Retire to Where? A Discrete Choice Model of Residential Location

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ABSTRACT

Many studies of migration attempt to identify attributes of places that influence residential location decisions. Most such studies relate an area's migration rates to its own attributes, or the flow of migrants bewteen two areas to both areas' attributes. We focus on retirement migration, and extend the literature by using a discrete choice framework in which a person's location decision depends on the attributes of all potential locational choices. This leads to a multinomial logit specification in which individuals face over 3000 county-level choices, which we apply to Census data on the location of as many as 8.9 million persons age 65-74. In order to make the estimation problem manageable, we employ a sampling-of-alternatives result due to McFadden, and use aggregated migratory-flow data for which existing estimation software is applicable.

Our results indicate that in general, persons around retirement age avoid high taxes and housing prices, while they are drawn to areas with relatively high spending on such services as fire, police, and recreation. Amenities such as coastline and warm weather are also valued.

Keywords: migration; retirement; location choice; multinomial logit

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1. INTRODUCTION

1.1 Retirement Migration

Retirement migration is an important demographic and social phenomenon in the United States. Examination of the age profile of migration rates reveals three peaks: the largest occur early in the life cycle (among persons age 20-25 and among children 0-5), yet there is a clear local peak around age 65 (Rogers 1988). The volume of migration accompanying retirement is considerable, with more than 380,000 persons moving across state lines annually to retire (Longino1995). Migration into popular destinations can have a substantial impact on an area's age distribution. Frey (1995) showed that nearly 15 percent of Nevada's 1990 population of persons 60 and older resulted from net inmigration during the period 1985-1990. Migration contributed substantially to the aging of Florida and Arizona during this period as well. Retirement migration can be expected to become more salient as the population continues to age: members of the "baby boom" generation, born during 1946-1964, will pass age 65 during the second and third decades of the 21st Century. During those years the pool of potential retirement migrants will reach all-time highs.

Retirement migration is also an important public policy issue. Many studies have concluded that migration of the elderly is economically beneficial to receiving areas, bringing with it recession-proof incomes and an increase in the property tax base while placing a relatively light burden on the public service budget (Fagan and Longino 1993). As a consequence, some analysts have advocated adoption of policies that would stimulate such inmigration (Deller 1995), although these views have not gone unchallenged (e.g., Stallmann and Siegel 1995).

1.2 Factors Associated With Retirees' Location Decisions

Conceptualizations of the migration decision making process emphasize the amenity-driven nature of migration that takes place around the time of retirement. A widely cited paper offers a threefold classification of residential mobility in older ages (Litwak and Longino 1987). According to this scheme, the typical sequence consists of a first move around the time of retirement, in which locational amenities play a prominent role, followed by a move made in order to be nearer family and friends, and prompted by actual or impending health declines. This is followed, in turn, by a move into an institution for those unable to live independently.

In response to direct survey questions, retirees indicate that they value mild climate, low crime rates, low living cost (including housing prices), low income taxes, access to an urban area with social and cultural amenities, and access to a good hospital when considering potential residential locations (Longino 1995). Numerous studies have attempted to quantify the relationships between factors such as amenities, fiscal variables, and other economic and social characteristics, and migratory and residential patterns. Older persons have been shown to be attracted to areas with sunny climates (Dresher 1993; Conway and Houtenville 1998), coastal access (Bures 1997), bodies of water (Meyer 1987; Schneider and Green 1992), with relatively high levels of public spending on police and on parks and recreation (Dresher 1993), with relatively high housing vacancy rates (Walters 1994a), and with existing high concentrations of older persons (Newbold 1996; Meyer 1987). Studies have also shown that older people are repelled by areas with high taxes, including property taxes (Cebula 1974) and death taxes

(Dresher 1993; Voss, Gunderson and Manchin 1990), with relatively high public spending on welfare (Cebula 1974) or on education (Conway and Houtenville 1998), with a humid climate (Walters 1994a) or with cold winters (Newbold 1996; Cebula 1974), and with relatively high levels of crime (McLeod et al. 1984; Cebula 1993). Past studies also, however, frequently find associations between area characteristics and migration rates that have the "wrong" sign; for a comprehensive review of past findings see Walters (1994b).

Potential locations vary in both the existence and levels of attributes, whether desirable or undesirable. In such a situation high levels of one desirable feature might be attainable only if low levels of other desirable features, or high levels of some undesirable features, are accepted. One must, in other words, make tradeoffs across desirable and undesirable attributes of potential locations.

