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Migration among Low-Income Households:

Helping the Witch Doctors Reach Consensus

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Abstract

Do states with high welfare benefits attract low-income people from other states? Using data from the County to County Migration Flow Files from the 1980 census, I investigate this question by reintroducing migration rates into the definition of welfare migrants and examining situations in which a person moves from one state to a neighboring state whose welfare benefits are appreciably higher. I find no compelling evidence in support of the welfare magnet theory; my results are as likely to validate as they are to refute the hypothesis.

Migration among Low-Income Households: Helping the Witch Doctors Reach Consensus

1. INTRODUCTION

Tom Corbett's 1991 *Focus* article, "The Wisconsin Welfare Magnet Debate: What Is an Ordinary Member of the Tribe to Do When the Witch Doctors Disagree?" presents a fine overview of recent research and policy discussions on this long-standing and emotive public policy issue. The notion of a welfare magnet is deceivingly simple—the interstate relocation of persons for the purpose of securing higher welfare benefits (Corbett 1991)—and in light of the research effort directed at measuring its force, one would expect a consensus to have emerged. However, the issue remains far from resolved for reasons that are not hard to understand. The operative word in the definition of a welfare magnet is *purpose*. In-migration by low-income individuals is not sufficient to identify a welfare magnet; instead, individuals must be drawn (and retained) with the intent of obtaining higher welfare benefits. With the existing data and statistical methodology, distinguishing this motive from all the other reasons people move is impossible. Consequently, efforts to confirm the existence of welfare magnets have relied on low standards of proof. The definitions of a welfare migrant used in many studies have been too general (e.g., "any nonnative state resident receiving AFDC") to be useful; such broad classifications capture other behaviors in addition to welfare migration. Indeed, the standards of evidence have been so low that it is common practice for studies to find "evidence" of welfare magnets without using data on migration rates (e.g., Peterson and Rom [1990])!

Although I too cannot isolate any one reason why someone may have relocated, I can still test the validity of the welfare magnet hypothesis. In this paper I reintroduce migration rates into the definition of welfare magnets and adopt a different perspective than has been employed in the existing literature. Whereas prior studies have used detailed covariates and highly aggregated geographical regions to analyze migration behavior, I employ fine-grained geographical information and crude covariate structures of the County to County Migration Flow File from the 1980 census. I examine short-distance moves between contiguous states; in most cases, the moves I consider are between contiguous counties in those states. Thus, the possibility that the people in my sample relocated in order to be in a different climate or a different labor market, or to be considerably closer to friends and family members, should not come into play. If my sample members moved from one county in one state to a contiguous county in another state, a likely reason was to take advantage of state-specific benefits, such as welfare. According to the welfare magnet hypothesis, individuals most likely to receive such benefits are more likely to move to a high-benefit state or remain in a high-benefit state. I evaluate this hypothesis by comparing the interstate migration rates of poor young women with those of nonpoor young women and poor young men. Contrary to the recent literature, I find no empirical support for the welfare magnet hypothesis. Migratory responses by poor young women are as likely to disagree as they are to agree with the conjectured forces of welfare magnets. When they do agree responses are weak and never statistically significant. The data provide no strong evidence that welfare magnets have either an attractive or retentive force.

The structure of the paper is as follows. Section two reviews the empirical evidence in support of the welfare magnet hypothesis. Section three presents my operational definition of welfare magnets. Section four introduces the County to County Migration Flow database and section five describes the simple statistical approach used to analyze these data. Section six contains the empirical results and section seven concludes the paper.

2. EMPIRICAL EVIDENCE ON WELFARE MAGNETS

There is a voluminous literature on this long-standing issue. The early studies from the 1960s and 1970s produced controversial and conflicting results and failed to settle the debate. Researchers during the 1980s did reach a consensus, however, in part because of the low standards of evidence applied.

The older analyses used aggregate data from the 1960 and 1970 decennial censuses. Much of this work correlated gross migration rates of blacks with AFDC benefits (though usually the rates were not disaggregated by gender). Covariates, such as the aggregate unemployment rate, were used to control for local economic conditions, though usually only in the destination state (and usually they were not disaggregated by race). Almost invariably the estimated regression coefficient of the benefit variable was positive and statistically significant. The historical context of the data makes the interpretation less than straightforward, as these censuses fall within the Great Migration of blacks from the rural South to the urban North.[1] Were individuals moving for better welfare benefits, or were they moving for better economic opportunities? better housing? less discrimination? It was not possible to sort out these motives with the available aggregate data or the regressions that were used.

Recent studies have used microlevel data from the Panel Study of Income Dynamics, the 1980 decennial census, and the demographic supplement of the Current Population Survey to measure the effects of welfare magnets. A consensus is slowly emerging:[2]

> . . . while interstate migration is indeed a rare event, its impact is not unimportant. . . . the probabilities indicate that if AFDC families should happen to make an interstate move, they are much more likely to go to a state with higher AFDC benefits. In the long run, even this sluggish and apparently unimportant mobility can alter the interstate distribution of the AFDC population substantially.
> Gramlich and Laren (1984, p. 506)

> I have found that welfare payments, along with other economic variables, have a significant effect on the location and migration decisions of female headed households.
> Blank (1988, p. 208)

> State redistributive policies are less generous than a national policy in part because low-income people are sensitive to interstate difference in welfare policy. . . . over time, as people make major adjustments about whether they should move or remain where they are, they take into account the level of welfare a state provides and the extent to which that level is increasing. The poor do this roughly to the same extent

> that they respond to differences in wage opportunities in other states. Peterson and Rom (1990, p. 83)

> Using a variety of data sets, covering periods up to 1985, the [recent] studies all show positive and significant effects of welfare on residential location and geographic mobility. Moffitt (1992, p. 34)

The most amazing aspect of these studies is that only Blank analyzed individual location decisions. Peterson and Rom correlated changes in the proportion of the state's population living in poverty with changes in AFDC benefits. Gramlich and Laren analyzed the distribution of AFDC recipients across states as a function of own-state benefits and lagged benefits from other states. Blank's study is superior to the other two, and yet invoked strong functional form assumptions and imposed a highly aggregated geographical definition of localities.

Yet, it is instructive to compare Long's (1988) conservative assessment of subsidized job-search and relocation-assistance programs with the growing consensus on welfare magnets just quoted.

> A number of experimental programs aimed at [persons who live in areas of persistent economic hardship, like Appalachia or the rural South, and are unlikely to secure employment where they live] have been tried from time to time as a means of reducing poverty and increasing national output by matching workers and jobs. Evaluating these programs has been difficult, however. Although the costs are known, measuring the benefits tends to be elusive. Almost any return migration may be interpreted as program failure, and a perennial question is whether the programs simply pay for migration that would have occurred anyway. (Pp. 169–170.)

Long cites an evaluation of a program during the late 1960s and early 1970s to relocate workers from the Mississippi delta to growing markets with a stronger demand for labor. Remarkably, within thirteen months fully 61 percent of the relocatees returned to their original locations. (This is after more than a quarter of the eligible population declined the opportunity to relocate.) I find it interesting that relocation programs are viewed as unsuccessful while interstate differences in welfare benefits are perceived as exerting positive and significant effects on residential choice and geographical mobility. While the conclusions from the two literatures need not be mutually inconsistent—the central issue of both literatures is the effect of economic incentives on geographical mobility—I find it unsettling that they reach different conclusions. It suggests we should take a closer look at the evidence before accepting the nascent consensus on welfare magnets.

3. A SIMPLE MODEL OF WELFARE MIGRATION

Two observations motivate my simple model of welfare migration. First, people move for any number of pecuniary and nonpecuniary reasons, suggesting that any interesting model of migration should not rely on differences in welfare benefits as the sole determinant of migration. Second, recent research on welfare dynamics reports that welfare spells are usually short (the median duration is twenty-four months) and that welfare dependency is best seen as a dynamic process in which individuals continuously enter and exit the welfare rolls (Blank and Ruggles 1993; Gottschalk and Moffitt 1994). Consequently, I adopt a dynamic perspective and consider a model with two locations. Each location is characterized by an income stream, y_t^j, $j=1,2$ (net of welfare benefits), and a location-specific amenity, a^j, $j=1,2$ such that $y_t^2 > y_t^1$ and $a^2 < a^1$.[3] To highlight non-welfare-related motives for migration, assume initially that welfare benefits in both locations equal zero. In each location j and at each instant t, individuals are "born" and "die" with rates k_t^j and e_t^j, respectively. "Birth" in this context means the creation of an individual potentially eligible to receive welfare benefits; "death" means an exit from eligibility for welfare (e.g., remarriage). While these rates are affected by economic conditions—for example, a growing economy will reduce birth rates and decrease death rates—I assume that the birth and death rates are independent of welfare benefit levels and consumer preferences.

Individuals are otherwise homogenous but differ in their valuation of the amenity. Denote preferences as $U[y^j(t), a^j; \alpha]$, indexed by the scalar parameter α defined on the unit interval ($\alpha \in [0,1]$) with distribution function $\rho(\alpha)$. Preferences are parameterized so that higher values of α denote greater preferences for income. Some individuals will be born in their preferred location while all others must move to their preferred location. I assume that the environment is stationary and that individuals face no cost of migration. Consequently, migration occurs immediately following birth. Finally, since the model focuses on migratory flows and not income and prices, it assumes that migration exerts no influence on prices and incomes.

