Do the Poor Move to Receive Higher Welfare Benefits?

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July 1998
This Version: September 14, 2000

Abstract

This paper examines the extent of welfare induced migration using 1980 and 1990 Census data. I discuss a number of methodological issues that studies of welfare migration must confront and which have biased past studies. I then examine the evidence for welfare induced migration using multiple techniques. I begin with several types of comparison group based methods, some of which are new. I then combine the ideas of these methods with that of a structural conditional logit model that relies on comparisons of the attributes of possible locations. The different methods all point toward the same result: there is welfare induced migration, but it is modest in magnitude.

I would like to thank Julie Cullen, Phillip Levine, Chris Taber and seminar participants at the NBER Summer Institute, the University of Michigan, Northwestern University, UCLA, the American Bar Foundation, Virginia Commonwealth University, the Bureau of Labor Statistics, the NBER Public Economics meetings, and the University of Texas for their comments, Brad Heim, Brian Jenn, Chris Jepsen and Colin McCormick for excellent research assistance, and the Household International, Inc. Research Chair and the NSF through SBR-9809425 for financial support.

1. Introduction

At the beginning of 1996 the AFDC benefit for a family of three in the most generous state in the continental U.S. was five times that provided in the least generous state. The cross-state differences were still very large after adjusting for the cost of living and when using broader measures of welfare benefits.[1] With the elimination of AFDC by the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), states gained even greater flexibility in designing their welfare programs. It is clear that many politicians believe that interstate benefit differentials induce welfare recipients to move from one state to another to receive more assistance. Thirteen states recently adopted restrictions which lowered the benefit level or tightened time-limits for individuals who had recently moved to the state (restrictions of this sort were ruled unconstitutional in the 1999 Saenz v. Roe decision). These restrictions point to the possibility that inadequate benefits may be provided by states as they try to avoid supporting more than their share of the poor. With the shift of responsibilities to the states under PRWORA, such a "race to the bottom" seems more likely, since under PRWORA, states bear the full cost of increases in their welfare rolls. Thus, the incentive to provide less generous benefits than other states has greatly increased.[2] Welfare migration is also important for a broader methodological and substantive reason. The bulk of research on welfare programs uses cross-state program differences to identify policy effects, taking location to be exogenous. Knowledge of the magnitude of welfare induced migration is necessary to determine the biases in the literature on effects of welfare programs.

In this study, I discuss a number of methodological issues that studies of welfare migration must confront and which have biased past work. I then examine the evidence for welfare induced migration using two large datasets and multiple techniques. I begin with several types of comparison group based methods, some of which are new. I then combine the ideas of these

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[1] The combined AFDC plus Food Stamp benefit differed by a factor of more than two.

[2] See Brown and Oates (1987) for a nice discussion of the issues and a formal analysis. Also see Brueckner (1999), Figlio et al. (1998), Saavedra (1998), and Wheaton (1998) for recent analyses of state interactions in setting welfare benefits.

methods with that of a structural conditional logit model that relies on comparisons of the attributes of possible locations. The different methods all point toward the same result: there is welfare induced migration, but it is modest in magnitude.

2. Past Work

A substantial literature on welfare migration exists, but this literature has reached little consensus. Moffitt (1992, p. 34) provides a good starting point. He argues that the early literature "found rather weak or inconsistent effects of benefits on migration," but was hampered by problems with data and estimation. Much of this work was done before residency requirements that prevented migrants from receiving welfare were declared unconstitutional in the Supreme Court's 1969 Shapiro decision. Moffitt states that more recent studies "all show positive and significant effects of welfare on residential location and geographic mobility." When one considers studies since Moffitt's survey, the picture is much less clear. Several studies, in particular Walker (1994) and Levine and Zimmerman (1995), find no effect at all of welfare on migration. On the other hand, the estimates in Enchautegui (1997) imply a high level of welfare induced migration. More importantly, the methodological problems with many of these papers have not been recognized in the literature.

Two of the most influential studies that Moffitt surveys are Gramlich and Laren (1984) and Blank (1988).[3] Gramlich and Laren use a subsample of the 1980 Census public-use micro data to examine changes in region between 1975 and 1980. They compare the migration rates of those who received welfare in 1979 to the migration rates of non-aged, non-AFDC two-parent families. Gramlich and Laren find extensive welfare induced migration. Their steady-state calculations imply that in the long-run their high benefit region will have twice as many welfare recipients as it would otherwise. Their method is straightforward and appealing.

Blank also finds substantial migration effects using data from a March 1979 supplement to the CPS. Her structural approach is still the most sophisticated one that has been used to analyze

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[3] Other papers of note include Clark (1990), Peterson and Rom (1989), and Borjas (1998).

welfare migration. She relates migration and welfare participation to AFDC benefits, wages, and expected hours of work. She allows single mothers to choose among 12 regions and between AFDC participation and non-participation. This structural approach has the advantage that it can be used to predict the migration effect of changes in benefits or earnings due to policy or to other exogenous changes in the economy.

Several recent papers such as Levine and Zimmerman (1995) and Walker (1994) do not find any effect of benefits on migration. Their estimates often have the opposite sign from that predicted by the welfare induced migration hypothesis. Levine and Zimmerman use National Longitudinal Survey of Youth (NLSY) data and rely on comparison group methods that are similar to, but more sophisticated than, those of Gramlich and Laren (1984). They also examine migration for several populations and use several comparison groups. Though their estimates are not very precise, they argue that confidence intervals around their estimates combined with a steady state calculation, rule out substantial increases in high welfare state caseloads due to welfare migration.

Walker (1994) relies on aggregate data on low income individuals from the 1980 Census. He examines migration counts between the border counties of three groups of contiguous states. His results tend to go in the opposite direction from that expected if there is welfare induced migration, but the standard errors are large. Walker (1995) reanalyzes the 1980 data and also examines 1990 Census data.[4] He continues to find no evidence of welfare migration in the 1980 data, but he finds strong evidence of migration in the 1990 data. His estimates imply that an $85 difference in monthly AFDC plus Food Stamp benefits between two states increases the in-migration of poor women by 39 percent.[5] He argues that the different results for the two decades could be due to changes in real wages between 1980 and 1990.

Enchautegui (1997) uses 1980 Census data on welfare recipients, single mothers and other groups of women defined by ethnicity or education. She estimates the effect of welfare, wages

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[4] The paper also contains a short preliminary analysis of NLSY data.

[5] These estimates seem very large, though if they only apply to border counties, the overall magnitude of welfare migration may not be great.

and unemployment on migration and finds extremely large effects of welfare.[6] A one standard deviation ($101/month) increase in the value of a state's welfare package leads to nearly a doubling of migration. Using her alternative measure of welfare (AFDC only), a one standard deviation increase ($116/month) leads to about a fifty percent increase in the migration rate.

Overall, these results suggest substantial welfare induced migration, though the magnitude of the effect is poorly determined. However, the next section shows that much of this work is likely subject to large biases. After accounting for these biases, the evidence suggests a smaller amount of welfare induced migration and less uncertainty about its magnitude.

3. Some Central Methodological Issues

The previous section discussed the findings of the papers in the welfare migration literature. A number of methodological issues need to be discussed before one can adequately interpret the results of these papers. This discussion also points to methods that may overcome some of these difficulties.

3.1 Endogenous Participation

A fundamental problem in this literature is that participation in welfare, as well as migration, is likely dependent on state welfare benefit levels. In fact, the weight of current evidence implies that the participation effect is strong (Moffitt, 1992), but the extent of a migration effect is less certain. A participation effect does not even require a behavioral response; participation is mechanically higher in high benefit states, as the implicit tax rates in the benefit formula imply that in a high benefit state recipients with high earnings can still receive AFDC. Endogenous participation biases many of the previous estimates of welfare migration and can

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[6] Enchautegui describes her results as small based on calculating the impact of a ten percent change in the average difference in benefits between states. This average is the mean of positive and negative values, so it is near zero. A standard deviation change or a change equal to ten percent of the mean absolute difference would have a very large effect.

easily lead one to incorrectly conclude that there is substantial welfare induced migration. The most common approach in the migration literature examines changes in location from period t-1 to t, conditioning on welfare receipt in period t. This is the form of the data used by Gramlich and Laren, and in some cases by Enchautegui (in both cases welfare receipt is recorded just prior to t).[7] When this approach is taken, there is likely to be a strong bias toward finding welfare migration.

The intuition behind this bias result is clear. If benefits levels affect welfare participation and are different across states, then some people who would not be on AFDC in a low benefit state would be if they were in a high benefit state. If one conditions on welfare receipt in period t, the number of people migrating from a low benefit to a high benefit state will include the additional endogenous participants in the high state in t, exaggerating the flow from low to high. To these endogenous participants, welfare recipiency is merely an incidental factor associated with migration, rather than a motivating factor. Similarly, if one conditions on welfare receipt in period t, women who received benefits in a high benefit state in t-1 but subsequently migrated to a low benefit state where they did not draw benefits in t will be ignored in the analysis, understating the flow from high benefit states to low benefit states. Both factors will lead to an overstatement of welfare induced migration. The bias is probably substantial since participation rates in high benefit states are much higher than those in low benefit states (see Tables 4 and 5 and the discussion in Section 5.3).

An easy way to derive these biases formally is to consider the case of two geographic areas: a high benefit region and a low benefit region. The population under study can then be divided into two groups: one group that always participates in welfare wherever they are located, and a second group that only participates when its members are located in the high benefit region. Let the matrix of flows for the first group be A, and for the second group be B, where A_{ij} = the number of women in the first group moving from region i in period t-1 to j in period t, $i,j \varepsilon \{H,L\}$

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[7] Blank uses data of this form, but the possible biases due to endogenous participation are different in her model.

where H=high and L=low. In other words $A = \begin{bmatrix} A_{HH} & A_{HL} \\ A_{LH} & A_{LL} \end{bmatrix}$.

Let a be the corresponding matrix of transition probabilities, so that a_{ij} = the probability that a woman in region i in period t-1 moves to j in period t, i.e. $a_{ij} = A_{ij}/\Sigma_j A_{ij}$. Define B and b analogously. Let C be the matrix of flows obtained by combining the two groups, i.e. $C_{ij} = A_{ij} + B_{ij}$, and define c and c_{ij} analogously. A natural measure of welfare induced migration is $d = c_{LH} - c_{HL}$, the probability of migrating from low to high minus the probability of migrating from high to low. In practice, one will probably want to subtract from d an estimate of what d would be in the absence of welfare induced migration, most likely an estimate of d for a comparison group that should not be affected by welfare benefit differentials. Subtracting this additional term does not affect the following argument.

The question we would like to answer is the direction of the bias in an estimate of d obtained from a sample which conditions on welfare receipt in period t. Such a sample is used by Gramlich and Laren and in the largest estimates in Enchautegui. In this case, the sample flows do not equal the true flows $C = \begin{bmatrix} A_{HH}+B_{HH} & A_{HL}+B_{HL} \\ A_{LH}+B_{LH} & A_{LL}+B_{LL} \end{bmatrix}$, rather they equal C' =

$\begin{bmatrix} A_{HH}+B_{HH} & A_{HL} \\ A_{LH}+B_{LH} & A_{LL} \end{bmatrix}$, where the quantities estimated from the conditional sample are denoted by a single prime. The extent of welfare migration is necessarily overstated under these assumptions because the only two cells that are understated are the ones which will lead the migration rate from low to high to be overstated and the migration from high to low to be understated. Formally,

$$d' = c_{LH}' - c_{HL}' = (A_{LH} + B_{LH})/(A_{LH} + A_{LL} + B_{LH}) - A_{HL}/(A_{HH} + A_{HL} + B_{HH})$$
$$> d = c_{LH} - c_{HL} = (A_{LH} + B_{LH})/(A_{LH} + A_{LL} + B_{LH} + B_{LL}) - (A_{HL} + B_{HL})/(A_{HH} + A_{HL} + B_{HH} + B_{HL})$$

because $c_{LH}' > c_{LH}$ and $c_{HL}' < c_{HL}$. Thus, the extent of welfare induced migration will necessarily be biased upwards if one uses a sample which conditions on welfare receipt in period t. While I defer an extensive discussion of the magnitude of the bias until Section 5.3, it should be clear that the bias is likely to be large since the size of group B is substantial.

