

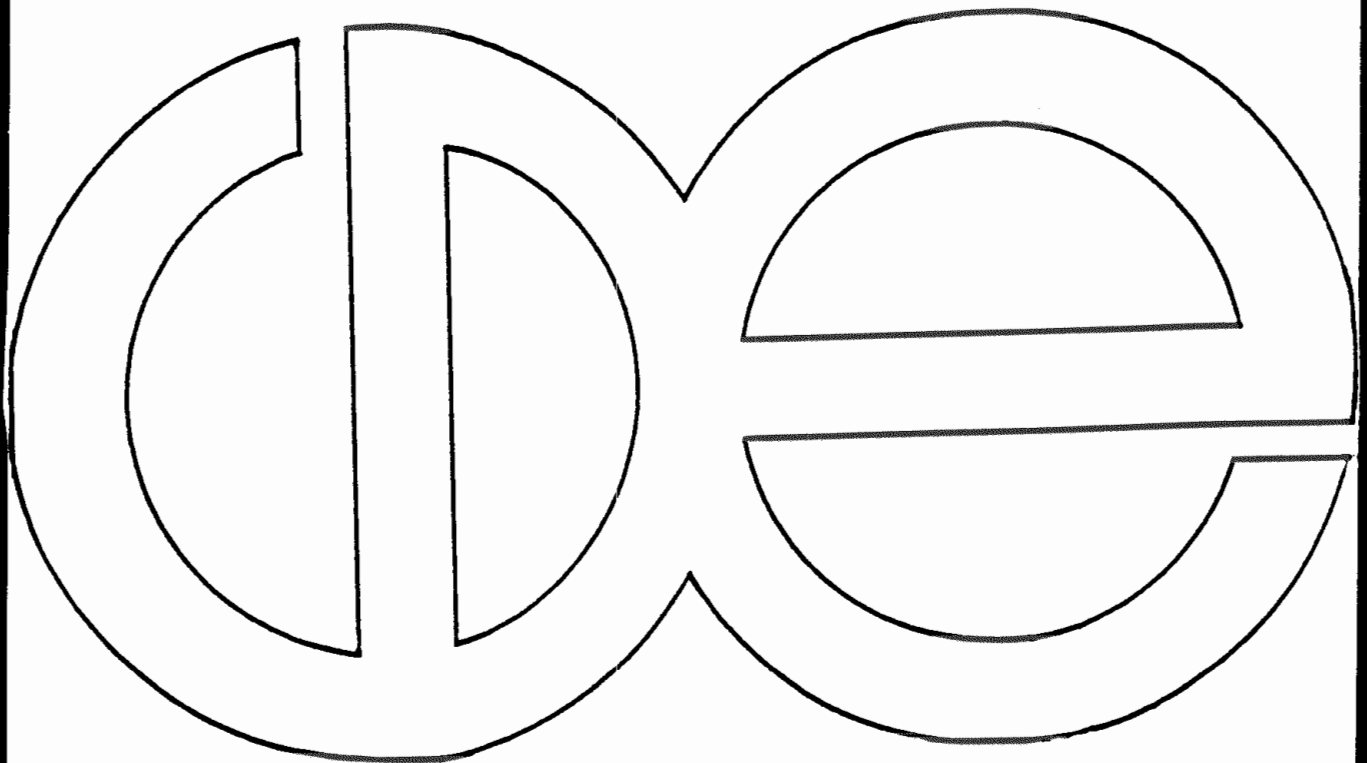
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OPPORTUNITY AND CHOICE IN SOCIAL STRUCTURED
LABOR MARKETS

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**OPPORTUNITY AND CHOICE
IN SOCIALLY STRUCTURED LABOR MARKETS¹**

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ABSTRACT

Employment outcomes depend on opportunity and choice, both of which are subject to structural influences. A new approach to studying the factors which determine employment outcomes develops a statistical technique, two-sided logit (TSL), directly from a model of the preferences and resources of employers and workers. Opportunity and choice are functions of these preferences and resources.

Application of the TSL model to 1972-1990 GSS data shows substantial variation in the importance of the worker characteristics of education, race and age to the opportunity of employment in different occupational categories. Relationships of TSL to other sociological and economic methods are also discussed.

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INTRODUCTION

Opportunity and choice determine employment outcomes in a free labor market.

Opportunity is provided by employers, who make jobs available. Workers choose among the opportunities provided, that is, among available jobs. The factors influencing opportunity and the factors influencing choice among opportunities are distinct in principle, since they are determined by different types of actors. Furthermore, the factors influencing opportunity are a main object of public policy, while the factors influencing choice among opportunities, though not irrelevant to policy, are within broad limits considered to be a matter of private freedom. Thus any discussion of the openness of the occupational system, of fairness, of systematic limits on mobility or achievement, would seem almost to require some distinction between the determinants and consequences of opportunity and the determinants and consequences of individual choice.

But the models used most often by sociologists to study these topics fail to make such a distinction. Linear regression models simply estimate the average effects of individual characteristics on occupational outcomes (SES or income, for example), without distinguishing whether a particular effect is due to opportunity or choice, or both. Log-linear models, even as augmented with exogenous variables (Yamaguchi 1983, Logan 1983, Hout 1984, DiPrete 1990, Breen 1994) make no fundamental distinction between the two types of effect. Some less widely applied models do represent opportunity clearly (e.g., Simon 1982 [1951], White 1970, Boudon 1974, Thurow 1975, Sørensen 1977, Stewman and Konda 1983, Boylan 1992), but fail to develop choice fully, presuming that workers will uniformly strive to "rise" in the system according to some universally accepted definition of "up," even though voluntary unemployment and retirement — not to mention alternative definitions of success — are obvious features of working life. Empirical economic models, on the other hand, have their own characteristic limitation: a ready assumption that either employers or workers, or both, act in a forward-looking, self-interested, "rational" manner (see, e.g., Devine and Kiefer 1991, Sattinger 1993), an assumption which facilitates estimation while

shrugging off sociological arguments that action is structured in a way not reducible to self-interested rationality (e.g., Giddens 1984, Sewell 1992).

The present paper proposes a new multivariate method for simultaneously investigating the determinants of individual opportunity, and the determinants of choice given opportunity, while according equal weight to both aspects. The parameters estimated by the model represent the preferences of employers, which determine workers' opportunities; and the preferences of workers, which determine their choices among opportunities. The data requirement is any random sample of individuals, both working and not working, which records their employment-relevant characteristics and the characteristics of jobs they hold. It is argued that estimating the preferences of employers, using such data, requires controlling for selection effects due to individuals' preferences, and vice versa. The model which is developed to make such doubly-controlled estimations is called a *two-sided logit model* (TSL), and is based on an underlying *random utility matching model* of the labor market, which itself is a stochastic variant of deterministic models studied in game theory (e.g. Roth and Sotomayor 1990). Though the underlying model represents individual jobs being evaluated by workers, actual estimation makes use of average characteristics of jobs within broad occupational categories rather than the characteristics of particular jobs.

The TSL model is constructed in such a way that estimates of employers' and workers' preferences are insensitive to changes in demand for jobs among occupational categories. Instead of directly estimating the effect of a worker characteristic on his/her likely employment outcome (as in linear regression), the model estimates the effect of the characteristic on the *rankings* of workers which are made by the employers hiring in the different occupational categories. The rankings are determined by utility functions in which the employers' preference parameters appear. Only by specifying levels of demand across occupational categories, assumed to be functions of exogenous economic causes, are the rankings of workers by employers translated into definite probabilities of their employment within occupations. This separates economic demand from socially structured preference effects very clearly, a result long desired but not convincingly achieved by log-linear or earlier models (see Harrison 1988).

