Standard Metropolitan Statistical Area (SMSA). This restriction is intended to exclude moves within the same labor market. Also, tracking migration at the county level allows a comparison of moves across states with moves within states. In the latter case, the benefit level is unchanged. If an individual is in one county in year t-1 and another county in year t then the **Move** equals one for that individual in year t. If the individual stays in the same county in year t+1 as she was in year t then Move equals zero for that individual in year t+1. **Ever Move** is a variable that indicates whether a person has ever moved since becoming a single mother. If a person has never changed counties it takes on the value zero. If the person lives in her county of origin in year t-1 and another county in year t then **Ever Move** takes on the

[3] Rischall (1998) provides the same analysis for a male subsample of the NLSY.

[4] For example, I might observe one particular woman for twelve years. The first five years this woman is neither married nor has children. In the next four years she has children, but is not married. The last three years she is married. By my selection criteria this woman is observed four times in my sample. Once a woman is married she can no longer come back into my sample.

value one in year t and in all subsequent years. **Years Since First Move** takes on the value zero if **Ever Move** equals zero. It increases by one for every year after the first move. It is unobserved in instances where the first move took place before the first survey year.

Earnings is the earnings a respondent received during the month of the interview. I use earnings rather than wages, because they are comparable to a state's maximum AFDC benefit level which is measured on a monthly basis. I use only the one month of earnings because I do not know exactly when during the a year a move takes place. Using only the one month ensures that I do not mix the earnings in two locations. Welfare benefits are measured by **Maximum Benefit Level.** This is the maximum amount of AFDC benefits an individual can receive and is a function of the number of children and state of residence. It should be noted that this measure of benefits only considers AFDC and ignores other benefits such as public housing, housing subsidies, Medicaid and Food Stamps. In addition to earnings and welfare benefits, I construct a measure of income. **Income** is defined as the maximum of the **Earnings** variable and the **Maximum Benefit Level** variable. This variable is a measure of income in the sense that if an individuals earnings are low than they can be supplemented by AFDC. The most AFDC that can be received is the **Maximum Benefit Level**. For simplicity, I assume income is bounded below by **Maximum Benefit Level**.[5]

Table 3 compares the characteristics of movers before a move to stayers.[6] There are many differences between movers and stayers. Among the black subsample, as standard human capital theory predicts, movers tend to be younger, more educated and have fewer children than stayers. However, the

---

[5] I examined the amount of benefits individuals claim to receive in the NLSY and I found this variable to be extremely error-laden. I believe that this measure of income is a better approximation than earnings plus claimed benefits.

[6] If a person lives in one county in year t-1 and another county in year t then the respondent has been characterized as a mover in year t. If the respondent has not changed counties then she is characterized as a stayer in year t. The summary statistics in Table 3 contain the individual's year t characteristics. In other words, these are the characteristics before a move-stay decision.

black movers have lower earnings than their staying counterparts. Furthermore, the black migrants have lower income. In the white subsample, movers and stayers are similar in terms of age and education. However, movers tend to have fewer children and are less likely to receive benefits. The major difference between the black and white subsamples is that movers have higher earnings than stayers in the white subsample. Also, white movers come from lower benefit states than white stayers, whereas black movers and stayers come from states with relatively similar benefit levels.

From Table 3, we see that the individuals who migrate are, as human capital theory predicts, the most able. The question now becomes how migration improves these individual's outcomes. Table 4 describes the association between migration and the outcomes -- earnings and income -- under two different specifications. The first specification, random-effects, does not control for an individual fixed-effect, whereas the second specification does. The coefficient on the **Move** variable in this specification can only be considered the effect of migration under an exogenous selection assumption. In other words, this assumption implies that there is nothing unobservably different between movers and stayers. However, if this not the case the random-effects estimates will give an inconsistent measure of the effect of migration. From random-effects specifications earnings decrease 13 percent after migration and income decreases ten percent after migration. However, when controlling for the individual fixed-effect, income and earnings decrease substantially more after the move. Furthermore, these outcomes do not improve much after the initial move. This is evidenced by the small coefficient estimates on the **Years Since First Move Variable**.

If one assumes exogenous selection, one could interpret the random effects coefficient estimates of **Ever Move** and **Years Since First Move** as the estimated effect of migration on outcomes. Alternatively, if one assumed that each individual's outcome differs by a fixed-effect that is constant over time and that is correlated with the decision to migrate, then one could interpret the fixed-effect coefficient estimates as the effect of migration on outcomes. If one interprets these coefficients in the fixed-effects model as the effect of migration, then migration causes these individuals to have lower incomes, and random effects estimates understate this effect. Furthermore, using a Hausman test one rejects the use of the random-effects model.

Thus Table 4 suggests that migration causes a significant decline in earnings and in income for single mothers. However, Rischall (1998) estimated fixed and random-effects models for male earnings and found that the effect of migration was, on average, a one percent increase in earnings for every year after the move.

Table 5 presents the effects of migration on the probability of receiving benefits under exogenous selection and fixed-effects assumptions. The exogenous selection results imply that the probability of receiving benefits increases right after a move, but then declines. Controlling for the fixed-effect implies that migration causes increased benefit receipt and that the probability of receiving benefits is increasing in time after the move.

Overall, the results from Tables 4 and 5 are a puzzle, suggesting that neither the exogenous selection assumption nor the fixed-effect assumption are appropriate ways to model the behavior of the single mother population. First, the large differences in the random-effects and fixed-effects results imply that there is selection into migration, and thus controlling for a fixed-effect is appropriate. Furthermore, the fixed-effects results suggest that these women make themselves worse off by migrating. They do not appear to be improving themselves in earnings, income or benefit receipt. However, males make large gains in earnings by migrating. So either there is something wrong with these models of migration or single mothers do not consider income an important factor in the migration decision.

A possible explanation for these results is that the exogenous selection and fixed-effect assumptions do not account for any of the relative changes in wages of movers to stayers before the move. Table 3 showed that black movers had much lower earnings than black stayers, despite having formed more human capital. Table 6 compares the earnings that working movers and stayers receive before a move-stay decision controlling for age, education, number of children, state unemployment level, AFQT score, a regional dummy variable and a series of time dummies. The difference between earnings among movers and stayers increases in the years before the move-stay decision. Single mother movers earn five percent more than similar stayers two years before the move, but they earn 13 percent less a year before the move. Furthermore, the decline is not being caused by the timing of the move. The earnings measure I use is the earnings at the time of the interview in the current location. Therefore, the measure is not picking up the potentially low earnings in the new location. Thus, the table indicates that among single mothers there are large negative changes in the earnings paths of movers relative to stayers in the years before the move-stay decision.