Our research reinvestigates the role of place characteristics, particularly amenity and fiscal factors, in location decisions. The place characteristics examined have, in nearly all cases, appeared in one or more past studies. However, we formulate the location choice problem as that of selecting one from a large number of discrete alternatives—over 3000 counties.

1.3 Migration Data

The types of data used in most empirical studies of migration include prospective panel studies and retrospective cross-sectional studies. Data such as that collected in the Panel Study of Income Dynamics (PSID), the Longitudinal Study of Aging (LSOA) and the Retirement History Survey (RHS) generally include a rich array of individual-level characteristics measured prior to observed residential moves, permitting prospective analyses of migration behavior. However, the public-use versions of these household panels typically do not include variables identifying geographic location, or do so only for large areas such as states or regions. One exception is the PSID, which includes codes indicating respondents' county of residence. However, the PSID, like other such panels, provides a small sample for purposes of studying location decisions. For example, Kallan's (1993) analysis, based on PSID data, is based on approximately 800 respondents (observed for 3,895 person-years), among which only 91 intercounty moves are recorded. Consequently, the panel-data sources cited have most often been used to address questions such as *who* moves, *when* they move, and the sequencing of moves relative to other life events such as retirement or the death of a spouse, rather than the question of *where* people move (see Henretta, 1986; Sommers and Rowell, 1992; and Venti and Wise 1989 for research based on the PSID, LSOA and RHS, respectively).

The most extensively used source of migration data is the decennial Census, which since 1940 has asked those enumerated to indicate their current place of residence as well as that of five years ago. Such retrospective data suffers three major weaknesses: it records transitions in locational space rather than moves (and, therefore, may miss intermediate and return moves); being retrospective in nature, it fails to record moves made during the relevant time interval by persons who fail to survive to the data-collection date; and, the values of possible correlates of moves are recorded at the end of, rather than at the beginning of, the time interval. Yet these Census data offer the advantages of complete enumeration of survivors and the ability to measure even very low levels of migratory flows between small local areas throughout the country.

Decennial Census migration data have been used in many studies of the effects of variations in local-area characteristics on the volume and nature of migratory flows. These studies vary with respect to the degree of geographic detail employed and with respect to the range of measured factors hypothesized to influence specific migration streams. Many studies develop models of net in-migration (to states, counties, or metropolitan areas) in which migratory flows depend on the attributes of the destination area only (see, for example, Bures 1997; Clark and Hunter 1992; Cebula 1974; or Meyer 1987; Walters 1994a analyzes gross in- and out-migration flows in an analogous manner). Other studies present models of either the gross, or the net, flows of persons between *pairs* of areas, in which those flows depend on the attributes of both origin and destination places (see, for example, McLeod et al. 1984; Conway and Houtenville 1998).

Yet if individual retirement decisions are governed by a consideration of the features of any given potential location, then they surely must, as well, be governed by consideration of a given location's attributes *relative to* the attributes of other potential locations. Furthermore, variations across persons in measured and unmeasured characteristics such as economic and health status, knowledge levels, the spatial distribution of relatives and friends, and preferences for specific amenities, implies that similar individuals will make dissimilar locational decisions. Under these circumstances the chances that an individual will choose to move from location j to location k will depend on not only the attributes of locations j and k, but on the attributes of many (and, in the limit, all) other potential locations as well. Some studies (e.g., Schneider and Green 1992) attempt to infer the preferences of retirees for various locational attributes, such as physical amenities, by examining the places to which movers relocate. Yet the vast majority of retirees do *not* move during the time intervals typically studied. Thus attempts to uncover the importance of factors allegedly influencing locational decisions should consider the behavior of both movers and of nonmovers.

To our knowledge no past research has investigated retirement migration at the national level, employing a statistical method that allows for the dependence of locational choices on the attributes of all possible locations while representing the decisions to change locations or to remain in place. Our research attempts to fill this gap, employing standard tools of discrete choice modeling and an extensive set of data on locational attributes to model the migration and location choices of the population of retirement-age persons in the United States. The statistical tools used are not new, although the multinomial logit (MNL) models we estimate are, we believe, of a uniquely large scale. Many past studies of locational choice used MNL models; many of those studies considered local areas in which relatively few (less than 12) distinct locational choices are distinguished (see, for example, Friedman 1981; Boots and Kanaroglou 1988; Gabriel and Rosenthal 1989; or Nechyba and Strauss 1998). Larger-scale models of this type include White and Hunter (1993), who modeled flows among a selection of 58 metropolitan areas, and Gresetz (1997), who modeled choices of residence from the set of 48 contiguous states plus the District of Columbia. Dresher's (1993; 1994) analyses of PSID data used the sampling-of-alternatives approach discussed below in her model of choices from the set of states and of counties, respectively. We also demonstrate the usage of widely available statistical software to estimate models that might otherwise be viewed as infeasibly large.