Similarly, if one conditions on welfare receipt in period t-1 in constructing the sample for analysis, the direction of the bias is uncertain and is likely to be much smaller. If those women who only participate in high benefit states are more mobile (this is likely to be true since most of the characteristics that make participation less likely also make mobility more likely), then conditioning on welfare receipt in period t-1 leads to a bias against finding welfare induced migration.[8] Using two primes to denote quantities from this sample, the combined population matrix equals $C'' = \begin{bmatrix} A_{HH} + B_{HH} & A_{HL} + B_{HL} \\ A_{LH} & A_{LL} \end{bmatrix}$. In this case $d''<d$ if those in the second group are more mobile, i.e. $b_{LH} > a_{LH}$. One will obtain this bias even if $b_{HL} > a_{HL}$ as well.

One should note that conditioning on welfare receipt in both periods t-1 and t also leads to estimates biased towards finding welfare migration, as the migration rate from high to low is understated. Using three primes to indicate quantities from this sample, $d''' > d$ since $c_{HL}''' < c_{HL}$, while $c_{LH}'''=c_{LH}$. Therefore, the estimated extent of welfare induced migration is necessarily biased upward if one conditions on AFDC receipt in both periods t-1 and t.

These bias results explain some of the empirical findings we have seen in the literature. Gramlich and Laren's large migration estimates are likely biased upward (their long-run estimates are also biased for other reasons mentioned below). Enchautegui's largest estimates suffer from the same bias.[9] Levine and Zimmerman do not condition on AFDC receipt in period t. In some cases, they condition on AFDC receipt in period t-1. Conditioning on AFDC receipt in period t-1

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[8] The reason that this result is not symmetric with the result for conditioning on welfare receipt in period t is that one conditions on the location at time t-1 in calculating transition rates.

[9] Enchautegui does offer a caution at one point that public assistance receipt may be endogenous, but she does not discuss the implications of this observation.

should have a bias in the opposite direction from conditioning on AFDC receipt in period t, i.e. making welfare induced migration harder to find. However, in this case the likely magnitude of the bias is small. This result could partly explain their finding of no welfare migration.[10]

The existence of endogenous participation also suggests that Blank's estimates are likely to be biased towards finding welfare migration even though she does not condition on AFDC receipt in defining her sample. Her more structural approach, however, makes the argument a little different. She examines whether more women have moved into <u>and</u> are on welfare in states with a higher combined wage and benefit package. Her results are entirely consistent with no AFDC migration effect but, instead, an effect of benefits on AFDC receipt combined with an effect of wages on migration. High benefits will make AFDC receipt more likely if increased benefits are associated with increased participation. If higher wages encourage in-migration (as she finds), and wages and benefits are strongly positively correlated (which they are), then both migration and welfare receipt will be higher in high wage and benefit areas, leading to the positive relationship between the wage/benefit bundle and migration that she finds.

There are several ways around the problem of endogenous participation. One can examine the migration rates of at-risk groups (single mothers, or better yet, low-educated single mothers) rather than welfare participants per se. Some of Levine and Zimmerman’s and Enchautegui's estimates are of this form. If one examines narrowly defined groups, then large samples are needed to obtain precise estimates. One also needs to recognize that a substantial fraction of any at risk group may not be likely welfare recipients, and thus effects on the overall group are likely to be watered down estimates of the effects on likely participants. One can also examine the welfare participation rates of migrants relative to natives. If those moving into high benefit areas are doing so because of welfare, then their participation rates should be higher than those of natives. Since it may take an in-migrant awhile to sign up for benefits, one may want to compare this difference to the analogous one between in-migrants and natives in low benefit

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[10] A potentially greater problem with Levine and Zimmerman as well as Walker's samples is the conditioning on people having income below the poverty line. It seems likely that there are many people who would be poor in a low benefit state but not in a high benefit state due to the higher benefits and wages. By an argument analogous to the one above, this situation would lead to a bias against finding evidence of welfare induced migration.

states.

3.2 Geographic Unit of Analysis

One of the key decisions in studying welfare migration is the geographic unit of analysis. One could look at areas near state borders, motivated by the idea that monetary moving costs may be low for such moves and one does not need to move far away from family and friends.[11] It is also likely that many locational characteristics will be held constant by this type of comparison. The papers by Walker (1994, 1995) were at least partly motivated by this idea. He focused on border counties, regardless of whether they were part of large urban areas.

There are several difficulties with studying border areas. In the few cases where there are large populations concentrated near state lines, the differences in state benefit levels tend to be small. Furthermore, very little inter-state migration is short distance, but between neighboring states. Focusing on movements between border states or counties misses most potential welfare induced migration. In addition, looking at this small piece of the full discrete choice problem involving all migration destinations is likely to give biased estimates because other important alternatives are omitted. In other words, this approach relies heavily on the independence of irrelevant alternatives (IIA) property which may well be violated here.

One research strategy that I use focuses on interregional migration by dividing the country into high (above median) and low benefit (below median) regions using the combined AFDC plus Food Stamp benefit. This division can be based on nominal benefits or, alternatively, on benefits adjusted for state living costs. This approach focuses on a large fraction of migration and considers cases where benefit differences are substantial. A second approach in this paper examines migration between nine regions of contiguous states. This approach captures an even larger fraction of interstate migration and all of the migration involving large changes in benefits. Ideally, one would want to consider migration between all continental states, but the econometric difficulties of this discrete choice problem are substantial.

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[11] In exploratory work several years ago (Kubik and Meyer, 1992), I looked at migration across state lines, but within multistate metropolitan areas.

3.3 Structural Methods

Only a few papers on welfare migration have adopted a structural approach. A structural approach should model migration as depending on income and leisure (non-market time) in different areas as well as on other attributes of locations. Blank (1988) is probably the most sophisticated structural paper. In her model, women choose among twelve regions and also choose whether to participate in welfare. She estimates a conditional logit model for these 24 possible choices with the argument of the logit function assumed to be linear in expected income and hours worked. In another approach, Enchautegui (1997) makes a number of simplifying assumptions to arrive at a binary probit model with an argument that is linear in benefits, wages and unemployment.

These structural models have some drawbacks. I discuss the problems with the specific models used in the past since they provide concrete examples. The most important problem with these models is that one cannot easily quantify many of the determinants of migration flows. These omitted determinants of migration may be related to characteristics of origin and destination areas, including geographic size, population size, population characteristics, industry composition, employment growth, transportation networks, and other factors harder to measure. The problem of omitted determinants of migration flows is also likely to be important because the grouping of geographic units is always partly arbitrary.[12] The advantages of a structural approach are also negated if the data are not well described by the model. While alternative explanations may exist, Enchautegui, for example, frequently obtains significant effects of wages and unemployment of the wrong sign. When central aspects of the data do not fit the structural model, the approach must be called into question.

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[12] A simple example can be used to illustrate the potential biases. For simplicity, divide the country into two regions and ignore other explanatory variables besides welfare benefits. If the larger region (in terms of flows) is the high benefit region, it will look like people are induced to migrate to receive high benefits, while if the larger region is the low benefit regions, the reverse will be true.

Blank assumes that utility is linear and that women do not know more about their potential earnings than the researcher (who can only estimate an average for a group). She also takes women to respond to a composite income variable that combines earnings and welfare. Therefore, one cannot infer if her findings are due to earnings or welfare. Another potential problem is that Blank uses a dummy variable for whether a given region is the one in which a person lived five years earlier. One would expect that the relationship between past region and current region would be more complicated, i.e. would depend on the size of the different regions, employment changes in the regions, etc. This point indicates the usefulness of having a way of summarizing the effects of omitted determinants of interregional flows.

3.4 Comparison Group Based Methods

A key difficulty of structural methods is that they do not account well for omitted determinants of migration flows. One possible approach is to find a group or groups for which migration tendencies are affected by economic and other forces in the same way as the AFDC prone population. One can then compare the migration of the AFDC prone (who are subject to an additional set of incentives due to interstate differences in welfare programs) to those of a comparison group. Another difference between AFDC recipients and other groups is that AFDC recipients are likely to be less affected by job opportunities than other groups since wages are a smaller share of their income. Since wages and AFDC benefits are positively correlated across geographic areas, some of the comparisons in this paper (those prior to Section 5.8) should understate the effects of benefits. The understatement occurs because the comparison groups are affected by wages more than AFDC prone populations, and wages and benefits are positively correlated. This point illustrates that comparison group based methods are only appropriate to the extent that comparison groups are in fact comparable to the group of interest.

A sample of potential welfare migrants defined by single motherhood is not completely exogenous, as the level of welfare benefits is likely to have some effect on fertility and marriage decisions. However, the consensus in the literature is that these effects are small.[13] Since we condition on single motherhood in the second of the two periods, by an argument analogous to the one above, the direction of any bias would be towards finding welfare induced migration. On the other hand, if the location decisions of our comparison groups (single women without children, married women) are partly affected by welfare benefits, our estimates will be biased downward. The extent of this bias is likely small relative to the true migration effect for single mothers, since the comparison groups should be affected to a much smaller extent than single mothers.

3.5 Combining Structural and Comparison Group Based Methods

The best aspects of comparison group based methods and structural models can be combined. Section 5.8 describes estimates which use comparison groups which account for hard to measure aspects of migration while incorporating the differences in economic attributes between different regions in a conditional logit framework.

3.6 Long-Run Calculations

Most studies of welfare induced migration do not consider the long-run implications of migration for the distribution of welfare recipients across states. Two exceptions to this rule are Gramlich and Laren (1984) and Levine and Zimmerman (1995). The steady-state distribution calculation in Gramlich and Laren implicitly assumes that current AFDC recipients never leave the welfare rolls. They calculate the steady-state distribution for a Markov chain with only Markov states where people are on welfare. This assumption sharply overstates the long-run effects of inter-state welfare benefit differences on the distribution of the welfare population across states. Levine and Zimmerman assume that a welfare recipient receives benefits for three years over her lifetime after moving. In Section 6, I describe a new approach which uses estimates of the

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[13] See Hoynes (1997), for example.

persistence of single motherhood or welfare receipt from panel data.

4. Data and Methods

The main data sources for this paper are the 1980 and 1990 Census of Population 5-Percent PUMS datasets.[14] These Census datasets allow me to obtain large samples for the segments of the population that are likely to be affected by interstate AFDC benefit differentials. One can obtain precise estimates even when examining narrowly defined groups such as single mothers with less than a high-school education.[15]

The main sample used throughout the paper is 18-54 year old women who lived in the lower 48 states at the time of the Census and five years earlier.[16] Welfare receipt is measured as receipt of public assistance income during the previous year.[17] To exclude those who receive non-AFDC public assistance income, I drop the aged and disabled from the sample. Migration in the Census data is indicated by a person living currently in a different location than she did five years earlier. Therefore, migration in the 1980 Census data refers to moves between 1975 and 1980. Similarly, the 1990 Census reports moves between 1985 and 1990. When I restrict the sample to single mothers, I define single as not currently married or married but separated.

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[14] The migration variables are only available for a random half of the 1980 data.

[15] The Census data may have another advantage over longitudinal data if the longitudinal data are subject to differential attrition by those who move. I compared migration rates of single mothers in the Census to those in the PSID to see if there was any suggestion of this problem. For the years surrounding 1980, the PSID data indicate an interstate migration rate of less than seventy percent of that indicated by the Census. This comparison strongly suggests a difficulty in following moves in the PSID. In the years surrounding 1990 however, the PSID data indicate a migration rate very close to that in the Census. These results suggest improved PSID procedures over time or a changing degree of recall bias in the Census. These calculations in both datasets were done with those 18-54, who were not disabled and had no location imputations.

[16] I exclude those with impute values for public assistance income or location (present or five years ago) and with disabilities (work limited status or work prevented status).

[17] Public assistance income includes "supplementary security income payments made by Federal or State welfare agencies to low-income persons who are aged (65 years or older), blind or disabled" as well as AFDC and General Assistance income.

I measure the welfare benefit differences across states using the combined AFDC plus Food Stamp benefit for a family of four. For migration between 1975 and 1980 I use the 1975-1979 average, and for migration between 1985 and 1990, I use the 1985-1989 average. I combine Food Stamps with AFDC because over ninety percent of AFDC recipients receive Food Stamps. I do not include the value of Medicaid in the calculation because its value is difficult to characterize, and the evidence of behavioral effects due to Medicaid is not nearly as strong as the evidence for AFDC and Food Stamps.[18] Over time, benefits are indexed using the Personal Consumption Expenditure (PCE) deflator.