Female migrants experience sharp declines in earnings relative to the stayers. These lower earnings could be an impetus for migration. Another way to phrase the problem is that lagged earnings are an omitted variable in the estimating equation. Lagged earnings are negatively correlated with the migration indicator. Both the migration indicator and lagged earnings are positively correlated with current earnings. This implies that the omission of lagged earnings in the estimating equation biases downward the estimated effects of migration. The following section considers a empirical model in which changes in earnings are a motivating factor for individuals to migrate.

III. Emprical Model

In the basic neo-classical model of migration an individual compares the discounted value of income gains with the cost of migration for a set of potential locations and moves to the location for which the net gains are highest. Building on this view of migration, McCall and McCall (1987) and Pessino (1991) have proposed Multi-Armed Bandit models of migration that also view migration as a learning process. Individuals do not have perfect information and the only way they can learn more about their wage prospects in a new location is to move to that location. Similarly, Kennan and Walker

(1997) view migration in these imperfect information terms. In Kennan and Walker's model an individual not only learns about prospects in the new location, but also gains some information on prospects in other locations. Furthermore, they assume welfare benefits provide a minimum income level, so that benefits provide a safety net for migrants.

The approach that this paper takes is that after controlling for individual-specific human capital, current earnings depend on last period's earnings if the individual stays in the same location. However, if the individual moves the dependence in past earnings decreases. This is similar to the Multi-Armed Bandit approach in that one obtains more information about what will happen next period in the current location, than about other locations.

From the data, we see that in the years prior to the move, the earnings of individuals who migrate change relative to the individuals who stay. In particular, the earnings of single mother movers decline sharply relative to single mother stayers. The declining relative earnings could be a motivating factor for migration. The model considers migration as an activity that changes an individual's labor market opportunities. An individual's earnings are positively correlated with her prior earnings. An individual with low earnings is likely to continue to have low earnings if she remains in her current location. However, if she migrates, the dependence in past earnings declines.

The underlying intuition for the model I propose is that migration partially restarts the earnings process. If an individual stays in the same location, temporary shocks to earnings are persistent. Examples of such shocks could be employer misconceptions of true marginal product of the worker or the ability of social networks in providing good advice in job search. Also, migration forces an individual to use different social networks. Furthermore, if employers form networks within labor markets, and it is costly for the networking to occur across markets, then employer misconceptions will not follow the worker.

I assume the earnings process takes on the following form:

$$\ln(w_{it}(l_{it})) = \delta' X_{it}(l_{it}) + \alpha_i + \epsilon_{it}(l_{it}). \qquad \textbf{(1)}$$

l_t is the location of the individual in period t. If $l_t = l_{t-1}$ the individual stayed in the same location. Otherwise, the individual migrated. $w_t(l_t)$ is the earnings at time t at location l_t.[7] X_t is a vector of individual and location covariates at time t at location l_t.[8] The α_i term is unobserved, individual-specific and time and location-invariant. It is correlated with the decision to migrate and some components of X. The ϵ_t terms are temporary components of earnings.

If $l_t = l_{t-1}$ then

$$\epsilon_{it} = \rho\epsilon_{it-1} + \nu_{it}. \qquad \textbf{(2)}$$

If $l_t \neq l_{t-1}$ then

$$\epsilon_{it} = \tau\epsilon_{it-1} + \zeta_{it}. \qquad \textbf{(3)}$$

The ϵ_t terms are unobserved and normally distributed with mean zero and variance $\sigma^2/(1-\rho^2)$ and are uncorrelated with X_t. The ν_t terms are unobserved, independent and distributed normally with mean zero and variance σ^2. The ζ_t terms are unobserved, independent and distributed normally with mean zero and variance $(1-\tau^2)\sigma^2/(1-\rho^2)$. The ν_t and the ζ_t terms are independent of each other. Equation (2) implies that the temporary component follows an AR(1) process if the individual stays in the same location. Equation (3) also implies that the temporary component follows an AR(1) process if the individual

---

[7] For ease of notation, from this point onward I will suppress the location specific function arguments.

[8] The covariates I use are **Age**, **Education**, **Children**, **AFQT, White, South, Unemployment** and a series of time dummies.

moves. However, if τ is less than ρ then the correlation decreases after a move.

Equations (1)-(3) can be interpreted as follows. If the individual does not change locations from the previous period her earnings are a function of individual and location specific variables and the previous period's temporary component. If the individual decides to migrate, the dependence of current earnings on past earnings decreases. In other words, the individual is allowed to partially restart her earnings process by migrating. Furthermore, migration is a risky venture. The variance of earnings conditional on current information is lower in the current location than in other areas. Specifically, the variance of earnings conditional on past information in the current location is σ^2. The variance of earnings in a different location is $(1-\tau^2)\sigma^2/(1-\rho^2)$. The variances are constrained to ensure the stationarity of the earnings process. One interpretation of this constraint is that each individual receives shocks in each period and in each location. However, the individual only fully observes the shock of the current location. Since the individual only observes part of the shocks in the other locations and these shocks accumulate each period, the variance of earnings conditional on past information in a new location is greater than that variance in the current location. If this is the case then the variance of earnings conditional on past information increases by a factor of $(1-\tau^2)/(1-\rho^2)$.

I formalize the empirical model below. The earnings equation can be rewritten:

$$\ln(w_{it}) = \delta' X_{it} + \alpha_i + (1-M_{it})\rho\epsilon_{it-1} + (1-M_{it})\nu_{it} + M_{it}\tau\epsilon_{it-1} + M_{it}\zeta_{it}. \tag{4}$$

Let $M_t = 1$ if $l_t \neq l_{t-1}$ and 0 otherwise. **Move** is my measure of M_t in the data. By estimating α, δ, τ and ρ, one can forecast the earnings that movers would have received had they never moved. One problem with estimating the parameters of Equation (4) is that earnings are censored for those people who do not work. This a large problem when considering the single mother population. In order to combat this problem, I assume that the unobserved term, ϵ, is distributed normally with mean zero. I also assume that if an individual receives benefits, her true earnings are censored below the maximum amount of benefit levels she can receive. These assumptions allow me to estimate Equation (4) using a Tobit specification.

