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Abstract

Hauser (1978) succinctly expressed a long-standing desideratum for the analysis of mobility regimes: to separate "rules of access" to social positions from "the interplay of supply and demand." When an explicit, random matching model of opportunity is constructed from rules of access, with provisions for demand effects, it appears that log-linear models, as functions of odds ratios, do not in general satisfy Hauser's requirement. Analysis and simulation show that the two-sided logit model proposed in Logan (1996a) is superior to log-linear and related models in this respect.

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> "... a *mobility regime* consists of a set of *rules or processes* governing access to social positions which is articulated with the flow of persons through the life cycle and the social organization of production. Thus arises a basic problem in mobility analysis: *How does one distinguish the rules of access from the interplay of supply and demand in the labor market* or from long-term processes of societal development and transformation?" (Hauser 1978:920, italics added)

In this admirably compact passage Hauser framed a question of method on whose answer the justification for log-linear mobility models largely rests. Following an extended series of elaborations and exchanges (Featherman and Hauser 1978; Hauser 1978, 1979, 1981, 1986; see also Hope 1981, Hout 1983, Jones 1985, MacDonald 1981) it has become widely accepted that the answer is to be found in the separation of interaction and marginal parameters in the log-linear model. That is, it is generally agreed that the marginal parameters of log-linear models "represent conditions of occupational supply and demand" (Hauser 1978: 930), while an "underlying" interaction structure is represented in the full set of odds ratios, and is free of supply and demand effects. Log-linear interaction parameters, as functions of odds-ratios, are therefore thought of as appropriate for describing the "rules of access" to positions, free of supply and demand effects.

Much work has been accomplished on the basis of this understanding. Many specifications of the interaction structure have been proposed, generating a host of log-linear and related mobility models, all relying on the "marginal invariance property" just described (Hauser 1986: 1062). Informative empirical research, especially comparative research, has been conducted under the assumption that the differences and similarities which are observed among interaction structures are not being contaminated by marginal effects. For example, Erikson and Goldthorpe, in their study of 12 national mobility regimes (1993), consider odds ratios, relative mobility rates, and "social fluidity" to be synonymous, and reach many of their conclusions by evaluating this fluidity.

But the marginal invariance or *margin insensitivity*[1] of log-linear models is in itself a purely mathematical property. It is true that multiplying the rows and columns of a table by constants does not affect the odds ratios, and thus produces a new table which has arbitrarily different margins but which preserves the interaction parameters of whatever log-linear model may have been fitted. Granted, we can imagine a separation of the "rules or processes" of a mobility regime from the "interplay of supply and demand in the labor market," so that the latter might change, while the former stayed constant. If that were to occur, we would

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[1] The latter term comes from Erikson and Goldthorpe (1993: 56), who seem to have constructed it as the opposite to "margin sensitivity," used by Bishop, Fienberg and Holland (1975: 375).

probably have different marginals. But does the lone fact that odds ratios stay constant while marginals change under a simple mathematical transformation make the odds ratios a suitable basis for measuring "rules or processes" in the face of changing supply and demand?

To give a clear answer to this question it is necessary to consider what might be meant by "rules or processes," and how their effects could be measured with or related to a model. It is necessary to consider how the effects of supply and demand might propagate through the economy, and hence through the mobility table. It is necessary, that is, to take Hauser's question -- about rules, processes, demand and supply -- at face value, and not to assume without reason that the simple row and column multiplications to which odds ratios are insensitive truly correspond to the influences of supply and demand which we hope to partial out of our models.

To address Hauser's question I propose a *constructive* answer to the problem of separating the rules of access to positions from the interplay of supply and demand in the labor market. I first define micro-level *rules and processes* which constitute an explicit mobility regime. This regime is an instance of a *random matching model* of opportunity. Certain parameters of the random matching model constitute substantive rules of access to positions, while other parameters account for occupational demand effects unrelated to the rules of access. The supply of individuals with certain background characteristics is taken as given. Thus I make clear from the first what is meant by rules, processes, supply and demand.

I then present two statistical methods which might be used to study the mobility regime: the extended log-linear model (Logan 1983, Breen 1994) and the two-sided logit (TSL) model of Logan (1996a). The extended log-linear model is the standard log-linear model considered in a multivariate specification allowing for effects of a number of exogenous variables, either continuous or categorical. The roots of the log-linear model are essentially statistical, in that it was not derived from a particular model of behavior, but rather as a means of describing associations among categorical variables of any type. The TSL model, in contrast, was derived directly from the proposed random matching model of opportunity, and provides explicit formulas for the probabilities of obtaining occupational positions when the random matching model applies.

In a tabular interpretation, to be developed below, TSL models can be constructed to imply probabilities for each cell of a mobility table, and thus a complete set of odds ratios for the table. Because the odds ratios implied by the TSL model are functions of rules of access and levels of demand (with given supply), analysis will be able to show conditions under which odds ratios, and therefore log-linear interaction parameters based on odds ratios, will change with simple shifts in demand. This will justify the conclusion that in principle log-linear interaction parameters are *not* free of demand effects, at least as defined these are defined in the random matching model of opportunity.

To amplify and extend the analytical result, a simulation of the mobility regime will then be used to compare the estimates obtained from TSL and the extended log-linear model under a simple demand shift. Because it is a mathematical derivation from the random matching model, it will be unsurprising but still reassuring to find that the TSL model gives estimates which accurately reflect constancy in the rules of access during the demand shift. The extended log-linear model, however, will incorrectly give indications of shifts in the rules of access to positions. The same will be true of a simple linear regression estimated on the same simulated data, and of two special cases of the TSL model, the conditional logit and sequential logit models.

Considered from the point of view of an explicit model of opportunity, with rules of access clearly distinguished from demand effects, the reason log-linear models fail to satisfy Hauser's requirement can be expressed very simply. *Margin insensitivity* -- the ability to multiply rows and columns without affecting odds ratios -- does not guarantee *demand insensitivity*, the ability of parameters to measure the rules of access without being affected by shifts in demand. Log-linear models possess the former but not the latter property, while the situation is reversed for TSL models. As Hauser's original statement of the problem makes clear, however, the basic requirement should be for demand insensitivity.

A Mobility Regime: Rules and Processes

I will now outline a model intended to approximate the circumstances of opportunity which pertain in actual economies. It is a general model of the matching of individuals to jobs, in what might be called an *opportunity system.* When attention is directed particularly to inter- or intra-generational movement among jobs or occupations, the opportunity system can be specified as a mobility regime by taking origins explicitly into account. Though the quotation which began this article spoke of "rules *or* processes" as defining a mobility regime, I find it convenient to consider rules *and* processes separately.