Under perfect certainty, an infinitely lived individual with preferences of type α will prefer to reside in location 1 if it offers the highest utility; that is, if

$$V_1(\alpha) = \sum_{t=0}^{\infty}(1+\delta)^{-t}U(y_t^1, a^1) \geq \sum_{t=0}^{\infty}(1+\delta)^{-t}U(y_t^2, a^2) = V_2(\alpha), \tag{1}$$

where δ is the discount rate and $V_j(\alpha)$ is the discounted lifetime utility flow of residing in location j. The marginal individual, defined as being indifferent between the two locations, has preferences α_n, implicitly defined as

$$V_1(\alpha_n) = V_2(\alpha_n). \tag{2}$$

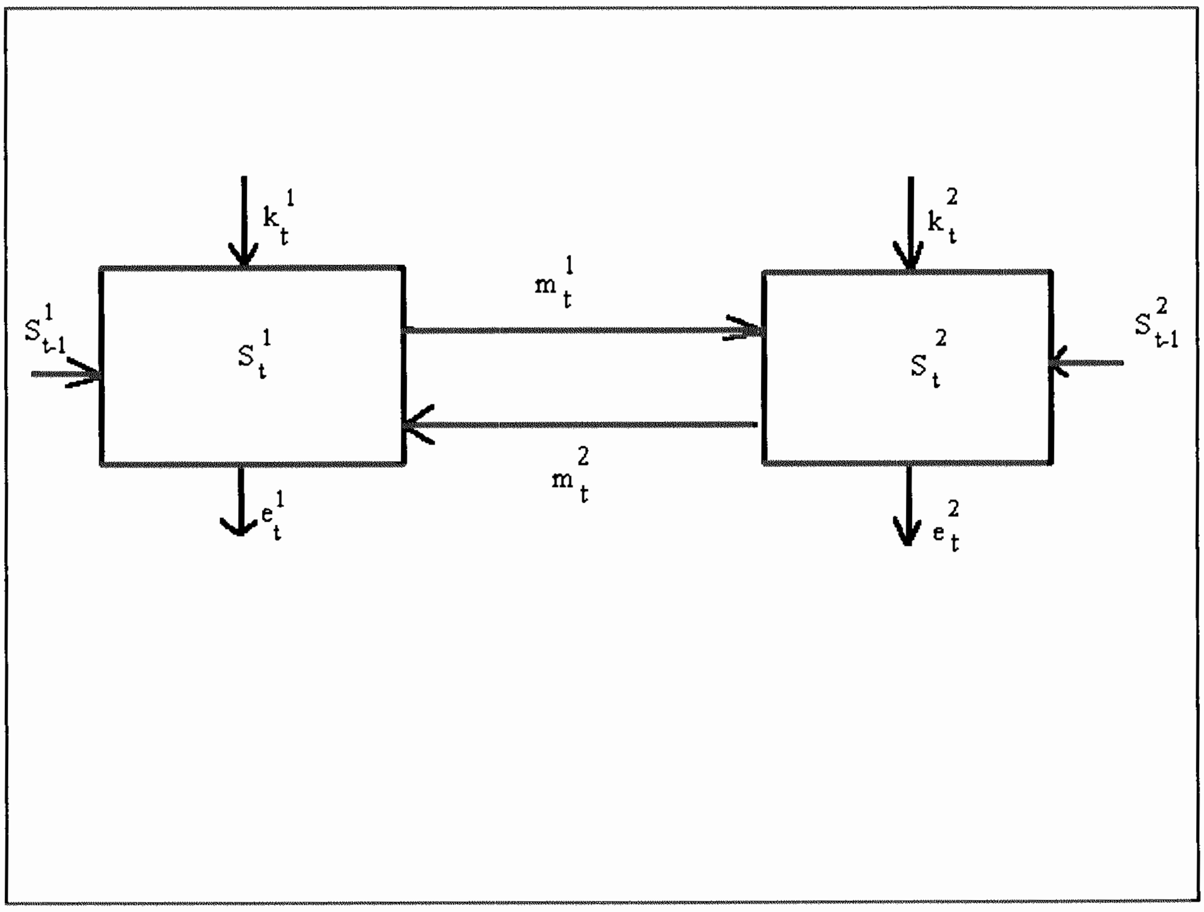
Since larger values of α correspond to stronger preferences for income, individuals with preferences indexed by α less than α_n will prefer location 1; conversely, those with preferences indexed by α larger than α_n will prefer location 2. The proportion of individuals who prefer location 1 is

$$G(\alpha_n) = \int_0^{\alpha_n} d\rho(\alpha) \tag{3}$$

and those who prefer location 2 equals $1\text{-}G(\alpha_n)$.

To define the equilibrium, denote the population at time t in location j as S_t^j and the migration flow from location j as m_t^j. Figure 1 presents the various flows in the system at time t. As Figure 1 indicates, the stock of individuals at location 1 at time t equals last period's stock plus this

Figure 1
A Diagrammatic Representation of
The Simple Model of Welfare Migration



where
e_t^i = exit rate from location i in period t;
k_t^i = inflow rate into location i in period t;
m_t^i = migration rate from location i in period t;
S_t^i = population in location i in period t.

period's births and in-migration less this period's deaths and out-migration; the same is true for location 2:

$$
\begin{aligned}
S_t^1 &= S_{t-1}^1 + k_t^1 + m_t^2 - e_t^1 - m_t^1 \\
S_t^2 &= S_{t-1}^2 + k_t^2 + m_t^1 - e_t^1 - m_t^2.
\end{aligned}
\tag{4}
$$

Assume exit rates are a fixed (exogenous) proportion of the stock at each location, $e_t^i = \delta^i S_{t-1}^i,\ \ i=1,2$.

The assumption that birth and death rates are independent of preferences implies that a proportion, $G(\alpha_n)$, of births will prefer to reside in location 1 and $1-G(\alpha_n)$ will prefer location 2. This means that $m_t^2 = G(\alpha_n)k_t^2$ individuals born in location 2 will move to location 1 and $m_t^1 = (1-G(\alpha_n))k_t^1$ individuals will move from location 1 to 2. Using the assumed stationarity of the environment ($k_t^1 = k^1$, etc.), we can substitute for the exit and migration rates and solve for the steady state populations at each location:

$$
\begin{aligned}
S^1 &= \frac{G(\alpha_n)(k^1 + k^2)}{\delta^1} \\
S^2 &= \frac{(1 - G(\alpha_n))(k^1 + k^2)}{\delta^2}.
\end{aligned}
\tag{5}
$$

Migration occurs in this model as people correct for the "accidents of birth"; even in the absence of differences in welfare benefits migration occurs as individuals move into their preferred location. Moreover, only if exit rates are identical will the share of the population residing in each locality be identical to the proportion of births preferring that location.

Now consider the effect of a difference in welfare benefits between the two locations. Assume location 1 is the welfare magnet and offers benefits b so that income there equals $y_t^1 + b$. Location 2 does not offer benefits and income remains unchanged at y_t^2. The additional income at location 1 will induce some individuals who previously preferred location 2 to now prefer location 1.

(Everyone who preferred location 1 previously will continue to prefer it.) Consequently, the indifferent individual will have preferences characterized by a larger value of α. Denote this critical value as α_b. The structure of the model is otherwise unchanged, and the steady state solution from equation (5) applies with a change in the critical value from α_n to α_b:

$$S^1 = \frac{G(\alpha_b)(k^1 + k^2)}{\delta^1}$$
$$S^2 = \frac{(1-G(\alpha_b))(k^1 + k^2)}{\delta^2}. \tag{6}$$

Notice population shares are relevant to the welfare magnet hypothesis only to the extent that sufficient information exists to control for economic and social factors leading to differences in birth and death rates. Assuming that such differences can be controlled, the model suggests two cross-sectional analyses that will estimate the force of welfare magnets. Since welfare benefits are attractive only to individuals who expect to be eligible to use them, comparisons of migration rates by groups according to their eligibility are informative. The equilibrium conditions in equation (5) assume no difference in benefits between regions and summarize the migration patterns of individuals not eligible to receive benefits. Individuals eligible to receive benefits will behave according to equation (6). The net migration rate (the difference between the in-migration rate and the out-migration rate) for location 1 (the welfare magnet) by individuals influenced by welfare benefits equals $M_b = G(a_b)k^2 - (1-G(a_b))k^1$, while the net migration rate of individuals uninfluenced by differences in welfare benefits across regions is $M_n = G(a_n)k^2 - (1-G(a_n))k^1$. While M_b and M_n may be positive or negative, the difference M_b - M_n must be positive, as $\alpha_b > \alpha_n$. The force of the magnet depends on the size of the locality's own birth rate and that of the sending locality.

By the same logic, equations (5) and (6) yield comparable predictions of the migration flows of the welfare-influenced subpopulation for magnets and nonmagnet regions. The net migration by the welfare-influenced group into the welfare magnet equals M_b, while that into the nonmagnet equals M_n.

The higher net migration rate by the welfare magnet can be decomposed into two sources: (1) the increased in-migration from location 2 (i.e., the "attractive" force of the magnet), which in equilibrium equals $[G(\alpha_b)-G(\alpha_n)]k^2$; and (2) the reduced out-migration from the magnet (i.e., the retentive force of the magnet) equal to $-[G(\alpha_b)-G(\alpha_n)]k^1$. Both forces are positive though not necessarily equal. Whether the attractive force or the retentive is larger depends on the relative magnitudes of birth rates. An analysis of only net migration rates, while informative, disregards precious information on its subflows.

It is also natural to think of intertemporal comparisons for subpopulations or regions. For example, an increase in relative benefits will induce in-migration and will retard out-migration. To recover these effects with cross-sectional data I must assume that the migratory response to a change in benefits falls neatly within the sample interval used to measure migration. A large but rapid response within a long interval or a modest but slow response over a short interval will both appear as negligible responses in the cross-sectional data. In practical terms the speed of adjustment relates to how quickly individuals learn about the change in benefits. Arguments supporting both fast and slow learning appear in the literature. With no data to discriminate any conjectured adjustment mechanism or to control for all other factors affecting migration (represented by the birth and death rates), I did not pursue time series comparisons.

Consideration of these time series comparisons, however, highlights the key assumption necessary for my analysis to recover the effect of welfare benefits on migration. Temporal comparisons invoke notions of disequilibrium and are fundamentally different than the equilibrium comparisons described above. Time series comparisons assume that the stocks of eligibles are fixed and migration occurs in response to (temporal) changes in benefits. In the equilibrium models presented above, benefit levels are constant and migration occurs from the churning of the population at risk generated by the birth and death processes. The assumed exogeneity of the births and deaths plays the central role in recovering migratory responses to differences in welfare benefits from cross-sectional data. Any intertemporal linkage between the population at risk and the benefit level invalidates my analysis. For example, recent work on the intergenerational transmission of welfare dependence suggests that daughters are more likely to receive welfare if raised in homes receiving welfare. With persistence in the relative generosity of benefits across states, if the mother moved in response to higher benefits the daughter would not need to move, and my measures of welfare-induced migration will understate the true effect. Similarly, if individuals move to a high-benefit area in anticipation of drawing benefits, the population at risk will not be independent of the benefit rate, and my analysis will again understate the true effect. Indeed, the understatement will increase the more foresight individuals have. For this problem a long migration window is an advantage.

The theoretical model offers little guidance on implementation and particularly on the proper level of geographical disaggregation. It is a nontrivial issue because data requirements and computational demands grow as the definition of locations becomes finer. The importance of labor market factors in locational decisions suggests that localities should be considered as different only if their labor markets are different. The size of the local labor market will differ depending on the individual's characteristics and labor market skills. However, local labor markets are presumably geographically small for low-income individuals, and so one would prefer a detailed, highly disaggregated representation of locations. Yet, discrete choice estimation procedures impose severe restrictions on the number of alternative locations. One can think of the existing studies as using fine covariates and aggregate geographical measures to measure welfare magnets. This study uses gross covariate structures and fine geographical partitions to measure the same behavior. Hence, this analysis provides alternative estimates of welfare magnets to assess the robustness of the earlier findings.