Ideally, I would like to estimate this model as a fixed-effects model with censoring. However, the fact that earnings are censored implies that one cannot difference equations as in a standard fixed-effects model. Honoré (1992) discusses the approach to estimating a fixed-effects Tobit with lagged dependent variables. His methods require that the error terms are independent and identically distributed, but an assumption of my model is that the error terms are correlated. Thus, Honoré's methodology cannot be used. Also, with a fixed-effects model one cannot observe the effects of variables that are constant over the sample period, such as race or AFQT score.

An alternative to assuming that each individual has a separate individual-specific unobserved term, α, is to assume that there are only finitely many individual-specific terms.[9] In other words, a fixed-effects model typically assumes that each individual has their own fixed-effects. In a sample of n individuals, one would like to identify n fixed-effects. An alternative to assuming that each individual has her own fixed-effect is to assume that there are $k < n$ fixed effects. Each individual will fall into one of these k types. The goal is to identify the k different α terms, and to find the probability that each individual falls into each type. A common way to estimate such a model is the Expectation Maximization (EM)-algorithm.[10] However, it is computationally slow and cumbersome. Instead I use the Estimation/Classification (EC) estimator developed by El-Gamal and Grether (1995).[11] A detailed description of the algorithm is contained in Appendix A. This method is computationally quicker, and

[9] This alternative also allows coefficients besides the constant to differ across types. Specifically, I allow the variance parameter, σ, to differ across types.

[10] See Dempster et al. (1977) for more on the EM-Algorithm.

[11] Properties of the estimator are discussed in El-Gamal and Grether (1996, 1997). The EC-estimator is consistent and asymptotically normal as the number of time periods and the number of individuals goes to infinity.

provides results similar to EM-algorithm estimates.[12]

The major difference between the two algorithms is that the EM-algorithm classifications of individuals are treated as nuisance parameters. The EC-algorithm identifies each individual's classification. In other words, the EM-algorithm identifies the probability each individual belongs to each type, whereas the EC-algorithm assumes that the probability an individual belongs to a type is either zero or one. Possible misclassifications may bias the EC-algorithm estimates, but as the number of observations on each individual goes to infinity the bias from misclassifications disappears. Thus, the EC-algorithm performs well for large T, where T is the number of times one observes each individual. In Monte Carlo studies, El-Gamal and Grether (1997) finds that the estimator performs reasonably for a T as small as three. On average, I observe each single mother 5.08 times.

One final consideration is the choice of the number of types. In general increasing the number of types increases the log-likelihood. For my sample I subtract a penalty function that increases in the number of types and I choose the number of types that maximizes the log-likelihood minus the penalty function. The description of the penalty function used appears in Appendix A.

IV. Results

Table 7 contains the results obtained by estimating the parameters of the earnings equations with the EC-algorithm. All estimates have the expected sign and most are statistically significant at the five percent level.[13] Also, the estimate of ρ is large, 0.44. This implies a large correlation in the temporary component of earnings among people who stay in the same location. The estimate of τ, 0.27, is also quite

[12] As a comparison I estimated my model on a subsample of 82 males who I observe a total of 470 times using both methods. There are no qualitative differences between the two sets of estimates, yet it took 24 times longer to obtain the estimates from the EM-algorithm. Estimates from this comparison are available upon request.

[13] Notable exceptions are the coefficients on **White**. However, these results are consistent with Neal and Johnson (1996). They find that controlling for AFQT reduces the coefficient on race variables.

large. However, one can reject $\rho = \tau$. This implies that although migration does not completely start over the earnings process, it causes a substantial decrease in the correlation in earnings over time.

The EC-algorithm classifies single mothers into two separate types. Among the two types there is very little difference in race or the tendency to migrate. However, Type 1 single mothers are less likely to receive benefits. The Type 2 single mothers receive benefits in 86 percent of the observations, whereas Type 1 single mothers receive benefits in only 19 percent of the observations. The other major differences between the two types are in education and AFQT score. Type 1 single mothers obtain one extra year of education, on average. The Type 1 single mothers obtain AFQT scores that average 0.21 standard deviations above the overall mean, whereas Type 2 single mothers have scores that average 0.18 standard deviations below the overall mean.

As mentioned previously a possible problem with the EC-algorithm is that it may misclassify individuals' types. These misclassifications will bias the estimates. To measure the degree to which misclassifications are a problem, I calculate the Average Normalized Entropy (ANE). This is the summary statistic that El-Gamal and Grether (1997) use to measure the problem. Appendix A describes the ANE statistic. Essentially the ANE is an aggregate measure of the dispersion of beliefs on the posterior probability that an individual falls into each type. If there is large dispersion then the EC-algorithm is a close approximation to the EM-algorithm. In other words, the EC-alogrithm will be a close approximation if I have strong posterior beliefs that I have correctly classified the individuals. The ANE measure lies between zero and one. An ANE close to zero implies that there are few misclassifications. The ANE is not high for the single mother subsample. The value of 0.293 implies that, on average, my posterior belief is that I have correctly classified individuals 94% of the time. Thus, the EC-algorithm estimates are a reliable approximation to the EM-algorithm estimates.

Using the results from Table 7, one can obtain estimates of the effects of migration on wages and welfare benefit receipt for those who migrate.[14] According to the model, migration partially restarts the earnings process. This means the effect of migration on earnings differs across individuals. In particular, those with high earnings in their original location will not receive any monetary benefit from migrating.

When considering the effects of migration for the single mother subpopulation one needs to consider welfare benefits as well as earnings. Table 8 presents the effects of migration for a Type 1, 22 year-old, black female single mother with one child, eleven years of education in a non-southern state with a seven percent unemployment rate for different sets of residuals, log benefit levels of original location and log benefit levels of the destination.[15] If the individual has a lagged temporary component equal to -0.2 then she can increase earnings 3.5 percent by migrating. Likewise, if the lagged temporary component were 0.2 then her earnings decrease by 3.5 percent. Notice that even when the individual migrates to a state with the same benefit levels and is increasing expected earnings by migrating, it is possible to increase the probability of receiving benefit levels. This is because of the risk involved with migrating. The variance of the earnings process conditional on past information increases when an individual migrates. Also, the expected income can increase for this same reason. In all of the cases where there are no expected earnings gains from migrating, the individual increases the probability of benefit receipt and increases expected income.