Across states, I consider adjusting benefit differentials using a state cost of living index based on housing costs. My approach is very similar to that proposed in National Research Council (1995).[19] Only housing costs (rent plus utilities) are accounted for in the calculation as most other costs do not differ very much across geographic areas. The housing share of expenditures is taken from the Consumer Expenditure Survey (CEX), while housing costs are calculated from the 1980 and 1990 Censuses. I use the weighted 20th percentile of the rent plus utilities distribution for a standardized unit: a five-room, two-bedroom apartment with plumbing and kitchen facilities (and non-zero rent).[20]

Figures 1 and 2 show which states have above median (high) and below median (low) welfare benefits using the unadjusted and housing costs adjusted measures of benefits. Figure 1 is for 1980 and Figure 2 is for 1990. Two features of these figures are striking. First, the low benefit region is nearly a contiguous area: the South, Rocky Mountains and lower Midwest. The high benefit region is nearly the union of two contiguous areas: the Northeast and upper Midwest, along with the West. Second, the housing cost adjustment does not change many states from high to low benefit or vice versa, and these states tend to be on the borders of the regions. In the first

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[18] See Meyer and Rosenbaum (1999) for a comprehensive discussion of the interstate differentials in welfare programs and taxes, and see Moffitt (1992) for a summary of the evidence on behavioral effects.

[19] See National Research Council (1995) for a discussion of the value of adjusting benefits for living costs and methods to make the adjustment.

[20] To calculate the index, I first calculate the state weighted 20th percentile of housing costs by weighting the 20th percentile for each county group by the number of apartments in the county group. Then, a state index is calculated as: 0.56 + 0.44*(state weighted 20th percentile /US avg 20th percentile).

set of analyses below, I divide the country into these two regions: high benefit and low benefit. Remaining somewhat agnostic as to whether the living cost adjustment is preferable, I report results below with and without this adjustment. Later in the paper, I divide the country into a larger number of regions.

5. Results

5.1 Key Migration Patterns

The motivation behind examining long distance migration comes from an initial examination of benefit differentials and migration across border areas. In 1980 there are only six multi-state metropolitan areas that are identified in the 5 Percent PUMS data and have at least 40 welfare recipients in each state. The average difference in the combined AFDC plus Food Stamp benefit between these states is just over ten percent. In 1990 there are fourteen metropolitan areas this large that can be identified, but the average difference in benefits is even smaller. In addition, very little inter-state migration is between states within multi-state metropolitan areas. Longer distance migration between regions with very different benefits is more common. These patterns hold both for all women and for single mothers as can be seen in Table 1. If one divides the country into high and low benefit regions in 1980 or 1990 the fraction of those moving across state lines that move between these regions (panels (4) and (12) of Table 1) is over forty percent in all cases. This situation occurs even though the high and low benefit regions are nearly contiguous geographic areas. Later in the paper, I divide the country into 9 regions of contiguous states. Now, over seventy-five percent of interstate migration involves moving between one of these regions (panels (5) and (13) of Table 1). On the other hand, consider those who either move out of a given multi-state metropolitan area or across state lines within the multi-state metropolitan area. Under fifteen percent of these individuals move across state lines yet within the metropolitan area (panels (8) and (16) of Table 1).

5.2 Migration Differences in Differences

In Tables 2 and 3 I report raw migration rates between the high and low benefit regions for a number of groups. Table 2 reports rates for all women, and Table 3 restricts the sample to women with a less than high school education. In panels (1) through (4) I report migration rates from the low to high regions as well as migration in the reverse direction. In panels (5) through (8) I report these statistics calculated for a welfare prone (or recipient) group relative to a comparison group that is unlikely to receive welfare (or non-recipients). The main statistics of interest are the differences in differences, i.e. the low to high migration rate minus the high to low rate for the welfare prone populations relative to the comparison groups. Panels (5) and (6) of Tables 2 and 3 report differences between welfare recipients and non-recipients. These estimates indicate very high rates of migration that are highly statistically significant and are consistent with welfare migration. This method is very similar to that used by Gramlich and Laren. However, these estimates are probably greatly overstated due to endogenous participation.

In panels (7) and (8) of Tables 2 and 3, I examine a highly welfare prone group, but I do not condition on welfare receipt in period t. These estimates of potentially welfare induced migration are dramatically different from those in panels (5) and (6). In the case of the results for all women in Table 2, the estimates often have the wrong sign and are significantly different from zero in several cases. These estimates should probably also be discounted, as the comparison groups tend to be more mobile so that their migration rates to most areas are much higher than those of single mothers. When I condition on women having less than a high-school education, I then have comparison groups with migration rates similar to the welfare-prone group. The estimates for high-school dropouts in Table 3 have the expected sign and are significant in a majority of the cases, though they average about one-tenth the size of those in panels (5) and (6). While one would expect smaller effects in panels (7) and (8) since not everyone in the welfare prone population is a likely welfare recipient, this difference is only a small part of the story. If one supposes that those not on welfare are completely unaffected by welfare benefits, then the migration rate effect for these groups should only fall to about one-quarter (in the case of Table 2) or about one-half (in the case of Table 3) of what it was for the welfare population, given the receipt rates for these groups reported in Tables 4 and 5. The changes in sign in Table 2 and the fall by a factor of ten in Table 3 are strongly suggestive of an endogenous participation bias.

The numbers in panels (7) and (8) of Table 3 also suggest the presence of welfare induced migration. All eight of the estimates are positive, and five are significantly different from zero. To interpret the magnitude of these estimates, it is useful to compare them to the interregional migration probabilities reported in the top half of Table 3 which average about 0.033 for single mothers. Take the 0.00473 estimate in the third column as representative, since four estimates are larger and three are smaller. The 0.00473 estimate captures both the effect of welfare in encouraging migration to high benefit states and in discouraging it to low benefit states. For purposes of interpretation, assume that half of the effect works through each of these two routes.[21] Then, our estimates suggest that about seven percent of migration to high benefit states is welfare induced and that migration to low benefit states would be about seven percent higher if not for the benefit differential. However, the estimates are not tightly clustered around seven percent, with some individual estimates implying that no migration is due to welfare benefits while others implying that twenty percent is due to welfare.

5.3 Assessing the Magnitude of Possible Biases

To assess the likely magnitude of the bias due to endogenous participation, I make some calculations using the framework of Section 3.1 and plausible parameter values from the data. For simplicity, assume that $a=b$, i.e. that the migration rates are the same for those that always participate and those that only participate in high benefit states. Also assume that $c_{HL}=c_{LH}=\rho$, i.e. that migration rates to and from the high benefit region are equal. Let k be the ratio of the size of the second group (that only participates in H) to the size of the first group (that participates in either H or L). One can then show (see Appendix 1) that the bias due to endogenous participation (in estimates such as those in panels (5) and (6) of Tables 2 and 3) is

$$(5.1) \quad d^{\prime} = \frac{\rho+\rho k}{1+\rho k} - \frac{\rho}{1+(1-\rho)k} \quad .$$

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[21] One may want to interpret the estimates in this way rather than trying to separately identify the two effects. The sum of these two effects is consistently estimated even when there is a constant difference in the migration probabilities to both regions between the welfare-prone group and the comparison group.

To implement equation (5.1) one only need estimates of ρ and *k*. ρ is approximately .04 in Tables 2 and 3, so the only remaining parameter one needs is *k*. I consider two ways of estimating k. First, one can look to the literature for an estimate of the AFDC caseload elasticity with respect to the AFDC benefit, and apply the elasticity to the benefit level difference between the regions. Blank (1997) provides a suitable estimate from aggregate state by year data with state and year fixed effects. Her basic specification estimate of the elasticity is .559. Combining this elasticity with the mean difference in AFDC benefits between the two regions, one obtains estimates of *k* for 1980 and 1990 of 0.52 and 0.54, respectively.[22] Second, *k* can be estimated directly from welfare participation logit equations using the 1980 and 1990 Census data. *k* is just the derivative associated with a dummy variable for being in the high benefit region, after controlling for other individual characteristics (age, education, race, Spanish origin, the number of children under 6, and the number of children under 18).

This second procedure has the advantage of being a direct examination of the regional differences in participation rates that we want to measure, but it may be biased for two reasons, one of which also applies to the first procedure. First, there are differences in wages and economic conditions across regions for which we cannot account. Second, such a measure of participation effects is biased due to welfare induced migration if likely welfare recipients move to places where benefits are high. This situation is another example of how participation and migration effects can be confused. The first type of bias is not easily corrected, but it is true that the benefit differences between the two regions are probably more important for single mothers than are wage differences.[23] We obtain an estimate which is free of the upward bias due to the second problem (and may be biased down due to selection) by estimating participation logit equations on the sample of individuals born in the state in which they currently reside. This

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[22] These values of *k* are calculated for the regions and benefits defined without the cost of living adjustment as the benefits in Blank (1997) are measured that way.

[23] This is especially true for high school dropout single mothers. In 1980 median hourly earnings for high school dropout childless women were $3.38 in the high region and $3.12 in the low region, while benefits differed by nearly a factor of two. If one looks at the income sources of high school dropout single mothers, those in the high region had $1137 more in welfare income in 1979 than those in the low region, but had $466 less in wage income than those in the low region.

analysis indicates that while there is a bias in the expected direction, it does not appear to be large.[24] This procedure gives an estimates of k of about 0.55 for 1980 and about 0.30 for 1990.[25] The lower magnitude in 1990 is expected given the narrowing of AFDC benefit differentials between the two periods. Using $k = 0.3$, equation (5.1) implies $d' = 0.02$; using $k = 0.5$, $d' = 0.032$. These magnitudes are similar or only slightly smaller than those reported in panels (5) and (6) of Tables 2 and 3, which suggests that the bias due to endogenous participation is large.

It was noted in Section 3.4 that this comparison group method does not account for wage differences between regions, leading to a downward estimate of the extent of welfare induced migration. One might expect that this bias will be of a smaller magnitude than the migration effect itself since the wage differences between regions are smaller than the benefit differences, especially for high-school dropouts. Further support for the plausibility of these migration estimates comes from the next approach which is not biased by wage differences across regions.

5.4 Participation Differences in Differences

Tables 4 and 5 provide an alternative way of examining the extent of any effect of welfare benefit levels on migration. If a segment of the population in the low benefit region moves to the high benefit region because of its higher welfare benefits, then in-migrants to the high benefit region should be expected to have higher welfare participation rates than those who already live there. Similarly, one would expect that individuals moving from the high region to the low region would be those who are unlikely to be on welfare, so that the participation rate of migrants in the low region should be lower than that of natives. Wage differences across regions should not bias these estimates, because wages affect natives and in-migrants alike. Panel (3) indicates that migrants to high benefit states have a much higher rate of welfare participation relative to natives

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[24] For example, using regions defined by benefits without the cost of living adjustment the 1990 participation rate difference is estimated to be 28.2 percent and 26.7 percent with and without regional movers, respectively. In 1980, the numbers are 61.9 percent and 54.7 percent, respectively.

[25] For 1980 the participation rate difference is 61.9 percent and 52.6 percent unadjusted and adjusted for cost of living differences, respectively. In 1990 the numbers are 28.2 percent and 33.8 percent, respectively.

than is the case for migrants to low benefit states. This result again suggests the presence of welfare induced migration. All of the statistics have the expected signs, and six of the eight are statistically different from zero. One can interpret the magnitude of these estimates of the excess participation rates of in-migrants by comparing them to the overall welfare participation rates in the top two panels of the tables. Take the fairly representative excess participation estimate of 0.063 in Table 5 and assume that it is evenly split into over participation in high benefit states and under participation in low benefit states.[26] Then, this estimate suggests that participation among migrants is about seven percent higher in high benefit states and about seven percent lower in low benefit states than it would be otherwise. Again, the range of the estimates is substantial, though here they range from just under two percent to almost twelve percent.

These excess participation estimates and the migration estimates of Section 5.2 provide two alternative ways of assessing the extent of welfare effects on location decisions. While both methods suggest significant location effects, it is useful to examine whether the magnitudes of the effects are also in agreement. While the details are reported in Appendix 2, theoretically the participation effect should be about the same magnitude as the migration effect. Thus, the clustering of both sets of estimates around the same number, seven percent in this case, fits our *a priori* expectations.