The basic premise of this paper is that each welfare magnet (defined below) is bordered by at least one state that should not be a welfare magnet. The analysis avoids determining subtle differences in individual decision-making by concentrating on the interstate movement of individuals among border counties of contiguous states (though I control for some county characteristics such as the crime rate and unemployment rate). Although welfare migrants may come from noncontiguous states, presumably potential magnetic effects should be strongest on border and near-border communities. These moves will be short-distance moves, and it is unlikely they are climate- or job-related or motivated by a desire to be closer to friends and family. Most importantly, individuals in border and near-border communities should be well-informed about welfare benefits and other local conditions in all surrounding counties. By assuming that all excess migration by low-income women of childbearing age is welfare induced, the analysis provides an upper bound on the magnitude of welfare magnets. Because it cannot identify the intent of migrants (except by assumption), the analysis cannot "prove" the existence of magnets, but it can invalidate the welfare magnet hypothesis.

4. DEFINING WELFARE MAGNETS IN 1980

The Food Stamp (FS) program and the program Aid to Families with Dependent Children (AFDC) are the two major assistance programs available to low-income households.[4] Whereas FS is a national program with a common set of rules across states, AFDC is administered locally and benefits are determined at the state level. AFDC benefits are set independently of FS transfers, but AFDC benefits are recognized as household income in the determination of FS eligibility. Consequently, families in a high AFDC benefit state (e.g., California) receive lower FS benefits than do families living in a low AFDC benefit state (e.g., Mississippi). To recognize these program interdependencies, I measure welfare benefits as the combined AFDC and FS monthly payment to a family of three.

Using this definition, I consider differences in monthly benefits between states of $85 or more to be larger for two reasons. First, policy debates in the Wisconsin legislature and the popular press during the mid-1980s labeled Wisconsin as a welfare magnet for Illinois residents. Since the mid-1970s the difference between Wisconsin and Illinois in FS-AFDC benefits for a family of three has remained between $90–$100.[5] Second, the empirical distribution of benefit differences across states suggests that a difference of $85 or more is large.

States with large benefits run the risk of being a magnet, while states with low benefits may be a source of migrants. The difference between the state's benefit and the minimum benefit in adjacent states identifies possible sources of in-migration, while the difference between the state's benefit and the maximum benefit in adjacent states identifies possible sources of welfare-driven out-migration. Table 1 shows the combined Food Stamp and AFDC monthly benefit for a family of three in constant 1980 dollars for calendar years 1975 and 1980. Columns three and six report the minimum combined benefit in an adjacent state for 1975 and 1980, while columns four and seven report the maximum combined monthly benefit in an adjacent state for those years. The decline in real benefits is striking; only three states increased their real benefits between 1975 and 1980. The decline in the variability of combined benefits is less striking but also present. Notice the decline in the standard deviation of benefits between 1975 and 1980 and the decline in the mean difference between the maximum and minimum in adjacent states. Apparently, states used the Food Stamp program to offset lower real AFDC benefits. As shown in the columns listing adjacent state maximum and minimum benefits, it is unusual for adjacent states to offer widely disparate benefit levels.[6] Notice that many of the differences are between 40 and 60 dollars per month with a few differences more than about $85.

TABLE 1

Total Combined Monthly Food Stamp and Aid to Families with Dependent Children Benefits in 1975 and 1980

		1975			1980		
State	Number of Adjacent States (1)	Own Combined Benefit (2)	Minimum Combined Benefit in an Adjacent State (3)	Maximum Combined Benefit in an Adjacent State (4)	Own Combined Benefit (5)	Minimum Combined Benefit in an Adjacent State (6)	Maximum Combined Benefit in an Adjacent State (7)
Alabama	4	$335	$244	$376	$279	$257	$347
Arizona	4	397	403	540	352	365	542
Arkansas	6	355	244	456	322	257	408
California	3	540	397	588	542	352	408
Colorado	6	456	403	570	414	365	463
Connecticut	3	598	502	582	543	449	486
Delaware	3	460	437	558	397	400	463
Florida	2	376	335	353	347	279	325
Georgia	4	353	317	376	325	279	347
Idaho	6	547	432	588	437	392	531
Illinois	5	504	349	593	412	342	521
Indiana	4	437	421	584	389	342	508
Iowa	6	541	349	593	463	384	521
Kansas	4	570	349	456	452	384	428
Kentucky	7	421	344	512	342	283	428
Louisiana	3	358	244	355	313	257	322
Maine	1	411	556	556	407	453	453
Maryland	4	437	444	543	400	355	443
Massachusetts	5	502	523	598	476	449	555
Michigan	3	584	437	593	508	389	521
Minnesota	4	580	529	593	502	435	521
Mississippi	4	244	335	358	257	279	322
Missouri	8	349	344	570	384	283	463
Montana	4	439	476	547	392	431	444
Nebraska	6	448	349	570	428	384	463
Nevada	5	432	397	588	394	352	542
New Hampshire	3	556	411	571	453	407	555
New Jersey	3	558	460	582	463	397	486
New Mexico	5	403	345	495	365	277	463
New York	3	582	543	598	486	443	555
North Carolina	3	419	317	512	345	283	428
North Dakota	3	529	439	580	444	392	502
Ohio	5	442	421	584	395	342	508
Oklahoma	6	456	345	570	408	277	452
Oregon	4	588	432	564	408	394	542
Pennsylvania	6	543	437	582	443	355	486
Rhode Island	2	523	502	598	449	476	543
South Carolina	2	317	353	419	290	325	345
South Dakota	6	535	439	580	435	392	502
Tennessee	9	344	244	512	283	257	428
Texas	4	345	355	456	277	313	408
Utah	6	495	397	547	463	352	437

(table continues)

TABLE 1, continued

State	Number of Adjacent States (1)	1975 Own Combined Benefit (2)	1975 Minimum Combined Benefit in an Adjacent State (3)	1975 Maximum Combined Benefit in an Adjacent State (4)	1980 Own Combined Benefit (5)	1980 Minimum Combined Benefit in an Adjacent State (6)	1980 Maximum Combined Benefit in an Adjacent State (7)
Vermont	3	571	502	582	555	453	486
Virginia	5	512	344	444	428	283	400
Washington	2	564	547	588	531	408	437
West Virginia	5	444	421	543	355	342	443
Wisconsin	4	593	504	584	521	412	508
Wyoming	6	476	439	547	431	392	463
Mean		$468			$410		
Standard Deviation		$89			$75		
Mean (Max - Min)			$124			$102	

Source: *1991 Green Book.*

Note: Benefits are for three-person families.

Figures 2 and 3 show the magnetic flows of welfare magnets in 1975 and 1980. In 1975, several large clusters of differences between state benefit levels existed. Benefits in Kansas and California exceeded benefits in all surrounding states while Missouri and Mississippi had significantly lower benefits than most of their neighbors. A couple of new differences appeared in 1980, but nearly all of the large differences were eliminated.

The analysis focuses on three magnets: Wisconsin (a magnet to Illinois), Michigan (a magnet to Indiana and Ohio), and Virginia (a magnet to Tennessee). The analysis uses the border counties of these states and border counties of all states contiguous to the three magnets. To be considered a magnet, in both 1975 and 1980 a state had to offer combined FS and AFDC benefits that were at least $85 greater than those offered by a neighboring state. This requirement eliminated several of the 1975 magnets. Long's (1988) comprehensive review of internal migration patterns documents the substantial, continual westward flow of migrants during the twentieth century. California's natural resources, climate, and historical position have made it a magnet for all Americans for the last century and a half. Consequently, I excluded California from the analysis. Also, because the populations on the Oklahoma-Texas and Utah-Arizona-New Mexico borders are sparse and the counties are large relative to counties east of the Mississippi, I excluded the Oklahoma and Utah magnets.

4. DATA

The data used for this analysis are from the County to County Migration Flow File developed from the 1980 census. It identifies all intercounty flows within states and each intercounty flow of at least 100 persons among states. Twenty-two separate cross-tabulations summarize the joint distribution of various combinations of the migrant's age, race, gender, income, occupation,

Figure 2
Welfare Magnet Flows 1975

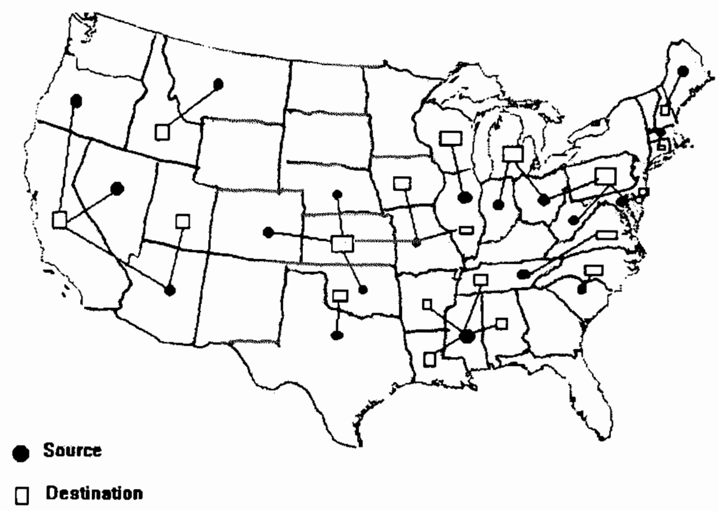
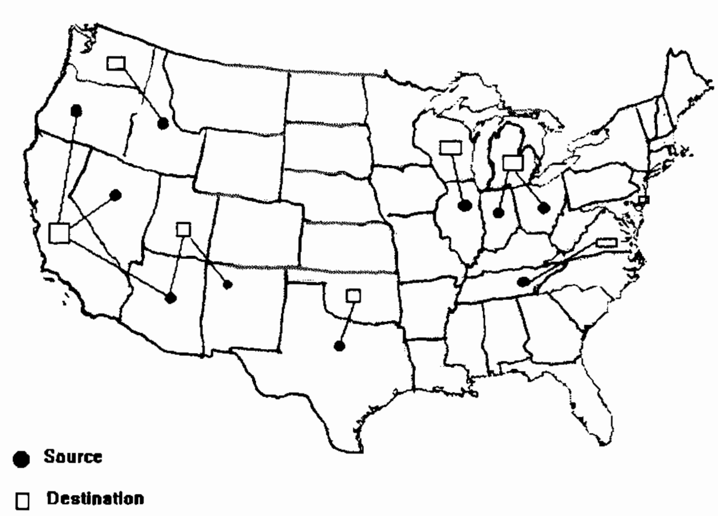


Figure 3
Welfare Magnet Flows 1980



education, industry, college attendance, and armed forces status. My analysis uses a three-way tabulation of migration by gender, age, and income.

The analysis selects all border counties of the conjectured magnets and the surrounding states. The basic unit of analysis is a county-to-county migration flow for each age, income, and gender cell. With a few exceptions associated with large metropolitan areas (e.g., Chicago and Milwaukee) the intercounty flows are restricted to be between contiguous counties. The analysis file includes therefore both intrastate and interstate migration flows. Information on county-specific conditions (unemployment rate, the crime rate, per capita tax rates, government expenditures, and the number of physicians) is matched from the County and City Data Bank.[7] "Great Circle" distances between counties are obtained for county population centroids from the Master Area Reference File 1980.[8]

Two serious limitations plague the County to County Migration Flow data. First, migration is defined relative to a five-year migration window so that sample migration rates underestimate population migration rates. Individuals living in different locations in 1975 and 1980 are considered migrants. Individuals who move and return to their 1975 county by 1980 are classified as nonmigrants. Similarly, individuals with repeated moves between 1975 and 1980 will have at most one move recorded during the migration window.