The preferences of employers and workers determine opportunities and choices only in conjunction with the resources which workers and employers bring to the labor market, since it is these resources or characteristics to which the preferences of potential employment partners will apply. Nonetheless the preference estimates themselves have clear interpretations which do not require explicit reference to resource holdings. Employers' preference coefficients estimate the change in opportunity, measured by the log-odds of an offer, which is associated with a one-unit change in a worker characteristic. The same coefficients are also estimates of the chance, again measured by a log-odds, that two workers who differ by one unit on a characteristic are ranked concordantly with that difference by employers in the relevant occupational category. Finally, the set of all preference coefficient estimates is used to estimate the proportion of variance in employers' utilities for workers which is explained by the model within each category, when the model fits well by an independent criterion. These various interpretations of the model coefficients can provide new insights into the structure of opportunity, compared with estimates from prevailing models.

Application of the TSL model, including appropriate variable selection methods, tests for goodness of fit and for structural change, is demonstrated using the 1972-1990 waves of the General Social Survey. The relatively simple model specification utilized suggests substantial differences in the preferences of employers hiring within broad occupational categories, and overall stability of these patterns across the two decades.

The organization of the paper is as follows. Section 1 develops the TSL model and discusses its estimation as well as discussing certain special cases corresponding to other, existing models. Section 2 then applies the model to study the determinants of occupational opportunity and attainment in the United States during 1972-1990, while developing parameter interpretations and statistical tests in the context of this example. Section 3 reviews a variety of other sociological and economic models of the determinants of employment outcomes in order to contrast them clearly with the model developed here.

1. THE TWO-SIDED LOGIT MODEL

Several principles underlie the model. It is asserted that the employment *opportunity* of a worker is essentially synonymous with the set of jobs which employers would be disposed to offer him or her if approached.² Studying the factors affecting employers' preferences or dispositions is therefore necessary to understanding opportunity. However, it is also necessary to study the factors influencing workers' employment preferences, so that these are not confounded with the effects of employers' dispositions. A two-sided approach explicitly combining models of employers' and workers' preferences, together with data on the characteristics or resources that each side values in the other, therefore provides an attractive and direct representation of the determinants of occupational opportunity and choice. Such an approach will represent each individual's opportunity by the *chance* of obtaining job offers in different occupations. Seen from the other side, each employer has an opportunity to hire workers which corresponds to the chance of obtaining acceptances of offers from particular types of workers.

It is important to emphasize at once that such an approach does not reduce the study of the determinants of employment outcomes to the study of preferences. Employers' and workers' preferences are only effective in constraining others to the degree that either commands *resources* desired by others. Conversely, the opportunities of any particular individual or employer are the result of its own holdings of resources, and of the distributions of preferences and resource holdings among all other actors. Understanding opportunity also involves understanding the existing distribution of resources, and the principles which may govern that distribution's

² The terms "worker" and "employer" are used as a convenience. Strictly speaking, the model includes all persons who may or may not decide to work; the model allows workers to choose or be forced into non-employment. Similarly, "employers" include private firms as well as non-private-sector actors like government agencies who may decide whether to make employment or employment-like benefits such as welfare available to "workers." Self-employed workers are also considered within the model framework; for them the "employer" is thought of as the financiers, franchisers or relatives who typically make self-employment possible.

development, stability and change through time.

Another principle is that mutual constraint on employers' and workers' choices, derived from the distribution of preferences and resources, is not a synonym for structure, in any useful sociological sense. Sociological inquiry should ultimately go beyond the description of constraint into the causes of its particular form in a given historical situation. The way in which the model preserves a place for structural effects will be discussed after it has been developed and contrasted with economic alternatives.

A final principle guiding the model development is that practical techniques require obtainable data. A practical approach to the idea of modeling opportunity as the outcome of a multitude of discrete choice problems must forgo data on all the choice situations each actor faces, and consider how estimation can be done with much more modest data, such as the widely available samples of workers containing characteristics only (or principally) of the individual him- or herself and the job currently held. Such data, from the General Social Survey, are used below.

The Modeling Strategy: Separate Discrete Choice Submodels

The extensive discrete choice literature in economics (reviewed in Ben-Akiva and Lerman 1985, Pudney 1989) has derived models of the probabilities that individuals will make particular choices from sets of discrete alternatives, under a wide range of assumptions. The most useful of these models in practice has been the multinomial conditional logit model, derived by assuming that individuals evaluate their alternatives using a linear utility function, which in practice must contain a random disturbance term to represent relevant factors unknown to the researcher. The model is obtained by assuming that the random disturbances have independent type 1 extreme value (or Gumbel) distributions. That is, by assuming the utility of alternative j for individual i is $V_i(j) = \alpha_i z_{ij} + v_{ij}$, where α_i is a row vector of i 's preferences, z_{ij} is a column vector of the characteristics of alternative j available to i , and v_{ij} is a random Gumbel error, it can be shown that the probability that i will choose alternative j from the set of all J available alternatives is the

multinomial conditional logit model:³

$$\Pr (C_{ij}) = \frac{\exp (\alpha_i z_{ij})}{\sum_{k=1}^J \exp (\alpha_i z_{ik})} \quad (1)$$

It should be understood that the linear model for the utility $V_i(j)$ is the basic model under consideration, and that model (1) is merely its implication at the level of observable, discrete choices. In practice, the α preference coefficients are assumed to be numerically equal across all individuals, or else within demographic subgroups of individuals, to achieve identification.

Use of the conditional logit model in either binary or multinomial form requires only modest behavioral assumptions about the decision makers. It is assumed that the preferences of individuals are *consistent* (cf. Ben-Akiva and Lerman 1985:38). That is, when confronted with the

³ This model, in which the observed data are characteristics of the alternatives, is often simply called the conditional logit model to distinguish it from the so-called multinomial logit model in which the data are characteristics of the decision makers. I however call it the multinomial conditional logit model to distinguish it from the binomial conditional logit model, where only two alternatives are available.

Understanding the derivation of the *discrete* probability model (1) from the assumption of an underlying, *continuous*-valued utility function is important for a full understanding of the proposed model. Readers are directed to Ben-Akiva and Lerman 1985, pp. 101-108, for a clear exposition. In brief, the derivation proceeds by integrating over the joint distribution of the utilities of all alternatives, subject to the condition that the utility for the chosen alternative, j , is the maximum among alternatives; the resulting probability is the cdf of the logistic distribution (see also Pudney 1989, pp. 293-297). The assumption of Gumbel disturbances is a convenience which allows the logit rather than probit form of the model to be derived when normal errors are theoretically appropriate. Without loss of generality, all Gumbel errors introduced in this paper will be in standard form, that is with distribution function $\exp(-e^{-x})$, mean 0.57722, and variance $\pi^2/6$ (Johnson and Kotz 1970). McFadden (e.g., 1974) is given primary credit for the development of this model in the economic context.

same set of alternatives with identical characteristics on separate occasions, individuals will make the same choices.⁴ The assumption of consistency does not, however, mean that individuals will never be observed to make *apparently* inconsistent choices, since the model assumes that some relevant characteristics of alternatives are unobservable (and are represented in the error terms). Neither does the use of a conditional logit model assume that decision makers have complete knowledge of all aspects of the labor market, or that they can or do make complex calculations of the optimal choice given market conditions. The modeling strategy I will use is to adopt a utility-based, conditional logit formulation both for the decisions of employers to make jobs available to workers, and for the decisions of workers regarding which jobs to accept of those they find available. Doing this assumes consistency of preferences for both parties.

The Employer's Decision

An underlying random utility model is defined to describe the decisions of employers whether or not to make jobs available to particular workers. For an employer j , the utility of hiring an individual i is defined as

$$U_j(i) = \beta_j x_i + m_j + \varepsilon_{1ij}, \quad (2)$$

while j 's utility of *not* hiring i is

$$U_j(-i) = b_j + s_j + \varepsilon_{0ij}, \quad (3)$$

with the definitions of right-side quantities given below. When expression (2) is greater in value than expression (3), employer j makes a job available:

$$o_{ij} \begin{cases} = 1 & \text{if } U_j(i) > U_j(-i) \\ = 0 & \text{otherwise} \end{cases} \quad (4)$$

The dummy variable o_{ij} is 1 when employer j makes an offer to i , and 0 otherwise.

