A CONDITIONAL LOGIT APPROACH TO U.S. STATE-TO-STATE MIGRATION*

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ABSTRACT. This paper uses a conditional logit approach to study interstate migration in the United States for each of eleven years, from 1986–1987 to 1996–1997. We test substantive hypotheses regarding migration in the United States and demonstrate the richness of the conditional logit approach in studies of place-to-place migration. We investigate migration responses to relative economic opportunities (unemployment rate, per capita income) and the associated costs of moving (distance between origin and destination and its square). We also investigate how noneconomic factors, such as amenities, affect migration between states through a state fixed effect. Finally, we study the magnitude of unmeasured costs associated with a particular migration. The conditional logit model also allows us to compute various trade-off and other values that are of interest in migration analysis.

1. INTRODUCTION

Early models of the determinants of migration used aggregate data and emphasized place characteristics (Greenwood, 1975). Individual characteristics like age and education were sometimes crudely proxied by variables relating to the (origin) population at risk to migrate, but variables relating to personal characteristics were frequently lacking significance or were of unanticipated sign. Such findings were hardly surprising because the aggregate variables were

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often virtually uncorrelated with the migrant traits of concern (Navratil and Doyle, 1977).

During more recent years, with the availability of various microdata sets, discrete-choice models of the decision to migrate have become fairly standard. For example, logit and probit models have greatly enhanced the understanding of the underlying determinants of the decision to migrate. Early versions of these models tended to include only personal characteristics (Linneman and Graves, 1983), but later versions incorporated both personal and place characteristics (Herzog and Schlottmann, 1986).

In the context of models based on aggregate data, as well as many models based on microdata, one of the most troubling problems is the treatment of alternative destinations. Whereas various investigators address this problem, until recently none of them account for opportunities at all alternative destinations. They consider only a single alternative destination, such as that with the best alternative income or the lowest alternative unemployment rate (Wadycki, 1974). In some cases when alternative destinations are taken into account, staying at the present location is not in the choice set (Blank, 1988; Bartel, 1989). This approach is often rationalized as a decision maker first deciding whether to move, and given a decision to move, then deciding where to move. However, the decision regarding whether to move cannot reasonably be separated from the decision regarding where to move. Presumably, the decision to stay or go is based on a rational consideration of the alternatives relative to the present location.

A better method of approaching this problem is in the context of a conditional logit model in which the decision to stay is one option, along with a consideration of all potential alternative destinations. The most important distinction between the conditional logit model and the approach used in early studies based on aggregate data is that the former has a sound microeconomic foundation. The conditional logit model is built on an individual utility maximization framework that is based on a random utility model. This is the methodology adopted in the present study. We use aggregate state-to-state migration flow data in the context of an individual random-utility-based conditional logit model to examine migration choices. In particular, each state (including the current state of residence) is treated as a potential destination choice. Based on utility maximization, individuals may choose to migrate to any state or to stay in the current state. Given that we observe how many individuals move between each pair of states, we develop a maximum likelihood function for estimation based on the conditional logit model.

Earlier models of state-to-state migration focused on migration over a given time interval. For example, models estimated with Census data typically analyze migration over five year intervals (e.g., between 1985 and 1990). Although some data sets have the potential to yield annual logit or probit estimates of the determinants of migration, they have not been used in this way. Thus, migration researchers have little information about the representativeness of their parameter estimates over time. In this paper, we estimate
our conditional logit model for eleven consecutive years (1986–1987 through 1996–1997) using repeated cross-sections of the Area-to-Area Migration Flow Data from the Internal Revenue Service. Although they are not panel data because we cannot follow specific individuals in different years, these data still provide us with some sense of the temporal pattern and stability of our parameter estimates. Furthermore, annual estimation imposes few restrictions on the model because all parameters are allowed to vary across time. This procedure is less restrictive than pooling data from multiple cross-sections and using time dummies to partially control for time trends.

Another way that the present study differs from earlier studies is in our treatment of the distance variable. In logit or probit models of the decision to migrate, a distance variable has no place because no specific destination is identified. However, in the conditional logit model developed here, various destinations are specified and thus distance has a role to play. In most earlier studies that include a distance variable, the implicit assumption is that the relationship between distance and migration is linear or linear in logarithms. However, the deterring effects of distance may decline at greater distances because the marginal cost of moving a unit distance farther is lower at greater distances. Thus, we include distance squared in the model.

Finally, we use our conditional logit approach to examine trade-offs related to the probability of migration for certain pairs of variables. By measuring the trade-off between a given variable and per capita income, we can place a rough dollar value on that trade-off. One such trade-off, that between distance and destination income, was noted by Sjaastad (1962, p.84).

Ideally, to study migration behavior both choice attributes and individual characteristics will be included in the model. However, with a large number of potential destination choices (states), the computation cost for this maximum likelihood estimation is very high. Therefore, we impose some additional restrictions on the model. First, the conditional logit model focuses on the effect of choice-specific attributes on the migration decision to identify how the characteristics of a state affect an individual's destination choice. The parameters are assumed to be constant across choices. The effects of individual characteristics generally cannot be directly identified with the conditional logit model. The conditional logit model is different from the multinomial logit model of migration that focuses on the effects of individual characteristics on the migration decision. For a multinomial logit model, the corresponding parameters are different for different choices (Schmidt and Strauss, 1975). However, it is difficult to incorporate this degree of flexibility when studying state-to-state migration. There are up to fifty potential destination choices so the number of parameters quickly becomes too large for computation. Moreover, we do not have data on individual characteristics such as age and education.