The mobility regime or opportunity system is made up of actors of two idealized types, individual persons and employers. The persons will be called workers for convenience, though not all workers are assumed to be employed. Employers include private-sector firms, public-sector and non-profit entities, and individuals who hire other individuals. Persons who are self-employed will be considered workers, with the role of employer for these workers taken implicitly by those who control access to self-employment: the bankers, franchisers and relatives with whom entrepreneurs must deal.[2] Everyone who is employed, then, is assumed to be employed because some other actor has *granted access* to a job.

The Rules of Access

The rules of access are of two types, formal and contingent. The formal rules define what is possible within the system, while the contingent rules govern which workers have access to which positions, and also which employers have access to which workers. In contrast to the formal rules, the contingent rules are parametric, in that parameters express the importance of various worker and job characteristics in the operation of the rules.

The formal rules are these. Workers can take at most one (primary) job, while employers can hire multiple workers. Workers have characteristics which employers observe, while employers offer jobs with characteristics which workers observe. Not all of these characteristics are known to the researcher, and no distinction is made between characteristics known to the actors prior to rather than after an employment match is made.[3] On the basis of their

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[2] The implication that some self-employed persons may be considered both as employers and workers will not play a role in the formal modeling.

[3] The latter limitation of the model could in principle be removed. However, as the model stands the effects of

observations of the characteristics of jobs, it is assumed that workers can determine a single available job which they prefer above all the others *available* to them. Employers are also assumed to evaluate workers, and to be able to determine the set they most prefer among those available to them. Workers and employers are both assumed to choose their best available matches. These formal rules, elaborated more fully than is warranted here, describe a two-sided matching game (Logan 1996b).

No assumption is made that either type of actor optimizes in the economic sense. Employers need not know the optimal number or type of workers to hire, and in fact may not be operating in markets giving them signals regarding optimal inputs and outputs. Workers need not prefer jobs solely on the basis of instrumental qualities like income or status, but may prefer jobs as well for their immanent qualities like job autonomy or morality of corporate purpose, according to any mix of traditional, habitual, value-rational or instrumental motivations (see Logan 1996b, Hechter 1994). It is assumed that actors exhibit some consistency of preference, whatever its source. It also assumed that employers hiring workers within different occupational categories may differ systematically in their preferences from those hiring in other categories, and that such

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knowledge gained on the job can be represented by suitable dummies or measures of job tenure.

differences are of interest to the researcher.

Contingent rules govern which workers are preferred by which employers, and which jobs are preferred by which workers. For example, it may be that employers do or do not prefer workers of certain educational levels, or of certain ethnicities or races. Workers may or may not value autonomy or status in jobs. The degree to which actors value certain characteristics in their opposite parties is represented by *preference coefficients* which weight characteristics in their linear utility functions. The preference coefficients of employers constitute contingent *rules of access* to jobs for workers, because access to a job depends on being preferred over other workers, and the preference coefficients determine who will be preferred. Note also that in one occupation employers may value a year of education twice as much as a year of experience, while in another occupation this relationship may be reversed. The rules of access therefore may differ between two occupations.

The preferences of workers may also be thought of as rules of access on the other side of the market, since they determine which firms will obtain access to which workers, by virtue of the characteristics of the jobs they offer them. However, there is typically less interest in these rules, at least among social scientists.

Aside from the contingent rules implied in their preferences for worker characteristics, the hiring decisions of employers are also influenced by exogenous demand and supply effects which are independent of the characteristics of potential workers. In times of high demand for their products, or short supplies of candidates for their positions, employers, while continuing to apply the same standards, or preference coefficients, to the relative evaluation of workers, necessarily accept some workers who would not otherwise qualify. In the reverse circumstances, otherwise qualified workers may not be hired.

The goal of the researcher is to determine the contingent rules of access to positions implied by employers' preferences, and the contingent rules of access to workers implied by workers' preferences, net of the shifting influences of supply and demand. The rule of access to positions will be formalized below as the probability, $Pr(O_{ij})$, that the relevant firm would offer a worker, i, access to a given job, j. On the other side of the labor market, the rule of access to workers will be formalized by the conditional probability, $Pr(A_{ij}|O_{ij})$, that worker i would accept job j if it were offered or made available.

Processes

Because the rules of the opportunity system just given have been analyzed in game-theoretic terms, it is known that they are by themselves insufficient to determine a unique matching of workers and jobs. Questions of strategy and information flow also influence matching. But it is also known that the two-sided matching game defined by the rules has at least one stable matching of workers and jobs no matter what the distribution of preferences, and that such a stable matching can be arrived at by any of several *matching processes* (Logan 1996b, Roth and Sotomayor 1990).

Logan (1996a) described one decentralized process which leads to a stable match. In this abstraction of the actual processes which pertain in a real labor market, there are two steps. First, with workers' characteristics assumed known to employers, the employers make job offers to all workers who meet their individual standards. In a second step, workers all choose the best offers they have received. Logan (1996b) showed that this two-step algorithm leads to stable matches, and is equivalent to a known algorithm in the game-theoretic literature, when the latter is suitably constrained.

In addition, Roth and Vande Vate (1990) proved a *random* decentralized matching process result for another game theoretic model which has implications for the present opportunity system, as discussed in Logan (1996b). Their result implies that, starting from any matching, a stable matching will be achieved with probability 1.0 if potential employment partners are allowed to learn of each other's availability through a random process of information flow.

The matching process which is posited for the opportunity system can therefore be construed rather broadly without jeopardizing the tendency of the system to achieve stable matchings. It is assumed that workers and employers choose each other in conditions of imperfect information. Both sides have knowledge of the salient characteristics of typical partners on the other side of the market, so that their choices are, broadly speaking, informed choices. In addition, a random flow of information about potential partners is assumed to exist so that mismatches are corrected over time, moving the system toward stability.

It must be understood that what would constitute stability of the matching is constantly evolving as external circumstances of supply and demand, and preferences themselves, change. It also needs to be emphasized that the preferences of workers and firms are *net* preferences, after taking into account the difficulties of abandoning present employment partners, such as a worker's cost of moving to a new location, or an employer's cost of firing an established employee. For new labor market entrants or employers with open positions these costs might not arise, but the rules and processes apply just the same.

Because the researcher will not observe all the relevant characteristics influencing preferences, the choices made by workers and employers will be *observationally random* (Logan 1996b). For this reason and also because of the assumption that a random information process acts to move the system toward stability, the opportunity model just described will be called a *random matching model*.

In summary, the opportunity system described by the random matching model is one of free mutual choice between workers and employers, where information flow is sufficient to move the system toward a constantly evolving stable state.

The operation of free mutual choice means that almost all workers and employers will find that their best *available* choices are not the same as those they would make if other actors were not competing for the same partners. When the research focus is on the role of occupational origins in determining destinations, the opportunity system may be considered a mobility regime, simply by considering origin characteristics as possible influences on the preferences of employers and/or workers.