⁴ Because the model below will imply the possibility that each individual's choice might have occurred in the context of an arbitrarily small choice set, the assumption of consistency can be shown to be tantamount to one of transitivity as well; this is of no practical importance in the present case (cf. Sen 1987).

The right-side terms in (2) and (3) are defined to give a behaviorally realistic characterization of the decision facing each employer. In equation (2):

- β_j is a row vector of employer j 's preferences for relevant characteristics of employees.
- x_i is a column vector of i 's measured values on the characteristics employers value.
- m_j is a scalar representing systematic contributions to j 's utility for making a hire which are unrelated to i 's characteristics. Two principle factors affecting m_j are the level of demand for the products of the employer and the level of staffing desired by the employer, relative to its current needs.
- ε_{1ij} is a random error representing factors which are not known to the observer, but which influence j 's utility of hiring i .

In equation (3):

- b_j is the baseline utility that employer j derives from its present state of staffing.
- s_j is a strategic increment to its baseline utility which j may require of an individual before making a decision to offer employment, representing j 's reluctance to hire the first worker who would increase its utility.
- ε_{0ij} is a random error representing factors which are not known to the observer, but which influence j 's utility of *not* hiring i .

This model of employer j 's decision is called a random utility model because it represents the decision rule, (4), as a function of utilities which have random components, the error terms in (2) and (3). The systematic scalar quantities m_j , c_j , b_j , and s_j are important for behavioral realism and for linking the random utility matching model to the game theoretic matching and economic job search literatures (see _____ 1994b), but do not complicate the estimation of the model when using standard data, as will be shown.

The exact probability that j will make an offer depends on the distribution of the differences between the two error terms, as well as on the non-stochastic parts of (2) and (3). If the two distributions are i.i.d. Gumbel then the probability that j will make an offer under the model is the *binary* conditional logit (cf. Ben-Akiva and Lerman 1985):

$$\Pr(o_{ij} = 1) = \frac{\exp(\boldsymbol{\beta}_j^* \mathbf{x}_i^*)}{1 + \exp(\boldsymbol{\beta}_j^* \mathbf{x}_i^*)} \quad (5)$$

where $\mathbf{x}_i^* = (1, \mathbf{x}_i^T)^T$ is the original vector of individual characteristics augmented by an entry of unity in the first position, and $\boldsymbol{\beta}_j^* = (\beta_{j0}, \boldsymbol{\beta}_j)$ is the original vector of employer j 's preferences, augmented by an intercept parameter in its first position. This intercept, β_{j0} , accounts for the net influence of all the systematic scalar terms in (2) and (3):

$$\beta_{j0} = m_j - b_j - s_j \quad (6)$$

In particular, β_{j0} accounts for all the exogenous influences on i 's chances of being offered a job by j which are not associated with his/her own characteristics; these include changes in market demand and staffing levels (m_j), baseline characteristics of employers (b_j), and strategic considerations of employers (s_j). For brevity, β_{j0} can be termed a *demand intercept*, since the net effect of these factors determines the level of demand for workers.

The formal conception is that each employer obtains access to information about workers in sequence, and makes any of them an offer when its evaluation of the individual's qualifications, shown in (2), exceeds the threshold given in (3).⁵ I assume that employers act independently of one another, conditional on the individual's characteristics in \mathbf{x}_i . The result is that each individual is presented some set O_k of offers from the employers as a whole. The possible sets, containing the indexes of employers making offers, are $O_1 = \{0\}$, $O_2 = \{0, 1\}$, $O_3 = \{0, 2\}$, $O_4 = \{0, 1, 2\}$, $O_5 = \{0, 3\}$, \dots , $O_R = \{0, 1, 2, \dots, J\}$. Set $O_1 = \{0\}$ represents no job offers, which forces unemployment⁶; set O_R , at the other extreme, represents offers from all employers, giving the

⁵ The success of the model does not depend on a literal circumstance in which all employers examine the qualifications of all individuals. The actions of employers which have a negligible chance of making an *acceptable* offer to an individual are irrelevant in practice and in the estimation method employed.

⁶ In this paper, "unemployment" will be used to mean any state of non-employment, rather a condition of searching for employment.

worker complete freedom of selection. The event that i experiences offering set O_k is denoted S_{ik} . The probability that i experiences any particular opportunity set O_k is found from the multiplication rule for (conditionally) independent events:

$$\Pr(S_{ik}) = \prod_{m \in O_k} \Pr(o_{im} = 1) \prod_{n \in \bar{O}_k} \Pr(o_{in} = 0) \quad (7)$$

where \bar{O}_k represents the complement of the employer indexes in O_k .

The Individual's Decision

The individual's choice of his/her most preferred offer from the available set is in turn specified as a second random utility model. The utility which i would obtain from the job offered by employer j is defined as:

$$V_i(j) = \alpha_i z_{ij} + v_{ij} \quad (8)$$

Vector z_{ij} contains the characteristics of the offered job, α_i contains the preferences of the individual, and v_{ij} is a random error representing unknown influences on the utility. The decision rule for the individual is to select the single job which offers the highest utility. If the v_{ij} are specified as independent Gumbel distributions, then the probability that i will select j from a set S_{ik} is this multinomial conditional logit:

$$\Pr(A_{ij} | S_{ik}) \begin{cases} = \frac{\exp(\alpha_i z_{ij})}{\sum_{h \in O_k} \exp(\alpha_i z_{ih})}, j \in O_k \\ = 0, j \notin O_k \end{cases} \quad (9)$$

where O_k is the set of integers corresponding to the indexes of employers making offers in S_{ik} . $\Pr(A_{ij} | S_{ik})$ is read as the probability i will accept an offer from employer j , conditional on the event S_{ik} that a particular set O_k of offers has been obtained. The formula specifies a zero probability of accepting an offer from j when $j \notin O_k$, since this means the offering set does not include an offer from employer j . Note that z_{i0} represents the characteristics of unemployment available to i , measured in the same terms as the characteristics of the offers; all sets O_k were defined to contain the integer zero, representing an "offer" of unemployment, since unemployment is always available to any individual.

Summary of the TSL–Random Utility Matching Model Relationship

The random utility matching model is specified by describing a matching procedure with reference to formulas (2), (3), (4) and (8), as follows:

- Step 1. Employers evaluate workers according to (2) and (3), and make offers according to decision rule (4).
- Step 2. Workers evaluate any offers and the possibility of unemployment according to (8), and choose the highest-utility alternative.

It is assumed that employers have complete knowledge regarding the measured characteristics of workers in \mathbf{x}_i , $i = 1, 2, \dots, n$. Relaxation of this assumption will be considered later.

The TSL model is specified by a corresponding combination of the preceding probabilities for each step. The probability of any single employer's offer in step 1 is given by (5), and the probability of any offering set across employers is given by (7). The probability of accepting any offer in step 2, given an offering set, is equation (9). Assuming that the distributions of error terms in (2), (3) and (8) are independent Gumbel, the final, unconditional probability that i will accept an offer from j is:

$$\Pr(A_{ij}) = \sum_{k=1}^R \Pr(A_{ij} | S_{ik}) \Pr(S_{ik}) \quad (10)$$

This formula, which completes the definition of the TSL model, takes into account all the possible offering sets that i may have experienced, weighting each by its probability of having occurred. It is a simple combination of the probabilities of offers, and acceptances conditional on offers, using elementary rules of conditional probability.

Under the model, the conditional probability that individual i will accept an offer from employer j , given that it is made, is:

$$\Pr(A_{ij} | o_{ij} = 1) = \frac{\Pr(A_{ij})}{\Pr(o_{ij} = 1)}, \quad (11)$$

the ratio of formulas (10) and (5). Note that (10) depends on the offering set probabilities $\Pr(S_{ik})$, $k = 1, 2, \dots, R$, and that these probabilities, given in formula (7), depend in turn on the probabilities of offers from all employers. Therefore the implication of (11) is that the probability that an offer from

any particular employer will be accepted depends on the dispositional states of all other employers, an illustration of the systemic nature of the model.