5.5 Migration Differences in Differences with Controls

The individuals for whom we compare migration rates between the high and low regions may not be comparable. For example, they may differ in their age, race, and number and ages of children. In order to account for the differences between the groups of individuals, I estimate a number of logit equations for the probability of migrating between period t-1 and t. I take the underlying tendency to move to be

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[26] This assumption is only for purposes of interpretation. One may want to estimate these effects together since the difference in difference approach allows for an effect of the disruptions of migration or migration itself on welfare receipt.

$$(5.2) \qquad Y_i^* = X_i'\alpha_0 + \alpha_1 L_i + \alpha_2 S_i + \alpha_3 L_i{*}S_i + \varepsilon_i ,$$

for person i, i=1,...,N. One only observes Y_i, which equals 1 if $Y_i^* \geq 0$, implying that person i migrates; Y_i equals 0 otherwise. X_i is a vector of individual-level characteristics, L_i is a dummy variable for being in the low benefit region in period t-1, S_i is a dummy variable for being a single mother, and ε_i is an individual specific logistic error term. I estimate the logit equations:

$$(5.3) \qquad Prob(Y_i=1) \ = \ \lambda(X_i'\alpha_0 + \alpha_1 L_i + \alpha_2 S_i + \alpha_3 L_i{*}S_i) ,$$

where λ is the cumulative logistic distribution function.

Table 6 reports average derivative estimates calculated from estimates of α_3 in equation (5.3). The individual controls are age, age-squared, indicator variables for race and Spanish origin, number of children under six and its square, and the number of children under 18 and its square. In the specifications which include all education groups, I also include indicator variables for levels of educational attainment. The migration rate comparisons give a similar picture after accounting for these control variables that affect the likelihood of migration. Again, most of our comparisons in Table 6 suggest there is welfare induced migration. The comparison of all single mothers to all single childless women does not show evidence of welfare migration, but when I restrict the sample to high school dropouts there is some evidence of welfare induced migration. When I compare single mothers to married mothers in the full sample or in the high school dropout sample, I find evidence of welfare induced migration.

5.6 Participation Differences in Differences with Controls

In order to examine whether the results of Tables 4 and 5 are affected by the inclusion of control variables, I also estimate equations similar to (5.3) but for participation using the sample of single mothers. These estimates are reported in Table 7. The logit equations that I estimate are

$$(5.4) \qquad Prob(P_i=1) = \lambda(X_i'\beta_0 + \beta_1 H_i + \beta_2 M_i + \beta_3 H_i{*}M_i) ,$$

where P_i is an indicator variable for welfare participation by person i, H_i is an indicator variable for residing in the high region in period t, and M_i is an indicator for having moved into the current region in the last five years. The key explanatory variable is an indicator for being a migrant from the low region to the high region, i.e. an interaction of H_i and M_i. The average derivatives of the participation probability with respect to this variable are reported in Table 7. The comparisons of participation rates tend to indicate a smaller extent of excess participation after adding controls for individual characteristics. However, there is probably a strong case not to control for individual characteristics here. The characteristics of in-migrants should be endogenous, for example those with young children should be more likely to move to high benefit states. This difference is expected and is something one may not want to hold constant. One can also think of these estimates with controls as examining whether there is excess participation based on unobservables, i.e. are those that migrate to high benefit states more likely to participate in welfare for reasons besides those that can be attributed to measured characteristics. The results suggest that there is excess participation based on observable individual characteristics, but little based on unobservable characteristics.

5.7 Migration Estimates with Predicted Participation

This section builds on the idea that people with certain characteristics are more likely to participate in welfare and are thus more likely to migrate to obtain higher benefits. I test for welfare induced migration in the following two-step procedure using the samples of single mothers. I first estimate a logit equation for the probability of welfare participation. Let the predicted probability of participation be $\hat{P}_i$. I then estimate migration logit equations including the key explanatory variable $\hat{P}_i$ interacted with being in the low benefit region in period t-1. The logit equations include main effects for being in the low benefit region and for the probability of welfare participation. Specifically, I estimate the logit equations

$$(5.5) \qquad Prob(Y_i=1) = \lambda(X_i'\gamma_0 + \gamma_1 L_i + \gamma_2 \hat{P}_i + \gamma_3 L_i * \hat{P}_i) ,$$

on the sample of single mothers. These results are reported in the bottom panel of Table 6.[27] For all single mothers there is again little evidence of welfare induced migration. However, when the sample is restricted to high school dropouts, the estimates indicate the presence of welfare induced migration.

5.8 Accounting for Multiple Regions and Wages with a Conditional Logit Model

In this section I combine the ideas of comparison group based methods with the idea of comparing attributes of possible locations in a more structured way. I also examine migration at a finer geographic level than in the earlier two region analysis. The advantages of using a larger number of regions are that additional dimensions to migration can be studied, and the benefit differentials between the new regions provide an additional source of variation in the key explanatory variable. There also may be some aggregation bias in using large regions which is reduced by using a finer geographic division. This new approach also allows us to directly account for wage and unemployment differences across geographic areas.

The approach in this section is motivated by a random utility model. Assume that person i who is in location j in period t-1 has utility in location k in period t given by $S_i{*}Z_k{'}\delta_0 + C_{jk} + \varepsilon_{ijk}$, where S_i is an indicator for being a single mother, Z_k is a vector of characteristics of state k with coefficients δ_0 , C_{jk} is (minus) the cost of moving from j to k. The coefficients on $S_i{*}Z_k$ capture the differential effect of the characteristics of state k on high school dropout single mothers relative to the comparison group of either high school dropout single women without children or married mothers. We expect welfare benefits and other variables to affect single mothers differently than the comparison group. Note that C_{jk} also captures unmeasured characteristics of location k relative to location j that are common to single mothers and the group to which they are being compared.

Let P_{ijk} be the probability that individual i moves from state j in period t-1 to state k in period t. Then the likelihood for a sample of observations is:

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[27] The standard errors for these specifications in the table are likely understated as they do not account for the estimation of the first stage coefficients.

$$(5.6)\quad L=\prod_{i}\prod_{k}P_{ijk}^{Y_{ijk}},$$

where $Y_{ijk}=1$ if person i is in region j in period t-1 and region k in period t, and 0 otherwise. Under the assumption that ε_{ijk} is distributed i.i.d. extreme value,

$$(5.7)\quad P_{ijk}=\frac{e^{S_i*(Z_k-Z_j)'\delta_0\ +\ C_{jk}-C_{jj}}}{\sum_{m}e^{S_i*(Z_m-Z_j)'\delta_0\ +\ C_{jm}-C_{jj}}}.$$

Without loss of generality, we can set $C_{jj}=0$ so that the above expression simplifies to

$$(5.8)\quad P_{ijk}=\frac{e^{S_i*(Z_k-Z_j)'\delta_0\ +\ C_{jk}}}{\sum_{m}e^{S_i*(Z_m-Z_j)'\delta_0\ +\ C_{jm}}}.$$

In practice, we augment the model to allow for moving costs that vary with individual characteristics, and we allow the effect of these characteristics to be different for single mothers. We also allow single mothers to have an extra fixed cost of moving than the comparison group. Thus moving costs are $1_{\{j\neq k\}}X_i'\delta_1 + S_i{*}1_{\{j\neq k\}}X_i'\delta_2 + S_i{*}1_{\{j\neq k\}}\delta_3$ so that

$$(5.9)\quad P_{ijk}=\frac{e^{S_i*(Z_k-Z_j)'\delta_0\ +\ C_{jk}\ +\ 1_{\{j\neq k\}}X_i'\delta_1\ +\ S_i*1_{\{j\neq k\}}X_i'\delta_2\ +\ S_i*1_{\{j\neq k\}}\delta_3}}{\sum_{m}e^{S_i*(Z_m-Z_j)'\delta_0\ +\ C_{jm}\ +\ 1_{\{j\neq m\}}X_i'\delta_1\ +\ S_i*1_{\{j\neq m\}}X_i'\delta_2\ +\ S_i*1_{\{j\neq m\}}\delta_3}}.$$

The variables that I include in Z_k are the average AFDC plus Food Stamp annual benefit, average hourly wages, and the unemployment rate. The latter two variables are calculated from the Census data for the comparison group (either single women without children or married mothers). Since C_{jk} captures all region characteristics common to single mothers and single childless women, these coefficients account for regional differences in population size, employment growth, distance, climate and other factors that would be difficult to account for well parametrically. X_i includes indicator variables for race and age groups, the number of children under eighteen and the number of children under six. This approach blends structural methods which account for geographic wage differences and individual characteristics with comparison group based methods which account well for unobserved determinants of migration.

In the analysis reported below I use nine regions defined based on geographic proximity and welfare benefit similarity (the region definitions are given in Appendix 3). Nine is the largest feasible number of regions without null flows between regions that would cause computational difficulties in a nonlinear model.[28] To estimate δ_0 in (5.9), we do not directly insert (5.9) in the likelihood (5.6). In stead, we use a two-stage method which accounts for the dependence between the observations in each region. In the first stage we estimate with $C_{jk} + D_{jk} * S_i$ as the argument to the part of the exponential functions in (5.9) that are not individual specific. In the second stage we regress the D_{jk} estimates on $Z_k - Z_j$ and a constant using GLS. The weighting matrix for this second-stage is $\Omega = \sigma^2 I + V_D$, where V_D is the 72x72 variance matrix of the D_{jk} estimates. This approach follows that of Borjas and Sueyoshi (1994) for probit models and gives the appropriate standard errors.

Table 8 reports the two-stage conditional logit estimates for 1980 and 1990. With the inclusion of the C_{jk}s, the coefficients on the variables provide their effect on single mothers relative to either single women without children (top panel) or married mothers (bottom panel). The coefficient on AFDC plus Food Stamp benefits should be positive if there is welfare induced migration. This coefficient is always positive and usually significantly different from zero. Since employment should be less important to single mothers than to single women without children, in the top panel the coefficient on average wages should be negative, and the coefficient on the unemployment rate should be positive. For both 1980 and 1990, nearly all of the coefficients have the expected sign and in one-half of the cases are significantly different from zero. For the comparison of single and married mothers in the bottom panel, the predicted signs of the coefficients on wages and unemployment are less obvious, because the relative importance of

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[28] I initially tried six regions (defined by combining the nine Census regions) and obtained very similar point estimates (though somewhat lower ones for 1990), but the imprecision of the estimates suggested that a larger number of regions was preferable.

wages and unemployment for married and unmarried women is less clear. However, the coefficients are consistent with wages being less important for single mothers than for married mothers.

The mean of the welfare benefit coefficients in Table 8 is about 0.060 for 1980 and 0.085 for 1990. These magnitude imply that a $1000 increase in the benefit in a region would increase the migration to that region by about six to eight percent and reduce migration from that region by about the same amount.[29] Overall, the estimates imply that about 12 percent of migration during the five years prior to 1980 and about 17 percent of the migration during the five years prior to 1990 were due to higher benefits in the destination states.[30] These conditional logit estimates of nine regions indicate a benefit effect that is about twice as large as the earlier estimates. However, at least for the single women comparisons, larger estimates of the effect of benefits on migration are expected, given the positive correlation between wages and benefits and the lesser importance of employment to those with children than to those without children.

Another way of gauging the implied extent of welfare induced migration may be more relevant to a state deciding whether or not to raise its welfare benefits. Take the case of the Pacific Region (California, Oregon and Washington) where benefits were the highest among the regions in 1990 and the second highest in 1980. If the states of the Pacific Region raised their annual welfare benefits by $1000 the 1980 coefficients indicate that it would increase the flow of high-school dropout single mothers to their region by about 6.0 percent and the 1990 coefficients indicate an increase of about 8.5 percent. However, the flows of single mothers across states are low, so that these numbers translate into just under a 0.42 percent increase in the population of high-school dropout single mothers in the region in 1980 and a 0.46 percent increase in 1990 due

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[29] Note that $(dP/dZ)/P = \delta(1-P) \approx \delta$ for small P such as the off-diagonal transition probabilities. Thus, one can directly interpret the coefficient estimates as the approximate percentage change in the migration probability with a unit change in Z.

[30] This calculation is based on the mean difference between benefits in each region and those in higher benefit regions weighted by migration flows. This difference, which is slightly more than $2,000 for unadjusted benefits and slightly less than $2,000 for adjusted benefits in both years, is then multiplied by the coefficients of Table 8.

to flows over the previous five years.[31] These magnitudes may be important in some policy calculations, but they seem modest.