Statistical Models

Having developed the random matching model in some qualitative detail, we are now in a position to consider how well alternative statistical models might do in separating the effects of the rules of access from shifts in labor market supply or demand. The type of statistical model of interest is one which can predict outcome occupational *category* on the basis of one or more pre-existing, independent variables. A categorical prediction is desired since shifts in the occupational structure can conveniently be represented as changes in the prevalences of categorical outcomes, and it is hoped that a suitable statistical model can isolate such shifts from the rules of access to positions.

Two basic types of models will be considered, an extended log-linear model and the TSL model. Rather than dealing with a specific log-linear model, it will be preferable to consider the whole class of extended log-linear models defined in Logan (1983) and elaborated in Breen (1994). These models can contain the interaction parameters of a wide range of log-linear mobility models as well as the effects of additional independent variables, either continuous or categorical. The TSL model, which was introduced as a multivariate technique in Logan (1996a), will also be considered in some respects for its potential as a tabular model of the bivariate distribution of origin and destination categories. This section defines the two types of models, while the next two examine them analytically and through simulation.

The Extended Log-Linear Model

The usual log-linear model, basis for many mobility models, is

$$\pi_{ij} = \exp\left(\mu + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY}\right)$$

in which π_{ij} is the probability of observing a case in the i-th row and j-th column of the table, with the sum of the π_{ij} across the whole table being defined to equal 1.0. The singly-subscripted parameters are row and column marginal effects, while the doubly-subscripted ones are interaction effects. Dividing both sides by the sum of the probabilities in a given row, $\pi_{i.}$, gives the conditional probability representation:

$$p_{ij} = \pi_{ij} / \pi_{i.} = \exp\left(\mu_i + \lambda_j^Y + \lambda_{ij}^{XY}\right)$$

where μ_i is a new normalizing constant for the row. The value of the constant is minus one times the log of the denominator of the following, equivalent logistic form in which the remaining λ superscripts have been suppressed:

$$p_{ij} = \frac{\exp\left(\lambda_j + \lambda_{ij}\right)}{\sum_{k=1}^{J} \exp\left(\lambda_k + \lambda_{ik}\right)} \qquad (1)$$

The conditional form of the log-linear model is inherently appropriate to the study of mobility, since occupational origin is a fixed condition temporally prior to the outcome.

Arranging all the parameters of (1) into a single row vector $\boldsymbol{\lambda}$, and introducing an appropriate column vector of dummies $\mathbf{x}_{ij}$ indicating which parameters are appropriate to which cells gives this representation of the log-linear model:

$$p_{ij} = \frac{\exp\left(\boldsymbol{\lambda}\mathbf{x}_{ij}\right)}{\sum_{k=1}^{J} \exp\left(\boldsymbol{\lambda}\mathbf{x}_{ik}\right)} \qquad (2)$$

Alternatively, placing the j-subscripted parameters into J separate vectors $\boldsymbol{\lambda}_j$, and specifying appropriate $\mathbf{x}_i$ dummy vectors allows the same log-linear model to be expressed as:

$$p_{ij} = \frac{\exp\left(\boldsymbol{\lambda}_j\mathbf{x}_i\right)}{\sum_{k=1}^{J} \exp\left(\boldsymbol{\lambda}_k\mathbf{x}_i\right)} \qquad (3)$$

If additional variables, either dummies or continuous measures, are added to the $\mathbf{x}$ vectors in (2) or (3), an extended log-linear model is the result. In this case the subscript i is usually taken to denote a particular sample member, rather than all the sample members originating in the same row category. Logan (1983) added such variables in form (3), which corresponds to a multinomial logistic regression with separate parameters for each outcome category *j*. Breen (1994) considered a conditional logit formulation in which parameters do not differ across outcome categories, consistent with (2), and a mixed model combining both multinomial and conditional logit effects which he called MCL. As Breen notes, his model is mathematically equivalent to the Logan (1983) model, but is more conducive to certain interpretations. In the conditional logit variant, probabilities of different outcomes depend on measured characteristics associated with the outcomes themselves.

The Two-Sided Logit Model

As suggested above, the two-sided logit, or TSL, model of Logan (1996a) is defined in essence by two probabilities, corresponding to decisions controlling the access to jobs and workers respectively. The first is $\Pr(O_{ij})$, the probability that a particular job *j* would be offered to a worker *i*. This probability is defined parametrically as a binary conditional logit:

$$\Pr(O_{ij}) = \frac{\exp(\boldsymbol{\beta}_j \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}_j \mathbf{x}_i)} \quad , \ j > 0. \tag{4}$$

Formula (4) is derived from an underlying behavioral model which states that the employer's decision is based on an evaluation of characteristics of the worker as well as on an evaluation of the employer's situation without the worker, the influence of market demand (where present), and a strategic consideration. Formally, this evaluation involves two linear utility functions, the first for the utility of hiring the worker, and the second for utility of not hiring him or her:

$$U_j(i) = \boldsymbol{\beta}_j^* \mathbf{x}_i^* + m_j + \varepsilon_{1ij} \quad (5)$$

$$U_j(\neg i) = b_j + s_j + \varepsilon_{0ij} \quad (6)$$

Vector $\boldsymbol{\beta}_j^*$ contains the preferences of firm j for the measured characteristics of workers, contained in vectors $\mathbf{x}_i^*$. The scalar quantities m_j, b_j and s_j represent respectively the influences of market demand, the baseline utility the firm would experience without the hire, and a strategic threshold whose value the firm is motivated to set in a manner described in Logan (1996b). The terms ε_{1ij} and ε_{0ij} are independent random disturbances representing the employer's evaluation of worker characteristics which are not observed by the researcher.

Under appropriate assumptions about the disturbances, formula (4) for the probability of an offer can be derived from the utility functions (5) and (6) (Logan 1996a). When this is done, an intercept term must be added to the $\boldsymbol{\beta}_j^*$ vector, producing the vector $\boldsymbol{\beta}_j$ which appears in equation (4); the $\mathbf{x}_i^*$ vector of worker characteristics then acquires a new first element equal to 1.0, becoming the $\mathbf{x}_i$ of (4). The new intercept term, β_{j0}, is mathematically equal to the net effect of the three scalar terms in (5) and (6):

$$\beta_{j0} = m_j - b_j - s_j \tag{7}$$

Thus the assumption that the actions of the firms follow the behavioral model implied by (5) and (6) leads to the conclusion that effects of market demand which do not depend on characteristics of worker i are represented in the intercept term β_{j0} of the derived offering probability, equation (4); this term is called the demand intercept for brevity. The remaining terms in $\boldsymbol{\beta}_j$ represent the preferences of firm j for the characteristics of workers; they constitute the contingent rules of access to positions controlled by j.

Subscript $j = 0$ is reserved in the model for the state of unemployment, with the stipulation that $\Pr(O_{i0}) = 1$, for all i; that is, unemployment is always available to all workers. Accordingly, equation (4) applies only for values of j greater than zero.