The model defined in (10) is termed the two-sided logit (TSL) model because it models the two sides of the job market separately, and is made up of J binary logits on the employers' side and a single multinomial logit on the workers' side; these components are seen in (5) and (9). A two-sided probit model is of course another possible statistical manifestation of the underlying utility model.⁷

Special Cases of the Two-Sided Logit Model

Three well-known models are special cases of the two-sided logit model, and help reveal its characteristics. The *multinomial conditional logit* model of McFadden (1974), discussed in section 1, is equivalent to a TSL model in which the offering probability from each employer is specified as $\Pr(o_{ij} = 1) = 1$, all i and j , rather than as (5) above. This in turn corresponds to a random utility matching model in which the condition in (4) is always true: all employers always make jobs available to all workers. Such a model seems unconvincing for employment matches.

If equation (8) is such that all workers always prefer higher-numbered employers to lower-numbered employers, where the numbering might correspond to a status ranking for example, the TSL model simplifies to the *sequential logit* model, discussed in Amemiya (1981), and closely related to survival models (Allison 1982). In this model, the probability of any lower-numbered outcome is equal to one minus the probability that all higher-numbered employers have failed to make offers. This model pertains if workers all share a strict preference ranking of employers. In such a situation, outcomes are then completely dependent on employers' decisions to make offers.

⁷ The idea of a two-sided logit or probit model should not be confused with the familiar bivariate probit model, in which two binary outcomes are modeled simultaneously. In the TSL model there are J binary outcomes on the employers' side, plus one multinomial outcome over $J + 1$ alternatives on the individuals'. The use of the term "two-sided" is consistent with Roth and Sotomayor's (1990) usage concerning matching processes in such markets.

The *partial observability probit* model of Abowd and Farber (1982; Sakamoto and Powers 1995) is closely related to TSL as the probit version of its single-employer special case. Abowd and Farber modeled the allocation of workers to union and non-union jobs as the outcome of a sequential decision process in which workers first decide whether to join a queue for union jobs, and employers (represented as a single actor) then decide whether to select them from the queue. Both are of course binary decisions. In the corresponding, single-employer TSL model the sequential decision process consists of the employer deciding, for each individual, whether to offer a job, and the individual then deciding whether to accept it or to remain unemployed. In each model the outcome of the first decision is assumed to be unobserved.

Showing the correspondence requires some additional notation.⁸ For the first decision in either the Abowd-Farber or the TSL case, define a decision indicator dummy variable $I_1 = 1$ if the decision is positive, and 0 otherwise; and define a similar indicator I_2 for the second decision. Then the TSL probability that an offer is made is

$$\Pr(I_1 = 1) = \Pr(o_{i1} = 1) = \frac{\exp(\beta_1^* x_i^*)}{1 + \exp(\beta_1^* x_i^*)} = L(\beta_1^* x_i^*)$$

using the notation $L(w)$ for the logistic cumulative distribution function. There are only two possible offering sets for workers in the single-employer case: $O_0 = \{0\}$ for no offer; and $O_1 = \{0,1\}$ when an offer is made. The TSL probabilities that the offer is accepted for these respective sets are $\Pr(A_{i1} | S_{i0}) = 0$, and

$$\begin{aligned} \Pr(A_{i1} | S_{i1}) &= \frac{\exp(\alpha z_{i1})}{\exp(\alpha z_{i0}) + \exp(\alpha z_{i1})} \\ &= \frac{\exp(\alpha z_{i1}^*)}{1 + \exp(\alpha z_{i1}^*)} \\ &= L(\alpha z_{i1}^*) \end{aligned}$$

where $z_{i1}^* = z_{i1} - z_{i0}$ is a vector of the employer's job characteristics measured as differences from

⁸ I am following the notation and exposition of Maddala (1983:278-281), and am omitting the underlying wage equations which correspond approximately to the utility equations underlying TSL.

the characteristics of unemployment. Then the unconditional probabilities of employment and unemployment are

$$\begin{aligned}\Pr(A_{i1}) &= \Pr(A_{i1} | S_{i0}) \Pr(S_{i0}) + \Pr(A_{i1} | S_{i1}) \Pr(S_{i1}) \\ &= 0 \cdot \Pr(o_{i1} = 0) + \Pr(A_{i1} | S_{i1}) \Pr(o_{i1} = 1) \\ &= L(\alpha \mathbf{z}_{i1}^*) L(\beta_1 \mathbf{x}_i^*)\end{aligned}$$

from (10) above, and

$$\Pr(A_{i0}) = 1 - L(\alpha \mathbf{z}_{i1}^*) L(\beta_1 \mathbf{x}_i^*)$$

by complementation.

Defining a second-level indicator $I = I_1 I_2$, equal to one only when the employer has offered and the individual has accepted, the likelihood corresponding to the probabilities can then be written as

$$\begin{aligned}\mathbf{L}_1 &= \prod_{i=1}^I \Pr(A_{i1}) \cdot \prod_{i=0}^I \Pr(A_{i0}) \\ &= \prod_{i=1}^I L(\alpha \mathbf{z}_{i1}^*) L(\beta_1 \mathbf{x}_i^*) \cdot \prod_{i=0}^I [1 - L(\alpha \mathbf{z}_{i1}^*) L(\beta_1 \mathbf{x}_i^*)]\end{aligned}$$

where the product ranges are over all i such that $I = 1$ and 0 respectively. The single-employer TSL model is thus the logit equivalent of the normal-based partial observability probit model of Abowd and Farber, whose likelihood is given in equation 9.56 of Maddala (1983):

$$\mathbf{L}_2 = \prod_{i=1}^I \Phi(\alpha \mathbf{z}_{i1}^*) \Phi(\beta_1 \mathbf{x}_i^*) \cdot \prod_{i=0}^I [1 - \Phi(\alpha \mathbf{z}_{i1}^*) \Phi(\beta_1 \mathbf{x}_i^*)]$$

represented here with the obvious substitutions for parameter and data vectors, and using $\Phi(w)$ to mean the cumulative normal distribution function.

That a logit version of Abowd and Farber's partial observability probit model is a special case of TSL gives an additional perspective on the model. TSL is seen to be a partial observability logit model, as well as a two-sided, multi-actor, discrete choice model. The partial observability is induced by decisions of the workers and employers which are not observed in full. TSL, like Abowd and Farber's model, is an estimation method which compensates for the censoring of information caused by two kinds of selection. In the TSL model these are the *self-selection* of workers into available occupations, and the *selection by employers* of which workers are to have

particular occupations from which to choose. From this point of view, TSL is estimating a *linear model of preferences* (namely, the random utility matching model) while correcting for sample selectivity.

Estimation

Practical use of the TSL model requires the solution of certain problems. First, the likelihood of the model is extremely nonlinear. The nonlinearity is so severe that quasi-Newton algorithms are very likely to diverge rather than find a maximum. My solution to the estimation problem has been to derive an EM maximum likelihood algorithm (_____ 1994a). EM algorithms (Dempster, Laird, and Rubin 1977) break complex estimation problems into simpler pieces by iteratively estimating unobserved data values, and are inherently stable insofar as the simpler pieces are themselves stable, which is the case here.⁹ The algorithm can be implemented by iterative use of standard conditional logit programs, but a much faster custom program has been developed for the purpose.