The second major limitation is that the income measure refers to the individual's 1979 income. Unfortunately, income for calendar year 1979 may reflect neither premigration nor postmigration income. Possible endogeneity issues arise as the reported income may be the result of the move. The sparseness of the covariate structure of the data precludes constructing potential instruments.[9] Moreover, nonworking married women may report having zero income, yet may live in households with substantial resources. Inspection of the data reveals that women are far more likely than men to have no income. As a partial solution, I exclude the lowest income group when defining low-income ("poor") households.

5. STATISTICAL PROCEDURES

I use two statistical approaches to measure the influence of welfare benefits on migration behavior. The first recognizes the discrete nature of the migration count data including the large number of zero migration flows. The second approach uses the panel nature of the data to estimate the equivalent of a fixed-effect model that controls for the identities of the sending and receiving counties. This parameterization has the advantage of a simpler interpretative basis at the cost of less attention to zeros and counts. I describe each approach in turn.

The first approach uses a simple nonlinear regression framework to model the discrete migration counts. Let Y_k denote the number of migrants for the kth intercounty migration stream (recall that the unit of analysis is a county-to-county migration flow) and X_k the associated (exogenous) covariate vector. I assume that for each observation k:

$$
\begin{aligned}
Y_k &= E[Y_k|X_k] + \epsilon_k \\
Y_k &= \lambda(X_k,\beta) + \epsilon_k \\
\lambda(X_k,\beta) &= \exp(x_k'\beta) \\
E[\epsilon_k|X_k] &= 0 \\
Var(\epsilon_k) &= \sigma^2(x_k) ,
\end{aligned}
\tag{7}
$$

where β is the parameter vector to be estimated. This representation of the conditional mean function has the desirable feature that all predicted counts from the model will be positive. As an added advantage, this representation is nearly identical to the popular Poisson regression model. Indeed, the only difference between it and my specification is that I do not impose the Poisson assumption that the conditional mean and variance are equal. At the cost of being less efficient than the Poisson regression model (when a Poisson is the true model), the nonlinear least squares estimator is consistent for a broad class of models. For example, except for the intercept term, the nonlinear least squares estimator is consistent for both the Poisson and negative binomial models or any member of the linear exponential family.[10] Gourieroux et al. (1984a, 1984b) label estimators for the linear exponential family a "pseudo maximum likelihood estimator" (more commonly referred to as a "quasi-maximum likelihood estimator"). Yet, nomenclature aside, the key property is the orthogonality condition specified in equation (7). Specification of the density only determines the most efficient estimator, which in practice means parameterizing the form of conditional heteroscedasticity. A more robust approach is to estimate robust (Huber-White) standard errors.[11] Since the nonlinear least squares estimator nests the Poisson regression model as a special case, the interpretative insight and intuition gained from the latter model can be applied directly. There seems to be little gained by thinking about quasi-maximum likelihood estimation; the estimation problem is more usefully thought of as recovering a conditional mean function (i.e., a standard regression problem).[12]

The second approach uses ordinary least squares with the dependent variable defined as the ratio of migration rates. An advantage of this procedure is that it controls for the characteristics of the receiving and sending counties. The analysis of the count data uses gross covariates to control for the characteristics of the sending and receiving counties. However, other unmeasured factors may make particular county-to-county flows different, such as chain migration, whereby past migration between counties has built strong informational and other connections between counties which serve to raise migration rates in the current period. Also, unmeasured aggregate shocks, such as labor market conditions, may affect all age groups or both genders equally, but will have differential spatial effects. There may be something special about Cook County (Chicago) which is not captured by the simple covariates of the first approach. The present analysis does so.

In this analysis the dependent variable is the ratio of county-specific migration rates of the welfare-influenced subpopulation to the migration rate of a comparable group expected to be uninfluenced by welfare benefits. Poor young women represent the welfare-sensitive group, while two parameterizations—nonpoor young women and poor young men—are employed for the comparison groups. Separately neither group is completely adequate, but together they are informative. Again, county-to-county flows are the unit of analysis. Rather than including all of the age, gender, and income groups, this analysis uses only those observations needed to construct the dependent variable.

To see the relationship between the count and rate regressions, let poor young men represent the comparison group, and index by k each of the county-to-county flows. For example, Milwaukee County to Cook County will be one flow and Cook to Milwaukee will be another. Let Y_k^F denote the migration rate (per thousand) of poor young women moving along the kth county-to-county flow; let Y_k^M denote the migration rate of poor young men moving along the same flow. Assuming a counting model with multiplicative errors is correct, then in logarithms, the counting model for these two subgroups is[13]

$$\begin{aligned} \log Y_k^F &= x_k'\beta^F + \nu_k^F \\ \log Y_k^M &= x_k'\beta^M + \nu_k^M. \end{aligned} \tag{8}$$

Taking differences, and assuming that the migration rate of males is nonzero, the estimating equation is

$$\log\left(Y_k^F / Y_k^M\right) = x_k'\delta + \eta_k, \tag{9}$$

where $\delta=\beta^F - \beta^M$.[14] The regressors will include controls for distance, an indicator variable for whether the flow crosses state boundaries, and a measure of welfare benefits at the sending and receiving locations. In this parameterization, if welfare magnets exist the estimated coefficient on the welfare benefit variable should be positive. That is, poor young women should have a greater responsiveness to the benefits than should poor young men or nonpoor young women. The primary advantage of this approach over the first is that it controls for idiosyncratic factors at the source and destination locations. I estimate equation (9) using ordinary least squares and report White-Huber standard errors.

6. EMPIRICAL RESULTS

I present three forms of evidence on the force of welfare magnets. The first is a descriptive analysis that compares unadjusted county-level migration flows. I then present evidence from the analysis of counts (regression approach 1, section 6.2) and the regression analysis of the pairwise ratio of migration rates which controls for source and end destination (regression approach 2, section 6.3).

6.1 Descriptive Analysis

Table 2 reports descriptive statistics on the variables used in the analysis. The unit of analysis is the migration flow from one border county to another. Relatively few individuals (approximately seven individuals, or slightly more than eleven per thousand) in each age, income, and gender cell migrate between counties, suggesting the usefulness of the counting model. Few individual characteristics are reported, reflecting the tabular nature of the data. To reduce the number of estimated parameters in the models I pooled some of the age and income cells. As an attempt to

TABLE 2

Descriptive Statistics: Border Counties of Migration Flow File
(Number of Observations 142,435)

Description		Mean	Std.
Migration and Population Variables			
cnt	Number of migrants	7.9728	64.724
exps	Population count	1098.0	5898.7
rate	Number of migrants per 1000 population	11.078	45.056
dist	Distance in miles between destination and origin	26.752	12.984
Individual Characteristics			
poor	Binary variable = 1 if 0 < income < $5000	0.2402	0.4272
young	Binary variable = 1 if age ≤ 44	0.5880	0.4922
female	Binary variable = 1 if female	0.4788	0.4996
ism	Binary variable = 1 interstate move	0.1832	0.3868
pf	Poor*female	0.1204	0.3254
py	Poor*young	0.1439	0.3510
yf	Young*female	0.2792	0.4486
pyf	Poor*young*female	0.0722	0.2588
Benefit Variables (and Interactions)			
db	Difference in benefits (destination - source)	-1.4167	27.368
fdb	Female*db	-0.6749	19.061
pdb	Poor*db	-0.3499	13.235
ydb	Young*db	-0.8264	21.075
pfdb	Poor*female*db	-0.1756	9.361
pydb	Poor*young*db	-0.2097	10.252
yfdb	Young*female*db	-0.3917	14.618
pyfdb	Poor*young*female*db	-0.1055	7.251
ATM	Binary variable = 1 if benefits in destination - source > $85	0.0190	0.1365
REM	Binary variable = 1 if benefits in source - destination > $85	0.0176	0.1317
fATM	Female**ATM*	0.0092	0.0957
fREM	Female**REM*	0.0086	0.0924
pATM	Poor**ATM*	0.0044	0.0658

(table continues)

TABLE 2, continued

Description		Mean	Std.
Benefit Variables (and Interactions), continued			
pREM	Poor**REM*	0.0041	0.0637
yATM	Young**ATM*	0.0113	0.1056
pfATM	Poor*female**ATM*	0.0022	0.0446
pfREM	Poor*female**REM*	0.0020	0.0451
pyATM	Poor*young**ATM*	0.0026	0.0510
pyREM	Poor*young**REM*	0.0024	0.0494
yfATM	Young*female**ATM*	0.0054	0.0736
yfREM	Young*female**REM*	0.0051	0.0711
pyfATM	Poor*young*female**ATM*	0.0013	0.0361
pyfREM	Poor*young*female**REM*	0.0012	0.0345
Location Characteristics			
f_wi	Binary variable = 1 if flow state = WI	0.0801	0.2713
f_mi	Binary variable = 1 if flow state = MI	0.0400	0.1959
f_va	Binary variable = 1 if flow state = VA	0.1127	0.3163
dcrate	Difference in crime rates	-3.5025	2046.0
dptax	Difference in property taxes	0.1788	59.549
dge	Difference in government expend	-2.6168	207.4
dphy	Difference in number of physicians	11.902	1297.2
dune	Difference in unemployment rate	-0.1969	21.435

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

approximate age groups with dependent children living in the household I pooled the three youngest age groups (ages 16–24, 25–34, and 35–44). Women in these age groups were defined as "young." The poverty line for a family of three was approximately $5000 in 1980. The three lowest income classes fell in or near the official poverty line in 1980. However, as mentioned above, the lowest income class was "no income." I suspected that many of the women reporting no income had no earned income, but lived in nonpoor households. Consequently, I excluded this group and only considered households having nonzero income below $5000 as "poor" (income groups 2 and 3). By this measure approximately 25 percent of the migratory flows represented movement by poor people. I defer the discussion of the benefit variables and county covariates until the review of the regression estimates. First, I present some descriptive evidence on migration patterns in my sample and preliminary evidence on welfare magnets.

Figure 4 presents box plots of mean migration rates by gender, age group, income group, and distance. Box plots offer a simple description of the distribution. The third and first quartile of the distribution define the top and bottom of the box; the distribution's median is the line in the interior of the box. The lines emanating from the box extend to the 10th and 90th percentiles. The patterns reported in Figure 4 replicate many of the migratory patterns documented in the literature (e.g., Long 1988). The most distinctive feature, representing the restriction to migration streams between contiguous (and nearly contiguous) counties, is the compressed distance distribution. For these short-distance streams, females are slightly more likely to migrate than are males, and the gradient of income is only weakly positive. A steep age gradient in migration rates appears, even for these short-distance moves. Of course, long-distance moves, for example to the sun-belt from north-central states, are excluded by the sampling frame, which may account for the steep age gradient.