5.9 Accounting for Endogenous Educational Attainment and Fertility

This paper has emphasized how other behaviors that are affected by welfare benefits, such as welfare participation, fertility, marriage and educational attainment can be confused with welfare induced migration. In Table 9, I try the nine region conditional logit estimates for two alternative estimates which should be free of some of these biases. In the top panel of Table 9 examines whether endogenous educational attainment could be biasing the earlier results. I examine women who are 24-54 and would have made their decision to drop out of high school prior to moving across state lines. The estimates here are very close to those of Table 8 and indicate that endogenous dropping out is not a source of significant bias.

In the bottom panel, I examine women with only children that are five years old or older. These women would have given birth to their children prior to moving across state lines. Thus, it is unlikely that it was the higher benefits in a destination state that led to their fertility. For this sample, we could not calculate the estimates for 1975-1980. The estimates for migration from 1985-90 tend to be much smaller than the full sample estimates. However, even if the earlier estimates are unbiased, smaller estimates for those without young children might be expected given that they are likely to be on welfare for a shorter time period in the future.

5.10 A Graphical Examination of the Comparability of Groups

One way to determine if single women without children or married mothers are reasonable comparison groups for single mothers is to compare their migration rates. If two groups are affected in the same direction and magnitude by omitted determinants of migration, a graph of the

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[31] These calculations use that 7.00 percent of high-school dropout single mothers in the Pacific Region in 1980 lived in another region five years earlier, while the comparable figure for 1990 was 5.36 percent.

migration rates between areas for the two groups should show points clustered along the forty-five degree line. Figure 3 shows four graphs which compare the seventy-two off-diagonal transition probabilities between the nine regions for single women with and without children. The graphs are for 1980 and 1990, and for high-school dropouts and all education groups. In panels (a) and (b) one can see that high-school dropout single women with and without kids migrate to and from the same places at about the same rate. The R-squared around the 45-degree line is 0.764 in 1980 and 0.910 in 1990. One should note that deviations from the equality of the two rates come from both sampling error in the estimation of the rates and from welfare-induced migration. The near equality of migration rates for these two groups reinforces our earlier conclusion that there is not a high level of welfare-induced migration and suggests that single women without children are a reasonable comparison group for those with children. If one does not condition on being a high-school dropout as in panels (c) and (d) one can see that single women without children are a much less suitable comparison group for single mothers. The R-squared around the 45-degree line is now 0.155 in 1980 and 0.032 in 1990.

Figure 4 graphs this same information for unmarried and married mothers. High-school dropout married women appear to be a slightly worse comparison group than single childless women. However, the suitability of married mothers as a comparison group does not deteriorate when one includes all education groups, as was the pattern for single childless women. The R-squared for high-school dropouts is 0.667 in 1980 and 0.800 in 1990. For all education groups the R-squared is 0.677 in 1980 and 0.842 in 1990.

6. Estimates of the Long-Run Effects of Benefit Differentials

This paper has focused on the rate of interstate migration over a five-year period. However, for many policy questions we would like to know how the long-run distribution of single mothers or welfare recipients across states is changed by benefit differentials which persist over decades. In this section, I provide a scaling factor that can be used to adjust upward the five-year migration flows to obtain a long-run effect of interstate welfare benefit differentials.

To begin, let N_j be the number of people in a demographic group that moved because of welfare benefit differentials during the five-year period ending j years ago. I consider two demographic groups: all single mothers, and single mothers receiving AFDC. I also consider the subsamples of these two groups that did not finish high school. Let P_j be the probability that a person is still a single mother or single mother welfare recipient, given that j years ago she was one. Then the long-run number of people in a given group who have changed locations because of welfare benefit differentials is $L = N_0P_0 + N_5P_5 + N_{10}P_{10} + N_{15}P_{15} + \ldots$ This expressions sums the number of people that moved over each five year period times the probability that they are still single mothers or welfare recipients. Note that $P_0 = 1$, by definition. If we assume that $N_j = N_0$ for all j, i.e. that migration flows do not change over time, then we can rewrite L as $N_0 (1 + P_5 + P_{10} + P_{15} + \ldots)$. If P_{20} and later terms are small, then we can approximate the expression which multiplies N_0 using $P = 1 + P_5 + P_{10} + P_{15}$. To obtain long-run estimates of the effects of migration we only need to multiply the five-year flows by the factor P.

To estimate P we use 25 years of PSID data from 1968-1992. I examine women who are 18-54 when they are initially a member of the demographic group in question. Table 10 reports the estimates of the scaling factor P, as well as P_5, P_{10}, and P_{15}, for several demographic groups. I report estimates of P for those who moved across state lines during the five-year period in the past as well as those who did not move, because these latter samples are much larger and provide more precise estimates. While overall, the estimates of P vary from about 1.41 up to 3.04, the estimates from the larger samples of nonmovers range from 1.84 to 2.28. The estimates are larger for those who did not complete high school than for the sample with all education groups. The sample sizes for those who moved across state lines are so small that one cannot compare with any confidence the estimates for those who moved to those who did not. For all education levels, the P_{15} terms are sufficiently small that they suggest that ignoring later terms does not substantially understate the scaling factor. For high school dropouts, P_{15} is larger, so that there is probably some substantial understatement of the scaling factor due to stopping after 15 years. However, these calculations ignore population growth, mortality, and return migration, which in all cases bias upward these estimates of the long-run effect of benefit differentials. Overall, the estimates suggest that the long-run effects of benefit differentials are about two to two and one-half times those that we see in the five-year migration estimates.

7. Conclusions and Possible Extensions

This paper begins by examining a number of methodological problems in estimating the extent of welfare induced migration. These problems include biases that result from conditioning on welfare receipt in defining the population to study, from focusing on small pieces of overall migration, and from not having a suitable counterfactual to the level of migration in the absence of benefit differentials. I show that the biases from these problems, particularly the first one, are likely to be very large in practice. I report new results using a number of different methods which do not suffer from these problems. The methods include direct examination of migration rates to high and low benefit states, examination of participation rates of migrants to high and low benefit states, and an analysis of the migration of welfare prone individuals. I also estimate a multi-region conditional logit model of location which incorporates wages and unemployment.

The new methods suggest significant welfare induced migration, particularly for high-school dropouts. Even for this group the estimates are fairly modest in size, suggesting that over a five year period less than two percent of high-school dropout single mothers are induced to migrate to receive higher welfare benefits. The calculations in the paper also indicate that the long-run effects of migration are only about twice these five year effects. Even these modest estimates of welfare induced migration are biased upward to the extent that high welfare benefits encourage fertility and discourage marriage.

These estimates suggest that state governors and legislators should be more worried about the effect of benefit levels on participation by their own constituents, than about the effects of benefits on migration of single mothers. Still, the estimates suggest large proportional effects on the migration rates between very low benefit and very high benefit states, even though the absolute level of the flows may be small.

Further work is needed to answer several closely related questions. Since the location of single mothers depends on the level of welfare benefits, there is a bias in past work on the effects of welfare benefits on program participation, fertility and marriage (and possibly other outcomes) overstating the effect of welfare on these behaviors. Further work is needed to assess the magnitude of these biases. Additional work is also needed to fully reconcile the estimates presented here with those reported in previous studies.

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Appendix 1: The Magnitude of the Bias due to Endogenous Participation

Here we assess the magnitude of the bias in migration estimates when one conditions on welfare receipt in the second of two periods when defining the sample. First, make the simplifying assumption that $a=b$, and let k be the ratio of the number of people in group two (those that only participate in welfare when benefits are high) to the number of people in group one (those that participate in welfare when benefits are high or low). Also assume $c_{LH} = c_{HL} = \rho$. Then there is no true migration, i.e. $d = c_{LH} - c_{HL} = 0$. However, our estimate of migration is not d, but rather

$$d' = \frac{A_{LH} + B_{LH}}{A_{LH} + A_{LL} + B_{LH}} - \frac{A_{HL}}{A_{HH} + A_{HL} + B_{HH}}$$

Let $A_{LL} = \psi A_{LH}$ which implies $A_{HH} = \psi A_{HL}$. Now we can rewrite d' as

$$d' = \frac{A_{LH} + kA_{LH}}{A_{LH} + kA_{LH} + \psi A_{LH}} - \frac{A_{HL}}{\psi A_{HL} + + A_{HL} + k\psi A_{HL}}$$
$$= \frac{1 + k}{1 + k + \psi} - \frac{1}{\psi + 1 + k\psi}$$

Now, $\rho = \dfrac{A_{LH}}{A_{LL} + A_{LH}} = \dfrac{A_{LH}}{\psi A_{LH} + A_{LH}} = \dfrac{1}{\psi + 1}$ which implies that $\psi = \dfrac{1}{\rho} - 1$.

Substituting this expression for ψ in the expression for d' above yields

$$d' = \frac{\rho + \rho k}{k\rho + 1} - \frac{\rho}{1 + k - k\rho}$$ which is equation (5.1).

Appendix 2: How to Compare Migration and Participation Effect Magnitudes

This appendix provides a way of comparing the relative magnitude of estimates of welfare induced migration and estimates of excess welfare participation of migrants. Let f be the fractional increase in migration to the high region and let migration to the low region be reduced by the fraction f. Then the difference in difference estimate of welfare induced migration as a fraction of the typical inter-regional migration flow is an estimate of

$$\frac{1 + f - (1 - f)}{1} = 2f.$$

Let p be the welfare participation rate of those who would migrate in the absence of welfare benefit differentials across regions. Now suppose that those induced to migrate have a participation rate of $g > p$. Then the difference in difference estimate of excess participation induced by migration as a fraction of the typical participation rate is an estimate of

$$\frac{\left(\frac{p + gf}{1 + f} - \frac{p - gf}{(1-f)}\right)}{p} = \frac{\left(\frac{2f(g-p)}{1 - f^2}\right)}{p}.$$

Now, if we focus on high school dropouts, p is approximately 0.50 as can be seen in Table 5. If we assume that g is close to one, then, for small f, the expression above is approximately $2f$, i.e. the same percentage effect as for migration.

Appendix 3: Region Definitions

Northeast: Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont

Mid-Atlantic: Delaware, District of Columbia, Maryland, Pennsylvania, Virginia, West Virginia

South: Alabama, Arkansas, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee

Southeast: Florida, Georgia

Southwest: Arizona, Nevada, New Mexico, Texas

Central: Illinois, Indiana, Missouri, Ohio

North Central: Iowa, Michigan, Minnesota, Wisconsin

Mountain: Colorado, Idaho, Kansas, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, Wyoming

Pacific: California, Oregon, Washington

Figure 1

High and Low Welfare Benefit States
(1975-1979 Average AFDC + Food Stamp Benefit)

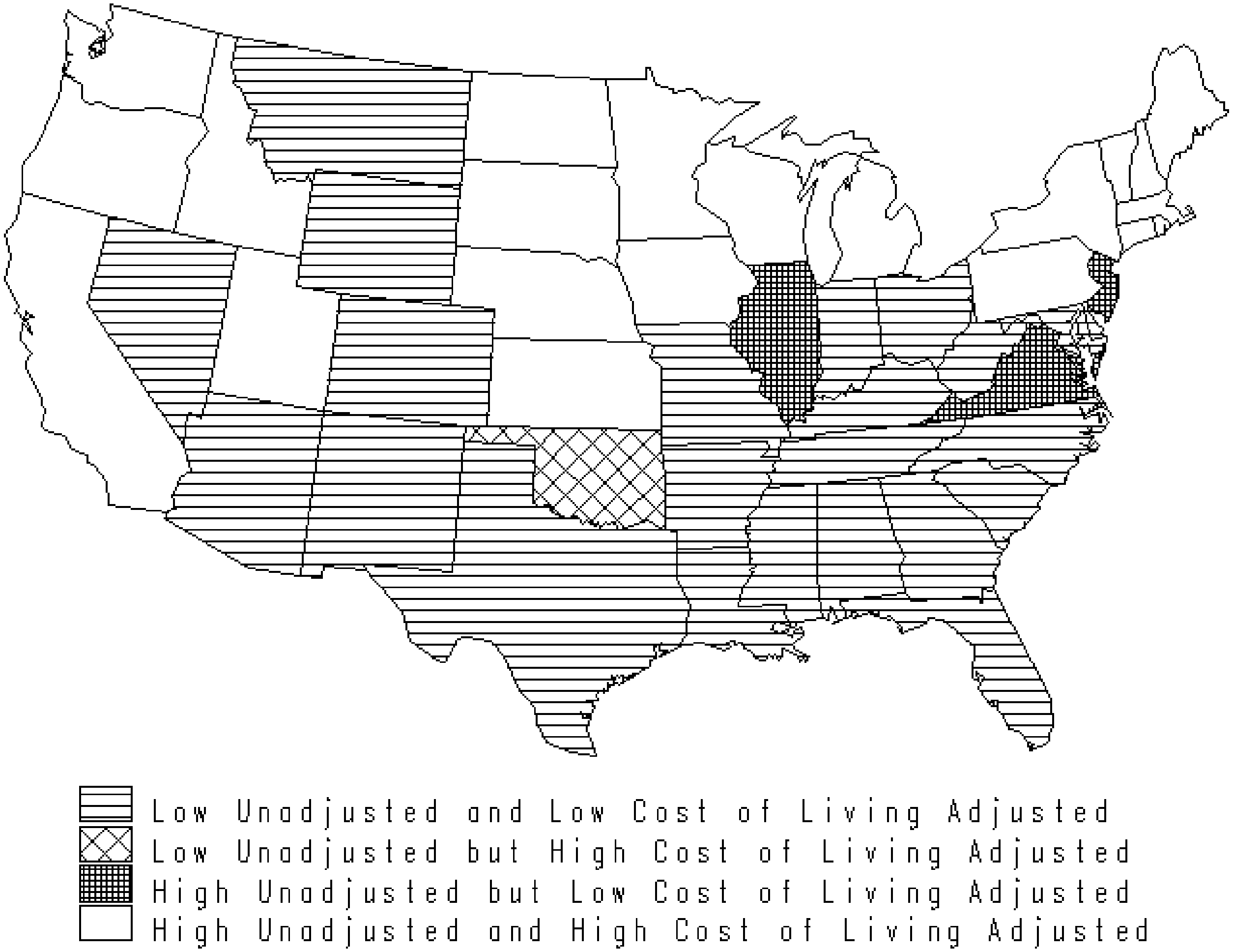


Figure 2

High and Low Welfare Benefit States

(1985-1989 Average AFDC + Food Stamp Benefit)