2. METHODS

2.1 Discrete Choice Model

We employ standard tools of discrete choice analysis (Ben-Akiva and Lerman 1985). In this framework, individuals are assumed to be confronted by a set of distinct alternatives from which one must be chosen, and individuals have the capacity to systematically and consistently rank those alternatives. Observed choices are by assumption those most highly ranked. In particular, for a set of potential counties of residence the relative ranking assigned to residence in county *j* is assumed to be represented by a linear additive utility function of the form

$$u_{ij} = X_j \mathrm{B} + e_{ij}, \tag{1}$$

where X_j is a (row) vector of measured attributes of county *j*, B is a (column) vector of unknown parameters and e_{ij} is a random disturbance specific to *i*'s evaluation of alternative *j*. B represents the average weights attached to respective elements of the vector X_j in the population, so X_jB represents the population average of the index by which alternative *j* is ranked, while the vector of e_{ij}s represents the differences between *i*'s ranking indices and the corresponding population averages. Differences across individuals in the relative rankings of alternatives can be incorporated by postulating separate B arrays for members of population groups, or by interacting individual attributes with elements of the X_j vector. Since there are costs to moving, the net utility attainable from a $j \rightarrow k$ move is

$$X_k \mathrm{B} - X_j \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk} - (e_{ij} - e_{ik}), \tag{2}$$

in which M_{jk} is a dummy variable indicating a move must take place (i.e., that $j \neq k$) and D_{jk} measures the distance between j and k. When $j = k$, $M_{jk} = D_{jk} = 0$, δ_0 thus represents the fixed costs of moving, while $\delta_1 D_{jk}$ represents the variable costs of moving.

In our analysis the set of locations from which locations can be chosen, S_j, contains 3068 counties of the contiguous 48 states of the U.S. Although all 3068 counties appear in the choice set for every origin county, j, we index the choice sets by origin county since j is an "origin" county only in set S_j. Under the usual assumption that all e_{ij} are independently and identically distributed according to the extreme value distribution,

$$\mathrm{pr}[e_{ij} \leq z] = \exp(-e^{-z}), \tag{3}$$

the probability that individual i chooses location k, given that i's initial location is j, is a conventional MNL expression,

$$p_{ijk} = \frac{e^{X_k \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}}}{\Sigma_{k \in S_j} e^{X_k \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}}} \tag{4}$$

(McFadden 1973).

2.2 Simplifying the Estimation Problem

As written, maximum-likelihood estimation based on (4) is unmanageably difficult, in view of the large size of the choice set (3068 elements per individual) and the large number of individuals (the entire population, in the Census data we use). In order to make the problem manageable, we make use of two results that simplify the analysis.

First, McFadden (1978) has shown that consistent estimates of the vector B can be obtained when the full choice set S_j is replaced with a subset S_j' containing (1) the observed choice and (2) a random sample from the remaining, but rejected, possible choices (this approach is, in fact, one of four sampling-of-alternatives schemes discussed in McFadden 1978). The exponents in the numerator of (4), and in each retained term of the denominator of (4), must in general be adjusted to account for the probability with which that term was sampled. We divide S_j into disjoint subsets S_{1j}, containing m_{1j} counties selected with probability $\pi_{1j} = 1$, and S_{2j}, containing m_{2j} counties randomly selected from the set $\{S_j - S_{1j}\}$ of rejected counties, with selection probability $\pi_{2j} < 1$. With this sampling scheme the choice probabilities in (4) become

$$p_{ijk}^{/} = \frac{e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}}}{\Sigma_{k \in S_{1j}}\, e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk} - \ln\pi_{1j}} + \Sigma_{k \in S_{2j}}\, e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk} - \ln\pi_{2j}}} \quad (5)$$

(McFadden 1978; Ben-Akiva and Lerman 1985), or

$$p_{ijk}^{/} = \frac{e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}}}{\Sigma_{k \in S_{1j}}\, e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}} + \pi_{2j}^{-1}\left(\Sigma_{k \in S_{2j}}\, e^{X_k\mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}}\right)} \quad (6)$$

since $\pi_{1j} = 1$. In other words, the m_{2j} counties in S_{2j} are weighted, with weights equal to the inverse of the sampling probability, in forming the denominator in (6).