Table 3 presents evidence pertaining to the welfare magnet hypothesis. It lists five hypotheses implied by the welfare magnet theory. The hypotheses have the structure of inequality restrictions on

Figure 4
Descriptive Statistics of the Analysis File
from the County to County Migration Flow Files 1980

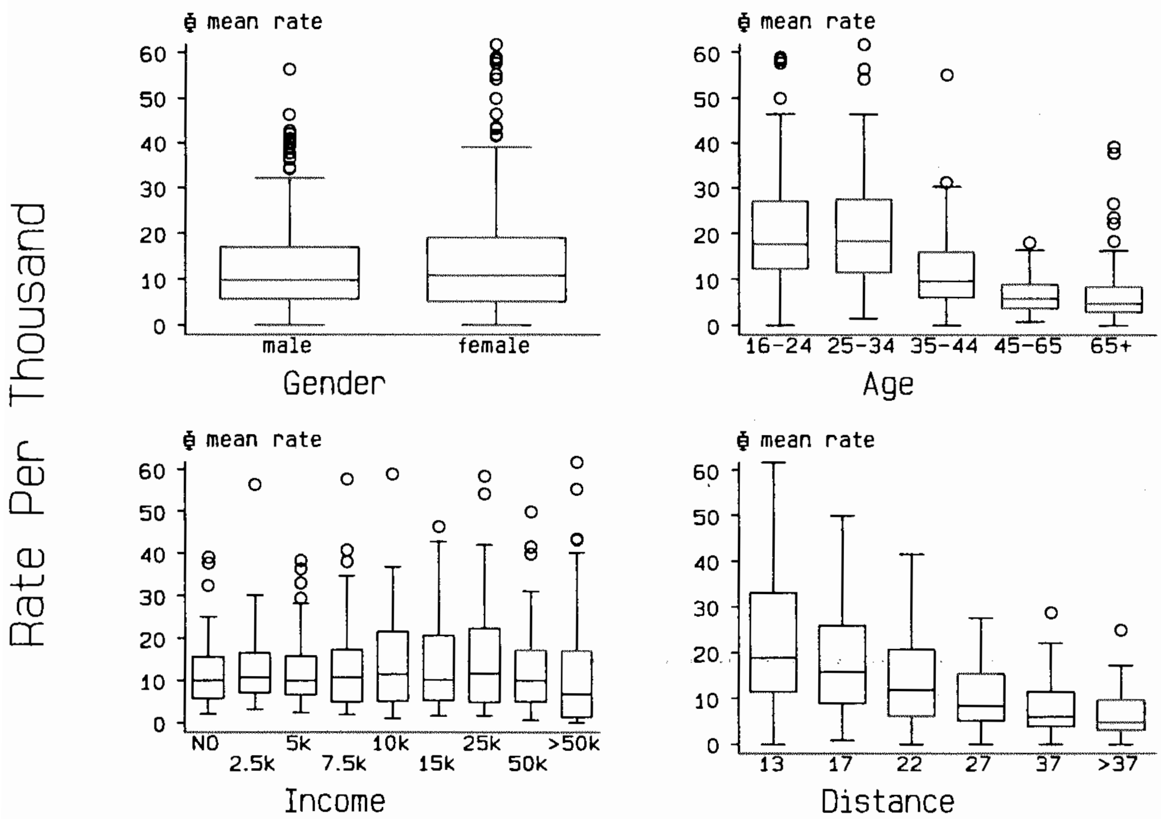


TABLE 3

Joint One-Sided Significance Tests of Directional Migration Flows

I. Exit rates from welfare magnets among poor young women should be lower than from attracted states

Comparison	Magnet Exit Rates (per 1000) (1)	Nonmagnet Exit Rates (per 1000) (2)	Difference (3)	Difference under Null (4)
IL v. WI	15.4	8.6	6.8	6.8
TN v. VA	11.4	11.2	0.2	0.2
IN v. MI	10.7	11.2	-0.5	0.0
OH v. MI	10.7	8.2	2.5	2.5
	Test Statistic = 33.63		P-value = 0.0000	

II. Exit rates from welfare magnets among poor young women should be lower than those among nonpoor young women

Magnet	Exit Rates among Poor Young Women (1)	Exit Rates among Nonpoor Young Women (2)	Difference (3)	Difference under Null (4)
Wisconsin	15.4	10.2	5.2	5.2
Michigan	10.7	16.2	-5.5	0.0
Virginia	11.2	14.5	-3.3	0.0
	Test Statistic = 1.83		P-value = 0.2923	

III. Exit rates from welfare magnets among poor young women should be lower than those among poor young men

Magnet	Exit Rates among Poor Young Women (1)	Exit Rates among Poor Young Men (2)	Difference (3)	Difference under Null (4)
Wisconsin	15.4	7.6	7.8	7.8
Michigan	10.7	8.8	1.9	1.9
Virginia	11.2	14.8	-3.6	0.0
	Test Statistic = 1.06		P-value = 0.4328	

(table continues)

TABLE 3, continued

IV. The attractive force of the magnet will cause the in-migration rates of poor young women to exceed those of nonpoor young women

Flow	Entry Rates of Nonpoor Young Women (1)	Entry Rates of Poor Young Women (2)	Difference (3)	Difference under Null (4)
IL to WI	3.0	4.2	-1.2	0.0
TN to VA	5.8	8.3	-2.5	0.0
IN to MI	7.8	6.0	1.8	1.8
OH to MI	4.8	5.9	-1.1	0.0
	Test Statistic = 0.047		P-value = 0.8852	

V. The attractive force of the magnet will cause the in-migration rates of poor young women to exceed those of poor young men

Flow	Entry Rates of Poor Young Men (1)	Entry Rates of Poor Young Women (2)	Difference (3)	Difference under Null (4)
IL to WI	4.0	4.2	-0.2	0.0
TN to VA	8.0	8.3	-0.3	0.0
IN to MI	7.6	6.0	1.6	1.6
OH to MI	5.1	5.9	-0.8	0.0
	Test Statistic = 0.283		P-Value = 0.7732	

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

Note: The test statistic is defined as $(\overline{\lambda_1 - \lambda_2})' \, \Sigma_\lambda^{-1} \, (\overline{\lambda_1 - \lambda_2})$, where $\overline{\lambda_1 - \lambda_2}$ is the difference in estimated migration rates under the null hypothesis, and Σ_λ^{-1} is the corresponding covariance matrix. As shown by Goldberger (1991) and Wolak (1987) the distribution of the test statistic is a mixture of chi squares.

sample migration rates for subgroups within the population. They were tested using simple (unconditional) migration rates and a multivariate extension of the univariate one-sided hypothesis test developed by Frank Wolak (1987). To define the test, I let λi denote a vector of mean migration rates. The hypotheses were of the form

$$H_o\colon \lambda_1 \geq \lambda_2 \qquad vs \qquad H_a\colon \lambda_1 < \lambda_2.$$

The test statistic assumed the usual quadratic form, $(\overline{\lambda_1 - \lambda_2})' \, \Sigma^{-1}_{\lambda_1 - \lambda_2} \, (\overline{\lambda_1 - \lambda_2})$, but was evaluated under the null hypothesis. Under the null, negative differences were reset to zero, probability mass accumulated at zero, and the distribution of the test statistic became a mixture of chi square random variables. For the small dimensional vectors arising here, computational formulas in Wolak (1987) permitted easy numerical evaluation of the appropriate tail probabilities to obtain p-values.

Since poor young women are most likely to be eligible for and receive welfare, their migration rates should be such that they give the most support to the welfare magnet hypothesis. In evaluating the hypotheses I constructed comparisons that should be most favorable to the welfare magnet hypothesis. In particular, I compared migration streams between the conjectured magnet and the attracted state (or in the case of Michigan, states). The first three hypotheses pertain to the retentive force of the magnet. According to the first hypothesis, exit rates by poor young women should be lower from magnets than from nonmagnets. As is usual in hypothesis testing for falsification purposes, the hypothesis test evaluated the converse of the conjecture. Columns one and two of the first block of Table 3 report exit rates from magnet and nonmagnet states. Evidence supporting the conjecture appears as negative (or small) differences in column three. For clarity, the final column reports the differences in means under the null. For three of the four comparisons, exit rates from magnets exceeded those of nonmagnets and the null was decisively rejected. Hypotheses two and three pertain to exit rates of poor young women vis-à-vis those of nonpoor young women and poor young men. These two subgroups should face many of the same migration incentives facing poor young women but should be less eligible to obtain welfare. These hypotheses were not rejected, yet in three of the six cases, exit rates by poor young women exceeded those of the comparison groups.

The remaining two hypotheses relate to the attractive force of magnets. Poor young women living in low-benefit states should be more likely to be pulled into the magnet than either nonpoor young women or poor young men. But in-migration rates of poor young women into magnets were not much different from in-migration rates of nonpoor young women and poor young men, and the hypotheses were not rejected at conventional test levels. In six of the eight comparisons, rates by poor young women were larger than rates for the comparison groups, but the difference between groups was small, on the order of one per thousand. However, the estimated variances were too large to reject the null hypothesis.

It is interesting to compare location-specific exit and entry rates, although they are not relevant to the welfare magnet hypothesis. As reported in the last block of Table 3, entry rates into the magnets by poor young women were 4.2 (IL to WI), 6.0 (IN to MI), 5.9 (OH to MI), and 8.3 (TN to VA). Exit rates by poor young women from the magnets to the attracted states were 4.9 (WI to IL), 12.9 (MI to IN), 9.4 (MI to OH), and 17.9 (VA to TN). In all four cases, exit rates were larger than the entrance rates for the group which supposedly was most likely to remain in the magnet. With one exception (flows between Indiana and Michigan by poor young men), the same pattern emerged for nonpoor young women and poor young men, suggesting that differences in state benefits affect poor young women in much the same way as they do these two subgroups of the population. It is consistent with the general finding in the migration literature that locations of high in-migration also exhibit high out-migration rates. This observation is also the primary argument against analyzing net migration rates.

The unconditional migration rates suggest two important patterns. First, there is no evidence in favor of the retentive force of welfare magnets. Whatever factors tie low-income persons to a location, the unconditional migration rates suggest that higher welfare benefits are not among them. Second, the data do not disprove that welfare magnets may exert some attractive force, yet if there is an attractive force it is weak.