Second, an individual's migration choice should be based on comparisons of the characteristics of possible destinations with those of the current state of residence. Therefore, the characteristics of the current state of residence can be thought of as a kind of individual characteristic. That is, a characteristic in a
destination state will be viewed differently for individuals in different origins. In the conditional logit model the effects of individual characteristics cannot be directly identified, so we incorporate these origin characteristics by using relative measures of attributes between potential destinations and the origin. Although this specification is somewhat restrictive, the use of relative measures is appealing in the sense that it captures the notion that the migration choice is based on comparisons of potential destinations with the origin.

Third, an important aspect of our model specification is that we include a set of choice dummy variables (state fixed effects). This greatly increases the number of parameters and causes convergence problems. To reduce the number of parameters, we combine some states and specify state-group fixed effects. Finally, the Independence of Irrelevant Alternatives (IIA) property is required for the conditional logit model. We conduct only limited tests of this property, but the tests cannot reject the validity of the IIA property.

Although these restrictions should be kept in mind in interpreting the results, our estimation results are consistent and robust across years. Furthermore, this study demonstrates that the conditional logit approach can provide a variety of results and is a powerful tool in studying migration. Results from alternative specifications are reported also. Although we do not include personal characteristics such as age and education in the model, this does not change the fact that the model is based on individual behavior. Each individual’s choice is based on utility maximization, and the probability of a particular choice for an individual entering the likelihood function independently. The likelihood function is constructed from the observed choices (migration) of the entire sample. In addition, individuals who move to the same destination state but from different origins are treated differently because the attributes of the origin states differ.

The rest of this paper proceeds as follows. Section 2 presents the econometric model and discusses some limitations of the approach. Section 3 describes the data. Section 4 discusses the results. Finally, section 5 provides a brief summary and conclusions.

2. ECONOMETRIC MODEL

The conditional logit model for migration choices is motivated by a random utility model. An individual at area $i$ faces $J$ choices, including moving to a different area or staying at the current location. Suppose that the utility level of choosing area $j$ for this individual is

$$U_{ij} = \beta'X_{ij} + \varepsilon_{ij}$$

where $X_{ij}$ is a vector of choice-specific attributes. For the conditional logit, the parameter $\beta$ is constant across choices. If the individual chooses destination $j$, then the utility $U_{ij}$ is the highest among all $J$ choices (i.e., $U_{ij} > U_{ik}$ for all $k \neq j$). Thus, when choice $j$ is made, the statistical model for the probability of moving from area $i$ to area $j$ can be represented as

Based on McFadden (1973), if and only if the $J$ disturbances are independent and identically distributed with the Weibull distribution, then the probability of an individual at area $i$ choosing area $j$ (where $j = i$ for nonmovers) is

$$P(y_i = j) = P(U_{ij} > U_{ik}) \quad \forall \ k \neq j$$

The log likelihood function for all individuals moving from any area $i$ to a specific area $j$ is

$$\ln L = \sum_i m_{ij} \ln P(m_{ij} = 1)$$

where $m_{ij} = 1$ if an individual in area $i$ chooses destination area $j$.

In this framework, if individuals do not move they choose to remain in the current location. This is an important aspect of our model because it allows us to estimate the unobserved difference between moving and staying. One alternative to this specification is to eliminate the current area of residence from the choice set and to focus on movers only. This specification would cause a selectivity problem because the possibility of a stayer moving under certain conditions is eliminated. Another specification is based on the nested logit model (McFadden 1984, Maddala 1983) where a person’s migration is treated as two separate decision procedures: first, the decision to move or to stay; second, given the decision to move, the choice of a destination. This nested approach is not adopted in this study because we believe that the decision to migrate and the choice of a destination are unlikely to be made sequentially. Rather, the decision regarding whether to move is intimately related to the possible destination choices.

We focus on migration between states in the coterminous U.S. Individuals who work in Washington, DC may reside in Maryland or Virginia so these three areas are combined into one destination choice. Thus, we have a total of 47 potential destination choices (including the current state of residence) for each individual. We have 47 source states because for each destination people can migrate from any other state. The corresponding log-likelihood function is

$$\ln L = \sum_{i=1}^{47} \sum_{j=1}^{47} N_{ij} \ln P(m_{ij} = 1)$$

where $N_{ij}$ is the number of people moving from state $i$ to state $j$ and
is the probability of moving from state $i$ to state $j$.\footnote{As pointed out by an anonymous referee, an alternative specification of the model would explicitly control for the quantity of opportunities available at the destination on the grounds that the probability of choosing destination state $j$ should be linearly homogeneous in the number of alternatives available in state $j$ (Ben-Akiva and Watanatada, 1981). Imposing linear homogeneity, the probability function is specified as}

$$P(m_{ij} = 1) = \frac{e^{\beta'x_{ij}}}{\sum_{k=1}^{47} e^{\beta'x_{ik}}}$$

The $x_{ij}$ vector includes choice-specific attributes such as economic factors that will affect individuals’ migration choices. Clearly, unobservable economic and noneconomic state characteristics such as amenities (Greenwood et al., 1991) also play an important role in the migration decision. To capture these effects we include a set of dummy variables for potential destinations (state fixed effects). These choice dummy variables are important for the specification of the conditional logit model because they function as constant terms (the inclusion of a separate constant term will drop out of the probability function).