To deal with the large number of individuals in the population studied, we make use of the aggregated data found in the Census Bureau's 1990 county-to-county (CTC) data files. For each origin county j (i.e., residence in 1985), containing a total of N_j individuals, we know the number who locate in county k in 1990, that is the series $n_{j1}, \ldots,$ $n_{j,\,3068}$, with $n_{jk} \geq 0$. We treat the outcomes $n_{j1}, \ldots, n_{j,\,3068}$ as the result of N_j repetitions of an IID random choice experiment. The aggregate choice set consists of N_j replications of the set S_j, and each n_{jk} is the number of times k is chosen from this larger set. County j thus contributes to the overall likelihood the term

$$L_j = \Pi_{k \in S_j} p_{ijk}^{n_{jk}}, \tag{7}$$

or equivalently

$$L_j^{/} = \Pi_{k \in S_{1j}} (p_{ijk}^{/})^{n_{jk}}, \tag{8}$$

since no elements of S_{2j} are ever chosen. In our application the set S_{1j} contains all counties chosen by *any* individuals initially located in county j, that is all k such that $n_{jk} >$ 0, while S_{2j} is a simple random sample from the set of "universally rejected" counties, that is the set of counties for which $n_{jk} = 0$.

Substituting (6) into (8), taking the natural logarithm and rearranging terms, it can be seen that county j contributes to the overall log-likelihood the term

$$\begin{aligned} \mathcal{L}_j^{/} = \Sigma_{k \in S_{1j}} n_{jk}(X_k \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}) \\ - N_j \ln[\Sigma_{k \in S_{2j}} e^{X_k \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}} + \pi_{2j}^{-1} (\Sigma_{K \in S_{2j}} e^{X_k \mathrm{B} - \delta_0 M_{jk} - \delta_1 D_{jk}})]. \end{aligned} \tag{9}$$

The overall log-likelihood is

$$\mathcal{L}' = \Sigma_{j\,=\,1,\,\ldots,\,3068}\, \mathcal{L}'_j, \tag{10}$$

in which a common parameter vector B is assumed to govern choice probabilities across all origin counties.

Expression (9) corresponds to Breslow's (1983) formulation of the partial log-likelihood for Cox's failure-time model in the presence of ties. The term in square brackets in (9) represents the full set of potential elements at risk of "failure," except that part of the risk set is represented by the random subsample S_{2j}. Whereas in the failure-time model each element in the risk set is an individual whose relative proneness to failure is captured by the expression $\exp(X_i B)$, in our application each element of the risk set is a potential residential location whose relative risk of being chosen is $\exp(X_j B)$. The first part of (9) corresponds to observed failures, with n_{jk} equalling the number of "ties," that is the number of individuals choosing location k.

In view of the correspondence between our discrete choice model and Cox's failure-time model, widely available software can be used to estimate the vector B of unknown parameters. We use SAS® proc phreg with the "ties=Breslow" option (see Kuhfeld 1996); the option "offset=" is used to incorporate the sampling probability adjustment $-\ln\pi_{2j}$, and the "freq" option is used to indicate that the data appear in aggregated form.

m_{1j} is the number of destination counties chosen by at least one person in origin county j, that is the number of elements in S_{1j}. For the results reported below we adopt a fixed sample size of 300 for m_{2j}, the number of randomly-selected counties in S_{2j}. Thus $\pi_{2j} = 300/(3068 - m_{1j})$. In our data the average of m_{1j} is under 20, so π_{2j} is, on average, slightly less than 0.1.

The sampling of rejected alternatives used to form the set S_{2j} introduces a type of sampling error into our parameter estimates. In an attempt to minimize such error, we have obtained 50 independent sets of estimates of B, each based on an independently-selected sample of rejected alternatives. Thus, with $\pi_{2j} \approx 0.1$ the expected number of times that any universally-rejected county will appear in a choice set used in the estimation is about 5. The probability that any universally-rejected county will *never* appear in a choice set is very small, about 0.005. Thus all available information contributes, with near certainty, to the estimates reported. We compute and report B*, the simple average of the 50 estimates of B, and substitute B* into the log-likelihood function (10) to obtain its covariance matrix.