The other essential probability of the TSL model is $\Pr(A_{ij}|S_k)$, the conditional probability that worker i will accept job j, given a set of offers S_k from one or more employers. This probability is of course necessarily zero if S_k does not contain an offer of job j, but otherwise is given by this polytomous conditional logit formula:

$$\Pr(A_{ij}|S_k) = \frac{\exp(\boldsymbol{\alpha}\mathbf{z}_{ij})}{\sum_{h \in S_k} \exp(\boldsymbol{\alpha}\mathbf{z}_{ih})}, j \in S_k \tag{8}$$

Like $\Pr(O_{ij})$, $\Pr(A_{ij}|S_k)$ is formally derived from utilities, in this case the utilities of workers for all the jobs j contained in the set of offers S_k, which are given by:

$$V_i(j) = \boldsymbol{\alpha}\mathbf{z}_{ij} + \upsilon_{ij} \tag{9}$$

The parameters in $\boldsymbol{\alpha}$ are the preferences of workers for the characteristics of jobs, which are contained in the vectors $\mathbf{z}_{ij}$.[4] The scalar υ_{ij} is a random disturbance representing the worker's evaluation of job characteristics not observed by the researcher.

Formula (8) is the usual conditional logit model derived in the economic discrete choice literature, for the case where different individuals may have different sets of alternatives from which to choose (e.g., Ben-Akiva and Lerman 1985). The coefficients in vector $\boldsymbol{\alpha}$ show the relative weights which workers place on the characteristics of the jobs offered by the firms, in the vectors $\mathbf{z}_{ij}$. For $j = 0$, the characteristics which i would experience in unemployment are placed in the vector $\mathbf{z}_{i0}$.

Assuming that the firms act independently of one another, given the observed characteristics in $\mathbf{x}_i$, the probability of any particular offering set S_k is given by the products of the probabilities of the (conditionally)

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[4] Dummy interaction terms can be added to $\mathbf{z}_{ij}$ to allow for different preferences among different groups or types of workers.

independent offers which produce the set:

$$\Pr(S_k) = \prod_{m \in S_k} \Pr(O_{im}) \prod_{n \in \bar{S}_k} [1 - \Pr(O_{in})] \tag{10}$$

Here $\bar{S}_k$ is the set of firms who have not made offers in set S_k.

Equation (10) for the probability of offering set S_k provides the connection between the two basic probabilities in formulas (4) and (8). In all, there are $R = 2^J$ possible offering sets from J firms, including the set containing no offers at all. Accounting for these R possible offering sets gives this formula for the overall probability that worker i will accept job j:

$$\begin{aligned} \Pr(A_{ij}) &= \sum_{k=1}^{R} \Pr(A_{j}|S_k)\Pr(S_k) \\ &= \sum_{k=1}^{R} \Pr(A_{ij}|S_k) \prod_{m \in S_k} \Pr(O_{im}) \prod_{n \in \bar{S}_k} [1 - \Pr(O_{in})] \\ &= \sum_{k: j \in S_k} \frac{\exp(\boldsymbol{\alpha}\mathbf{z}_{ij})}{\sum_{h \in S_k} \exp(\boldsymbol{\alpha}\mathbf{z}_{ih})} \prod_{\substack{m \in S_k \\ m > 0}} \frac{\exp(\boldsymbol{\beta}_m \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}_m \mathbf{x}_i)} \prod_{\substack{n \in \bar{S}_k \\ n > 0}} \frac{1}{1 + \exp(\boldsymbol{\beta}_n \mathbf{x}_i)} \end{aligned} \tag{11}$$

Equation (11) is the TSL model, which is estimable *without* requiring observations of the decisions of each employer regarding whether to hire each sample member. Details of the derivation are in Logan (1996a), while Logan (1996c) presents and compares appropriate estimation algorithms. Note that the acceptance probability $\Pr(A_{ij})$ could also be written more compactly as p_{ij}, in the notation used for the extended log-linear model, and that this will be done in certain places below.

Since the number of offering sets, $R = 2^J$, is extremely large for any reasonable value of J, equation (11) is estimated in practice using occupational categories instead of individual jobs. The mean characteristics of jobs in each category replace the job characteristics in the vectors $\mathbf{z}_{ij}$, and the parameter vectors $\boldsymbol{\beta}_j$ represent the shared preferences of firms hiring in each of the J occupational categories. Logan (1996a) presents empirical estimates based on such category means, using General Social Survey data.

There is no reason in principle why (11) must contain continuous, measured variables in its **x** and **z** vectors. It would be reasonable instead to use dummy variables in either or both of these vectors to designate in which cells of a mobility table each of the α and β parameters were to apply. Thus the TSL model and the extended log-linear model of equation (2) are both essentially multivariate models which can, if desired, be specified for the bivariate mobility table using dummy variable designs.

Responses to Demand Shifts: Analysis

Since the TSL model gives the probabilities of outcomes implied by the random matching model of the opportunity system, it also can produce implied odds ratios in the tabular context. The probabilities and therefore the odds ratios being explicit functions of the rules of access and the demand effects contained in the parameters of equations (5), (6) and (9), it is possible to find the influence of demand changes on the odds ratios by analytical means. This is done the present section, leading to the demonstration of one circumstance where demand changes must change odds ratios. The section which follows shows parallel results via simulation.

The effect of a change in the demand intercept β_{j0} on an outcome probability $p_{ij'}$, where j' may or may not equal j, is given by the derivative of $p_{ij'}$ with respect to β_{j0}, which can be obtained from (11) as:

$$\begin{aligned} \frac{\partial p_{ij'}}{\partial \beta_{j0}} &= \sum_{k=1}^{R} \Pr(A_{j'}|S_k)\Pr(S_k)\left[\omega_{jk} - \Pr(O_j)\right] \\ &= \Pr(A_{j'} \cap O_j) - \Pr(A_{j'})\Pr(O_j) \\ &= \Pr(O_j)\left[\Pr(A_{j'} \mid O_j) - \Pr(A_{j'})\right] \end{aligned} \tag{12}$$

where $\omega_{jk} = 1$ if $j \in S_k$, and 0 otherwise.

If it is assumed that the underlying opportunity system treats all workers from the same occupational origin as essentially equivalent, then it is reasonable to fit a purely tabular log-linear or TSL model to the data. In this case, the subscript i can be taken to refer to all the workers from the same origin, rather than to a particular worker, and $\Pr(A_{ij}) = p_{ij}$ becomes the cell probability for a mobility table. From the cell probabilities, odds ratios are formed in the usual way.