Another consideration is the choice of the current state if an individual chooses not to move. A substantial difference should exist between this choice (the current state) and all other choices (another state) because no migration occurs if the current state is chosen. The difference between moving and staying cannot be controlled by state fixed effects alone because it also is related to unobserved costs associated with moving. To control for these unobserved factors, we include a nonmigration dummy variable in the model that is equal to one if the current state of residence is chosen and zero otherwise.

In the conditional logit model, only the effects of choice-specific attributes can be identified. A migration decision is based on the comparison of destination state characteristics with the characteristics of the current state of residence, so source state characteristics will certainly affect the migration choice. For example, people in a high-income source state $i$ will view the income level in a potential destination state $k$ differently than people in a low-income source state $j$. However, because source state characteristics do not vary across choices for an individual, they will drop out of the probability function.

Several options are available for treating this problem. The first is to use only the characteristics of a potential destination state, ignoring those of the source state. This option is clearly very restrictive. The second option is to
interact origin state variables with the destination choice dummy variables (state fixed effects). However, this procedure increases the number of parameters dramatically due to the large number of destination choice dummies. In fact, if all variables for an origin state are interacted with all destination choice dummies, the conditional logit model becomes the multinomial logit model because the parameters effectively vary across choices. The third option is to use relative measures of variables for the destination and origin by creating explanatory variables that take the form of destination-to-origin ratios. The further the value of the ratio from one, the larger the relative difference between the destination and the origin, and thus, the larger the influence of the variable on the probability of moving. This approach is restrictive because it essentially requires symmetric responses for changes in an origin state and a destination state characteristic.

Among these options, the second appears to be the best. However, perhaps due to the large number of parameters, the likely correlation between the destination characteristics and the state fixed effects, and large scaling differences between the independent variables, it fails to converge in computation. We adopt the third option and use ratio measures of destination and origin characteristics in our estimation to avoid computation problems. More importantly, we feel that ratio measures of the independent variables are better suited to capture the likely influence of differences between destination and origin characteristics on migration choice. We test the sensitivity of our specification by running alternative specifications using only destination characteristics. In our preferred specification, the destination choice dummy variables are replaced by 26 state-group dummies, where states are grouped based on similarity in terms of geography and amenities. As a result, the coefficients on the variables representing location characteristics (i.e., population, unemployment rate, and per capita income) are largely identified by differences within the state groups. This approach is justified because the state groupings result in sets of states that are likely to be similar with respect to unmeasured characteristics.

Finally, the conditional logit model depends on the independence of irrelevant alternatives (IIA) assumption. That is, the relative probabilities between choices must be independent of other alternatives. The IIA assumption follows from the initial assumption that the disturbances are independent and homoskedastic for the random utility model. Two types of tests are available for the IIA assumption, a Hausman-type specification test (Hausman and McFadden, 1984) and a Lagrange multiplier test (McFadden, 1987). These tests can be conducted by eliminating a subset of the choices from the choice set and reestimating the model. If the parameters of the restricted model are not systematically different from the parameters of the full model, then the IIA property holds. In this study with 47 potential
destination choices, the number of subset combinations to test is enormous. Furthermore, these tests do not offer a guideline for selecting the subset of states to eliminate.

Nevertheless, we conduct limited tests of the IIA property by first eliminating Florida from the choice set and then eliminating Colorado. Although the choice of these states is somewhat arbitrary, both states are similar in terms of their importance as receiving states of internal migrants, whereas they differ greatly in many other respects. The IIA test is conducted following Hausman and McFadden (1984). The test statistic is

\[ \chi^2 = (b_s - b_f)' (V_s - V_f)^{-1} (b_s - b_f) \]

It has the \( \chi^2 \) distribution with \( k \) degrees of freedom, where \( k \) is the rank of \( (V_s - V_f) \). The parameter estimates based on the restricted subset of states and the full subset of states are \( b_s \) and \( b_f \), respectively. \( V_s \) and \( V_f \) are the respective estimates of the asymptotic covariance matrices.

In both tests, \( k \) is equal to 31. (The state dummy variable that cannot be identified in the restricted choice set also is removed from the full parameter vector.) The corresponding \( \chi^2 \) test statistic is 1.13 when Florida is eliminated and 0.11 when Colorado is eliminated. The critical value for the \( \chi^2 \) statistic with 31 degrees of freedom at the 10 percent level is 41.33. Clearly, in both cases, we cannot reject the hypothesis that the IIA property holds for the choice set. Although the IIA test generally has low power, these limited results do not offer evidence against the conditional logit approach.