2.3 Independence of Irrelevant Alternatives

The MNL approach is often criticised because it imposes an "independence of irrelevant alternatives" (IIA) property (Ben-Akiva and Lerman 1985). This property follows from the assumption that the e_{ij}*s* in (1) are IID across choices for each decision maker: the unmeasured attributes of choices are assumed to be uncorrelated. Consequently the ratio of any two choice probabilities depends only on the attribute vectors of the respective choices, despite the fact that any one choice probability depends on the attributes of *all* choices. The usual objection to IIA rests on the fact that if a hypothetical new choice option, with observed and unobserved attributes similar to an existing choice option, is introduced into a choice set, then the MNL model will assign an inappropriately high choice probability to it. In the limit, if the new and the existing choice have identical observed and unobserved attributes, then the combined choice probabilities for the identical options in the augmented choice set should equal the choice probability for the original choice in the original set of choices. Such an objection is of limited relevance to our application, since the set of counties from which choices are made has remained fixed for many years and can be expected to remain so for many more years.

Despite its IIA property MNL remains widely used, including applications to residential location data (Gresenz 1997; Nechyba and Strauss 1998). In some location choice applications, statistical tests have failed to reject the independence assumption (Gabriel and Rosenthal 1989; Nechyba and Strauss 1998); Gresenz (1997) rejects IIA but finds that the results of restricted and unrestricted models are very similar. In our application, we use an extensive array of choice-specific attributes, strengthening the implied claim that unmeasured attributes of counties are unique. We also include several variables that will tend to make the rankings of "similar" counties similar to each other. This includes variables that are uniform within states, and therefore identical across counties within a state, and variables that have similar or identical values among geographically close alternatives, such as weather conditions.

Furthermore, the sampling-of-alternatives approach discussed above is applicable only if the independent-disturbances assumption is maintained. Finally, there appears to be no practical alternative to MNL for choice problems as large as that modeled here. The principal alternative to MNL is multinomial probit (MNP), in which the e_{ij} are assumed to be distributed multivariate normal, and in which computation of choice probabilities over a set of k choices involves evaluation of k-dimensional multivariate normal integrals. Applications of MNP have progressed rapidly due to the development of simulation-based estimators (McFadden 1989). However, choice sets with over 3000 alternatives remain well beyond the reach of the MNP estimators so far developed.

3. DATA

3.1 Universe of Potential Locations

We combined data from several sources in order to estimate the model developed above. These sources adopted divergent reporting approaches, making it necessary that we aggregate the areas reported in some sources in order to make them conformable with those used in other sources. For example, in some sources the five boroughs (counties) of New York City are reported separately, while in others they are aggregated. Details of the areal aggregation used in this analysis are reported in Robbins (1998). We confine our analysis to the 48 contiguous states plus the District of Columbia (treated as the equivalent of a county), but discard two counties from Texas (Loving and King Counties) that were found to be substantial outliers with respect to fiscal variables. After applying these restrictions a total of 3,068 counties appear in our analysis.

3.2 Aggregated Locational-Choice Data

The Census Bureau's CTC data contains nonzero cells from a cross-tabulation of 1985 and 1990 county of residence among survivors to 1990. We discarded data recording transitions between the 3068 counties included in our analysis and either excluded counties (i.e. counties of Alaska and Hawaii) or other locations outside the U.S. The CTC data are tabulated separately for selected individual characteristics (including age group, sex, race, and education level) as well as some combinations of those individual characteristics.

3.3 Attributes of Places

We combined data on place attributes from several published sources, supplemented with some newly coded variables. The sources include the Advisory Council on Intergovernmental Relations' *Significant Features of Fiscal Federalism*, the Commerce Clearing House's *State Tax Reporter*, the National Oceanic and Atmospheric Administration's *National Environmental Sattelite Data and Information Service*, the *City and County Data Book,* the *Census of Governments,* the Census Bureau's STF1A and STF3A summary files , and the Health Care Financing Administration's *Area Resource File*. Names, definitions, sources, and average values of variables measuring the attributes of counties, most of which are self-explanatory, are presented in Table 1. The measures pertain to 1987 except where otherwise noted.

Estate and inheritance tax rates were evaluated for an estate of $822,000, the median value of taxable estates in 1987. Income tax rates represent the average rate on a taxable income of $50,000. Effective sales tax rates were estimated as the sum of state-plus-county sales tax rates (from ACIR's *Significant Features of Fiscal Federalism*) times the share of purchases made by persons 65-74 in each of eight spending categories (found in the U.S. Department of Labor's Consumer Expenditure Survey), times the proportion of sales in the respective category subject to taxation (using information in the *Census of Service Industries* and *Census of Retail Trade*, ACIR's *Significant Features of Fiscal Federalism,* and the Federal of Tax Administrator's *Sales Taxation of Services: Who Taxes What?*). Where public expenditure categories include state spending, the state spending was allocated to each county within it by multiplying state-level spending per household times the number of households in the county. Property taxes and government spending are from the *1987 Census of Governments*.