Table 8 describes which groups should be made better off with respect to earnings by migrating. Table 9 checks to see if the people in these groups are the ones migrating. Type 1 single mothers are predominantly wage earners, and the ones who move have the tendency to improve their earnings by

[14] The prediction of the probability of benefit receipt is the predicted probability of being censored. The prediction of income is based on the following assumption: income equals earnings if earnings is greater than the maximum benefit level. Income is equal to the maximum benefit levels otherwise.

[15] Again, these estimated effects are keeping unemployment rate and region constant.

migrating. On average, they increase earnings and income ten percent by migrating. Also, the ones who move to a new state have a tendency to go to a higher benefit state. However, for the most part they are not using the benefits.

The model predicts most stayers would increase their earnings and income had they moved, but these increases are not as much as the increases experienced by those who actually move. It is not surprising that everyone who would increase their earnings by migrating does not move. Migration is costly. Also, we see some individuals migrate that the model predicts are worse off (monetary-wise). This implies that there are reasons to move besides money. However, modeling the earnings process in a manner that controls for migration reducing the persistence in negative earnings shocks shows that money is a more important factor in migration than simple fixed-effects models would indicate.

Contrary to Type 1s, Type 2 single mothers use benefits when they move, but they would have used benefits had they stayed in their original location. They improve their earnings, but this does not matter. Their earnings are still below the benefit levels of their state of residence. These women also have a tendency to move to higher benefit states. Type 2 single mothers go to states with eleven percent higher benefits than their original states. This is opposed to the five percent increase that Type 1 single mothers experience. However, among the moves these women make, most of them are within state borders. The moves within state borders cannot be for the purpose of increasing benefits. Also, only slightly more than half of the Type 2 single mothers who move out of state go to higher benefit states. Nevertheless, the ones who do go to higher benefit states are going to states with substantially higher benefits. This implies that there are moves among the single mother population that merely result in the women receiving increased benefit levels. However, most moves among the Type 2 single mothers do not change earnings and income outcomes much.

From these results one sees that some single mothers increase the welfare benefits they receive by migrating. Others increase earnings substantially by migrating. However, the single mothers who do increase their earnings by migrating might be using welfare benefits as a safety net. Although these women predominantly earn wages, there are periods where they are observed receiving benefits. Declining benefit levels increase the riskiness of migration and may prevent these women from partaking in this valuable human capital investment. In order to examine the sensitivity of migration behavior among wage earning single mothers, I analyze Type 1 single mothers who stay in the same state. In particular, wage earning single mothers from low benefit states should be less likely to move within their home state than similar wage earning single mothers from high benefit states. For this analysis, I regress the migration indicator variable on the natural log of state benefit levels using a probit specification.[16] The parameter estimate of the coefficient on the natural log of state benefit levels is 0.008. This estimate has a standard error equal to 0.21. The estimate is not statistically significant at a five percent level and it is small. The results imply that a wage earning single mother is 0.009 percentage points more likely to move within a state with average benefit levels than a similar single mother in a state with 25 percent less benefit levels. Thus, it appears that a wage earning single mother’s migration behavior is not sensitive to overall changes in state benefit levels.

Overall, the results from this section imply that models which do not account for migration partially restarting the earnings process understate the effects of migration on earnings and income. Also, most single mothers increase their earnings by migration. The increase is substantial for single mothers who are primarily wage earners, but is negligible for single mothers who primarily receive AFDC benefits. Furthermore, the migration behavior of wage earning single mothers does not appear to be sensitive to overall changes in benefit levels. In other words, if all states reduced their benefit levels there would be little change in the migration behavior of the wage earning migrants. However, it is also

[16] Other explanatory variables are **Age, Education, Children, Unemployment, AFQT, South, White** and a series of time dummies. 1812 observations are used in estimation. A full set of results are available upon request.

clear that a small proportion of the single mothers are moving to higher benefit states and increase the amount of benefits they receive by migrating.

V. Conclusion

The aim of this paper has been to determine whether there is any evidence for the notion that migration provides individuals with a "fresh start." Examining single mothers, results suggest that migration gives people the opportunity for a new beginning with respect to earnings. Migration causes the correlation between past and current earnings shocks to decline significantly. Furthermore, if one does not consider the possibility of a fresh start one understates the effect of migration.

The results from fixed-effects models that do not account for the possibility of a fresh start imply single mothers make themselves worse off by migrating with respect to earnings and overall income. Results imply migration decreases single mother earnings 40 percent and overall income 21 percent. Results also suggest that the earnings of migrants decline relative to non-migrants in the years before a move. Thus, it is the individuals who have faced negative earnings shocks who are most likely to move. If earnings shocks are persistent and migration provides people with a fresh start, it is the individuals with negative earnings shocks who will benefit the most from migration.

Once I take into account persistence in the earnings process and the possibility that the persistence can change with migration, I find that correlation in earnings shocks declines from 0.44 to 0.27 if a person migrates. Furthermore, there is a group of single mother migrants who increase their incomes and earnings an average of 10 percent by moving. There is another group of single mothers that receive welfare whether or not they migrate. Their earnings and income outcomes do not change much because of migration.

Overall the results give new insight to welfare migration. If one accounts for the possibility that migration provides single mothers with a fresh start then one finds that single mothers improve earnings by moving. The welfare magnet literature might be overstating the importance of benefit levels as an impetus for migration.

Appendix A

The EC-algorithm estimation works in the following manner. Let Q_{it} be the vector of observable variables for individual i in period t. Let T_i be the number of times individual i is observed. Let *f(•)* be the likelihood function. For this paper *f(•)* =

$$\frac{1}{\sigma}\phi\left(\frac{y_{it}-\alpha_i-\delta' X_{it}-\rho(y_{it-1}-\alpha_i-\delta' X_{it-1})}{\sigma}\right) \ \ if\ \ M_{it}=0\ \ and\ \ y_{it}\ \ is\ \ observed,$$

$$\Phi\left(\frac{y_{it}-\alpha_i-\delta' X_{it}-\rho(y_{it-1}-\alpha_i-\delta' X_{it-1})}{\sigma}\right) \ \ if\ \ M_{it}=0\ \ and\ \ y_{it}\ \ is\ \ censored,$$

$$\frac{1}{\sigma\sqrt{\frac{1-\tau^2}{1-\rho^2}}}\phi\left(\frac{y_{it}-\alpha_i-\delta' X_{it}-\tau(y_{it-1}-\alpha_i-\delta' X_{it-1})}{\sigma\sqrt{\frac{1-\tau^2}{1-\rho^2}}}\right) \ \ if\ \ M_{it}=1\ \ and\ \ y_{it}\ \ is\ \ observed,$$