3. DATA AND EXPLANATORY VARIABLES

The migration data used in this paper are the Internal Revenue Service (IRS) Area-to-Area Migration Flow Data (hereafter referred to as “the IRS data”). The IRS data provide a 51 \times 51 matrix of internal migration flows for all 50 states and the District of Colombia annually beginning in 1975–1976. Nonmovers are on the diagonal of the matrix. Our data cover the eleven-year period from 1986–1987 through 1996–1997. We focus attention on moves within the coterminous United States and collapse Maryland, Virginia, and the District of Colombia into a single location. This leaves us with a 47 \times 47 matrix of state-to-state migration flows and nonmovers.

Although this is a rich source of temporal state-to-state migration data, some limitations should be noted. The flows are calculated by matching Social Security numbers from individual income tax returns and comparing addresses across years. Approximately 94 percent of the population is covered, but treatment of spouses and dependents in households is unclear. Migration in the IRS data is based on the Social Security number of the primary tax payer, so spouses

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\( ^2 \)For example, if we choose a single state as the subset, there are 47 different combinations \( (C) \) to test. If we choose two states as the subset, there are \( C^2_{47} \) combinations to test.
and dependents may not get counted as either migrants or nonmigrants. Furthermore, individuals who leave a household and move during the same tax year (e.g., divorce and move) may not be properly counted as movers. The extent of these problems is largely unknown. Finally, personal and household characteristics are not reported due to privacy and confidentiality restrictions. These potential problems notwithstanding, the IRS data hold great potential for temporal analyses of state-to-state migration.

Based on the discussion in the previous section, we include state fixed effects and a nonmigration dummy variable in our specification. In addition, state population is included as a comprehensive measure of the quality and quantity of all opportunities and social or family connections that are important to migration. The population variable is constructed as the ratio of destination-to-origin state population. A large state has more locations from which to choose, as well as more connections, more opportunities, and more widely available information that may serve to reduce the search costs and psychological costs associated with migration. Therefore, population is a reasonable proxy for the number of locations and opportunities available at potential destinations. Other proxies such as population density are used in alternative specifications.

State per capita income is included to represent the potential economic gains or losses from migration. It is measured as the ratio of destination-to-origin per capita income. The hypothesis that we test is that migrants are attracted to destinations with relatively higher per capita incomes. The ratio of destination-to-origin state unemployment rates is included as a comparison of different job opportunities (or the lack of job opportunities) between destination and origin states. The hypothesis here is that relatively higher destination unemployment rates deter migration. Distance, measured in thousands of miles between states, is used as a proxy for the direct economic costs and indirect psychological costs related to migration. Distance squared is included to account for nonlinear effects associated with increased distance.


3Ideally, per capita income is adjusted for state cost-of-living differences. McMahon (1991) computes state cost-of-living indices; however, they do not cover the entire period of our data. Even if we were to adjust for interstate differences in cost-of-living, intrastate differences in cost-of-living would still remain.

weighted averages. Distance from the Maryland-Virginia-District of Colombia location is measured from the District of Colombia.

Initially, we created one dummy variable for each state, resulting in 46 dummy variables and a total of 52 parameters to be estimated. The computation failed to converge, perhaps due to the large number of parameters to be estimated and the likely correlation between the state fixed effects and the destination characteristics. To reduce the number of parameters, we combine “similar” states for the state dummy variables, based on similarity in terms of geographic location and amenities. This specification may also help to reduce the correlation between the individual state dummy variables and the destination characteristics. A total of 26 state-group dummies are created with California as the omitted choice (see Table A1 for the state-group combinations).

After incorporating these variables, the probability function for an individual at state $i$ to move to state $j$ is (for simplicity, we drop the origin notation $i$)

$$P_j = \frac{e^{\beta x_j + \alpha z_j + \gamma w_j + \delta s}}{\sum_{j=1}^{47} e^{\beta x_j + \alpha z_j + \gamma w_j + \delta s}}$$

where $x_j = (x_{j1}, x_{j2}, x_{j3})$ = destination-to-origin population ratio, destination-to-origin unemployment rate ratio, and destination-to-origin per capita income ratio, respectively; $z_j = (z_1, z_2, \ldots, z_{26})$ = state-group dummy variables; $w_j$ = distance (thousands of miles) between $i$ and $j$; and $s$ = the nonmigration dummy variable.

4. RESULTS

The conditional logit model described above is estimated separately for each of eleven years, 1986–1987 through 1996–1997. Estimated coefficients for the primary explanatory variables for each year are presented in Table 1. A number of alternative specifications also are estimated. The results from some of these alternative specifications are presented in Table A2.

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4The computer software package used is GAUSS. It takes 1 to 5 hours for convergence for each year, depending on the starting values, on a Pentium II 300 processor.
5The destination-to-origin population ratio is included in the vector of choice-specific attributes to control for the quality and quantity of opportunities offered at the destination relative to the opportunities available at the origin. In one alternative specification, we impose linear homogeneity (as described in footnote 1) using destination state population as a proxy for the quantity of opportunities available at the destination. The results, (available from the authors on request) are very similar to the results of our original specification (Table 1) in all respects (sign, magnitude, and significance). Given this and noting that the specification imposing linear homogeneity is more restrictive, we prefer the original specification.
6The results from the alternative specifications in Table A2 are very similar to the results presented in Table 1. One difference is that the coefficient for population density in column 1 is negative and significant, whereas the coefficient of the population ratio variable is always positive and significant. We believe that although greater population density may represent greater potential opportunities, it also may represent greater congestion, thus leading to the negative coefficient.