The dummy variables indicating the presence of recreational lakes or a coastal location were developed by examining a standard commercial highway atlas; counties on a seacoast or containing all or part of a lake bearing symbols indicating the presence of camping, boating, or other recreational facilities were coded one. Weather information from NOAA is for weather stations; counties are assigned to the closest weather station that shares the same type of geography (see Robbins, 1998).

4. APPLICATION TO 1985-1990 U.S. MIGRATORY FLOW DATA

We estimated county-level location choice models for four demographic groups: white males, white females, nonwhite males, and nonwhite females, all aged 65-74 in 1990. Each group thus contained 60-69 year olds at the beginning of the five-year period over which location transitions are recorded. Within each racial group, it is not possible to combine men and women since a substantial number in each group were married to each other throughout the observation period, and thus should be viewed as a single migratory decision making unit. However the CTC files are tabulations of individuals' rather than of couples' moves. Also, each group contains a certain number of individuals who are unmarried at the end of the time interval but were married earlier in the interval, and whose migratory behavior was undertaken while married. Finally, a substantial number of individuals in each group are, at the end of the interval, married to persons in other age groups. Accordingly, it is necessary to consider the gender groups separately, yet we anticipate very similar patterns of estimated parameters across gender groups, within racial groups. We estimated separate models for whites and nonwhites in view of the distinctive settlement and migratory patterns of both the African-American and Hispanic populations (Longino and Smith 1991; Angel and Angel 1998) in comparison to the white population.

Results of the logistic regressions are presented in Table 2. As would be expected in view of the very large sample sizes, the parameters are very precisely estimated. Significance levels are less than 0.0001 for all but eight of the 132 parameters reported.

The results are broadly consistent with expectations: persons around retirement age are drawn to locations rich in amenities, and in medical and public services, while repelled by high taxes. In all four groups the results indicate a desire to avoid inheritance, property, and sales taxes. Whites, but not nonwhites, are also repelled by income taxes. Housing costs, an important element of living costs, are negatively related to a county's ranking, except among nonwhite females.

With respect to public services, all groups are attracted to counties with comparatively high public-sector spending on public safety and recreational services, while they seek to avoid areas spending heavily on public welfare and housing. Although it is often claimed that older persons are unsupportive of public-school expenditures, we find no evidence that locational decisions are influenced by per-capita educational expenditures (holding constant enrollments). Medical services have mixed findings: the presence of hospitals offering wide range of services is uniformly positive, yet areas rich in medical specialists appear to be unattractive to whites while attractive to nonwhites. The latter contrast might reflect the well-known fact that older nonwhites are, on average, in poorer health than older whites (Smith and Kington 1997). All four groups are found to be repelled by areas with high levels of nursing home beds, which might be explained by the fact that nursing homes are of greater relevance to the "oldest old" (those 85 and older) than to persons around retirement age.

With respect to amenities, we find that whites, but not nonwhites, are attracted to coastal counties. However, in contrast to past research we fail to find an attractive effect of recreational lakes. We also find that older persons are repelled by cold winters and humid summers. The failure of whites to be attracted to sunny locations (measured by "Clear Days") is unexpected. Yet coastal counties tend to have fewer clear days (mean = 95.7, n = 298) than do noncoastal counties (mean = 106.0, n = 2770; t for difference in means = 6.39). The combined effects of "Clear Days" and "Coast", evaluated at these means, indicates that coastal areas are, on average, preferred to noncoastal areas by whites. The negative coefficient on "Clear Days" may, therefore, primarily reflect the relatively low rankings assigned to noncoastal counties with comparatively clear weather. Nonwhites, on the other hand, appear to be attracted to inland destinations with sunny climates.

Persons in all four groups, but especially whites, are attracted to areas where older people are already concentrated. All four groups also give low rankings to counties with high levels of unemployment; this presumably reflects the general undesirability of such counties rather than the retirees' hopes to obtain employment. Whites give low rankings to counties in which nonwhites are more prevalent, while nonwhites give them high rankings. The coefficients on "FH Households" appears to reflect similar racial-affinity effects, given the association between the prevalence of nonwhites and of female-headed households (r = 0.592).