6.2 Regression Analysis of the Count Data

I employ two parameterizations of the benefit variables. The first, *db*, is the difference in monthly benefits, defined as benefits at the destination less benefits at the origin. The benefit variable is nonzero only for interstate migration. This parameterization gives information on the importance of the quantitative difference in benefits between the origin and destination sites. Since greater benefit levels in the destination county should increase in-migration while greater benefits in the origin county should lower out-migration, the algebraic sign of this variable is expected to be positive. The other parameterization defines two main benefit variables. *ATM* equals one if combined monthly AFDC and Food Stamp benefits at the destination are at least 85 dollars per month greater than the combined monthly benefits in the origin site. *REM* equals one if combined benefits in the origin location are at least 85 dollars greater than combined monthly benefits in the destination site. While less informative on the importance of the quantitative differences in benefits, this parameterization permits asymmetric responses and captures the two conjectured forces of magnets. Thus, *ATM* measures the attractive force, while *REM* measures the retentive force of the magnet.

The last group of variables listed in Table 2 are included as gross controls for county characteristics that may be expected to influence the migration rate. Least precise in this group are three dummy variables for the three alleged magnets. Also included among the county characteristics are the crimė rate per 100,000 individuals in 1978, the per capita property tax rate in 1978, the per capita local government expenditures, the number of physicians in all the county (as of 1980), and the unemployment rate in 1978. To the greatest extent possible I obtained covariate values defined near the approximate mid-point of the migration window. Reflecting the notion that relative, not absolute, values matter, county characteristics enter the model specification in difference form (destination - origin), as did the benefit variable.

Regression estimates of the counting model are reported in Tables 4 and 5. The baseline specification appears in the left-most column in Tables 4 and 5. This specification includes the main and interactive terms of the personal characteristics and the benefit variable(s). Since the primary subpopulation of interest is poor young females, all second-order interaction terms are included to properly parcel out the effect of benefits on this group. The middle group of estimates adds indicator variables for the magnet states as destination locations. The right-most group of estimates adds differences in county characteristics to the second specification. At the foot of each table are the number of observations and the Pseudo R^2.

The estimated coefficients of the covariates common to Tables 4 and 5 reveal remarkably similar patterns across the two specifications.[15] The full set of interaction terms of the individual characteristics and the benefit variables makes it difficult to glean behavioral patterns from reviewing the estimated coefficients. However, a couple of patterns do emerge. First, notice the large negative estimated coefficient on the interstate dummy variable. Even for border counties, interstate migration is approximately 40 percent less frequent (e.g., 1-exp(-.8725)) than within-state intercounty migration. Similarly, the young are 2.7 times more likely to move than the old. Notice as well that the inclusion of the destination-state dummies and the county-level covariates has little impact on the other estimated coefficients (compare the right-most estimates with estimates of the baseline). However, a

TABLE 4

Regression Estimates—Benefit Variable; Dependent Variable: Number of Intercounty Migrants (Robust Standard Errors)

Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
intercept	-3.9356	0.3200	-3.8970	0.4328	-3.8750	0.2999
poor	-0.0305	0.2915	-0.0272	0.2817	-0.0469	0.2351
young	0.9920	0.3598	0.9930	0.3245	0.9975	0.2690
female	-0.0416	0.3048	-0.0421	0.2987	-0.0376	0.2356
py	-0.4150	0.4070	-0.4159	0.3521	-0.3988	0.3035
pf	0.0285	0.3914	0.0135	0.3815	0.0312	0.3182
yf	0.0268	0.4166	0.0206	0.3693	0.0173	0.3023
pyf	0.3065	0.4929	0.3098	0.4487	0.2933	0.3872
ism	-0.8725	0.1019	-0.8510	0.1381	-0.8368	0.0847
dist	-0.0520	0.0078	-0.0567	0.0114	-0.0534	0.0096
db	-0.0005	0.0026	-0.0017	0.0024	-0.0017	0.0021
ydb	-0.0011	0.0039	-0.0011	0.0033	-0.0010	0.0026
pdb	0.0030	0.0031	0.0032	0.0028	0.0034	0.0026
fdb	-0.0005	0.0032	-0.0005	0.0029	-0.0005	0.0023
pydb	-0.0007	0.0051	-0.0010	0.0032	-0.0012	0.0042
pfdb	-0.0018	0.0042	-0.0020	0.0038	-0.0021	0.0033
yfdb	0.0007	0.0047	0.0005	0.0039	0.0005	0.0031
pyfdb	0.0007	0.0062	0.0008	0.0050	0.0008	0.0050
f_wi			0.2627	0.2287	0.3582	0.3067
f_mi			0.5491	0.1936	0.4786	0.2684
f_va			-0.3486	0.3456	-0.4922	0.2395
dcrate					0.0001	4.7E-5
dptax					0.0005	0.0009
dge					0.0046	0.0002
ydph					0.0001	3.5E-5
dune					-0.0076	0.0051
Pseudo R^2	0.3327		0.3552		0.4005	
N = 142,435						

TABLE 5
Counting Model Regression Estimates—Benefit Variables: *ATM* and *REM*;
Dependent Variable: Number of Intercounty Migrants
(Robust Standard Errors)

Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
intercept	-3.8812	0.3079	-3.8729	0.4191	-3.8200	0.3000
poor	-0.0316	0.2909	-0.0326	0.2792	-0.0537	0.2334
young	0.9924	0.3577	0.9931	0.3225	0.9976	0.1068
female	-0.0362	0.3007	-0.0371	0.2925	-0.0325	0.2304
ism	-0.9810	0.1137	-0.9456	0.1704	-0.9092	0.1068
dist	-0.0544	0.0074	-0.0592	0.0114	-0.0554	0.0098
ATM	0.3025	0.3519	0.0826	0.4405	0.0187	0.4404
REM	0.7493	0.4175	0.8383	0.4541	0.6423	0.4093
py	-0.4271	0.4057	-0.4289	0.3506	-0.4073	0.3019
pf	0.0184	0.3902	0.0125	0.3770	0.0303	0.3152
yf	0.0133	0.4127	0.0133	0.3641	0.0099	0.2977
pyf	0.3200	0.4916	0.3218	0.4455	0.3052	0.3851
pATM	0.3764	0.3617	0.4290	0.3408	0.4610	0.3185
pREM	-0.2245	0.4446	-0.2358	0.4320	-0.2321	0.4180
fATM	-0.1568	0.3441	-0.1495	0.3178	-0.1575	0.2862
fREM	-0.0862	0.3938	-0.0835	0.3807	-0.0867	0.3423
yATM	-0.0686	0.4028	-0.0637	0.3577	-0.0671	0.3370
yREM	0.1093	0.4339	0.1063	0.4018	0.0956	0.3600
pfATM	-0.1213	0.4806	-0.1659	0.4555	-0.1700	0.4284
pfREM	0.2220	0.5916	0.2352	0.5722	0.2332	0.5517
pyATM	0.1220	0.4904	0.0716	0.4355	0.0464	0.4419
pyREM	0.2510	0.5600	0.2583	0.5081	0.2656	0.4930
yfATM	0.1876	0.4930	0.1922	0.4315	0.1933	0.3983
yfREM	0.1830	0.5111	0.1827	0.4638	0.1844	0.4211
pyfATM	-0.1724	0.6345	-0.1531	0.5684	-0.1443	0.5767
pyfREM	-0.3756	0.7189	-0.3859	0.6713	-0.3848	0.6580
f_wi			0.2347	0.2293	0.3299	0.3216
f_mi			0.5244	0.1882	0.4562	0.2606
f_va			-0.3903	0.3351	-0.5200	0.2480
dcrate					0.0001	4.7E-5
dtax					0.0004	0.0009
dge					0.0005	0.0002
dphy					0.0001	3.5E-5
dune					-0.0077	0.0051
Pseudo R^2		0.3362		0.3562		0.4022
N = 142,435						

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

comparison of the Pseudo-R^2 values implies that the additional covariates substantially improve the fit. The estimated coefficients for the county characteristics do not always have the expected algebraic sign. In particular, the estimated coefficient of the difference in crime rates should be negative, as higher crime rates in the destination location should reduce in-migration and lower crime rates at the original location should reduce out-migration. However, discussions with experts at the Census Bureau suggest the crime variables may be ridden with error.[16] The estimated coefficient on the difference in property tax rates also violates expectations (but with large standard errors). Interestingly, although it is defined only at a point in time during the middle of the migration window, the difference in unemployment rates operates according to expectations regarding the importance of labor market conditions as a primary determinant of migration. The statistical significance of the county-level characteristics suggests that the sample restriction to adjacent counties does not entirely purge the effect of local conditions.

The large number of interaction effects within the nonlinear model makes it difficult to visually determine the effect of welfare benefits on migration rates. Table 6 reports joint tests of the statistical significance of the estimated coefficients. Once again, I compare estimates for poor young women with those for nonpoor young women and poor young men. The top half of Table 6 reports test statistics and p-values for the *db* parameterization, while the bottom portion reports results for the dummy variable (*ATM*, *REM*) representation of benefits. The first rows of each block report test statistics comparing poor young women and nonpoor young women, while the third row compares poor young women and poor young men. Rows two and four report the difference in estimated benefit effects between poor young women and the two control groups. Reflecting the large standard errors in Tables 4 and 5, few of the comparisons in Table 6 are statistically significant at conventional test levels. Both benefit parameterizations indicate that the migratory behavior of poor young women is different from that of nonpoor young women. The important result from the table, however, is that

TABLE 6

Tests of the Equality of Estimated Coefficients

Comparison	Base Model		Add Destination Dummy Variables		Add County Characteristics	
	Test Statistic	P-Value	Test Statistic	P-Value	Test Statistic	P-Value
Benefits parameterized by *db*						
Poor young women versus nonpoor young women	1.85	.0632	2.13	.0296	1.74	.0838
Effect of benefits on poor young women versus nonpoor young women	0.47	.7565	0.57	.6820	0.74	.5633
Poor young women versus poor young men	1.49	.1537	1.98	.0442	1.42	.1803
Effect of benefits on poor young women versus poor young men	0.24	.9148	0.33	.8567	0.37	.8295
Benefits parameterized by *ATM & REM*						
Poor young women versus nonpoor young women	1.35	.1799	1.80	.0419	1.54	.0926
Effect of benefits on poor young women versus nonpoor young women	1.07	.3839	1.33	.2212	0.94	.4790
Poor young women versus poor young men	1.21	.2714	1.61	.0798	1.14	.3227
Effect of benefits on poor young women versus poor young men	0.33	.9529	0.48	.8697	0.39	.9279

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

poor young women's responses to differences in welfare benefits are not different from either those of nonpoor young women or poor young men. Differences between poor young women and the comparisons are not due to differential responses to welfare benefit differences. This inference appears in all six models reported in Table 6.