Under the model, the derivative with respect to β_{j0} of an odds ratio which involves category j is found from (12) to be:

$$\frac{\partial}{\partial \beta_{j0}}\left(\frac{p_{ij}p_{i'j'}}{p_{i'j}p_{ij'}}\right) = \frac{\Pr(A_{ij})}{\Pr(A_{i'j})\Pr(A_{ij'})^2}$$
$$\times\left[\Pr(A_{ij'})\Pr(A_{i'j'}|O_{i'j})\Pr(O_{i'j}) - \Pr(A_{i'j'})\Pr(A_{ij'}|O_{ij})\Pr(O_{ij})\right]$$

Assuming the Pr(A_{ij}) are non-zero, this derivative will be zero, and therefore indicate that demand changes will have no effect on odds ratios, only when the following condition is true:

$$\frac{\Pr(A_{ij'}|O_{ij})\Pr(O_{ij})}{\Pr(A_{ij'})} = \frac{\Pr(A_{i'j'}|O_{i'j})\Pr(O_{i'j})}{\Pr(A_{i'j'})} \qquad (13)$$

To help interpret (13), consider a scenario in which preferences across categories are strict and universal, so that all workers will either prefer j to j', or else all workers will prefer j' to j, for any pair of j and j'. Workers will never make choices which violate the stated order of preference. This would occur if the $\mathbf{z}_{ij}$ vector of utility function (9) contained some characteristic of jobs which varied concordantly with the universal ranking and was valued with a nearly infinite weight in the α preference vector. Obviously this is a caricature of reality. In such a case, if j were strictly preferred to j', then Pr($A_{ij'}|O_{ij}$) and Pr($A_{i'j'}|O_{i'j}$) would both equal zero, since an offer of j in either case would preclude the acceptance of j'. Then (13) would reduce to the equation 0 = 0, which is always true. The implication is that changes in demand for a single category j would *not* affect odds ratios formed from that category and other categories j' which are strictly less preferred than j.

However, considering odds ratios where j' is strictly preferred to j, $\Pr(A_{ij'}|O_{ij})$ reduces to $\Pr(A_{ij'})$ since an offer of j can have no effect on the probability of accepting j'. $\Pr(A_{i'j'}|O_{i'j})$ reduces to $\Pr(A_{i'j'})$ for the same reason, and condition (13) then becomes:

$$\Pr(O_{ij}) = \Pr(O_{i'j}) \tag{14}$$

Consulting equation (4) we see that condition (14) will be true in the tabular case if the β effect parameters applying to cells (i,j) and (i',j) are equal, but will not be true in general. So, even when preferences are strict and universal, shifts in demand in single categories *will* cause shifts in certain odds ratios defined across cells having different structures of β effects.

Of course it is condition (13), not (14), which determines whether demand shifts will affect odds ratios in the more realistic case where preferences across categories are not strict and universal. Since it is not true in general that condition (13) will hold, the general conclusion must be that changes in demand will have effects on odds ratios, an unfavorable result for log-linear models of mobility tables.

Simulating a Demand Shift

The preceding analytical result demonstrated an inappropriate response on the part of odds ratios and therefore log-linear models in one highly simplified situation. In principle, showing even one circumstance where demand shifts must alter odds ratios is enough to disprove the general assertion that the mathematical property of margin insensitivity guarantees the substantive property of demand insensitivity. However, it is not clear how important the demand sensitivity of odds ratios might be in a less abstract situation. For this reason a stochastic simulation of a demand shift in an opportunity system is now examined for its influences on extended log-linear and TSL estimates. Using a simulation will also allow the observation of demand shift effects on a simple regression estimation analogous to a status attainment model.

Table 1 shows the parametric values used to simulate a baseline opportunity system composed of three employers and 4000 workers.[5] In the simulation, the rules of access employers impose on workers take account of years of education and experience, while workers evaluate only the status of the jobs offered by the employers. Substantive variables of this sort rather than dummy variable effects were simulated in order to add realism and to show the operation of both types of models in their fuller, multivariate forms. It is presumably the effects of such substantive variables which are picked up by dummy variable models in any event, since it is unlikely that mobility regimes operate on the basis of rules concerning gross

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[5] This would correspond to three occupational categories in which all employers within a given category share the same utility function.

categories of occupational origin and destination. It can be imagined that the effects of origin work completely through the measured variables in this particular system, and that dummies are therefore unnecessary.

The first two lines of table 1 show that education was simulated as a random variable with a mean of 12 years and a standard deviation of 3 years, while experience had a mean of 15 years, a standard deviation of about 5 years, and was slightly negatively correlated with education because of the inclusion in the second equation of the disturbance from the first equation. The random components of each equation in the table are shown as variables z_1 through z_{11}, and were generated as independent standard normal variates.

Lines 3 through 5 show that the statuses of the jobs offered to workers by each employer *j* differed among the workers as a weak function of their years of education and experience, introducing some degree of plausible collinearity between the qualifications of workers and the status resources offered to them. These three lines show that employer 1 adjusted rewards only for experience, employer 3 only for education, and employer 2 for both. The mean statuses offered by the employers rise steeply from employer 1 through employer 3, as the three constant terms imply.

Lines 6 through 8 show the utility-of-hiring functions (5) for the three employers. The functions show that employer 2 weighted experience more heavily than employer 1, while employer 3 gave greater weight to education when deciding whether to allow access to jobs. Rather than explicitly simulating the non-hiring utility of equation (6), I set this value to zero for all three employers; with normally-distributed disturbances, this is an inconsequential technical difference. Line 9 shows that workers positively valued the statuses of the offered jobs in deciding among offers, though the large random disturbance implies the existence of other, unmeasured factors. In line 10 the alternative to accepting any offer, namely unemployment, was assigned a constant utility of 3.19 rather than the stochastically varying utility shown in equation (9); this again makes no difference when errors are normal. I adjusted the parameters shown in table 1 to achieve moderate realism and a complete variety of all eight possible offering patterns from the three employers.

The top panel of table 2 gives the resulting distributions of offers to workers and their acceptances of jobs in the baseline scenario. As mentioned, there are eight possible offering patterns that may confront any worker; the realized pattern becomes the worker's opportunity set. The pattern "000" in the top margin indicates cases where no offers were made, while "100" indicates an offer only from employer 1, and so on. The left margin indicates which offered job, if any, was accepted by the workers.

Note that for each offering pattern in which workers were given a choice between employer 3 and another employer, a minority chose the other instead of the nominally higher status employer 3. This occurred either because a particular offering from employer 3 had a lower status than an alternative employer's offer, or because of unexplained variations in the worker's utility, due to the random disturbance in equation (9). Similar minority choices for employer 1 in preference to 2, or for unemployment in preference to an offered job, occurred for the same reasons. Note that the line labeled "unemployment" includes individuals not in the labor force, as well as those who would be called unemployed in the standard terminology; this means the figure of 25.4 percent is not extraordinarily high.

The second panel of table 2 shows the distribution of offers and acceptances in an *expansion scenario* where employer 3 has increased its willingness to make offers, considered here to have occurred because of a change in external demand for its product. This change is represented by a shift in β_{30}, the employer's demand intercept, from -21.44, as shown in line 8 of table 1, to a new value of -19.34 . In the baseline scenario, employer 3 was willing to offer a job to workers with average levels of education and experience about 17 percent of the time, while in the expansion scenario it offers a job to such workers about 53 percent of the time.[6] So the demand shift is fairly

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[6] Line 8 of table 1 implies firm 3's baseline utility of hiring an average person is a normal random variable with mean = -21.44 + 1.0(12) + 0.5(15) = -1.94, and a variance of

dramatic.