$$\Phi\left(\frac{y_{it}-\alpha_i-\delta' X_{it}-\tau(y_{it-1}-\alpha_i-\delta' X_{it-1})}{\sigma\sqrt{\frac{1-\tau^2}{1-\rho^2}}}\right) \ \ if\ \ M_{it}=1\ \ and\ \ y_{it}\ \ is\ \ censored,$$

where $\phi(\bullet)$ is the standard normal probability distribution function and $\Phi(\bullet)$ is the standard normal cumulative distribution function.[17] Let $\omega = \{k; \delta, \rho, \alpha_1, ..., \alpha_k, \sigma_1, ..., \sigma_k\}$ be the set of parameters to be estimated. This set of parameters includes the number of classifications k. Let $\omega_h = \{\delta, \rho, \alpha_h, \sigma_h\}$. For each individual, i, let $lf_i(h;\omega)=\sum_{t=1}^{T_i}\log f(Q_{it};\omega_h)$. For each i and for each h $\in$ {1,..., k}, calculate

$lf_i(h;\omega)$. Choose h to maximize $lf_i(h;\omega)$. Call the maximal value $lf_i(\omega)$. Sum the obtained log-

[17] The y_{it-1} - α_i - $\delta' X_{it-1}$ in *f(•)* represent ϵ_{it-1}. In cases where y_{it-1} is censored, I use E(ϵ_{it-1} | conditional on y_{it-1} being censored).

likelihoods $lf_i(\omega)$ over individuals i $\in$ {1,..., n}. Call the outcome $lf(\omega)$. The estimate of ω is $\hat{\omega}$, the value that maximizes $lf(\hat{\omega})$-penalty(n,k′). The estimate of k is k′. Increasing k′ will always cause the log-likelihood to increase. Including the penalty function allows one to maximize over the possible set of k's.

I use the same penalty function as El-Gamal and Grether (1997). They choose their penalty functions on the basis of prior beliefs. In particular the penalty function is based on the prior belief that the probability the true k = k′ is $(0.5)^{k'}$. Furthermore, they assume that all distributions of individuals within the k′ groups are equally likely. This implies a penalty function, penalty(n,k′) = k′log(2) +nlog(k′) - log(k′!).

As mentioned before, the EC-algorithm provides an approximation to the results that would be acquired by the EM-algorithm. The problem with the EC-estimator is that it can misclassify individuals. These misclassifications could cause small sample biases. To measure the degree of this problem El-Gamal and Grether describe a summary statistic, the Average Normalized Entropy (ANE).

$$ANE(k) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k} p_{ij}\log_k(p_{ij}). \qquad \textbf{(A1)}$$

The p_{ij} terms are estimates of the posterior belief that individual i belongs to type j. If these probabilities are all close to zero or one then the ANE is close to zero and there are few misclassifications. A high ANE implies that one should estimate the parameters via the EM- algorithm.

The calculation of the p_{ij} terms are based on the EM-algorithm. The EM-algorithm consists of an M-step procedure which estimates the parameter set {k; δ, ρ, α_1, ...,α_k, σ_1,...,σ_k}, and an E-step which estimates the probability each individual belongs to each classification. These probabilities are based on the estimates obtained from the M-step. The M-step is then repeated with the new probability estimates. To calculate the ANE, the M-step is passed by in each iteration. Instead of using new estimates for each

E-step, the estimates from the EC-estimator are used in each E-step.

Table 1
Variable Definitions

Variable	Definition
Age	Age of the respondent.
Children	Number of respondent's own children living in the household.
Education	Number of years the respondent has spent in school.
Ever Move	Indicator of whether the respondent has ever moved across county lines since becoming a single mother. (People who move across county lines, but are moving within the same Standard Metropolitan Statistical Area (SMSA), are not considered movers.)
Move	Indicator of whether the respondent's county of residence changed since the previous interview. (People who move across county lines, but are moving within the same Standard Metropolitan Statistical Area (SMSA), are not considered movers.)
Years Since First Move	Number of years since the respondent's first move after becoming a single mother. For males it is the number of years since the respondent's first move since 1979. The variable takes on the value 0 for those respondents who have never moved.
Unemployment	Unemployment rate in the respondent's current state of residence.
State Benefit Level	Maximum monthly AFDC payment to a family of two in the respondent's state of residence, measured in 1992 dollars.
Maximum Benefit Level	Maximum monthly AFDC payment adjusted for family size, measured in 1992 dollars.
AFDC Participant	Indicator of whether the respondent received AFDC benefits during the month of the interview.

Table 1 continued
Variable Definitions

Earnings	Earnings the respondent received during the month of the interview, measured in 1992 dollars.
Income	Maximum of the **Maximum Benefit Level** and the **Earnings** variables. This variable is considered to be a measure of income. Respondents can work and receive a wage, but if their earnings are low they can be supplemented by AFDC.
AFQT	The individual's age adjusted AFQT score. The number can be interpreted as standard deviations above or below the mean. The mean and standard deviation are male and single mother specific.
South	Indicator of whether the respondent lives in the South.
White	Indicator of whether the respondent is white.

Table 2
Summary Statistics

Variable	Black Mean	Black Standard Deviation	White Mean	White Standard Deviation
Age	24.86	3.43	24.17	3.14
Children	1.74	0.95	1.42	0.91
Education	11.83	1.82	11.16	1.87
Ever Move	0.45	0.50	0.50	0.50
Move	0.04	0.19	0.10	0.30
Years Since First Move	3.60	4.75	2.98	3.73
Unemployment	7.19	2.19	6.88	2.27
State Benefit Level	332.78	159.17	451.11	160.84
ln(State Benefit Level)	5.69	0.49	6.03	0.42
Maximum Benefit Level	386.71	195.84	496.23	217.65
ln(Maximum Benefit Level)	5.83	0.51	6.11	0.45
AFDC Participant	0.56	0.50	0.49	0.50
Earnings	548.83	709.83	582.06	688.08
ln(Earnings)	6.82	0.67	6.68	0.81
Income	767.67	576.77	848.63	525.73
ln(Income)	6.28	0.73	6.47	0.60
AFQT	-0.13	0.72	0.56	0.90
South	0.54	0.50	0.19	0.39
# individuals	613		216	
# obs	3427		786	

Note: The single mother subsample has been broken up into black and white subsamples and consists of mothers in the NLSY who have never been married. Although I observe most of these women more times than are included in this Table, I have omitted the observations where the respondent had no children, or where the respondent had been married at some point in the past. Also, there are 36 observations among the black single mothers where **Years Since First Move** are unobserved. Among the black single mothers, there are 1,716 observations of **Earnings** = 0. Among the white single mothers, there are 333 observations of **Earnings** = 0.