To investigate whether differences between groups are significant from a substantive viewpoint, Tables 7 and 8 report predicted migration rates for the two baseline models. Table 7 reports predictions from the baseline model (left-most column) in Table 4, and Table 8 presents predicted migration rates for the baseline model in Table 5. Predicted rates for eight distinct subpopulations are listed; columns one through four report rates for men, and columns five through eight report rates for women. Each table reports four sets of predicted rates and within each set, rates for three distances: 15, 20, and 25 miles. These distances approximate the quartiles of the distance distribution and hence report the response rate for the middle 50 percent of the distance distribution. In each table the first set of predicted rates are for intrastate moves. The second set are for interstate migration rates assuming no differences in welfare benefits across states. The last two sets of predicted rates capture the effect of benefit differences. Table 7 reports interstate migration rates assuming benefits in the neighboring state are \$50 greater than in the origin location. Predicted interstate migration in the presence of a \$100 difference in benefits is shown in the last block of Table 7. According to the definitions applied in this paper, the pull of the welfare magnet should appear in the differences in migration rates of the last block versus the preceding blocks. The third block of predicted rates in Table 8 corresponds to interstate migration into a welfare magnet ($ATM=1$). The last block in Table 8 corresponds to interstate migration rates from a welfare magnet ($REM=1$).

Predicted migration rates vary only slightly between the two specifications. Because of this similarity, except for the discussion of the effect of the benefit variables, I discuss only rates reported in Table 7. The difference between rows within a block recovers the effect of distance on migration.

TABLE 7

Predicted Migration Rates (per 1000), Based on Estimates Reported in Table 4

	Men				Women			
	Old		Young		Old		Young	
	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor
Intrastate								
15 miles	8.95	8.68	24.13	15.46	8.59	8.50	23.64	21.00
20 miles	6.90	6.69	18.61	11.92	6.62	6.55	18.22	16.19
25 miles	5.32	5.16	14.34	9.19	5.10	5.05	14.05	12.48
Interstate, no difference in welfare benefits								
15 miles	3.74	3.63	10.09	6.46	3.59	3.55	9.88	8.78
20 miles	2.88	2.80	7.78	4.98	2.77	2.74	7.61	6.77
25 miles	2.22	2.16	5.99	3.84	2.13	2.11	5.87	5.22
Interstate, difference in welfare benefits = $50								
15 miles	3.65	4.11	9.28	6.66	3.41	3.58	9.07	8.52
20 miles	2.81	3.16	7.16	5.13	2.63	2.76	6.99	6.57
25 miles	2.17	2.44	5.52	3.96	2.03	2.13	5.39	5.06
Interstate, difference in welfare benefits = $100								
15 miles	3.55	4.65	8.54	6.86	3.24	3.60	8.33	8.27
20 miles	2.74	3.58	6.59	5.29	2.50	2.78	6.42	6.38
25 miles	2.11	2.76	5.08	4.08	1.93	2.14	4.95	4.92

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

TABLE 8

Predicted Migration Rates (per 1000), Based on Estimates Reported in Table 5

	Men				Women			
	Old		Young		Old		Young	
	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor
Intrastate								
15 miles	9.12	8.82	24.60	15.52	8.79	8.67	24.04	21.28
20 miles	6.95	6.72	18.74	11.83	6.70	6.60	18.31	16.21
25 miles	5.29	5.12	14.28	9.01	5.10	5.03	13.95	12.35
Interstate, no difference in welfare benefits								
15 miles	3.42	3.31	9.22	5.82	3.30	3.25	9.01	7.98
20 miles	2.60	2.52	7.03	4.43	2.51	2.47	6.87	6.08
25 miles	1.98	1.92	5.35	3.38	1.91	1.89	5.23	4.63
Interstate, flow into magnet ($ATM = 1$)								
15 miles	4.63	6.52	11.65	12.10	3.81	4.85	11.74	12.74
20 miles	3.52	4.97	8.88	9.22	2.91	3.69	8.95	9.70
25 miles	2.68	3.78	6.76	7.02	2.21	2.81	6.81	7.39
Interstate, flow from magnet ($REM = 1$)								
15 miles	7.23	5.59	21.76	14.10	6.40	6.29	23.43	18.27
20 miles	5.51	4.26	16.58	10.74	4.87	4.78	17.85	13.92
25 miles	4.20	3.24	12.63	8.19	3.71	3.65	13.60	10.60

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

Because distance enters the model only as a main effect with no interaction terms, the relative change is constant in all blocks of the panel. For example, intrastate migration among poor young women declines 23 percent (compare the last number of the first and second rows of the first block) as distance increases from 15 to 20 miles ([16.19/21.0] - 1). Similarly, increasing the distance by another 5 miles, from 20 to 25 miles, reduces migration rates by another 23 percent ([12.48/21.00] - 1). The steep distance gradient is apparent—migration rates decline by 40 percent as distance increases from 15 to 25 miles. Even at these short distances with controls for distance present, there is a substantial difference in migration propensities between intrastate and interstate movement. Holding distance constant, interstate migration is about 40 percent the rate of intrastate migration (for any group, compare the first row of the first block with the first row of the second block). Relative changes for comparisons involving age and gender are not uniform but depend on the point of evaluation. For example, for intrastate moves nonpoor young women are 2.75 times more likely to migrate than are nonpoor old women, whereas nonpoor young men are 2.7 times more likely to move than a nonpoor old man and 2 percent more likely to move than a nonpoor young woman. Among older age groups there is little difference in migration rates for either gender or income; this is not true among younger age groups. Among old men, migration rates of the poor are only 3 percent lower than rates of nonpoor counterparts; among old women migration rates of the poor are 1 percent lower than nonpoor counterparts and roughly 2 percent lower than comparable male rates. Migration rates of poor young women are much more resilient. Assuming no difference in welfare benefits, migration rates of poor young women are only 11 percent lower than those of nonpoor young women, while migration rates of young poor males are approximately one-third lower than those of their nonpoor counterparts.

Now consider the effects of differences in welfare benefits. First, note that increasing the difference in welfare benefits to $100 reduces migration by poor young women by 6 percent, while it increases the migration rate of poor young men by 6 percent (compare the first row of the second block with the first row of the last block). This pattern is exactly the opposite postulated by the welfare magnet hypothesis. Moreover, in the presence of a 100 dollar difference in welfare benefits, migration rates by nonpoor men and women decline by 15 to 16 percent. Consequently, the difference in migration rates declines to 1 percent between poor and nonpoor young women, to 20 percent between poor and nonpoor young men, and to 21 percent between poor young women and poor young men (with young women still the more likely to move).

The estimated effect of differences in welfare benefits from the estimates reported in Table 5 is different and slightly richer. Here, the asymmetric parameterization of the attractive and retentive forces of the magnet is useful. Whereas the *db* parameterization (estimates reported in Table 4) captures differences in migration rates for all levels of differences in benefits, the estimates from the dummy variable model identify the welfare magnet effect only from extreme differences in benefits. For interstate moves of 20 miles, the attractive force of the welfare magnet increases migration rates of poor young women a nonnegligible 60 percent or by roughly 3.5 per thousand (compare the second row of the second and third blocks of Table 8). However, the attractive force of the magnet also increases the migration rates of nonpoor young women by 2 per thousand and of poor young men by 4.75. Yet according to the welfare magnet hypothesis the pull should be the strongest on poor young women.

Directional evidence on the retentive force of the magnet is even more damaging to the welfare magnet hypothesis. Among poor young women, higher benefits at the initial location increase, indeed more than double, out-migration rates. For moves of 20 miles, migration rates of poor young women increase about 7.8 per thousand. Yet, this is less than the absolute increase experienced by nonpoor young women, whose migration rate increases by 11 per thousand in the presence of a retentive magnet. Migration rates by poor young men increase 6.3 per thousand, which is nevertheless a larger percentage increase than that experienced by poor young women (147 percent for men versus 129 percent for women).

The evidence in favor of the welfare magnet is mixed at best. Among poor young women changes in migration rates refute the welfare magnet hypothesis. The estimated effect of an attractive magnet is to reduce migration and the estimated effect of a retentive magnet is to increase migration. Yet, comparisons relative to the two control groups are more favorable (though still mixed). The estimated effect of an attractive magnet reduces migration rates of poor young women less than it does those of nonpoor young women but more than it does those of poor young men. Similarly, the increase in migration rates of poor young women to the retentive magnet is, in absolute terms, less than the increase for nonpoor young women and more than the change experienced by poor young men.

Since identification of the welfare magnet effects comes from these differences-of-differences of migration rates between poor young women and the two control groups, it is important to ask if the estimated effects are statistically significant. Table 9 reports the test statistics for the difference-of-differences effects for the two parameterizations of benefits. The first two rows of Table 9 present estimates of the effects of welfare magnets using the estimates from Table 4. The difference-of-difference estimate of the welfare magnet effect obtained by comparing poor young women with nonpoor young women is 0.8 per thousand (row 1), while the comparison between poor young women and poor young men yields -0.7 per thousand (row 2). Neither of these differences is statistically significant. Comparisons using the estimates from Table 5 yield much the same pattern; each hypothesized effect has one effect which is the correct algebraic sign (according to the welfare magnet hypothesis) and one which is of the wrong sign. The attractive force of the welfare magnet is 1.5 per thousand (row 3) or -1.17 per thousand (row 4). Similarly, the retentive force of the magnet is either -3.14 per thousand or 1.53 per thousand. Comparisons between nonpoor young women and

TABLE 9

Comparison of Predicted Migration Rates: Interstate Migration and Distance Equal to 20 miles (Based on Estimates Reported in Tables 4 and 5)

Comparison	Difference of Differences	Test Statistic	P-Value
Estimates from Table 4 *(db)*			
Poor young women versus nonpoor young women	(6.38 - 6.77) - (6.42 - 7.61) = 0.80	.5768	.4478
Poor young women versus poor young men	(6.38 - 6.77) - (5.29 - 4.98) = -0.70	.2485	.6181
Estimates from Table 5: Attractive force *(ATM)*			
Poor young women versus nonpoor young women	(9.70 - 6.08) - (8.95 - 6.87) = 1.54	.4258	.5141
Poor young women versus poor young men	(9.70 - 6.08) - (9.22 - 4.43) = -1.17	.2429	.6222
Estimates from Table 5: Retentive force *(REM)*			
Poor young women versus nonpoor young women	(13.92 - 6.08) - (17.85 - 6.87) = -3.14	1.0095	.3150
Poor young women versus poor young men	(13.92 - 6.08) - (10.74 - 4.43) = 1.53	.2256	.6348

Note: Variances of the difference in predicted rates are obtained using the delta method. Let $\lambda_i = \exp(x_i b)$ denote the predicted rate for the ith group with covariates x and estimated parameters b, b $\sim$ N(β, Σ). The estimated covariance between predicted rates is:

$$COV(\lambda_i,\lambda_j) = \left(\frac{\partial \lambda_i}{\partial b'}\right) \Sigma \left(\frac{\partial \lambda_j}{\partial b}\right) = \lambda_i \, x_i' \, \Sigma \, x_j \, \lambda_j \, .$$

The estimated variance of a pairwise comparison is:

$$VAR(\lambda_i - \lambda_j) = VAR(\lambda_i) + VAR(\lambda_j) - 2COV(\lambda_i,\lambda_j) \, .$$

poor young women always yield estimated effects with the correct algebraic sign. Comparisons between poor young women and poor young men always produce estimated effects with the incorrect algebraic sign. Yet these comparisons are statistically insignificant. Hence the most favorable evidence of welfare magnet effects is that the attractive force is 1.5 per thousand and is one-half that of the retentive force. To claim that welfare magnets exist requires disregarding the comparisons involving poor young men and the higher out-migration rates of poor young women from welfare magnets. There is no compelling reason to disregard this information.