Comparing the two panels of the table shows that the shift in employer 3's preferences also affects the distributions of acceptances for employers 1 and 2, as well as affecting the number of unemployed. This occurs because workers tend to prefer the newly-offered higher status jobs from employer 3 to their other opportunities. Note that the effect of the demand shift in employer 3 has not been to reduce the employment for employers 1 and 2 by identical proportions. The reduction for employer 1 is by a factor of 841/1090 = .772, while the factor for employer 2 is 831/1008 = .824. In both the baseline and expansion scenarios, there are many people who prefer unemployment even though they have been offered jobs. This tendency is strongest among those who have only been offered jobs by employer 1, since on average its offered status produces the least improvement over the utility of unemployment.

$2^2 = 4$. The probability this utility exceeds 0, which is the implicit probability of not hiring in this simulated system, is Pr(N(0,1) > 0.97) = .1660. For the expansion scenario, this probability becomes .5319.

The same set of pseudo-random disturbance values for z_1 to z_{11} were used in the baseline and expansion simulations. This type of matching is used to remove extraneous random influences from scenario comparisons (see Ripley 1987:137-139).

Note that this simulation involves the direct use of the utility functions (5), (6) and (9) of the random matching model, rather than the probability formulas (4), (8), (10) and (11), derived from the utilities. The derived probabilities are the foundation of the TSL statistical model used in the next section to estimate the parameters governing rules of access and levels of demand.

Responses to the Demand Shift: Comparative Estimations

Tables 3 and 4 report estimations of a variety of models in the simulated baseline and expansion scenarios. Comparing these estimates will clarify how the models respond in this artificially controlled experiment in which a single demand shift is the only structural change. Unlike any possible comparisons involving actual data, in this simulation it is clear a priori that the underlying rules of access are unchanged between the two observations, while the level of demand in a single category has been altered. Therefore, any substantial changes in estimates between the two tables can only be attributed to the demand shift. If, as it will in fact turn out, some models show changes in the estimates of parameters which are not intended to capture demand effects, this will indicate that those models are confounding demand shifts with shifts in the rules of access, failing to satisfy Hauser's basic methodological requirement.

The first line in table 3 reports the parameter values used for the baseline simulation, rescaling them appropriately for comparison with the TSL estimates appearing later in the table. The rescaling is necessary because the simulations were based on normally-distributed disturbances, as shown in table 1, while the TSL model assumes that disturbances have type 1 extreme value (Gumbel) distributions (Logan 1996a). Normal disturbances are a good choice for the simulations because of the usual central limit theorem argument about the effects of many unobserved additive components, which is the role the disturbances are intended to play in the utility functions. On the other hand, the use of Gumbel distributions to derive logit models is a mathematical convenience, producing equations approximating the more complex probit formulas which come from assuming normal disturbances (e.g., Ben-Akiva and Lerman 1985). A note gives details of the rescalings.[7] The first line of table 4

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[7] The decisions made by workers and employers are functions of differences in the utilities of their available alternatives. The distributions of these differences correspond to the distributions of differences in the independent error terms of the respective utility functions. For employers the relevant differences are $\varepsilon_{1ij} - \varepsilon_{0ij}$, while for workers they are $\upsilon_{ij} - \upsilon_{ij'}$, the differences between the disturbances in the individual's evaluations of any two offers. For the normal disturbances in the simulated opportunity system the distributions of these differences are normal, while for the standard type I extreme value

disturbances assumed in TSL the distributions of the differences are logistic, with variance $\pi^2/3$ (see Pudney 1989). Since the logistic distribution is a symmetric distribution similar in shape but not scale to the normal, only a scale adjustment is required to make the parameters of table 1 comparable to the estimates resulting from the TSL method. The essential adjustment converts models from a scale appropriate to *standard* normal disturbances to one appropriate to standard extreme value disturbances by multiplying the parameters by a factor of 1.7, a rough average of two adjustment factors recommended in the literature (cf. Maddala 1983: 23). Line 1 of tables 4 and 5 shows all table 1 parameters rescaled by 1.7 *after* adjusting the original coefficients to reflect a standardization of the normal errors in table 1 and a centering of the education and experience variables on their means. For example, the rescaling factor for α_1 is found by dividing 1.7 by the standard deviation of the normal disturbance in line 9 of table 1, that is, .34 = 1.7/5; this produces the value .170 = .34(0.5) shown in line 1 of table 3. Similarly, the rescaling factor for the β_1 preference coefficients is 1.7/2 $\doteq$ .85, giving a rescaled value for β_{11} of .85(0.5) = .425, shown as .43 in table 3. Rescaling the demand intercepts $\beta j0$ must take explicit account of the centering of the education and experience variables.

shows the rescaled parameter values after the demand shift for employer 3.

Regression Estimates .

The simulated data were first used to estimate a linear regression model to determine how it would react to the change in demand for employer 3. Line 2 of table 3 shows ordinary least squares estimates from a regression of attained status on workers' years of education and experience, in the baseline scenario. Estimated standard errors are in parentheses. Attained status is the particular status of the job which the worker has accepted, if any. As in the status attainment literature, workers who do not have employers are excluded from the estimation. The coefficients are listed under the heading for employer 1 as a convenience, but there is no actual correspondence between the preferences of any particular employer and the regression estimates. Line 2 of table 4 shows estimates for the same equation in the expansion scenario. Since the regression estimates do not correspond to parameters of the random matching model, the only question to be asked is whether the shifts in estimates between tables 3 and 4 are informative or misleading.

Line 2 of table 5 shows the answer in the differences between the baseline and expansion scenario estimates in raw form, and as standardized by the estimated standard errors from the baseline equation. Both the intercept and the coefficient for experience have shifted very significantly, with differences of 14.83 and -5.56 standard errors respectively. Since none of the three employers' preference coefficients for experience in the opportunity model actually changed between the scenarios, I conclude that linear regression has produced estimates confounding demand shifts with shifts in the rules of access to positions.

Extended Log-Linear Estimates

Line 3 of table 3 reports baseline scenario estimates for a special case of the extended log-linear model of equation (3), as developed in Logan (1983). This is a multinomial logistic regression model estimated with choices of the three employers plus unemployment as the four dependent variable outcomes. Its difference from more complete extended log-linear models is the omission of dummy variable effects. Because of the usual identifying constraints in a log-linear model, there are only three sets of constants and coefficients. Comparing the baseline estimates in table 3 with the expansion scenario estimates in table 4 is again facilitated with the differences given in table 5. Line 3 of this table shows there are shifts from the baseline to the expansion scenario of more than 2 standard errors in each of the three constant terms rather than only in one, though the shift for the term which would normally be associated with employer 3 is by far largest. There are also shifts of more than 2 standard errors in the education coefficients listed under employers 1 and 2, and in the experience coefficient listed under employer 3, though no employer's evaluation of education or experience actually changed.[8] These coefficient estimates evidently were not insulated from the demand shift by the presence of the marginal parameters, listed here as intercepts and called λ_j in the log-linear notation of (1) and (3).