Table 3
Comparison of Movers to Stayers Before Move

BLACKS	STAYERS		MOVERS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Age	23.88	3.44	23.46	3.20
Children	1.59	0.93	1.54	1.03
Education	11.74	1.79	12.18	1.82
Earnings	458.93	679.67	329.20	556.42
ln(Earnings)	6.81	0.69	6.52	0.93
Income	701.38	554.23	588.92	450.72
ln(Income)	6.29	0.73	6.12	0.72
AFDC Participant	0.50	0.50	0.47	0.50
State Benefit Level	331.22	162.65	331.19	168.51
ln(State Benefit Level)	5.68	0.51	5.67	0.51
Maximum Benefit Level	369.83	209.37	362.10	221.52
ln(Maximum Benefit Level)	5.59	1.24	5.49	1.43
AFQT	-0.14	0.71	0.12	0.86
South	0.54	0.50	0.59	0.49
Unemployment	7.28	2.30	7.39	2.22
# obs	3299		128	
WHITES	STAYERS		MOVERS	
Age	23.16	3.19	23.27	2.58
Children	1.26	0.97	1.14	0.51
Education	11.09	1.83	11.11	2.11
Earnings	467.35	653.85	561.14	593.32
ln(Earnings)	6.62	0.85	6.81	0.64
Income	769.45	508.66	794.67	405.64
ln(Income)	6.47	0.61	6.54	0.54
AFDC Participant	0.44	0.50	0.37	0.49
State Benefit Level	452.80	161.69	420.34	164.37
ln(State Benefit Level)	6.03	0.43	5.95	0.44
Maximum Benefit Level	451.96	268.93	423.88	200.41
ln(Maximum Benefit Level)	5.51	1.89	5.71	1.39
AFQT	0.53	0.88	0.77	1.01
South	0.19	0.39	0.25	0.44
Unemployment	6.98	2.31	7.08	2.46
# obs	707		79	

Note: There are 1,912 observations where the wages for black single mother stayers equals zero. There are 82 observations where the wages for black single mother movers equals zero. There are 369 observations where the wages for white single mother stayers equals zero. There are 36 observations where the wages for white single mother movers equals zero.

Table 4
Changes in Earnings and Income After Migration: Single Mother Subsample
Dependent Variables:
(1) ln(Earnings)
(2) ln(Income)

	Random Effects		Fixed Effects	
	(1)	(2)	(1)	(2)
Constant	5.61*	4.49*	3.90*	4.44*
	(0.40)	(0.28)	(0.39)	(0.19)
Ever Move	-0.13*	-0.10*	-0.40*	-0.21*
	(0.06)	(0.03)	(0.08)	(0.05)
Years Since First Move	0.01	0.00	0.00	-0.01
	(0.01)	(0.004)	(0.01)	(0.005)
Children	-0.10*	0.03*	-0.06	0.05*
	(0.03)	(0.01)	(0.03)	(0.01)
Age	0.03*	0.05*	0.05*	0.04*
	(0.01)	(0.01)	(0.01)	(0.005)
Education	0.07*	0.08*	0.16*	0.10*
	(0.01)	(0.01)	(0.03)	(0.01)
AFQT	0.13*	0.18*	---	---
	(0.04)	(0.03)	---	---
South	0.04	-0.27*	0.08	-0.56*
	(0.05)	(0.03)	(0.13)	(0.07)
Unemployment	-0.04*	-0.01	-0.02	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
White	-0.17*	0.05	---	---
	(0.06)	(0.05)	---	---
# individuals	603	822	603	822
# obs	2145	4177	2145	4177

Note: Time dummies were included in the estimated equations. Parameter estimates of the coefficients of the time dummies are available upon request. Observations where **Earnings** = 0 are omitted when ln(**Earnings**) is the dependent varaible. The 36 observations where **Years Since First Move** are missing have also been omitted. ***** estimate is significant at a 5% level. (standard errors in parentheses)

Table 5
Changes in AFDC Participation After Migration: Single Mother Subsample
Dependent Variable: AFDC Participant
Estimation Technique: Logit and Fixed-Effect Logit

	Logit	F. E. Logit
Constant	4.09*	---
	(0.63)	---
Ever Move	0.25	0.78
	(0.14)	(0.44)
Years Since First Move	-0.01	0.15*
	(0.02)	(0.05)
Children	0.59*	0.47*
	(0.05)	(0.16)
Age	-0.08*	-0.31*
	(0.02)	(0.05)
Education	-0.26*	-0.34*
	(0.03)	(0.14)
AFQT	-0.55*	---
	(0.06)	---
South	-1.28*	-3.00*
	(0.08)	(1.17)
Unemployment	0.16*	0.09
	(0.02)	(0.08)
White	-0.40*	---
	(0.11)	---
# obs	4177	1667

Note: Time dummies were included in the estimated equations. Parameter estimates of the coefficients of the time dummies are available upon request. ***** estimate is significant at a 5% level. (standard errors in parentheses).

Table 6
Changes in Earnings in the Years Prior to a Move
Dependent Variables:
(1) ln(1 Year Ago Earnings)
(2)ln(2 Year Ago Earnings)

	Random Effects		Fixed Effects	
	(1)	(2)	(1)	(2)
Constant	5.06**	5.20**	4.19**	4.98**
	(0.42)	(0.45)	(0.46)	(0.53)
Move	-0.12*	0.06	-0.13*	0.05
	(0.07)	(0.07)	(0.07)	(0.08)
Children	-0.11**	-0.07**	-0.07*	0.00
	(0.03)	(0.03)	(0.04)	(0.05)
Age	0.05**	0.04**	0.05**	0.06**
	(0.01)	(0.01)	(0.01)	(0.01)
Education	0.07**	0.06**	0.13**	0.03
	(0.02)	(0.02)	(0.03)	(0.04)
AFQT	0.10**	0.14**	---	---
	(0.04)	(0.04)	---	---
South	0.11**	0.14**	0.09	0.11
	(0.05)	(0.05)	(0.17)	(0.17)
Unemployment	-0.04**	-0.02	-0.04**	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)
White	-0.12	-0.10	---	---
	(0.07)	(0.08)	---	---
# individuals	554	503	554	503
# obs	1814	1570	1814	1570