Aside from the technical difficulties due to the shape of the likelihood, a very severe computational problem arises from the combinatorial complexity of the model. The model specifies that each worker chooses the best alternative from the set of jobs which employers are disposed to make available, but that the actual set of available jobs is not observed by the researcher. The likelihood function of the model requires the evaluation of the probabilities of accepting jobs under

⁹ The likelihood of the TSL model is not globally concave, so that local maxima are possible results of the algorithm. Experiments with random starting values have so far failed to find alternative solutions on test data sets. However, a local maximum was found in the data to be analyzed below, where it was recognizable by virtue of inflated standard errors and a reversal in the sign of a coefficient, compared to similar subsamples. An alternate set of starting values located a higher-likelihood maximum qualitatively similar to the estimates in other subsamples; these are the estimates reported below. Methods for choosing starting values and for exploring for local maxima will be reported in a separate paper.

all possible sets of offers which contain each job, as can be seen from (5), while the number of such sets increases geometrically with the number of jobs. There are $R = 2^J$ sets, where J is the number of jobs: 4 sets for 2 jobs, 32 for 5, 1024 for 10, over a million for 20. Clearly, there is no prospect of using the TSL model directly on job-level data in broad labor markets, and some form of data reduction must be used. A practical solution is to use the mean characteristics of jobs within a few, broad occupational categories rather than using characteristics of individual jobs directly. Since some reduction in the number of separate sets of preference coefficients across employers is also necessary, it is convenient to use the same occupational categories to classify the employers into sets with equivalent preferences according to the occupational categories in which they are hiring.

The strategy of introducing occupational categories involves two types of categorization which should be carefully distinguished. With regard to the worker's evaluations of jobs, represented in (8) above, the characteristics of all jobs within an occupational category j are represented by a category mean vector \bar{z}_j which takes the place of z_{ij} . With regard to the employers' evaluations of workers, represented in (2), the utility functions of all employers offering jobs within a given occupational category j are considered to be identical, so that β_j represents the shared preferences of the employers in the category. The latter type of categorization is actually desirable for interpretative purposes, since there is little point in attempting to estimate separate preference structures for each of a vast number of employers. The former type of categorization, replacing the job characteristics in (8) by mean occupational characteristics, is less desirable because it does not make optimal use of all the information in the sample concerning the characteristics of each worker's job, and because it can be shown to induce a downward bias in the estimates of the preferences of the workers (cf. Ben-Akiva and Lerman 1985). However, this form of categorization does not bias estimates of the shared preferences of employers within the categories, which become the main interest in studies of the occupational opportunities of individuals (____ 1992). By using mean characteristics of jobs within occupational categories, and by estimating shared preferences of employers offering jobs within the same categories, the TSL

model becomes computationally tractable for studies of large labor markets.¹⁰

Estimation of the TSL model can be performed with data from a random sample of individuals (both working and not working) which records their employment-relevant characteristics and the characteristics of the job (if any) held by each. Characteristics of jobs held by the sample individuals are averaged within each occupational category to obtain the mean vectors \bar{z}_j described above. The EM algorithm produces maximum likelihood estimates, which make possible standard likelihood ratio and BIC tests of model fit, to be described in the next section.

3. OPPORTUNITY IN THE UNITED STATES, 1972-1990

This section applies the TSL model to consider the structure of opportunity for younger men and women in the United States during 1972-1990, and also develops parameter interpretations and test statistics in the context of this example. Data from the General Social Survey were divided into two periods, 1972-1980, and 1982-1990, which I will refer to approximately as the seventies and eighties. Separate analysis files of men and women ages 25 through 44 were created for each period.¹¹ The restriction to younger workers is intended to sharpen the focus on a more

¹⁰ The reader may feel inclined to object that the TSL model has now become a model of workers and occupational categories, rather than of workers and employers, and that the preceding exposition of the preferences of employers was therefore beside the point. This is incorrect for two reasons. First, it would make no sense to justify the utility model underlying TSL in terms of the preferences of broad occupational categories, since categories do not have preferences or make choices. As the preceding paragraph has shown, the categorization does not involve any assumption that categories make choices, but rather that the employers offering jobs within each category share a common preference structure. Second, developing the model explicitly from the employer and worker level makes it possible to address such issues as the bias in workers' preference estimates induced by the use of categorized job data, and to progressively refine the TSL model to alleviate such problems.

¹¹ The analysis files include all individuals in the main yearly samples with nonmissing values of

homogeneous group than all adults. Table 1 reports descriptive statistics for all variables to be used in the analysis. Education and age are measured in years, while nonwhite is a dummy variable. Prestige is the Hodge-Siegel-Rossi score, the derivation of which is described in the GSS codebook. Supervisor is a dummy variable indicating that the respondent reported having a supervisor on his/her current or last job.

A relatively simple TSL specification is estimated for each of the four combinations of gender and period. Occupations are classified into five categories: Professional; Managerial (including salaried and self-employed managers, non-retail sales workers, farmers, and farm managers); Clerical, Sales (retail) and Service; Manufacturing Blue Collar (crafts, operatives, and laborers); and Other Blue Collar (including farm laborers). Employers are specified as evaluating the education, age, and race of workers in making their offering decisions. Workers are specified as evaluating the prestige and autonomy of offered jobs. Following Hout (1988: 1367), autonomy in each category is measured as the odds of having a supervisor (multiplied by -1 so that higher scores mean higher autonomy). Prestige is measured as the category mean. Note that prestige and supervisor data are not available for unemployed individuals: the mean prestige and supervisor scores shown for the unemployed in table 1 are values for the last jobs held, among those who had held previous jobs. Prestige for the non-employed was therefore set somewhat arbitrarily to the value 18, about 50 percent of the mean prestige of the last job held. Autonomy for the non-employed was set to minus the average odds of having a supervisor, as calculated across all employed sample members for both genders and periods.¹²

education, marital status, race and age, and, if employed at the time of the survey, nonmissing occupational category data. Black oversample cases from 1982 and 1987 were omitted.

¹² It seems unclear to me whether the unemployed as a whole are high or low on autonomy, considering the possible dependency implied by their status. _____ (1994a) discusses the problem of the unavailability of measures of job characteristics for the unemployed, and reports that estimates of employers' preferences (the most direct determinants of workers' opportunities) are relatively insensitive to differences in the values assigned to such characteristics. Estimates of

Table 2 presents simultaneous maximum likelihood estimates of the preferences of employers and workers for the characteristics of their employment partners.¹³ There are separate sets of estimates for each of the five categories of employers, as well as for workers, who are modeled as sharing a single preference structure in each of the gender-period samples. Asymptotic t statistics are shown in parentheses, with single asterisks indicating effects for which there is strong evidence according to the BIC criterion, and double asterisks indicating very strong evidence (that is, $|t| \geq \sqrt{(\ln N + 6)}$, and $|t| \geq \sqrt{(\ln N + 10)}$, respectively; see Raftery 1995).¹⁴

The estimates in table 2 show several interesting patterns. First, each gender-period subtable shows that education is most highly valued by professional employers, as would be expected; their preference coefficients range from .674 to .988, with an average t statistic of 15.1. (BIC indicates very strong evidence for each effect.) The values placed on education by managerial employers are substantially smaller, ranging from .228 to .431 (though BIC indicates very strong evidence that they are nonzero), and overlap the range of estimates for clerical/service employers, which is .138 to

workers' preferences are of course more strongly affected. It would be desirable to collect direct measures of prestige, autonomy and similar characteristics of the unemployed.

¹³ All estimations were performed with TSLogit, version 1.0, a Fortran program implementing the EM maximum likelihood algorithm described in _____ (1994a), and written by the author. The program, which has many features intended to increase its flexibility and ease of use, is available from the author, and is suitable for use by researchers comfortable with standard statistical estimation programs.

¹⁴ The asymptotic " t statistics" are the estimates divided by their estimated standard errors. The EM algorithm, unlike other estimation methods, does not automatically produce estimates of standard errors. Though iterative methods are available for finding standard errors with the EM method, the estimates shown here were calculated using analytical formulas for the first and second derivatives in order to save considerable computer time. BIC calculations are justified for the TSL model since it satisfies classical regularity conditions: the likelihood is twice continuously differentiable in the parameters, and the range of the data values is not restricted by the parameters.