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*All estimated coefficients are statistically significant at the one percent level. Standard errors are in parentheses.

bDestination-to-origin ratio

cAll log L values are divided by ten million.
The results for most of the primary independent variables are strong and consistent across time. The last three rows of Table 1 show that the log-likelihood ratio is much larger at convergence \((\log L_{\text{at convergence}})\) than when evaluated with all coefficients set to zero or at the sample shares of migration flows. This is a general indication that our model explains the data better than no model \((\beta = 0)\) and better than a simple description of the data based on sample shares.\(^7\)

For the conditional logit model, the direct marginal effects for continuous variables are

\[
\frac{\partial P_i}{\partial x_i} = P_i(1 - P_i)\beta
\]

and

\[
\frac{\partial P_i}{\partial w_i} = P_i(1 - P_i)(\gamma + 2\theta w_i)
\]

The marginal effects of a one standard deviation change in the unemployment rate ratio and the per capita income ratio for selected \(i-j\) pairs of states in 1996 are discussed in the text below. Table 2 presents the marginal effect of a one hundred mile increase in distance between the origin and destination for the same \(i-j\) pairs of states in 1996.\(^8\) The marginal effects are scaled by the probability of moving from state \(i\) to state \(j\), allowing the marginal effects to be

A migrant stock variable is sometimes included as an independent variable in models of migration (Greenwood, 1969) to proxy for the effect of having family and friends at the potential destination. The coefficient for migrant stock in column 4 is negative and significant, whereas we expected it to be positive. To the extent that the previous year’s migration flow from state \(i\) to state \(j\) may not be stable (e.g., many of these migrants may move on to other destinations or may return to the origin) and that new migrants may provide negative information to family and friends at the origin (e.g., homesick, unhappy with new job or residence), it may not accurately reflect the family and friends effect as in Greenwood (1969). Other constructions of migrant stock, such as the sum of flows from state \(i\) to state \(j\) over the previous five years, may suffer from even greater measurement error because we cannot identify how many of these migrants stay in state \(j\). As noted by an anonymous referee, our proxy for migrant ‘stock’ is actually a ‘flow’ measure. A better measure would cross-tabulate state of current residence by state of birth from decennial census data. However, at best such a measure (from the 1990 census) would be applicable to our 1991 and 1992 migration data; therefore, we do not follow this approach. As noted in Greenwood (1997), if migrant stock is not included, the distance variable (and in this case, distance squared) reflects the importance of relatives and friends at the destination, as well as the direct economic costs of moving.

\(^7\)On average, our model over-predicts out-migration. The maximum value of the predicted-to-actual out-migration ratio occurs for Maine and Vermont in each year. The minimum value occurs for Florida in each year.

\(^8\)Four states, one from each Census region, are followed throughout the discussion of results. These states are Arizona, Illinois, Massachusetts, and Tennessee. These states were chosen arbitrarily apart from the desire to include one state from each Census region. Clearly, other states could have been chosen and would display somewhat different results. The results from 1996 are presented because this is the most recent year of our data.

interpreted as proportional changes. Thus, the $P_j$ term drops out of the equations above when considering proportional changes.

The result in Table 1 that migrants are more likely to move to relatively more populous states may suggest that people move to places of greater perceived economic and social opportunity. To the extent that information is more widely available about locations and potential opportunities in more populous states, search costs and psychologival costs associated with migration may be lower, thereby increasing the probability of migrating to a relatively more populous state. The results across years for population are very consistent—the estimated coefficient is between 0.029 and 0.038 for each of the eleven years of our analysis.

In models of place-to-place migration, unemployment-rate variables consistently have had insignificant coefficients and unanticipated signs (Greenwood, 1975, 1997). However, it is notable that this is not the case in our conditional logit model. Migrants are significantly less likely to move to a destination with a relatively higher unemployment rate. Table 1 shows that the direction and significance of this result is consistent across all eleven periods. We attribute this result to the inclusion of state-group dummies. As shown in column 6 of Table A2, when state-group dummies are excluded, the only substantive change in the results is that the coefficient on the unemployment rate ratio becomes positive and significant. This finding suggests that unmeasured differences between states are important and that including state-group dummies helps to identify the parameters. Therefore, we prefer the specification in Table 1 to the specification without state dummies in column 6 of Table A2 (in Appendix).

Although the sign and significance of the unemployment rate coefficient is consistent over time, the magnitude of the coefficient varies considerably, calling into question the temporal representativeness of previous estimates of the relationship between the unemployment rate and the probability of migration based on a single cross-section of data. The range of estimated coefficients for the unemployment-rate ratio extends from –0.22 in 1991 to –0.78 in 1986 (Table 1). This finding appears to be driven by state variations in unemployment rates. For 1986, the year for which the unemployment-rate coefficient is largest
in absolute value, the mean state unemployment rate is 7.0 percent with a variance of 4.8. For 1991, the year for which the unemployment-rate coefficient is smallest in absolute value, the mean and variance are 6.4 percent and 2.1, respectively. The lower variance of state unemployment rates may provide less information for prospective migrants to use in making their location choices; hence, the absolute values of the estimated coefficients are smaller for those years. In other words, for these years, the unemployment rate plays a less important role in the prospective migrant’s decision-making process because state unemployment rates are more evenly distributed across the nation. As evidence in favor of this hypothesis, we note that for the period 1986–1996, the correlation between the estimated coefficient on the unemployment-rate variable and the variance in state unemployment rates is –0.52 and is statistically different from zero at the 10 percent significance level.