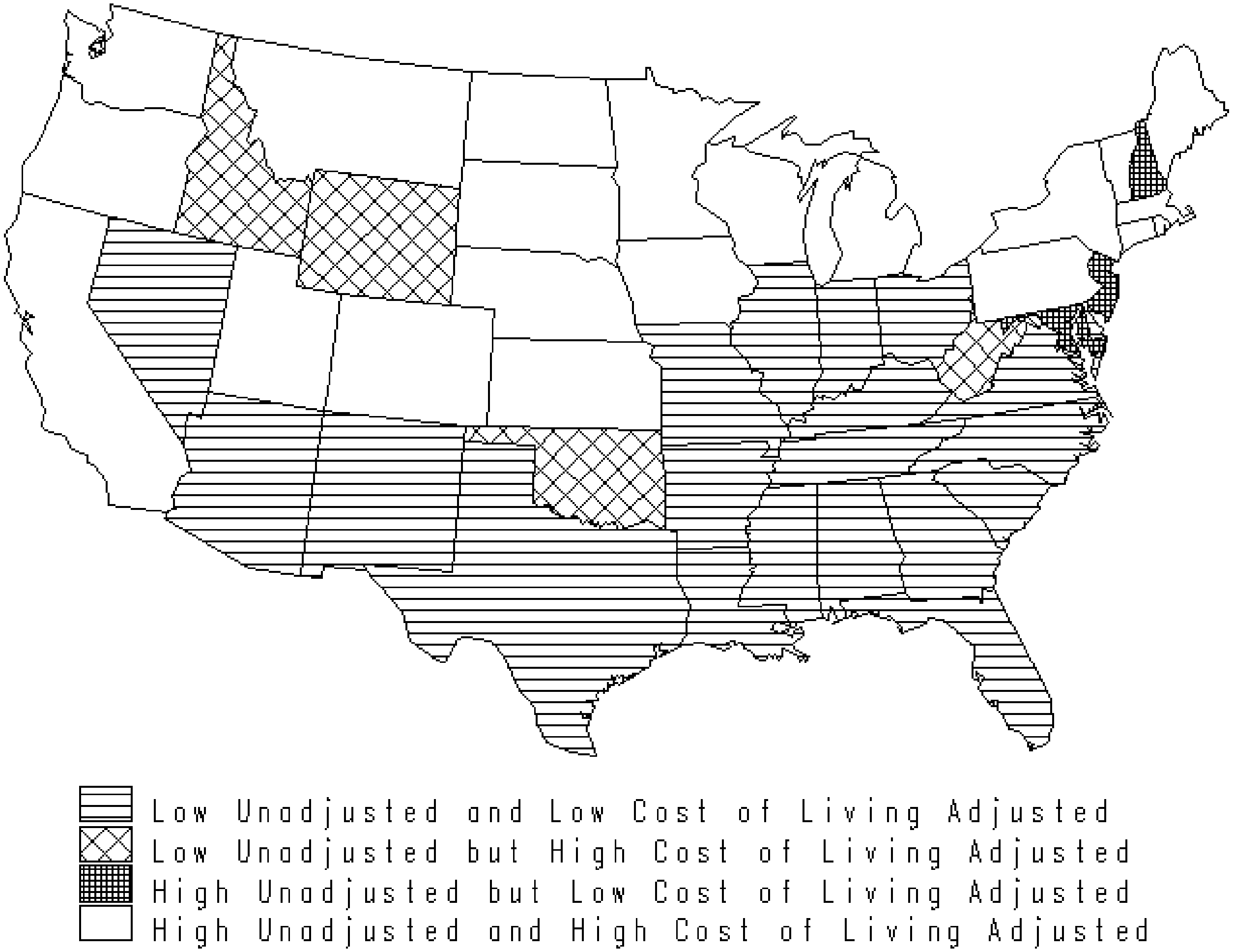


Figure 3

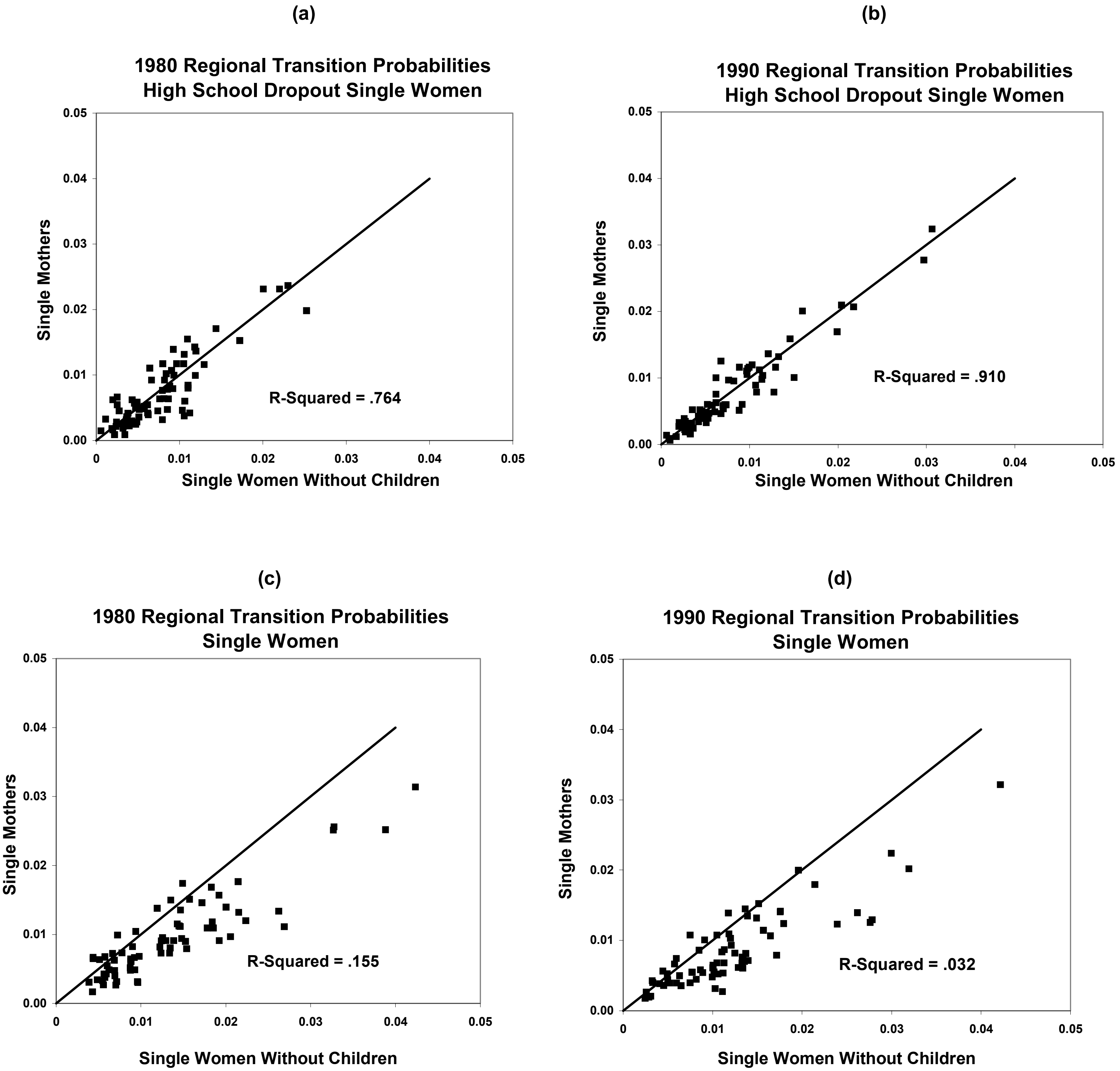
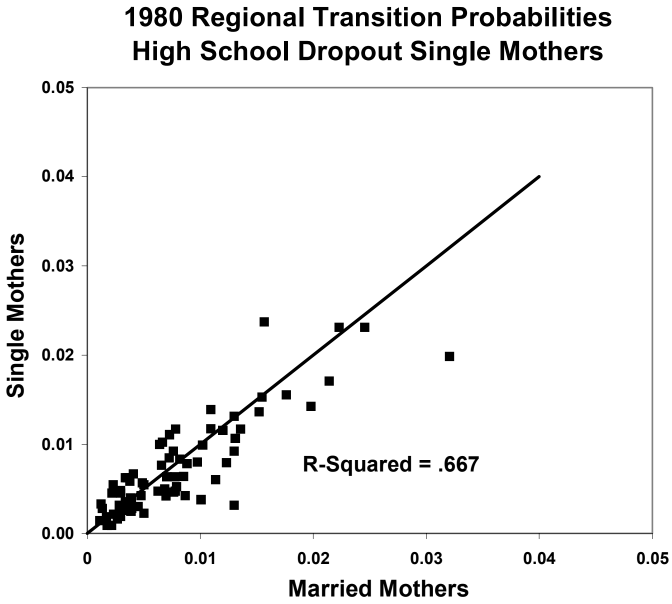
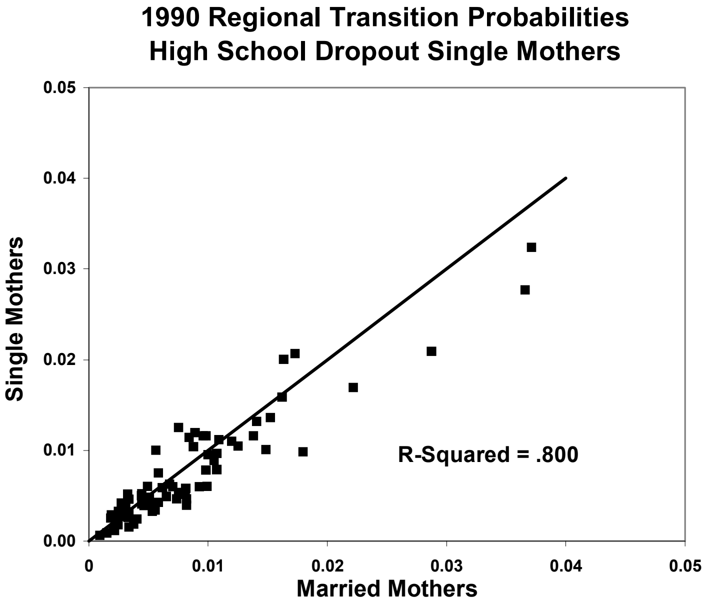