.370. Perhaps surprisingly, manufacturing blue collar employers seem to place a negative value on formal education, with preference coefficients ranging from -0.691 to -1.068, an average absolute t statistic of 4.4, and very strong evidence of each effect according to BIC. Among other blue collar employers there is weaker evidence of the same pattern. The negative coefficients imply that the probability of manufacturers' offers of blue collar employment *decline* with workers' years of education. This may be a reflection of the average blue collar employer's distaste for worker traits associated with formal education, or it may reflect an omission of other relevant variables in the model.¹⁵

Age is positively valued by managerial employers in the two male samples, but in no other categories, using BIC as the criterion. This finding for men is plausible, since promotion to managerial positions often comes with experience and therefore age. The managerial category also includes self-employed managers (entrepreneurs as well as farmers), for whom the acquisition of sufficient capital to become self-employed may take substantial time, that is, age. The age effects for women in this category are significant by the conventional standard of $t \geq 2.0$, but not according to

¹⁵ It may be tempting to conclude that the negative coefficients in the less desirable blue collar occupations are simply an implication of the positive value of education for obtaining white collar work, but this is not the case. Though the positive valuation of education by white collar employers does imply that low education will be associated with either blue collar employment or unemployment, or both, it does not imply that the estimated preference coefficients of blue collar employers will be negative. It is entirely possible in the TSL framework for employers in each category to have the same, positive valuation of education. Then, assuming that workers value the characteristics of white collar work over blue collar work, white collar employers will obtain more of the highly educated workers, with blue collar employers obtaining the most highly educated among the workers not taken as white collar employees, and with the least educated workers winding up unemployed. Lack of education would then be associated with blue collar employment and unemployment, but the TSL model would correctly estimate the positive coefficients for education among both blue collar and white collar employers. The data do not show such a pattern.

BIC.

The coefficients for the nonwhite dummy variable are strongly negative for managerial occupations in the male samples: the coefficients are -1.570 and -1.693 respectively in the seventies and eighties, with BIC indicating very strong evidence. For women, there is strong evidence of a negative effect in the eighties, but not in the seventies; the magnitudes of the two estimates are also lower for the women. In no other occupational category is there strong evidence for an effect of the nonwhite dummy. These results suggest that qualified nonwhites' opportunities for advancement to higher-level positions are most seriously blocked in managerial occupations, while the professions are relatively open (assuming sufficient education). The estimated effects of race on managerial opportunity are very strong: the eighties' estimated coefficient of -1.693 transforms the 69 percent chance of a managerial offer for a college-educated white male to a 29 percent chance for the corresponding nonwhite male.¹⁶ There is no strong evidence for apparent racial discrimination in occupational categories other than management; the effect appears to be localized there.

Regarding the estimated preferences of workers shown in the bottom panel of table 2, it

¹⁶ Calculations of implied offering probabilities will be described below. How much of this apparent racial effect among managerial employers may be due to the preferences of banks and other financiers of the self-employed managers rather than to the preferences of the employers of the salaried managers was examined in a separate run combining the males' data for the two decades and removing self-employed managers and farmers from the managerial category to form a sixth category. The estimated coefficient for nonwhite was then -1.876 ($|t| = 7.03^{**}$) for the remaining, salaried managers (and non-retail salespersons), compared to -1.747 ($|t| = 4.91^{**}$) for the self-employed managers and farmers; strong racial discrimination is suggested in both subcategories. Age was also found to be significant in both categories (salaried = .082, with $|t| = 6.30^{**}$; self-employed = .065, with $|t| = 5.0^{**}$). The effect of education was stronger for the salaried than for the self-employed (.579, $|t| = 12.1^{**}$, versus .120, $|t| = 4.3^*$). The constant term was much more negative for the self-employed, indicating less overall opportunity at comparable levels of qualifications (-1.527, s.e. = .097, versus -.205, s.e. = .122, for the salaried).

appears that men and women place a positive value on prestige, but that men value it more strongly. Women appear to value autonomy more than prestige, while there is no strong evidence of an autonomy preference for men in this model.

The demand intercept values in table 2 were obtained after centering the continuous characteristics of workers on their means during estimation. This allows the intercepts to be transformed directly to the estimated probabilities of offers within occupations for individuals with gender-period mean values of education and age, and zero values on nonwhite. So for example the probability that a white female with average values of education (13.25 years) and age (33.65 years) would be able to obtain a professional offer in the 1982-90 period is given by a simple transformation of the relevant demand intercept: the probability is $\exp(-1.563)/[1 + \exp(-1.563)] = 0.173$, as implied by equation (5). To find the estimated probability of an offer for an otherwise similar woman with 16 years of education, it is necessary to subtract the overall mean from 16 before applying the formula: this probability is $\exp[-1.563 + .791(16 - 13.25)]/[1 + \exp[-1.563 + .791(16 - 13.25)]] = 0.648$. The difference indicates the strength of the preference for formal education among employers of professional women. For employers of professional men in the period, the corresponding offering probabilities are 0.157 and 0.517. (In comparing these estimates it is important to keep in mind that many of the women's professional opportunities are in traditionally women's professions.)

Interpretation of Parameter Estimates

The estimated preference coefficients in table 2 can be interpreted most directly and naturally as the relative weights which employers and workers place on each other's measured characteristics. For example, in the estimates of preference coefficients for managerial employers of women in the eighties, the values of .311 for education and -.864 for nonwhite imply that being white was equivalent to $.864/.311 = 2.78$ years of education in the eyes of the employers. To managerial employers of men in the same period, the estimated value of being white was equal to $1.693/.431 = 3.93$ years of education. It is also permissible to compare the same coefficients across types of employers, to say for example that professional employers of women valued education

approximately two and one-half times as much as managerial employers of women during the eighties ($.791/.311 = 2.54$).¹⁷

Aside from these direct interpretations of the coefficient estimates as evaluative weights, various indirect interpretations are helpful for understanding implications of the model. One interpretation involves a parallel with linear regression, where a coefficient's value gives the absolute change in the observed, dependent variable which results from a unit change in an independent variable. The TSL model does not allow this exact interpretation, since there is no observed quantitative dependent variable. However, a similar interpretation can be made for the change in *opportunity* implied by a unit change in an independent variable.

Occupational opportunity is defined in the TSL model as the chance that an individual would be offered work in a given occupational category, if he or she desired it. This chance can be expressed either as a probability or an odds without any fundamental change in concept. Thus the 0.173 probability calculated above for a professional offer to a white woman of average age and education in the eighties corresponds to odds of $0.173/(1 - 0.173) = 0.210$.¹⁸ With a single additional year of education the probability becomes $\exp[-1.563 + .791(1)] / \{1 + \exp[-1.563 + .791(1)]\} = 0.316$, corresponding to odds of 0.462. The log of the ratio of these two odds, $\ln(0.462/0.210) = 0.791$, gives a measure of the increase in opportunity associated with a increase of one year in education. It is easy to confirm that this log-odds is mathematically equal to the estimated preference coefficient for education reported in table 2. The general rule is that for any worker characteristic, the magnitude of the preference coefficient is an estimate of the change in opportunity associated with a one unit change in the characteristic, where the change in opportunity is measured by the log-odds of offers with and without the change in the characteristic.

A second indirect interpretation of the preference coefficients concerns the relative rankings

¹⁷ This interpretation is valid because the error terms in the utility functions of all employers are constrained to have the same variances. See the explained-variance interpretation of the parameters, developed below.

¹⁸ Calculations were carried out with more digits than reported here.

of different workers made by employers. Under the model, the employers within each occupational category share a utility function which serves to rank all potential workers from low to high as desirable employees. Consider two workers who differ on their observed characteristics only in that the first has one more year of education than the second. Then equation (2) above gives the respective utilities for the two workers, $U_j(1)$ and $U_j(2)$. Since each utility contains a random disturbance, it is not clear whether $U_j(1)$ actually exceeds $U_j(2)$ in any particular case. But since the disturbances in the utilities for the two workers are independent, the mathematics which leads from equations (2) and (3) to (5) can be adapted to show that the probability the *unobserved* utility for the first worker exceeds that for the second is:

$$\begin{aligned} \Pr [U_j(1) > U_j(2)] &= \frac{\exp(\beta_j x_2 + \beta_1 + m_j)}{\exp(\beta_j x_2 + \beta_1 + m_j) + \exp(\beta_j x_2 + m_j)} \\ &= \frac{\exp(\beta_1)}{1 + \exp(\beta_1)} \end{aligned}$$

where β_1 is the coefficient of education in the employers' utility function. The log of the odds that the first, unobserved utility exceeds the second is thus equal to $\log[\exp(\beta_1)] = \beta_1 = 0.791$. A one year difference in education between two otherwise similar women in the eighties thus implies a log-odds of 0.791 that the woman with the greater educational attainment actually ranks higher than the other in the estimation of professional employers; this is the second indirect interpretation of the numerical value of the education coefficient.