For 1996, a one-standard deviation change in the destination-to-origin unemployment rate ratio reduces the probability of migration by between 18 percent and 20 percent, depending on the pair of states (results not shown). As an example, consider a one-standard deviation increase in the Arizona-Illinois destination-to-origin unemployment rate ratio (from 1.04 to 1.38) caused by an increase in the destination unemployment rate for Arizona (from 5.5 percent to 7.3 percent). The proportional effect of this change is a 19.43 percent reduction in the probability of migration from Illinois to Arizona. The proportional effect of a change in the unemployment rate ratio on the probability of migration is quite stable across pairs of states in 1996.

Relative per capita income has the expected positive sign and is highly significant for each year (Table 1), indicating that migrants are more likely to move to destinations with relatively higher per capita incomes or greater perceived economic opportunities. The estimated coefficient on per capita income has a mean of 0.71 and a standard deviation of 0.17 across the years of our analysis. The variation in the coefficient estimates over time is considerable but does not appear to follow a consistent pattern. For 1996, a one-standard deviation change in the destination-to-origin per capita income ratio increases the probability of migration by between 16 percent and 17 percent, depending on the pair of states (results not shown). For example, a one-standard deviation increase in the Illinois-Massachusetts destination-to-origin per capita income ratio (from 0.90 to 1.11) caused by an increase in destination per capita income for Illinois (from 26,855 dollars to 33,087 dollars) increases the probability of migration from Massachusetts to Illinois by 16.25 percent. As is the case with the unemployment rate ratio, the proportional effect of a change in the per capita income ratio on the probability of migration is very stable across pairs of states in 1996.

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9Means and variances are calculated from state unemployment rates for the 47 units used in the analysis—46 coterminous states plus a combined unit including the District of Colombia, Maryland, and Virginia.

Table 1 indicates that the effect of distance on the probability of moving from state $i$ to state $j$ is negative, highly significant, and very stable across the eleven periods. The finding that greater distance between origin and destination deters migration is consistent with previous research. However, we also include distance squared as an explanatory variable to explore the possibility that the effect of distance on migration is not linear. The results in Table 1 indicate that the deterrent effect of distance on the probability of migration decreases as distance increases. That is, as distance between origin and destination increases, the probability of migration decreases, but at a diminishing rate.

Proportional changes in the probability of migration resulting from a one hundred mile increase in distance between origin and destination are presented for 1996 in Table 2. These effects vary widely across pairs of states, are predominantly negative as expected, and are quite large in some cases.\textsuperscript{10} Although a one hundred mile increase in distance between Illinois and Arizona reduces the probability of migration between the two states by only 2.6 percent, the same change in distance between Illinois and Tennessee leads to a 14.3 percent decrease in the probability of migration.

The nonmigration dummy variable identifies the decision to stay in the origin state as distinct from the decision to move. The nonmigration variable allows us to obtain some measure of the unobserved costs of moving from state $i$ to state $j$. These unobserved costs of moving can be thought of as psychic costs and time costs of moving. Psychic costs include leaving family and friends, and concerns about adjusting to the surroundings in the new location. Time costs of moving include packing and unpacking. The estimated coefficient on the nonmigration variable is positive and highly significant for all eleven periods (Table 1). The magnitude of the coefficient is stable over time, ranging between 6.09 and 6.17. Moreover, the magnitude of the nonmigration coefficient relative to the coefficients for the other primary explanatory variables suggests that unobserved costs of moving are important in the decision to stay or move.

To interpret the coefficient of the nonmigration dummy variable, suppose there exists a hypothetical state $j$ that is exactly the same as state $i$ (origin) in all respects, including observable characteristics, amenities, and even distance (i.e., $w_{ij} = 0$). That is, one can stay in origin $i$ without moving, or one can “jump” to destination $j$ in which all of the costs associated with migration mentioned above will be incurred. Then, all measured factors are the same, and the only difference between choosing state $i$ and state $j$ is conceptual migration. In this

\textsuperscript{10}The marginal (proportional) effects become positive only for distances greater than approximately 2,500 miles. For 1996, only 2.88 percent of all moves involved state pairs that are more than 2,500 miles apart. Furthermore, only 0.15 percent of the at risk population (i.e., movers plus stayers) made a move of greater than 2,500 miles. The effect for the tails of the distribution may not be properly identified because such a small proportion of moves occurred between states more than 2,500 miles apart.

situation, the percentage difference in the probability of moving or not moving is measured by

\[
P(moving) - P(not\ moving) \over P(not\ moving) = e^{-\delta} - 1
\]

For example, for 1996, all unobservable costs associated with the migration decision make the probability of moving 99.8 percent lower than the probability of not moving.