6.3 Regression Results Using Ratios of Migration Rates

Estimates from the second approach are reported in Tables 10 and 11. Table 10 contains results using the difference in welfare benefits to measure the force of welfare magnets, while the effects reported in Table 11 use the indicator variables *ATM* and *REM*. Both tables report only the estimated coefficients for the benefit variables. The top portion of each table includes results using nonpoor young women as the comparison group, while the bottom portion of the table consists of results using poor young men as the comparison group. Within each comparison group, estimates are reported for several sets of additional covariates. All specifications include the interstate dummy and control for distance. They also include a proxy for the complementary flows. For example, in the comparison between poor young women and nonpoor young women the log of the comparable ratio (poor young men to nonpoor young men) appears as a regressor. This regressor is included to control for all factors other than the difference in welfare benefits that affect the migration decisions. Three sets of covariates complete the covariate controls. The first set (*dcc*) controls for differences in county characteristics that may affect migration decisions: the crime rate, the per capita property tax rate, government expenditures, the number of physicians, the unemployment rate, and the log of the population. The last two sets are nine indicator variables for the state of residence in 1975 and a group of twenty-three indicator variables for the state of residence in 1980. Covariates are added to

TABLE 10

**Estimated Effects of Benefits Using Pairwise Comparisons of Migration Rates:
Dependent Variable = log(PYF/Comparison Group)
(Poverty Definition Number One)**

Poor Young Women versus Nonpoor Young Women (n=1125)

db	|t|	RMSE	Covariates
-.0020	.285	.7329	*isd, dr13*
.0004	.056	.7325	*isd, dr13, dcc*
-2.0e-5	.003	.7346	*isd, dr13, dcc, bs*
-.0063	.201	.7326	*isd, dr13, dcc, bs, fs*

Poor Young Women versus Poor Young Men (n=1215)

db	|t|	RMSE	Covariates
-.0069	.811	.8415	*isd, dr23*
-.0028	.446	.8419	*isd, dr23, dcc*
-.0014	.156	.8331	*isd, dr23, dcc, bs*
-.0213	.523	.8337	*isd, dr23, dcc, bs, fs*

Source: Author's calculations based on County to County Migration Flow File from the 1980 census.

Covariate Sets:

isd = covariates include interstate dummy and distance

dr13 = log(rate of poor young men / rate of nonpoor young men)

dr23 = log(rate of nonpoor young women / rate of nonpoor young men)

dcc = difference in six county characteristics: crime rate, per capita property tax, per capita government expenditures, number of physicians, unemployment rate, and log population

bs = set of 9 indicator variables for state of residence in 1975

fs = set of 23 indicator variables for state of residence in 1980

TABLE 11

Estimated Effect of Benefits Using Pairwise Comparisons of Migration Rates: Dependent Variable = log(PYF/Comparison Group) (Poverty Definition Number One)

Poor Young Women versus Nonpoor Young Women (n=1125)

ATM	|t|	*REM*	|t|	RMSE	Covariates
-.1269	.775	-.1585	1.292	.7328	*isd, dr13*
-.1086	.646	-.1868	1.509	.7322	*isd, dr23, dcc*
-.1162	.685	-.2385	1.773	.7342	*isd, dr23, dcc, bs*
.0374	.083	-.1820	.437	.7332	*isd, dr23, dcc, bs, fs*

Poor Young Women versus Poor Young Men (n=1217)

ATM	|t|	*REM*	|t|	RMSE	Covariates
-.1610	.874	.1364	.764	.8415	*isd, dr23*
-.1354	.725	.1142	.178	.8419	*isd, dr23, dcc*
-.1384	.724	.0418	.227	.8333	*isd, dr23, dcc, bs*
-.1153	.303	.0636	.164	.8343	*isd, dr23, dcc, bs, fs*

Covariate Sets:

isd = covariates include interstate dummy and distance

dr13 = log(rate of poor young men / rate of nonpoor young men)

dr23 = log(rate of nonpoor young women / rate of nonpoor young men)

dcc = difference in six county characteristics: crime rate, per capita property tax, per capita government expenditures, number of physicians, unemployment rate, and log population

bs = set of 9 indicator variables for state of residence in 1975

fs = set of 23 indicator variables for state of residence in 1980 see the robustness to an expanding set of controls, attempting to control for other reasons why individuals migrate.

The results in Tables 10 and 11 reveal that welfare benefits exert no discernable influence on migration decisions of poor young women. In Table 10, the estimated coefficients of the difference in welfare benefits are usually negative, though the estimated effects are extremely small and not even remotely statistically significant at conventional test levels. The results in Table 11 are not much different. When nonpoor young women are used as the comparison group, the estimated coefficient on *REM* (the indicator variable equal to one if the individual lived in a high-benefit state in 1975) is negative (as it should be because of the retentive force of the magnet). The estimated coefficients are not significant at conventional test levels. However, even this modest result disappears when poor young men are used as the comparison, as the estimated coefficient on *REM* is positive, though again with little precision in the estimated results. Across both comparison groups, the estimated coefficient on *ATM* is usually negative though not precisely determined. These results imply that high-benefit states do not "pull" residents in contiguous states toward them.[17]

Although a finer partition of individuals at risk may yield conflicting results, the evidence from the aggregate flows of the County to County Migration Files strongly implies that state differences in combined Food Stamp and AFDC benefits have no influence on interstate migration flows.

7. CONCLUSION

The basic premise of this paper is that an alternative look at welfare magnets focusing on short-distance migration patterns provides a new perspective on this long-standing policy issue. Analyzing all interstate migratory flows between contiguous states yields a much richer behavioral picture than obtained from the conventional review of only flows into prospective magnets. The data offer no compelling evidence in support of the welfare magnet hypothesis. Migration propensities are as likely to invalidate as they are to support the welfare magnet hypothesis. Moreover, none of the estimated effects of welfare benefits are statistically significant at conventional levels. Comparing migration rates of poor young women with those of nonpoor young women yields estimated effects most favorable to the welfare magnet hypothesis (but the estimated effects are not statistically different). By these measures, the attractive force of the magnet is 1.5 per thousand and the retentive force is 3 per thousand. Taken at face value, these two rates can be used to rationalize the findings of Peterson and Rom (1990), who used differences in the proportion in poverty to recover estimates of welfare magnets. My estimates suggest that increasing poverty and the retention of the currently poor may have driven Peterson and Rom's results.

Nevertheless, to accept these (statistically insignificant) favorable estimates requires that one disregard several conflicting estimates obtained from comparing poor young men and poor young women. Most importantly, if one accepts the favorable estimates, one must disregard the finding that an increase in current-location benefits increases out-migration rates. There is no compelling reason to disregard this finding.

The interpretation best supported by the data is that estimated effects of differences in welfare benefits across states have no substantive or statistically significant effect. The longevity of this issue in public debates owes more to voter perceptions than to migration flows observable in the census. The interesting question that remains for future work is to investigate the consequences of migration for low-income individuals and for locations sending and receiving them.

Endnotes

[1]The single largest movement of blacks occurred during World War I, as 500,000 moved from the rural South to the urban North and Midwest. The migration continued steadily until the early 1970s; from 1916 to 1970 more than six million blacks moved. During the 1970s and 1980s the pattern of migration reversed as more blacks moved to the South than left (Long 1988; Lichter and De Jong 1990). It is important to realize the mass exodus started long before the expansion of welfare programs in the mid- to late 1960s. Until 1969, states set residency requirements as a condition of eligibility for public assistance, so many more people migrated than were eligible for welfare programs.

[2]See Glazer's (1987) insightful review of this literature as well.

[3]In the absence of moving costs there must be a negative relationship between income and amenity levels for both locations to be inhabited.

[4]The other major program, Medicaid, varies significantly across states though most of the variation (e.g., coverage of nursing home expenses) has a greater impact on older individuals and should have little effect on younger individuals.

[5]All benefits are denominated in constant 1980 dollars. I use the Consumer Price Index for Food to convert Food Stamp benefits and the CPI to convert AFDC benefits into constant dollars.

[6]The similarity of benefits across states is an interesting observation in its own right, which will not be pursued here, but see Orr (1976). The narrowing of the dispersion of state benefits may reflect a legislative response to welfare migration or *perceived* welfare migration. It may be good politics for a rational legislator to vote to reduce state welfare benefits if constituents believe their state is a magnet whether or not this belief is correct.

[7]I thank Kate Dresher for providing me with an extract of the City and County Code Book.

[8]Great Circle distances recognize the spherical nature of the earth. Let (x_i, y_i) denote the latitude and longitude of location $i=1,2$, and θ the angle between the two locations, $\cos(\theta) = \sin(x_1)\sin(x_2) + \cos(x_1)\cos(x_2)\cos(y_1 - y_2)$, and distance equals $69.16\cos^{-1}(\theta)$ (69.16 miles per degree).

[9]Future analyses of individual longitudinal data (National Longitudinal Survey of Youth) will estimate the size of the bias from this limitation.

[10]Random variable X is a member of the linear exponential family if its density can be written as $f(x,\theta) = \exp\{A(\theta) + B(x) + C(\theta)\, x\}$ with parameter θ. See Gourieroux, Monfort, and Trognon (1984a).

[11]The robust estimator of the covariance matrix of the estimated parameters is

$$Var(\hat{\beta}) = \left[\sum_k \hat{\lambda}_k x_k x_k'\right]^{-1} \left[\sum_k \hat{\lambda}_k^2 x_k x_k'\right] \left[\sum_k \hat{\lambda}_k x_k x_k'\right]^{-1}.$$

[12]See Cameron and Trivedi (1990) as well.

[13]This parameterization is subsumed in equation (7). If Y is a counting random variable with expectation $\lambda(x)$, then with multiplicative errors $Y=\lambda(x)\epsilon$, with $E(\epsilon)=1$.

[14]In cases when both the numerator and denominator are zero, I define the ratio as equal to one. Otherwise when the denominator is zero and the numerator is nonzero, the ratio is undefined; such county-to-county flows are excluded from the analysis.

[15]Several other specifications were estimated, including models with only some or no interaction terms, models with indicator variables for state of origin and destination, and models with controls for the population at risk. These models exhibited the same qualitative pattern of estimated coefficients as reported in Tables 4 and 5.

[16]I thank Kate Dresher for bringing this problem to my attention.

[17]Moreover, calculations available from the author show that the results are robust to the sample definition and the definition of "poor."

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