The interpretation of the preference coefficients as the log odds that observed differences in characteristics indicate concordant rankings by employers also has an implication concerning the stratification of workers by measured characteristics. If we consider the difference in employers' utilities between otherwise similar women who have a four-year difference in years of education, for example, the log-odds that the more highly educated woman is preferred by professional employers is $4(0.791) = 3.164$, corresponding to a probability of 0.959; at 8 years of difference the probability becomes 0.998. Thus it becomes increasingly unlikely that women of such different levels of education will be substantially interspersed in the preference rankings of professional employers. Similarly, if the preference coefficient itself were to rise over time the same calculation would show

that workers of different levels of education were increasingly less likely to be interspersed in the preference rankings of the employers; there would be increasing stratification of offers of employment according to levels of workers' educations, and thus increasing stratification of the obtained professional positions as well. If the educational preference coefficients of employers in all occupational categories were observed to rise over time, and if workers maintained a constant set of preferences across the occupational categories, then increased stratification by education levels across occupational categories would be implied.

A third and final indirect interpretation of the coefficients follows from observing that when workers' preferences are constant, occupational outcomes in the model depend only on the employers' staffing requirements and their rankings of workers. The staffing requirements being determined by economic factors, a key question for sociological research is how completely the employers' rankings can be determined from the available data. Since the employers' rankings are completely determined by their unobserved utilities for the workers, the question of the completeness of the determination of rankings by the data is answered in practice by calculating the proportion of the variance in the employers' utilities which can be explained by worker characteristics. Such a calculation is easily made. If the systematic part of the employers' utility for a worker is defined as $V_j(i) = \beta_j x_i + m_j$, then the total utility given in (2) is $U_j(i) = V_j(i) + \varepsilon_{1ij}$. Call the sample variance of $V_j(i)$ across all cases s_j^2 .¹⁹ Since the variance of the standard Gumbel disturbance is fixed at $\pi^2/6$ and the disturbance is assumed independent of the systematic part of the utility, the variance of the total utility is estimated by $s_j^2 + \pi^2/6$, and the proportion of the total variance in utilities which is attributable to the measured characteristics of workers is estimated by $R_U^2 = s_j^2 / (s_j^2 + \pi^2/6)$. R_U^2 provides a summary measure of the joint importance of the complete set of measured worker characteristics for the employers in a particular occupational category. Its

¹⁹ The actual estimate of s_j^2 used below is obtained with a formula which weights each case by the probability that an offer from an employer in the category would be accepted; this appropriately discounts contributions from cases whose outcomes are relatively less informative about the utilities in the relevant category. The effects of this weighting procedure are not large, however.

advantage over a simple examination of the magnitudes of the preference coefficients is that it simultaneously considers the contribution of all measured worker characteristics, while accounting for the observed variability of each. However, it should be emphasized immediately that R^2_{ij} is not a measure of the goodness of fit of the model as a whole or in part, and its values are not meaningful if the model does not fit well for a particular occupational category. Goodness of fit for the model as a whole and with respect to particular categories will be considered below.

The R^2_{ij} values shown in table 2 indicate that, for men, the worker characteristics included in the model — education, age and race — explain over 70 percent of the variance in the utilities for employers of professional and manufacturing blue collar workers, about 50 percent for employers of managerial and other blue collar workers, and a negligible amount for employers of clerical workers. The patterns are somewhat similar for the women's samples, but evidence will be presented below indicating a lack of fit in some occupational categories for these samples, so it is inappropriate to assert that the R^2_{ij} values are meaningful measures of the proportions of variance explained for employers' decisions regarding women workers.

Selection of Variables

Since the EM algorithm produces maximum likelihood estimates, it is a simple matter to apply likelihood ratio tests for variable selection and nested testing of alternative models, just as in structural equation or log-linear models. Alternatively, if the researcher has no strong theoretical reasons to prefer a particular set of independent variables, the use of BIC statistics may be preferable (Raftery 1995). Both approaches are illustrated here.

Table 3 presents statistics relevant to determining whether any of the variables in the table 2 model might be dropped. The table 2 model itself is labeled model 1 in table 3, with succeeding rows of the table corresponding to models dropping one or more job or worker characteristics. The numbers of estimated parameters are indicated for each model, as well as the identity of the model within which each successive model will be tested when using the likelihood ratio approach. Boldface numbers indicate statistics pertaining to models preferred either by the likelihood ratio or BIC procedures.

The final row of the table, model 8, concerns the null TSL model, in which workers and employers have no preferences for any measured characteristics of their potential partners, and the demand intercept parameters are fixed at zero, implying a 50 percent chance of an offer from each category for each case. The log-likelihood for the null model is $L_0 = N_0 \log p_0 + (N - N_0) \log[(1 - p_0) / J]$, where N is the total sample size; N_0 is the number of unemployed in the sample; J is the number of occupational categories (not counting unemployment); and $p_0 = (2^{J+1} - 1) / [2^J (J + 1)]$ is the probability that unemployment will be the outcome (the Appendix shows the derivation). This model is used as the baseline for calculating the BIC test statistics shown in the table (see Raftery 1995).

The columns labeled 2LL report twice the log-likelihoods for the various models; differences in entries between nested models in the same columns are distributed as χ^2 under the null hypothesis that the coefficients for variables omitted from each nested model are zero in the nesting model. Asterisks beside the likelihood statistics indicate that all nested models can be rejected in favor of model 1, using $p < 0.05$ as the criterion, except in the case of the seventies women's sample, where model 6 is not rejected. Thus the likelihood ratio tests suggest that all variables in model 1 should be retained in both the men's samples and in the eighties women's sample, but that the age variable should be omitted in the seventies women's sample.

The BIC statistics give different results. In both women's samples, model 7, which omits age and nonwhite, is preferred to any other model, though the evidence against including nonwhite is not strong for the eighties. BIC suggests the full model 1 for the seventies men's sample, but indicates, though not strongly, that age should be dropped for the eighties sample. Thus the BIC results are also somewhat ambiguous, suggesting that neither age nor race is important in the women's models, but that race should be included in the men's models while age may be less important. (See Raftery 1995 for the definitions of strong and very strong evidence used here.)

The likelihood ratio and BIC procedures are presented here to demonstrate their application to the TSL model. Since I have a relatively strong prior belief that race and age are relevant to hiring decisions, and since the number of variables under consideration is not excessive, I will retain model

1 for further analysis in all samples.

Goodness of Fit

Neither the likelihood ratios nor BIC provides a suitable test of the absolute goodness of fit of individual-level models such as TSL (cf. Hosmer and Lemeshow 1989: 136-140; Raftery 1995, note 6); they are tests of relative fit. Applying the Hosmer-Lemeshow test within each occupational category provides a reasonable check on the absolute goodness of fit of the TSL model.²⁰ The Hosmer-Lemeshow test statistic, \hat{C} , allows a chi-square test comparing the proportions of outcomes actually observed in each decile of risk with the proportions which are expected according to a model. For each occupational outcome, deciles of risk are formed across the observations by collecting the first ten percent of cases which have the lowest predicted probabilities of accepting a job within the occupation, followed by the ten percent with the next lowest probabilities, and so on. The test statistic should be distributed approximately as $\chi^2(8)$ when calculated as just described.