Lines 4 of tables 3, 4 and 5 show estimates and changes in estimates for a multinomial model which excludes workers who do not have jobs, the standard practice in mobility table studies. These estimates show the same basic problems. Shifts of two or more standard errors occur in the education coefficient listed under employer 2 and in both the education and experience coefficients listed under employer 3 (the last shift exceeding 6 standard errors). Yet the rules of access regarding education and experience have not changed in the underlying opportunity model.

In this simulation both regression and multinomial methods failed to give an informative accounting of the shift in demand for employer 3. Users of either technique could be misled into inferring that a change in the importance of education or experience had occurred. The claimed advantage of the log-linear class, represented here by the multinomial regression, is not evident; both methods confounded demand

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[8] I say "listed under" rather than "associated with" or some other stronger term because there is no reason to associate these parameters with specific firms (or occupational categories), as the evidence of their shift under the simulated structural change makes clear.

shifts with changes in the internal parameters constituting the rules of access to positions.

Two-Sided Logit Estimates

Lines 5 through 8 of tables 3 and 4 present estimations using four variants of the TSL statistical model developed in Logan (1996a).[9] Each estimation used a different type of data from the same simulations:

TSL1 This estimation used the individual values of job status which would have been offered to each worker by each of the employers, had an offer been made. Though this stops short of using actual information on which employers made offers, it is not data which would realistically be available in practice. As in all the model estimations, individual-level education and experience data are used.

TSL2 This estimation used the means of statuses in jobs which employers had available, regardless of whether offers were made, across the sample of 4000 cases. These means (3 in all, one for each employer) would not be available from sample data on workers.

TSL3 This estimation used the manifest means of the statuses of jobs actually held by workers who have accepted jobs from the three employers. This type

[9] TSLogit, a flexible, easily-used program for TSL estimation, is available from the author.

of data is available in surveys, and this is the method which was used in Logan (1996a).

TSL4 This used the actual status of the job the worker has accepted, and mean accepted statuses for the other jobs (employers). This data is also available in surveys.

Comparing line 1 of table 3 with lines 5 through 8 shows that the baseline estimates using each of the four TSL models are reasonably good for the β_j parameters. However, the single element of α, the worker's preference for higher status, is underestimated more and more seriously as the quality of the data used declines from TSL2 to TSL4. In the β_j estimates, the two-to-one ratios between the coefficients of education and experience for employers 2 and 3 (which run in opposite directions) are picked up well. The same basic pattern of good estimates for the employers' β_j parameters and progressively deteriorating estimates for the workers' α status parameter also appears in table 4, the expansion scenario estimations.

For the four TSL models in tables 3 and 4, a *t* statistic is reported for each estimate, in addition to its estimated standard error. This is not the usual *t* statistic for the test that a parameter is zero. Instead, since the parameter values are known, this is a *t* statistic representing the deviation of the estimate from the true value, as standardized by the estimated standard error. Some biases can be seen in the estimates, where several *t* statistics exceed 2 in absolute value. I detected these biases as persistent, non-significant deviations in earlier simulations of samples of size 500, and then increased the final sample to 4000 so that the biases could be seen clearly. Though the biases are real, they are not very large in substantive terms, which is why they become significant only in larger samples. Bias is not a problem in TSL1, but neither TSL1 nor TSL2 is a practical method for most data. The exception to the rule that the biases are not large is, as mentioned before, the increasingly severe downward bias in the estimate of the status coefficient α_1 in moving from TSL2 to TSL4 (though the estimate remains much greater than its standard error, so that the presence of the effect, as opposed to its proper magnitude, is always detected).

Lines 5 through 8 of table 5 strongly suggest that the TSL preference estimates, though biased to some degree, are *not* sensitive to demand shifts. As line 1 of this table shows, all parameters have remained unchanged in the shift from the baseline to the expansion scenario, except for the upward change of 1.785 in employer 3's intercept, which represents the shift in demand. Ideally, all four sets of TSL estimates would show the same pattern of a near-zero shift in all the coefficients but one, and a change of +1.785 in the employer 3 demand intercept. This is approximately what happens. All four models show the appropriate shifts in the constant, and none of the other estimates shows a shift approaching 2 in standardized value. This includes the highly biased estimates for the status coefficient α_1, which thus appear to be insensitive to demand shifts as well.

Conditional and Sequential Logit Estimates

Conditional and sequential logit models are special cases of the TSL model which arise when substantive assumptions are made about the preferences of the two types of actors. Since these special cases may seem plausible when considered without regard to an explicit model of opportunity, it is worth pausing to see how they arise in the context of the proposed model.

If all the employers relax their hiring standards to the point at which they offer jobs to all workers, then $\Pr(O_{ij}) = 1.0$ for all i and j, and equation (11) reduces to the usual conditional logit model (McFadden 1974):

$$\Pr(A_{ij}) = \frac{\exp(\boldsymbol{\alpha} \mathbf{z}_{ij})}{\sum_{h=1}^{J} \exp(\boldsymbol{\alpha} \mathbf{z}_{ih})}$$

This derivation provides an interpretation for the conditional logit model when it is applied to occupational choice, at least when there are no direct observations on the restriction of choices for particular workers: the conditional logit model ignores the actions of the employers, and presumes that workers are simply choosing among all jobs, rather than choosing among jobs made available by the choices of other actors.

On the other hand, if all workers share a strict preference ordering across the employers' jobs, so that they always choose the highest-ranked employer which makes an offer, equation (5) reduces to the sequential logit model, found in the economic discrete choice literature (Amemiya 1981) and closely related to survival analysis models (Allison 1982). This model is:

$$\Pr(A_{ij}) = \frac{\exp(\beta_j \mathbf{x}_i)}{1+\exp(\beta_j \mathbf{x}_i)} \prod_{k=j+1}^{J} \frac{1}{1+\exp(\beta_k \mathbf{x}_i)}$$

In this special case, the probability that worker *i* will accept a job from employer *j* is the probability it will be offered by *j*, times the product of the probabilities that all higher-ranked (higher-subscripted) employers will not make offers. This model is suitable for vacancy chain analyses within employers, if it is assumed that a single ladder of promotions can be identified such that every employee wants to move up. In this case, the decision maker controlling each position in the chain takes the place of an employer. In classical vacancy chain analyses, offers would be driven solely by open positions, but in the TSL model, including the sequential logit special case, offering probabilities can be functions of many variables and offers can also occur without the presence of vacancies, representing the generation of new positions.[10]

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[10] Harrison (1988) showed that the classical, position-driven, vacancy chain model produces changed in odds ratios when the numbers of positions in the system is varied.