(a)
1980 Regional Transition Probabilities
High School Dropout Single Women
Single Mothers
Single Women Without Children
R-Squared = .764
0.00
0.01
0.02
0.03
0.04
0.05
0
0.01
0.02
0.03
0.04
0.05
(b)
1990 Regional Transition Probabilities
High School Dropout Single Women
Single Mothers
Single Women Without Children
R-Squared = .910
(c)
1980 Regional Transition Probabilities
Single Women
Single Mothers
Single Women Without Children
R-Squared = .155
(d)
1990 Regional Transition Probabilities
Single Women
Single Mothers
Single Women Without Children
R-Squared = .032

Figure 4

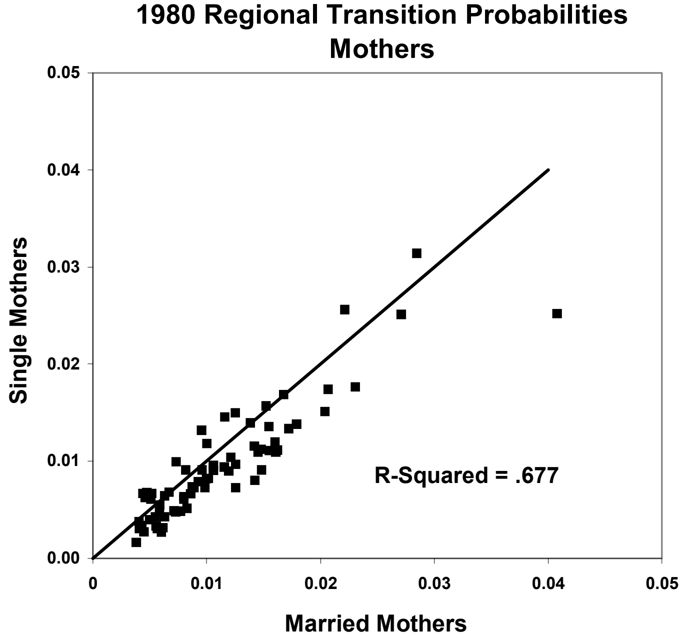
(a)



(b)



(c)



(d)

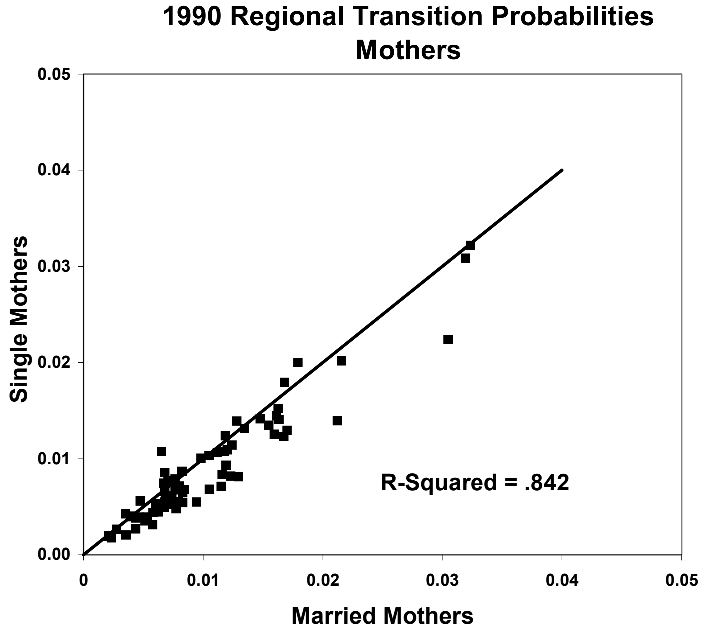


Table 1
Migration Rates Across Different Types of Geographic Areas

All Women	1975-1980	1985-1990
(1) Between States	0.11570	0.10681
	(0.0003)	(0.0002)
	N=1,159,975	N=2,553,159
(2) Between 2 Regions	0.05020	0.04421
	(0.0002)	(0.0001)
Adjusted for Housing Costs	0.05028	0.04752
	(0.0002)	(0.0001)
	N=1,159,975	N=2,553,159
(3) Between 9 Regions	0.08899	0.08222
	(0.2847)	(0.2747)
	N=1,159,975	N=2,553,159
(4) = (2) / (1)	0.43388	0.41391
Adjusted for Housing Costs	0.43457	0.44490
(5) = (3) / (1)	0.76914	0.76975
(6) Out of Multi-State Metro Areas		0.14244
		(0.0004)
		N=610,416
(7) Between States within Metro Areas		0.02170
		(0.0002)
		N=610,416
(8) = (6) / { (6) + (7) }		0.13220
SINGLE MOTHERS		
(9) Between States	0.09154	0.08579
	(0.0009)	(0.0006)
	N=96,576	N=248,080
(10) Between 2 Regions	0.04243	0.03687
	(0.0006)	(0.0004)
Adjusted for Housing Costs	0.04016	0.03796
	(0.0060)	(0.0004)
	N=96,576	N=248,080
(11) Between 9 Regions	0.07081	0.06717
	(0.2565)	(0.2503)
	N=96,576	N=248,080
(12) = (10) / (9)	0.46353	0.42978
Adjusted for Housing Costs	0.43864	0.44252
(13) = (11) / (9)	0.77356	0.78297
(14) Out of Multi-State Metro Areas		0.10347
		(0.0013)
		N=59,264
(15) Between States within Metro Areas		0.01667
		(0.0005)
		N=59,264
(16) = (15) / { (14) + (15) }		0.13875

Notes: (1) Standard errors are in parentheses, with sample sizes below them.
(2) The sampleconsists of those between the ages of 18 and 54 without imputed location in either year or imputed public assistance income.

Table 2
Migration Rates between High and Low Benefit Regions

	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) Single Women with Children on AFDC				
Low to High	0.06270	0.05102	0.04544	0.04600
	(0.0025)	(0.0020)	(0.0012)	(0.0012)
	N=9,186	N=12,231	N=28,629	N=29,828
High to Low	0.02589	0.02961	0.03379	0.03581
	(0.0012)	(0.0015)	(0.0011)	(0.0011)
	N=16,687	N=13,642	N=29,210	N=28,011
(2) Single Women with Children				
Low to High	0.04114	0.03455	0.03258	0.03064
	(0.0010)	(0.0008)	(0.0005)	(0.0005)
	N=43,117	N=53,455	N=132,495	N=140,615
High to Low	0.04347	0.04710	0.04180	0.04755
	(0.0009)	(0.0010)	(0.0006)	(0.0006)
	N=53,459	N=43,121	N=115,588	N=107,465
(3) Single Women without Children				
Low to High	0.05940	0.05317	0.04930	0.04641
	(0.0007)	(0.0006)	(0.0004)	(0.0003)
	N=119,792	N=155,817	N=327,291	N=362,714
High to Low	0.05399	0.06280	0.05210	0.06360
	(0.0005)	(0.0006)	(0.0004)	(0.0004)
	N=190,067	N=154,042	N=389,043	N=353,620
(4) Married Women with Children				
Low to High	0.04323	0.03817	0.03879	0.03709
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
	N=225,525	N=275,227	N=503,663	N=529,632
High to Low	0.05116	0.05751	0.04442	0.05331
	(0.0004)	(0.0005)	(0.0003)	(0.0003)
	N=283,260	N=233,258	N=515,831	N=489,862
(5) = (1) - (3)				
Low to High	0.00330	-0.00215	-0.00386	-0.00041
	(0.0026)	(0.0021)	(0.0013)	(0.0013)
High to Low	-0.02810	-0.03318	-0.01831	-0.02780
	(0.0013)	(0.0016)	(0.0011)	(0.0012)
Difference	0.03140	0.03103	0.01445	0.02738
	(0.0029)	(0.0026)	(0.0017)	(0.0017)
(6) = (1) - (4)				
Low to High	0.01947	0.01285	0.00665	0.00891
	(0.0026)	(0.0020)	(0.0013)	(0.0012)
High to Low	-0.02527	-0.02789	-0.01063	-0.01750
	(0.0013)	(0.0015)	(0.0011)	(0.0012)
Difference	0.04474	0.04074	0.01728	0.02641
	(0.0029)	(0.0025)	(0.0017)	(0.0017)
(7) = (2) - (3)				
Low to High	-0.01826	-0.01862	-0.01673	-0.01577
	(0.0012)	(0.0010)	(0.0006)	(0.0006)
High to Low	-0.01052	-0.01570	-0.01031	-0.01605
	(0.0010)	(0.0012)	(0.0007)	(0.0008)
Difference	-0.00774	-0.00292	-0.00642	0.00028
	(0.0016)	(0.0015)	(0.0009)	(0.0010)
(8) = (2) - (4)				
Low to High	-0.00209	-0.00362	-0.00622	-0.00645
	(0.0010)	(0.0009)	(0.0006)	(0.0005)
High to Low	-0.00769	-0.01041	-0.00263	-0.00576
	(0.0010)	(0.0011)	(0.0007)	(0.0007)
Difference	0.00560	0.00679	-0.00359	-0.00069
	(0.0014)	(0.0014)	(0.0009)	(0.0009)

Notes: See Table 1.

Table 3
Migration Rates between High and Low Benefit Regions
High School Dropouts Only

	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) Single Women with Children on AFDC				
Low to High	0.04647	0.03959	0.03646	0.03599
	(0.0029)	(0.0024)	(0.0016)	(0.0016)
	N=5,100	N=6,770	N=13,276	N=13,919
High to Low	0.02472	0.02945	0.02803	0.02923
	(0.0018)	(0.0022)	(0.0015)	(0.0016)
	N=7,849	N=6,179	N=11,453	N=10,810
(2) Single Women with Children				
Low to High	0.03014	0.02500	0.02638	0.02621
	(0.0014)	(0.0012)	(0.0009)	(0.0008)
	N=14,301	N=17,762	N=33,739	N=35,488
High to Low	0.03501	0.03949	0.03480	0.03910
	(0.0015)	(0.0018)	(0.0012)	(0.0013)
	N=15,312	N=11,851	N=24,997	N=23,248
(3) Single Women without Children				
Low to High	0.03129	0.02556	0.02639	0.02446
	(0.0011)	(0.0009)	(0.0007)	(0.0007)
	N=23,939	N=29,660	N=55,401	N=58,923
High to Low	0.03706	0.04082	0.03717	0.04327
	(0.0011)	(0.0013)	(0.0009)	(0.0010)
	N=27,550	N=21,829	N=49,287	N=45,765
(4) Married Women with Children				
Low to High	0.02456	0.02121	0.02519	0.02548
	(0.0007)	(0.0006)	(0.0006)	(0.0006)
	N=54,036	N=63,569	N=78,845	N=79,778
High to Low	0.04370	0.04592	0.03834	0.04406
	(0.0009)	(0.0011)	(0.0008)	(0.0008)
	N=48,580	N=39,047	N=60,538	N=59,605
(5) = (1) - (3)				
Low to High	0.01518	0.01403	0.01007	0.01154
	(0.0032)	(0.0025)	(0.0018)	(0.0017)
High to Low	-0.01234	-0.01137	-0.00914	-0.01403
	(0.0021)	(0.0025)	(0.0018)	(0.0019)
Difference	0.02752	0.02540	0.01921	0.02557
	(0.0038)	(0.0036)	(0.0025)	(0.0025)
(6) = (1) - (4)				
Low to High	0.02191	0.01839	0.01127	0.01051
	(0.0030)	(0.0024)	(0.0017)	(0.0017)
High to Low	-0.01898	-0.01647	-0.01031	-0.01483
	(0.0020)	(0.0024)	(0.0017)	(0.0018)
Difference	0.04089	0.03485	0.02158	0.02534
	(0.0036)	(0.0034)	(0.0024)	(0.0025)
(7) = (2) - (3)				
Low to High	-0.00115	-0.00056	-0.00001	0.00175
	(0.0018)	(0.0015)	(0.0011)	(0.0011)
High to Low	-0.00206	-0.00133	-0.00237	-0.00417
	(0.0019)	(0.0022)	(0.0014)	(0.0016)
Difference	0.00091	0.00077	0.00236	0.00592
	(0.0026)	(0.0027)	(0.0018)	(0.0019)
(8) = (2) - (4)				
Low to High	0.00558	0.00379	0.00119	0.00072
	(0.0016)	(0.0013)	(0.0010)	(0.0010)
High to Low	-0.00870	-0.00643	-0.00354	-0.00496
	(0.0018)	(0.0021)	(0.0014)	(0.0015)
Difference	0.01428	0.01022	0.00473	0.00568
	(0.0024)	(0.0025)	(0.0017)	(0.0018)

Notes: See Table 1.