Note: Time dummies were included in the estimated equations. Parameter estimates of the coefficients of the time dummies are available upon request. Observations are omitted when the dependent variable equals $-\infty$. ** estimate is significant at a 5% level. * estimate is significant at a 10% level. (standard errors in parentheses)

Table 7
Earnings Equation Estimates
Dependent Variable: ln(Earnings)
Estimation Technique:
Estimation\Classification Algorithm

	Single Mothers
Children	-0.1342*
	(0.02)
Age	0.0439*
	(0.01)
Education	0.0575*
	(0.01)
AFQT	0.1661*
	(0.03)
Unemployment	-0.0311*
	(0.01)
South	0.1696*
	(0.04)
White	0.0052
	(0.04)
Type 1 Constant (α_1)	5.4364*
	(0.25)
Type 2 Constant (α_2)	3.1166*
	(0.26)
Type 1 Standard Error (σ_1)	0.4523*
	(0.01)
Type 2 Standard Error (σ_2)	1.2505*
	(0.06)
Cov($\epsilon_t,\epsilon_{t-1}$) if $M_t = 0$ (ρ)	0.4445*
	(0.01)
Cov($\epsilon_t,\epsilon_{t-1}$) if $M_t = 1$ (τ)	0.2709*
	(0.05)
Log-Likelihood	-2257.59
ANE	0.293
# individuals	829
# obs	4213

Note: Time dummies were included in the estimated equations. Parameter estimates of the coefficients of the time dummies are available upon request. 49% of the 829 single mothers are Type 1's. ***** estimate is significant at a 5% level. (standard errors in parentheses).

Table 8
Estimated Effects of Migration
Single Mother Subsample

Lagged ϵ	Ln(Benefits) of Old State	Ln(Benefits) of New State	The Effect of Migration on Earnings	Benefit Receipt	Income
-0.20	5.75	5.75	0.035	0.004	0.036
-0.20	5.75	6.00	0.035	0.067	0.052
-0.20	5.75	6.25	0.035	0.186	0.090
-0.20	6.00	6.00	0.035	0.003	0.037
-0.20	6.00	6.25	0.035	0.123	0.075
-0.20	6.25	6.25	0.035	-0.005	0.037
0.00	5.75	5.75	0.000	0.008	0.002
0.00	5.75	6.00	0.000	0.060	0.014
0.00	5.75	6.25	0.000	0.166	0.046
0.00	6.00	6.00	0.000	0.014	0.005
0.00	6.00	6.25	0.000	0.121	0.037
0.00	6.25	6.25	0.000	0.017	0.009
0.20	5.75	5.75	-0.035	0.009	-0.033
0.20	5.75	6.00	-0.035	0.052	-0.023
0.20	5.75	6.25	-0.035	0.146	0.004
0.20	6.00	6.00	-0.035	0.021	-0.029
0.20	6.00	6.25	-0.035	0.114	-0.003
0.20	6.25	6.25	-0.035	0.034	-0.022

Note: The effect of migration is being calculated for a Type 1, 22 year-old black single mother with one child and eleven years of education in a state with a seven percent unemployment rate not located in the south.

Table 9
Predictions of Who Improves Outcomes by Migrating

	Movers			Stayers		
	# obs	Proportion Who Improve	Average Improvement	#obs	Proportion who Improve	Average Improvement
Type 1 Single Mothers						
Earnings	101	0.76	0.10	1860	0.63	0.05
Income	101	0.77	0.10	1860	0.64	0.05
Reduction in Benefit Receipt	101	0.47	0.00	1860	0.39	0.01
Increase in Benefit Levels Conditional on New State	47	0.66	0.04			
Type 2 Single Mothers						
Earnings	106	0.71	-0.01	2146	0.88	0.01
Income	106	0.65	0.07	2146	0.88	0.02
Reduction in Benefit Receipt	106	0.68	0.00	2146	0.88	0.01
Increase in Benefit Levels Conditional on New State	49	0.51	0.11			

This table is read in the following manner: of the 101 Type 1 single mothers who moved, the model predicts that 76 percent increase their earnings by moving. Among the 101 single mother movers the average change in earnings is a 10 percent increase. If the 1860 Type 1 single mothers who stayed moved within their home state, the model predicts 63 percent would increase their earnings. The average change in earnings would be 5 percent.

References

Ashenfelter, Orley. "Estimating the Effect of Training Programs on Earnings." Review of Economics and Statistics, February 1978, 60, pp.47-57.

Blank, Rebecca, "The Effect of Welfare and Wage Levels on the Location Decisions of Female-Headed Households," Journal of Urban Economics, September 1988, pp.186-211.

Corbett, Thomas, "The Wisconsin Welfare Magnet Debate: What is an Ordinary Member of the Tribe to do When the Witch Doctors Disagree?," Focus, Volume 13, 1991.

Dempster A., N. Laird, and D. Rubin. "Maximum Likelihood from Incomplete Data Via the EM Algorithm." Journal of the Royal Statistical Society, 1977, pp.1-38.

El-Gamal, Mahmoud A. and David M. Grether, "Are People Bayesian? Uncovering Behavioral Strategies," Journal of American Statistical Association, 1995, pp.1137-1145.

El-Gamal, Mahmoud A. and David M. Grether, "Unknown Heterogeneity, the EC-EM Algorithm, and Large T Approximation," Social Systems Research Institute Working Paper #9622, October 1996.

El-Gamal, Mahmoud A. and David M. Grether, "A Monte Carlo Study of EC-estimation in Panel Data with Limited Dependent Variables and Heterogeneity," Social Systems Research Institute Working Paper #9703, March 1997.

Honoré, Bo, "Trimmed LAD and Least Squares Estimation of Truncated and Censored Regression Models with Fixed Effects," Econometrica, 1992, pp.533-565.

Kennan, John and James R. Walker, "Geographical Wage Differentials, Welfare Benefits and Life-Cycle Migration," May 1997, mimeo.

McCall, B.P. and J.J. McCall, "A Sequential Study of Migration and Job Search," Journal of Labor Economics, October 1987, pp.452-476.

Mincer, Jacob. "Family Migration Decisions," Journal of Political Economy. 1978, pp.749-773.