Several past studies have found, contrary to expectations, a positive relationship bewteen crime and an area's attractiveness. Therefore we allowed for nonlinearities in the effect of crime rates. We find statistical evidence of such nonlinearities, yet the effect of crime on an area's attractiveness is positive throughout nearly the full range of our data. The level at which the partial effect of crime (measured here as violent crimes per 1000 persons) turns from positive to negative is lowest for nonwhite males: 8.93, a level surpassed by only 54 of our 3068 counties. The corresponding point is highest for white males, 16.25, a level surpassed by only 8 counties.

The estimated coefficients can be used to rank all 3068 counties, even for the nonwhites, who do not even live in all 3068 counties (see Table 2, which indicates that nonwhite males were found in only 2408 of the 3068 counties studied, while nonwhite females were found in 2480 counties). We have computed and assigned to each county the index by which it is ranked among persons in the four demographic groups, that is the value $X_j\hat{\mathrm{B}}$. Spearman rank-order correlations of the rankings across the racial/gender groups are shown in Table 3. Unsurprisingly, counties are very similarly ranked by the men and the women within each racial group, with correlations approaching one. However, the racial groups rank the counties somewhat differently, as would be expected in view of the race-specific patterns uncovered in Table 2. The rankings of whites and of nonwhites are correlated between 0.73 and 0.77, depending on gender.

5. CONCLUSION

Our research demonstrates the feasibility of employing a discrete-choice framework to analyze the locational choices of large numbers of individuals (nearly nine million) facing large numbers of choices (more than 3000). Multinomial logit models adapted to aggregated (count) data can be estimated, using widely available software, in this situation. The estimated models have the property that changes in the levels of a valued characteristic in *one* county, holding all other characteristics throughout the country constant, lead in general to changes in the aggregate flows of individuals among *all* pairs of counties.

We investigated the roles of an extensive set of area characteristics, including fiscal, amenity, and other social and economic facts, on the residential location decisions of persons around retirement age. The results are generally consistent with patterns established by past research: on average people between ages 60 and 74 seek to avoid high levels of taxes, yet are attracted to areas spending comparatively large amounts on relevant public services such as safety and recreation. Physical and climactic amenities are also valued, as is access to medical services. Racial differences in the weights attached to these factors cause the rankings assigned to counties by whites to differ somewhat from those assigned by nonwhites.

A useful extension of this work consists of reestimation of the model using individual- (or couple-) level panel data. Our model produces a set of average weights with which areas are ranked according to their characteristics, within each of four population groups. Yet there is considerable heterogeneity within those groups. In particular, some have incomes low enough that they face effective income tax rates of zero, while others face much higher marginal or average tax rates. People in poor health can be expected to value health services more than those in good health. Thus the mix, as well as the numbers, of retirees attracted to each area can be expected to vary according to area characteristics.

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Table 1: Definitions, Sources, and Mean Values of County-Attribute Variables

Variable	Definition	Source[a]	Mean
Estate Tax	Average state tax rate on $822,000 bequest to spouse	CCH	0.009
Inheritance Tax	Average state tax rate on $822,000 bequest from spouse	CCH	0.085
Income Tax	Effective state + local tax rate on $50,000 taxable income	ACIR	0.045
Property Tax	County property tax revenues per household ($)	CCDB	1.172
Sales Tax	Average effective state + local tax rate (x 1000), persons 65-74	A	0.860
Expenditures: Public Safety	Local spending on police and fire per household ($)	CCDB	0.202
Expenditures: Welfare	State + local spending per household ($)	CCDB	0.791
Expenditures: Housing	State + local spending per household ($)	CCDB	0.066
Expenditures: Recreation	State + local spending per household ($)	COG	0.067
Expenditures: Education	Total expenditures per household ($)	CCDB	1.936
Clear Days	Annual days of sunshine	NOAA	105.033
Cold	Annual heating degree days	NOAA	49.643
Humidity	Relative humidity in July	NOAA	0.563
Housing Costs	Median housing values ($1,000s), 1980	CCDB	34.954
Vacancy Rate	1 - (Occupied Housing Units/Total Housing Units)	CCDB	0.135
Crime Rate	Violent crimes per 1,000 population	CCDB	2.269
Land Area	ln (Area in square miles)	CCDB	6.516
Coast	Dummy: county borders ocean	A	0.097
Lakes	Dummy: county has recreational lake(s)	A	0.423
Population Density	1986 Population (1000s) ÷ Area in square miles	CCDB	0.173
Urban	Proportion of population in urban areas	CEN	0.365
Enrollment	School enrollment per household	CEN	0.519
Unemployment	Unemployment rate of persons 16 and older	BLS	0.077
FH Households	Proportion of households headed by women, 1985	CCDB	0.083