Table 4
AFDC Participation Rates of Migrants and Non-Migrants In High and Low Benefit Regions

	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) Migrants				
High	0.32469	0.33785	0.30144	0.31848
	(0.0111)	(0.0110)	(0.0070)	(0.0071)
	N=1,774	N=1,847	N=4,316	N=4,308
Low	0.18589	0.19892	0.20431	0.19628
	(0.0081)	(0.0089)	(0.0058)	(0.0056)
	N=2,324	N=2,031	N=4,831	N=5,110
(2) Non-Migrants				
High	0.31788	0.32217	0.25483	0.26387
	(0.0021)	(0.0023)	(0.0013)	(0.0014)
	N=51,135	N=41,090	N=110,754	N=102,355
Low	0.20826	0.22491	0.21320	0.20876
	(0.0020)	(0.0019)	(0.0011)	(0.0011)
	N=41,343	N=51,608	N=128,179	N=136,307
(3) = (1) - (2)				
High	0.00681	0.01568	0.04661	0.05461
	(0.0113)	(0.0112)	(0.0071)	(0.0072)
Low	-0.02237	-0.02599	-0.00889	-0.01248
	(0.0083)	(0.0091)	(0.0059)	(0.0057)
High-Low	0.02918	0.04167	0.05550	0.06709
	(0.0140)	(0.0144)	(0.0092)	(0.0092)

Notes: See Table 1.

Table 5
AFDC Participation Rates of Migrants and Non-Migrants In High and Low Benefit Regions High School Dropouts Only

	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) Migrants				
High	0.54988	0.60360	0.54382	0.53871
	(0.0240)	(0.0232)	(0.0167)	(0.0163)
	N=431	N=444	N=890	N=930
Low	0.36194	0.38889	0.36897	0.34763
	(0.0208)	(0.0225)	(0.0164)	(0.0158)
	N=536	N=468	N=870	N=909
(2) Non-Migrants				
High	0.51807	0.52684	0.46139	0.47976
	(0.0041)	(0.0047)	(0.0032)	(0.0033)
	N=14,776	N=11,383	N=24,127	N=22,339
Low	0.35061	0.37545	0.38942	0.38827
	(0.0041)	(0.0037)	(0.0027)	(0.0026)
	N=13,870	N=17,318	N=32,849	N=34,558
(3) = (1) - (2)				
High	0.03181	0.07676	0.08243	0.05895
	(0.0243)	(0.0237)	(0.0170)	(0.0167)
Low	0.01133	0.01344	-0.02045	-0.04064
	(0.0211)	(0.0228)	(0.0166)	(0.0160)
High-Low	0.02048	0.06332	0.10288	0.09959
	(0.0322)	(0.0329)	(0.0238)	(0.0231)

Notes: See Table 1.

Table 6
Logit Migration Equation Estimates

SINGLE WOMEN	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) All Single Women				
No Controls	-0.15870	-0.14630	-0.20060	-0.12390
	(0.0359)	(0.0363)	(0.0239)	(0.0236)
	{-0.0079}	{-0.0074}	{-0.0090}	{-0.0059}
	N=406,435	N=406,435	N=964,414	N=964,414
With Controls	-0.20210	-0.15020	-0.23550	-0.13450
	(0.0361)	(0.0365)	(0.0240)	(0.0237)
	{-0.0100}	{-0.0075}	{-0.0105}	{-0.0064}
	N=406,435	N=406,435	N=964,414	N=964,414
(2) High School Dropouts Only				
No Controls	0.02050	0.01170	0.06780	0.17650
	(0.0820)	(0.0840)	(0.0601)	(0.0591)
	{0.0007}	{0.0004}	{0.0020}	{0.0055}
	N=81,102	N=81,102	N=163,424	N=163,424
With Controls	0.01110	0.02540	0.05960	0.19430
	(0.0823)	(0.0845)	(0.0604)	(0.0594)
	{0.0004}	{0.0008}	{0.0018}	{0.0060}
	N=81,102	N=81,102	N=163,424	N=163,424
MOTHERS				
(1) All Mothers				
No Controls	0.11920	0.10720	-0.11740	-0.07740
	(0.0349)	(0.0354)	(0.0235)	(0.0232)
	{0.0053}	{0.0047}	{-0.0046}	{-0.0032}
	N=605,361	N=605,361	N=1,267,574	N=1,267,574
With Controls	0.11890	0.13330	-0.13450	-0.07360
	(0.0350)	(0.0357)	(0.0237)	(0.0234)
	{0.0053}	{0.0058}	{-0.0052}	{-0.0030}
	N=605,361	N=605,361	N=1,267,574	N=1,267,574
With Predicted Probabilities	0.37360	0.19010	-0.26790	0.18200
	(0.1841)	(0.1881)	(0.1315)	(0.1306)
	{0.0151}	{0.0073}	{-0.0095}	{0.0066}
	N=96,576	N=96,576	N=248,080	N=248,080
(2) High School Dropouts Only				
No Controls	0.44140	0.32590	0.14780	0.15320
	(0.0748)	(0.0767)	(0.0575)	(0.0561)
	{0.0142}	{0.0096}	{0.0044}	{0.0049}
	N=132,229	N=132,229	N=198,119	N=198,119
With Controls	0.51410	0.41180	0.18910	0.22940
	(0.0752)	(0.0773)	(0.0581)	(0.0569)
	{0.0164}	{0.0121}	{0.0056}	{0.0072}
	N=132,229	N=132,229	N=198,119	N=198,119
With Predicted Probabilities	1.56820	1.22890	1.14780	1.46150
	(0.3996)	(0.4105)	(0.3246)	(0.3226)
	{0.0493}	{0.0365}	{0.0332}	{0.0440}
	N=29,613	N=29,613	N=58,736	N=58,736

Notes: (1) The coefficient reported is that on the interaction of being in a low benefit state in year t-1 * being a single mother or of being in a low benefit state in year t-1 * the predicted probability of welfare participation. (2) Standard errors are reported in parentheses and average derivatives in braces. (3) The controls in the all single women and all mothers samples are education dummies, race dummies, age, age squared, number of children under 7, number of children under 7 squared, number of children under 18, and number of children under 18 squared. In the dropout sample, education dummy variables are dropped.

Table 7
Logit Participation Equation Estimates

SINGLE MOTHERS	1975-1980	1975-1980 Adjusted for Housing Costs	1985-1990	1985-1990 Adjusted for Housing Costs
(1) All Single Women				
No Controls	0.17270	0.22670	0.28640	0.34250
	(0.0752)	(0.0757)	(0.0497)	(0.0490)
	{0.0333}	{0.0439}	{0.0511}	{0.0609}
	N=96,576	N=96,576	N=248,080	N=248,080
With Controls	-0.14880	-0.12870	0.07160	0.07040
	(0.0829)	(0.0840)	(0.0544)	(0.0537)
	{-0.0235}	{-0.0204}	{0.0107}	{0.0106}
	N=96,576	N=96,576	N=248,080	N=248,080
(2) High School Dropouts Only				
No Controls	0.07850	0.25610	0.41740	0.45110
	(0.1343)	(0.1379)	(0.0988)	(0.0974)
	{0.0188}	{0.0615}	{0.1011}	{0.1091}
	N=29,613	N=29,613	N=58,736	N=58,736
With Controls	-0.08770	0.07580	0.27750	0.27040
	(0.1433)	(0.1471)	(0.1037)	(0.1021)
	{-0.0184}	{0.0160}	{0.0606}	{0.0589}
	N=29,613	N=29,613	N=58,736	N=58,736

Notes: (1) The coefficient reported is a dummy variable for being a migrant to the high region. See notes (2) and (3) of Table 6.

Table 8
Nine Region Conditional Logit Estimates for High School Dropout Single Women and Mothers

Explanatory Variables	Time Period and Specification					
	1975-1980			1985-1990		
	Mean (S.D.)	(1)	(2)	Mean (S.D.)	(3)	(4)
SINGLE WOMEN						
Hourly Wage ($)	3.104 (0.335)	-0.525 (0.358)	-0.423 (0.278)	4.635 (0.723)	-0.239 (0.062)	-0.173 (0.044)
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.788)	0.047 (0.041)		8.581 (1.575)	0.072 (0.018)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.491 (1.530)		0.046 (0.039)	8.588 (1.089)		0.107 (0.018)
Unemployment Rate (%)	12.78 (02.82)	6.149 (2.164)	8.631 (2.195)	14.24 (02.45)	-1.180 (2.160)	0.878 (1.940)
Single Mother Indicator		0.020 (0.083)	0.021 (0.083)		-0.061 (0.055)	0.071 (0.055)
Sample Size	51,489	81,102	81,102	104,688	163,424	163,424
MOTHERS						
Hourly Wage ($)	2.488 (0.444)	-0.068 (0.188)	-0.035 (0.194)	4.247 (0.693)	-0.109 (0.098)	-0.067 (0.070)
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.787)	0.075 (0.020)		8.581 (1.576)	0.064 (0.024)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.490 (1.530)		0.078 (0.024)	8.588 (1.089)		0.103 (0.023)
Unemployment Rate (%)	10.70 (02.89)	2.247 (2.042)	2.575 (2.097)	11.50 (02.44)	-2.551 (1.712)	-1.375 (1.473)
Single Mother Indicator		-0.244 (0.065)	-0.244 (0.066)		-0.347 (0.051)	-0.342 (0.050)
Sample Size	102,616	132,229	132,229	139,383	198,119	198,119

Notes: (1) The numbers reported are the coefficient estimates, with standard errors in parentheses underneath.(2) The wage, benefit and unemployment rate variables are interacted with an indicator for single motherhood. (3) All specifications include indicator variables for interactions of each origin and destination region.

Table 9
Nine Region Conditional Logit Estimates from Alternative Samples

Explanatory Variables	Time Period and Specification					
	1975-1980			1985-1990		
	Mean (S.D.)	(1)	(2)	Mean (S.D.)	(3)	(4)
High School Dropout Single Women and Mothers Age 24-54						
SINGLE WOMEN						
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.788)	0.062 (0.051)		8.581 (1.575)	0.098 (0.021)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.491 (1.530)		0.068 (0.048)	8.588 (1.089)		0.130 (0.023)
Sample Size	51,489	46,637	46,637	104,688	101,171	101,171
MOTHERS						
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.787)	0.059 (0.022)		8.581 (1.576)	0.051 (0.026)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.490 (1.530)		0.064 (0.026)	8.588 (1.089)		0.083 (0.026)
Sample Size	102,616	112,236	112,236	139,383	171,813	171,813
High School Dropout Single Women and Mothers Only with Kids 5+						
SINGLE WOMEN						
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.788)			8.581 (1.575)	-0.001 (0.022)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.491 (1.530)			8.588 (1.089)		0.025 (0.024)
Sample Size	51,489			104,688	136,416	136,416
MOTHERS						
Annual AFDC+Food Stamp Benefit (1000s 1996$)	9.531 (1.787)			8.581 (1.576)	0.004 (0.026)	
Adj. Annual AFDC+Food Stamp Benefit ($1000s)	9.490 (1.530)			8.588 (1.089)		0.040 (0.026)
Sample Size	102,616			139,383	115,579	115,579

Notes: See Table 8.

Table 10
Ratio of Long-Run Effects to Five-Year Migration Rates

	P_5	P_{10}	P_{15}	Ratio = $1+P_5+P_{10}+P_{15}$
All Welfare Recipients				
Movers	0.310	0.156	0.063	1.529
	N=227	N=119	N=59	
Non-Movers	0.449	0.299	0.127	1.876
	N=4,399	N=2,543	N=1,072	
HS Dropout Welfare Recipients				
Movers	0.392	0.230	0.082	1.704
	N=105	N=64	N=37	
Non-Movers	0.532	0.372	0.197	2.101
	N=2,565	N=1,585	N=689	
All Single Mothers				
Movers	0.556	0.373	0.180	2.110
	N=644	N=340	N=161	
Non-Movers	0.555	0.368	0.208	2.131
	N=10,020	N=5,680	N=2,336	
HS Dropout Single Mothers				
Movers	0.607	0.604	0.372	2.583
	N=191	N=107	N=56	
Non-Movers	0.614	0.425	0.268	2.307
	N=4,382	N=2,747	N=1,187	

Notes: These numbers are calculated using the 1968-1992 PSID excluding the low-income subsample and are weighted. P_x is the probability that a person with given characteristics (single mother, welfare recipient) has those characteristics x years later. See the text for further details.