Lines 9 and 10 of table 5 show that the two special cases of TSL do not perform well under the demand shift. Both show inappropriate standardized shifts well above 2.0 in value. The sequential logit model, which suppresses the estimation of the status effect since preferences are assumed to be strict, produces very large shifts in the estimates of employer 3's preferences for education and experience. The conditional logit model, which suppresses all employer preference effects since workers are assumed to have free choice among jobs, produces a large standardized shift in the preference of workers for status. These inappropriate responses to the demand shift show the importance of estimating the full TSL model rather than either special case.

Conclusion

From the point of view of an explicit model of opportunity, the failing of the standard "marginal invariance" justification for log-linear models is that no argument is made that supply or demand shifts should have the same effect on mobility tables as does the simple mathematical operation of multiplying rows and columns by constants.

Of course it is not impossible that this multiplicative reallocation *could* occur. Certainly a centralized economy might be able to achieve it. But when specific rules of access in a decentralized, random matching model for opportunity and mobility are considered, it turns out that multiplicative reallocation does not result from simple demand shifts. Instead of odds ratios remaining constant while demand changes, it is another set of parameters which shows stability, namely, the α and β coefficients expressing the contingent rules of access to workers and jobs. The TSL statistical model is able to estimate these stable parameters in the face of changing demand, while the log-linear model instead estimates the changing odds ratios, or functions of them.

Considering the TSL and extended log-linear models side-by-side has made it clear that the two are rather similar from a data processing perspective. Both are multivariate models of categorical outcomes, and may incorporate both continuous and categorical explanatory variables. In principle both can be used to model the bivariate mobility table as such, without the use of additional variables, though this has not yet been demonstrated empirically for TSL. In the tabular context, both are suited to the construction of complex structures of dummy variable effects over the cells of the mobility table, if this should be desired. Both are able to accommodate changes in marginal distributions while parameters governing the allocations of cases to cells of the table stay constant.

The key difference is that the TSL parameters governing the allocations of cases to cells of the table, or, more generally to categorical outcomes, have a substantive interpretation developed directly from a model of rules of access, processes of matching, and influences of exogenous demand, while the log-linear parameters do not. Two problems undermine the validity of the log-linear parameters governing the same allocations. First, the association of the odds ratios with "rules of access" and of the marginal parameters with demand effects can only be valid if the effects of demand shifts are to create multiplicative row- and column-reallocations across the table, something which it seems has never been explicitly justified. Second, arguing constructively from a micro-level model of voluntary matching suggests that the effects of demand shifts will *not* be manifested as multiplicative, odds-ratio-preserving reallocations in the mobility table, so that log-linear models, while they are margin insensitive by definition, cannot be considered demand insensitive structures in the context of mobility or attainment studies.

Aside from the findings reported in Logan (1996a), it remains to be seen to what degree application of TSL models will lead to substantively different conclusions than those which have been or could be drawn from log-linear and related models. But the present comparison of the two types gives clear reasons for preferring TSL results over log-linear results when conflicting findings are obtained.

REFERENCES

Allison, Paul D. 1982. "Discrete-Time Methods for the Analysis of Event Histories." Pp. 61-82 in *Sociological Methodology 1982*, edited by Samuel Leinhardt. San Francisco: Jossey-Bass.

Amemiya, Takeshi. 1981. "Qualitative Response Models: A Survey." *Journal of Economic Literature* XIX:1483-1536.

Ben-Akiva, Moshe, and Steven R. Lerman. 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, MA: MIT Press.

Bishop, Y.M.M., S.E. Fienberg, and P.M. Holland. 1975. *Discrete Multivariate Analysis*. Cambridge, MA: MIT Press.

Breen, Richard. 1994. "Individual Level Models for Mobility Tables and Other Cross-Classifications." *Sociological Methods and Research* 23(2):147-173.

Erikson, Robert, and John H. Goldthorpe. 1993. *The Constant Flux*. Oxford: Clarendon.

Featherman, David L., and Robert M. Hauser. 1978. *Opportunity and Change*. New York: Academic.

Harrison, Roderick J. 1988a. "Do Odds Ratios Really Control for the Availability of Occupational Positions in Status Contingency Tables?" *European Sociological Review* 4: 65-79.

Hauser, Robert M. 1978. "A Structural Model of the Mobility Table." *Social Forces* 56:919-953.

______. 1979. "Some Exploratory Methods for Modeling

Mobility Tables and Other Cross-Classified Data." Pp. 413-459 in *Sociological Methodology 1980*, edited by Karl F. Schuessler. San Francisco: Jossey-Bass.

______. 1981. "Hope for the Mobility Ratio." *Social Forces* 60:572-84.

______. 1986. "Reinventing the Oxcart: Jones' Obsolete Proposal for Mobility Analysis." *Social Forces* 64(4):1057-1065.

Hechter, Michael. 1994. "The Role of Values in Rational Choice Theory." *Rationality and Society* 6:318-333.

Hope, Keith. 1981. "The New Mobility Ratio." *Social Forces* 60(2):544-56.

Hout, Michael. 1983. *Mobility Tables.* Quantitative Applications in the Social Sciences # 31. Beverly Hills, CA: Sage.

Jones, Frank Lancaster. 1985. "New and (Very) Old Mobility Ratios: Is There Life After Benini?" *Social Forces* 63:838-50.

Logan, John Allen. 1983. "A Multivariate Model for Mobility Tables." *American Journal of Sociology* 89(2):324-349.

______. 1996a. "Opportunity and Choice in Socially Structured Labor Markets." *American Journal of Sociology* 102(1; July, 1996): forthcoming.

______. 1996b. "Rational Choice and the TSL Model of Occupational Opportunity." *Rationality and Society* 8(2; May, 1996): forthcoming.

______. 1996c. "Estimation of Two-Sided Logit Models." CDE

Working Paper 96-07, Center for Demography and Ecology, 1180 Observatory Drive, University of Wisconsin, Madison.

MacDonald, K.I. 1981. "On the Formulation of a Structural Model of the Mobility Table." *Social Forces* 60(2):557-71.

Maddala, G.S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

McFadden, Daniel. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." Pp. 105-142 in *Frontiers in Econometrics*, edited by Paul Zarembka. New York: Academic.

Pudney, Stephen. 1989. *Modelling Individual Choice.* Oxford: Basil Blackwell.

Ripley, Brian D. 1987. *Stochastic Simulation.* New York: Wiley.

Roth, Alvin E., and Marilda A. Oliveira Sotomayor. 1990. *Two-Sided Matching.* Cambridge; New York: Cambridge University Press.

Roth, Alvin E., and John H. Vande Vate. 1990. "Random Paths to Stabiilty in Two-Sided Matching." *Econometrica* 58:1475-80.