The conditional logit model also allows for the calculation of cross-marginal effects because we are able to specify numerous alternative destinations. Cross-marginal effects can be interpreted as the effect of a change in a characteristic of alternative destination \( k \) on the probability of moving from origin \( i \) to destination \( j \). For continuous variables, the cross-marginal effects are

\[
\frac{\partial P_j}{\partial x_k} = -P_j P_k \beta
\]

where \( P_j \) is the probability of moving from state \( i \) to state \( j \) and \( P_k \) is the probability of moving from state \( i \) to state \( k \). The magnitudes of the cross-marginal effects are very small, as expected. Such estimates may be useful in the context of a specific application. We are unaware of any previous use of the conditional logit approach to estimate cross-marginal effects associated with migration. Bartel (1989) uses the conditional logit approach to examine the location choices of immigrants to the United States, but does not explore cross-marginal effects.

As described above, state-group fixed effects are included to capture unobservable economic and noneconomic state factors associated with the migration decision, such as amenities. The vast majority of the estimated coefficients are statistically significant (Table A1). The coefficients are predominantly negative, indicating that the state group is a relatively less attractive destination than the omitted choice, California. Texas and Florida, with consistently positive estimated coefficients, appear to be relatively more attractive destinations than California. The coefficients for Georgia are negative for the first few years and then turn positive, indicating that Georgia’s attractiveness relative to California has changed over the period of our analysis. Still other states and state groups, such as Illinois, Michigan, Ohio, North Carolina/South Carolina, and Washington/Oregon/Idaho, have coefficients that change sign more than once between 1986 and 1996. This temporal pattern suggests that the attractiveness of these state-group destinations relative to California is fluctuating through the late 1980s and 1990s. Further research on the temporal patterns of the state-group fixed effects could make useful contributions to the literature on the relative effects of amenities and other unobservable factors on the migration decision.

For certain pairs of independent variables, examination of trade-offs related to the probability of migration is of interest. We noted above that Sjaastad (1962) calculated the trade-off between distance and destination
income. The conditional logit approach allows us to calculate not only this trade-off, but others as well. By measuring the trade-off between any given variable and per capita income, we can place an approximate dollar value on that trade-off. Three trade-offs are derived and discussed below: the trade-off between the unemployment rate and per capita income, the trade-off between distance and per capita income, and a money measure of unobserved costs associated with migration.  

If everything else is held constant, and only the unemployment-rate ratio and the per capita income ratio are allowed to change, then we can derive an iso-probability curve in unemployment-income space. The probability of moving from state \(i\) to state \(j\) is held constant \((dP_j = 0)\) and

\[
\frac{dx_{j3}}{dx_{j2}} = \frac{\frac{\partial P_j}{\partial x_{j3}}}{\frac{\partial P_j}{\partial x_{j2}}} = -\frac{\beta_2}{\beta_3}
\]

For example, in 1996, this ratio is 0.76, which means that if the ratio of the unemployment rate between destination \(j\) and origin \(i\) increases by one, the corresponding ratio of per capita income should increase by 0.76 to keep the probability of moving constant. That is, if initially the unemployment rate in both the origin and destination is 4 percent, but now the destination unemployment rate increases to 8 percent, the per capita income ratio should increase by 0.76 to compensate. If per capita income in both states is $10,000 initially, then destination per capita income must increase by $7,600 to $17,600 to compensate. Table 3 shows the increase in destination per capita income required to keep the probability of moving constant, resulting from a one-standard deviation increase in the unemployment-rate ratio and holding origin unemployment rate and per capita income constant. Among the four selected origin states, this dollar amount ranges from $5,428 for Arizona to $7,584 for Massachusetts. Some of the variation across states is likely due to state cost-of-living differences. The magnitude of the unemployment rate–per capita income trade-off varies substantially over the time period of our analysis as a result of changes in the relevant coefficients (per capita income also varies over time).

Following the same procedure but for distance and per capita income, we obtain

\[
\frac{dx_{j3}}{dw_j} = -\frac{\frac{\partial P_j}{\partial w_j}}{\frac{\partial P_j}{\partial x_{j3}}} = -\frac{\gamma + \theta w_j}{\beta_3}
\]

11 We can calculate trade-offs between amenities based on the state fixed effects also. However, because of space constraints, we do not present these estimates here.

12 The iso-probability curve is basically the same concept as the marginal rate of substitution (MRS). These trade-offs measure the MRS between two variables while holding utility constant.
Conceptually, we are considering a move from origin \(i\) to a new destination that is exactly the same as destination \(j\) in all respects except that \(w_{ij}\) has increased by one mile. We then calculate the change in the per capita income ratio between states \(i\) and \(j\) required to compensate for the greater distance.

Table 4 calculates the change in per capita income in 1996 required to offset the cost of a one-mile increase in distance at various distances from the origin, holding origin income constant. For each mileage there is some variation in the compensation amounts across origins. For example, at a distance of 500 miles, a one-mile increase in moving distance from Arizona must be compensated by a $45 increase in destination per capita income. At this same distance, a one-mile increase in moving distance from Massachusetts can be offset by a $63 increase in destination per capita income. These values appear to be higher than those calculated by Sjaastad (1962). The trade-off decreases as distance increases, which reflects decreasing marginal costs of moving as distance increases. The income compensation for an additional mile from Tennessee falls from $47 at 500 miles from the origin to $28 at 2,000 miles from the origin. Corresponding values for Illinois are $56 and $34. The values of these trade-offs change over the time period due to changes in the estimated coefficients and changes in per capita income levels.