(Table 1 continued)

Teen Pregnancy	Births to teen mothers per 1000 population, 1980	CCDB	2.925
Nonwhite	Proportion of population in nonwhite groups	CCDB	0.060
Age Group	Proportion of population in age range 65-74	CCDB	0.067
Medical Specialists	Specialist physicians per 1000 population	ARF	0.198
Hospital Services	Proportion of all available services provided in area hospitals	ARF	0.317
Nursing Home Beds	Beds per 1000 population	ARF	9.701

[a] Key: CCH = Commerce Clearing House; ACIR = Advisory Council on Intergovernmental Relations; CCDB = *City and County Data Book*; COG = *Census of Governments*; NOAA = National Oceanic and Atmospheric Administration; A = authors; BLS = Bureau of Labor Statistics; ARF = *Area Resource File*. For details see text.

Table 2: Estimates of Logistic Model, Four Demographic Groups

Variable	White Males	White Females	Nonwhite Males	Nonwhite Females
Estate Tax	0.2204	0.1190	-0.5173	-0.4249
Inheritance Tax	-0.6871	-0.4634	-0.6675	-0.4007
Income Tax	-3.3118	-2.9735	-0.1067 [a]	0.1349 [a]
Property Tax	-0.2105	-0.1752	-0.1062	-0.1205
Sales Tax	-0.1285	-0.1110	-0.1182	-0.1145
Expenditures: Public Safety	0.2897	0.2675	0.4306	0.3688
Expenditures: Welfare	-0.0142	-0.0173	-0.0333	-0.0189
Expenditures: Housing	-0.2087	-0.1585	-0.1718	-0.1840
Expenditures: Recreation	0.5148	0.5731	0.7076	0.2983
Expenditures: Education	0.0002 [a]	0.0006 [a]	-0.0030 [a]	0.0298 [b]
Clear Days	-0.0020	-0.0014	0.0053	0.0061
Cold	-0.0309	-0.0248	-0.0275	-0.0275
Humidity	-0.5365	-0.4574	-0.4765	-0.2597
Housing Costs	-0.0061	-0.0008	-0.0034	0.0048
Vacancy Rate	2.2435	1.3303	0.6318	-0.2315
Crime Rate	0.1105	0.0971	0.0929	0.0863
Crime Rate Squared	-0.0034	-0.0033	-0.0052	-0.0039
Land Area	0.3830	0.3356	0.3034	0.3788
Coast	0.0349	0.0135	-0.0668	0.0303 [b]
Lakes	-0.0190	-0.0301	-0.0611	-0.0568
Population Density	-0.0484	-0.0452	-0.0506	-0.0513
Urban	0.1257	0.1405	0.2084	0.1778
Enrollment	-1.0248	-0.7949	-0.7750	-0.8804
Unemployment	-2.8669	-2.6806	-1.5402	-1.4535

(Table 2 continued)

FH Households	-8.6534	-6.2517	9.4999	11.4635
Teen Pregnancy	0.0639	0.0540	0.0048 [a]	-0.0444
Nonwhite	-1.5027	-1.3497	0.5383	0.3535
Age Group	6.8172	5.7032	1.1029	0.4108
Medical Specialists	-0.0353	-0.0133	0.1114	0.0937
Hospital Services	1.0607	1.1618	1.2548	1.2555
Nursing Home Beds	-0.0176	-0.0155	-0.0248	-0.0212
$-\delta_0$	-1.4459	-1.3465	-2.7682	-2.9460
$-\delta_1$	-1.8373	-1.8398	-1.5943	-1.5631
Number of individuals	7,092,173	8,958,928	807,996	1,155,485
Number of counties	3068	3068	2408	2480
Mean of $-\ln\pi_{2j}$	2.044	2.012	2.281	2.274

[a] $p > .05$; [b] $.05 \geq p > .0001$; otherwise $p \leq .0001$

Table 3: Rank-order Correlations of Empirical Rankings of Counties

	White Males	White Females	Nonwhite Males
White Females	0.982		
Nonwhite Males	0.756	0.776	
Nonwhite Females	0.734	0.769	0.992