Moffitt, Robert, "Incentive Effects of the United States Welfare System: A Review," Journal of Economic Literature, March 1992, pp.1-61.

Nakosteen, Robert A. and Michael Zimmer, "Migration and Income: The Question of Self-Selection," Southern Economic Journal, 1980, pp.840-851.

Neal, Derek A. and William R. Johnson. "The Role of Pre-Market Factors in Black-White Wage Differences," Journal of Political Economy, 1996, pp.869-895.

Pessino, C., "Sequential Migration Theory and Evidence from Peru," Journal of Development Economics, 1991, pp.55-87.

Rischall, Isaac C. Migration, Education and Income: Three Essays in Labor Economics, Dissertation, University of Wisconsin-Madison, 1998.

Walker, James, "Migration Among Low-Income Households: Helping the Witch Doctors Reach Consensus," Institute for Research on Poverty Discussion Paper #1031-94, 1994.

CILN Working Papers (downloadable)

wp43 **John Flemming John Micklewright**
Income Distribution, Economic Systems and Transition

wp42 **John Micklewright Kitty Stewart**
Is Child Welfare Converging in the European Union?

wp41 **W Bentley Macleod**
A Note on the Optimality of Bonus Pay

wp40 **Xin Meng Robert G Gregory**
Impact of Interupted Education on Earnings:
The Educational Cost of the Chinese Cultural Revolution

wp39 **Miles Corak**
Death and Divorce: The Long Term Consequences of Parental Loss on Adolescents

wp38 **Lori Curtis Martin Dooley**
Child Health and Family Socioeconomic Status in the Canadian National Longitudinal Survey of Children and Youth

wp37 **Heather Antecol**
An Examination of Cross-Country Differences in the Gender Gap in Labor Force Participation Rates

wp36 **W. Craig Riddell**
Canadian Labour Market Performance in International Perspective: Presidential Address to the Canadian Economics Association

wp35 **Shelley Phipps**
Economics and Well-Being of Canadian Children

wp34 **W. Craig Riddell**
Measuring Unemployment and Structural Unemployment

wp33 **Susan Johnson**
Automatic Certification or Mandatory Representation Votes? How the choice of union recognition procedure affects union certification success.

wp32 **James Andreoni Eleanor Brown Isaac C. Rischall**
Charitable Giving by Married Couples: Who Decides and Why Does it Matter?

wp31 **Herb Schuetze Peter Kuhn**

Self-Employment Dynamics and Self-Employment Trends: A Study of Canadian Men and Women, 1982-1995

wp30 **Isaac C. Rischall**
The Effect of High School Effort on Future Earnings

wp29 **Isaac C. Rischall**
The Roles of Education, Skill and Parental Income in Determining Wages

wp28 **Isaac C. Rischall**
The Value of a Fresh Start: Earnings Persistence and the Migration of Single Mothers

wp27 **Martin Browning Tom Crossley**
Shocks, Stocks and Socks: Consumption Smoothing and the Replacement of Durables During an Unemployment Spell

wp26 **Heather Antecol Kelly Bedard**
Against All Odds: The Surprising Labor Market Success of Young Mexican Women

wp25 **Heather Antecol**
Why is there Inter-Ethnic Variation in the Gender Wage Gap? The Role of "Cultural" Factors

wp24 **Martin Browning Tom Crossley**
Unemployment Insurance Benefit Levels and Consumption Changes

wp23 **Heather Antecol Peter Kuhn**
Employment Equity Programs and the Job Search Outcomes of Men and Women: Actual and Perceived Effects

wp22 **Thomas F. Crossley**
Firms and Wages: Evidence from Displaced Workers

wp21 **Jennifer Stewart Martin Dooley**
The Duration of Spells on Welfare and Off-welfare among Lone Mothers in Ontario

wp20 **Peter Kuhn Arthur Sweetman**
Vulnerable Seniors: Unions, Tenure and Wages Following Permanent Job Loss

wp19 **Kelly Bedard**
Human Capital Versus Signaling Models: University Access and High School Drop-outs

wp18 **Peter Kuhn Arthur Sweetman**
Assimilation and Economic Success in an Aboriginal Population: Evidence from Canada

wp17 **Martin D. Dooley**
The Evolution of Welfare Participation Among Canadian Lone Mothers From 1973 - 1991

wp16 **Lori Curtis Martin D. Dooley Ellen L. Lipman David H. Feeny**
The Role of Permanent Income and Family Structure in the Determination of Child Health in the Ontario Child Health Study

wp15 **LaDonna A. Pavetti**
A New Social Contract: Moving to a Work-Based Assistance System

wp14 **Gary Burtless**

The Job Prospects of U.S. Welfare Recipients: Lousier Pay but Bigger Earnings Supplements

wp13 **J.B. Burbidge L. Magee A.L. Robb**
Cohort, Year and Age Effects in Canadian Wage Data

wp12 **Martyn Andrews Alan Harrison**
Testing for Efficient Contracts in Unionized Labour Markets

wp11 **Herb J. Schuetze**
Taxes, Economic Conditions And Recent Trends in Male Self-Employment: A Canada-U.S. Comparison

wp10 **Peter Kuhn**
Canada and the "OECD Hypothesis": Does Labour Market Inflexibility Explain Canada's High Level of Unemployment?

wp9 **Stephen R. G. Jones W. Craig Riddell**
The Measurement Of Unemployment: An Empirical Approach

wp8 **Pierre Lefebvre Philip Merrigan Martin Dooley**
Lone Female Headship and Welfare Policy in Canada

wp7 **Heather Antecol Peter Kuhn**
Gender as an Impediment to Labor Market Success: Why do Young Women Report Greater Harm?

wp6 **John Myles Paul Pierson**
Friedman's Revenge: The Reform of "Liberal" Welfare States In Canada and the United States

wp5 **Jeff Borland**
Earnings Inequality in Australia: Changes and Causes

wp4 **Jeff Borland**
Union Effects and Earnings Dispersion in Australia, 1986-1994

wp3 **Robert Gregory Boyd Hunter**
The Macro Economy and the Growth of Income and Employment Inequality in Australian Cities

wp2 **Peter Kuhn**
Labour Market Polarization: Canada in International Perspective

wp1 **Peter Kuhn A. Leslie Robb**
Shifting Skill Demand and the Canada-US Unemployment Gap: Evidence from Prime-Age Men

Last updated March 27, 2000