The third trade-off calculates a money measure of the unobserved costs associated with migration. Consider a hypothetical destination state \(j\) that is exactly the same as the origin state \(i\), and assume that the distance between state \(i\) and state \(j\) is zero (i.e., \(w_{ij} = 0\)). Then the only difference between origin \(i\) and destination \(j\) is that in order for a person to get to destination \(j\), all of the unmeasurable costs associated with moving must be incurred. To compensate for moving, the change in per capita income in state \(j\) must satisfy

\[
\Delta x_{ij} \beta_3 = \delta
\]

where \(\delta\) is the estimated coefficient on the nonmigration dummy variable. For example, for 1996, \(\delta\) is equal to 6.12, implying that the ratio of destination to origin per capita income must increase by a factor of 8.01 to induce people to move. Table 5 shows that, for origin state Arizona, destination per capita income must increase by nearly $171,000 to compensate for the unobserved costs of migration. Similarly, for origin state Massachusetts, destination per capita income must increase by over $238,000 to compensate for the unobserved costs associated with migration. These estimates are rather large, but we are unaware
of any existing study that provides estimates against which ours may be compared.13

5. SUMMARY AND CONCLUSIONS

This paper employs a conditional logit approach to estimate a model of interstate migration in the United States from 1986 to 1996. Because the model is estimated using annual migration data for each of eleven consecutive years, we are able to approximately assess the temporal stability of the model. The conditional logit model also allows for the computation of marginal effects and various trade-off values that are of interest in migration analysis.

13The magnitude of this trade-off, and the dollar values attached to it, vary widely over the time period of our analysis. The adjustment factor for each year is shown in the table below

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Given that the coefficient δ does not change much over the period (Table 1), the temporal variation in the money measure of unobserved costs associated with migration results from changes in the coefficient on per capita income (per capita income levels also vary over time).

One objective of this study is to explore temporal aspects of place-to-place migration. The conditional logit estimates are relatively stable over time. Several of the coefficients hardly change for the eleven years over which we have estimated them (population, distance, distance squared, the non-migration dummy, and many of the state fixed effects). This is an important finding because it indicates that when the data allow estimates to be obtained for migration that occurred over a single period, representative estimates can be obtained. However, the coefficients for per capita income, the unemployment rate, and several of the state fixed effects change substantially over the period of our analysis, thus warranting further study of the temporal features of state-to-state migration.

Many prior studies of place-to-place migration found troublesome results concerning unemployment-rate variables, with coefficients frequently of unanticipated signs (Greenwood, 1975, 1997). The conditional logit framework adopted here yields the expected sign and statistically significant coefficients on the unemployment-rate variable for each year. One possible reason for our findings is that the methodology accounts for unemployment rates in each of the alternative locations, not just in the destination chosen.

Another objective of this study is to demonstrate the potential richness of the conditional logit approach to studying place-to-place migration. Accordingly, we have calculated a number of measures that can be derived from the conditional logit estimates and that are of potential interest to students of migration. For example, we present the direct marginal effects on the probability of moving due to changes in the unemployment rate, per capita income, and the distance between destination and origin. We also point out the potential for calculating cross-marginal effects from the conditional logit estimates. The cross-marginal effect is the effect of a change in a characteristic of alternative destination \( k \) on the probability of moving from state \( i \) to state \( j \).

Moreover, because per capita income is one of the independent variables of the model, we are able to calculate the rough dollar value of various trade-offs, such as that between distance and income. For example, we ask, what increase in per capita income is required to exactly compensate for a move that is one mile more distant (at various distances), leaving the average migrant indifferent between alternative destinations? We employ the concept of the iso-probability curve to show the dollar values of three types of trade-offs: (1) unemployment rates; (2) distance; and (3) unobserved costs of migrating. Our results shed some light on these trade-offs, but other estimates for the purpose of comparison are not available.

In general, the conditional logit approach to the study of place-to-place migration holds great promise. It has the potential to yield important measures that go well beyond what have been calculated to date and that enrich our understanding of migration phenomena.
REFERENCES


## APPENDIX


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*aEstimated coefficient is not statistically significant at the five percent level.*
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$^a$In column 1, we replace the population ratio with the population density ratio. In column 2, we replace the population ratio with destination population. In column 3, we replace the per capita income ratio with destination per capita income. In column 4, we add migrant stock, measured as a one-year lag of the migration flow from state $i$ to state $j$. In column 5, we replace all of the ratio variables with destination variables. In column 6, we return to ratio measures of population, unemployment rates, and per capita income, but exclude state-group dummies. Column 7 repeats column 5, but excludes state-group dummies.

$^b$Estimated coefficient is not statistically significant at the five percent level.

$^c$All log $L$ values have been divided by 10 million. Log $L$ at $\beta = 0$ and log $L$ at sample shares are the same for each specification, $-7.99 \times 10^8$ and $-7.15 \times 10^8$, respectively.