\hat{C} statistics are shown in table 2 for each sample and occupation. For eight degrees of freedom the expectation of χ^2 is 8.0, and critical values for the null are 13.36 for $p = 0.10$, and 15.51 for $p = 0.05$. The range of \hat{C} values for the men's samples, from 3.49 to 15.47, suggests that the fit is acceptable, though the 15.47 value for managerial occupations in the seventies is suspect. On the other hand, four of the ten statistics for the women's samples are unacceptable. Though introducing, for example, nonlinear terms in education does improve the fit for women, I prefer to avoid arbitrary curve fitting, and conclude instead that the models do not include sufficient relevant variables to fit women's observed outcomes very well in an absolute sense.

Tests for Structural Change

Taking both the men's and women's models in the two decades as provisionally acceptable,

²⁰ I am following the spirit of Hosmer and Lemeshow's own recommendation for assessing the fit of the multinomial logit model, which is to calculate separate binary model test statistics for each outcome category, even though neither theoretical nor simulation justification is given for their recommendation. The results should be approximately correct here as well, I believe.

it is interesting to ask how much evidence the data give for changes in either the workers' or employers' preferences between the seventies and eighties. Here again either likelihood ratio or BIC methods can be applied. Table 4 shows relevant statistics.

All the models in table 4 contain the full set of preference coefficients from the preferred model 1 of table 3: that is, they all contain employers' preferences for education, age, and nonwhite status, and workers' preferences for prestige and autonomy. The models in table 4 differ in the specification of which preferences will be held fixed across the seventies and eighties, and which will be allowed to differ. (Technically, interactions with a period dummy are introduced to free the estimates across periods.) Abbreviating the consideration of table 4 to conserve space, the fact that the smallest BIC' statistic for the men's data is found in model 9 suggests that there is no evidence for any change in the circumstances of opportunity of men between the seventies and eighties, including changes in the overall levels of demand in the five categories. For women, the minimal value of BIC' in model 10 indicates very strong evidence of changes in overall demand in the categories (demand rises strongly except in blue collar manufacturing occupations); there is no evidence of change in the preferences for the measured characteristics of education, age and race, however. That model 10 for women is only weakly favored over model 11 does suggest that an increase in women's preferences for high prestige jobs should not be ruled out entirely.

4. OTHER MODELS OF EMPLOYMENT OUTCOMES

The preceding sections having developed the TSL model and applied it to questions of occupational opportunity and choice in the United States, it is appropriate to conclude with some comments about the differences between TSL and other models, comments which would have been less understandable if made earlier in the paper. The models to be reviewed in this section share the goal of understanding how jobs with differing characteristics come to be held by different types of individuals, though they differ in the ways in which the job outcomes are characterized, measuring them variously by socioeconomic status, occupational category, or income. Both economic and sociological models are considered, with some emphasis on the long-standing sociological goal of estimating relevant effects independently of economic influences on overall demand for particular

occupations.

Linear Regression and Status Attainment Models

By far the most productive method for understanding individual-level determinants of occupational outcomes has been direct, linear regression of employment outcomes on individual characteristics. This type of regression appears in structural equations models as well as in the single equation models often used by economists. The proposed TSL method can be used to evaluate the importance of the same types of variables studied with regression, such as education, experience, gender and race, which raises the question of the relative benefits of the two approaches.

There is no doubt that linear regression is appropriate for obtaining descriptive knowledge of the background factors differentiating subjects on a quantitative dependent variable in a given set of labor market conditions. Linear regression has much to recommend it in its well-developed treatment of measurement issues, indirect causation and many other technical points. However, there are certain advantages of TSL over linear regression. TSL estimates have a direct, behavioral interpretation as the preferences of employers and workers, and consequently a direct relationship to relevant sociological ideas of structure, briefly discussed below. TSL estimates of the importance of various individual characteristics are also differentiated by occupational category, so that a trait like formal education, as was seen above, may have different effects on chances of employment in different occupations. In contrast, in linear regression the effect of a variable like education appears uniformly beneficial or harmful no matter what the range of occupations an individual may be destined for; TSL estimates can and do contradict this appearance.²¹

Because of its construction from an underlying random utility matching model, TSL estimates have an invariance property under conditions of change in the demand for occupational categories which is not shared by linear regression estimates. The lack of this property in linear regression means that estimates of the importance of individual traits will change when demands for occupations change, even if employers maintain the same preference coefficients for individual

²¹ See the earlier elaboration of this point in footnote 15.

traits. _____ (1992) presented a simulation study which demonstrated the sensitivity of linear regression estimates to demand changes, and the approximate stability of TSL estimates.

Log-Linear and Related Multinomial Models

Log-linear and related multinomial models have been sociologists' main tool for research on structural factors in occupational mobility for twenty-five years. Though primarily restricted to the analysis of categorical variables alone, methods for extending log-linear models to include continuous or categorical background variables have long been available (e.g., Yamaguchi 1983, Logan 1983, Hout 1984, DiPrete 1990, Breen 1994). The ability to combine continuous and categorical variables is shared by TSL, and TSL could also be applied to a multivariate analysis of mobility table patterns. This makes the relative merits of TSL and log-linear and related multinomial models important to consider. An advantage of log-linear and related models is their high state of technical development, and the ease with which they can be estimated using standard software. Like a simple regression, these models can be regarded as providing a description of the bivariate distribution of data in a specific set of historical circumstances. When augmented with background variables, the models describe the bivariate categorical distribution of parents' and offspring's occupations conditional on these variables.

However, log-linear models have no mathematical relationship to any behavioral model of actors. This makes it hard to determine what the mechanisms of the various structural effects proposed in the models might be. Is a "barrier" in a log-linear model to be associated with the actions (or inactions) of persons or employers blocking the individual's mobility? If so, it is not clear how the parameters are related to these actions. By comparison with the TSL model, the structures of log-linear models are vague and allusive: disembodied "barriers," "levels," and symmetries abound, untied mathematically to any behavioral referents. In the TSL model, all parameters have behavioral referents.

The lack of behavioral referents for the log-linear parameters makes it difficult to justify the claims of log-linear modelers that the parameters describing association within tables are insensitive to exogenous changes in occupational structure. In fact, the intercept parameters of the TSL model,

β_j0 in equation (6) above, are able to fit changes in marginals due to changes in demand for occupations while the preference parameters of the model remain constant, just as the marginal parameters of log-linear models can accommodate changing outcome distributions while the association parameters stay constant. Thus the mere fact that a parametric structure accommodates shifting marginals does not automatically justify it as a model of opportunity or mobility, since both TSL and log-linear models satisfy this requirement using completely different structures. Simulation with the behavioral random utility matching model shows that exogenous changes in demand do not significantly affect TSL estimates of preferences, while the parameters of comparable multinomial models are strongly affected.²² On the other hand, it is not possible to simulate a system of workers and employers in which the log-linear/multinomial association parameters are constant under changes in demand: the reason is that log-linear/multinomial models have no behavioral implications which can be simulated.

Discrete Choice Models

Economic discrete choice models, briefly considered in section 1 above, seem to provide a natural framework for the study of occupational outcomes. Boskin (1974) provides an early example of such an application, using the multinomial conditional logit model. The problem with the direct application of such a simple model to occupational choice is that the standard models assume either that all alternatives are freely available to all workers, or that the researcher can determine which alternatives are available to which workers *a priori*. As Pudney (1989:17) puts this assumption, "in general in applied work [the set of available alternatives] either is observed directly or can be constructed without statistical estimation." While certain alternatives can reasonably be ruled out for decision makers in certain types of studies, as when households not owning cars are

²² _____ 1992 performed such a simulation using a conditional logit variant of Logan's 1983 multinomial model; Breen (1994) also independently developed such a variant. See Harrison 1988 for related observations on the sensitivity of log-linear/multinomial parameters to changes in demand for occupations.

excluded from the private automobile alternative in transportation studies (e.g. Swait and Ben-Akiva 1986), the breadth and imprecision of occupational categories make this strategy impractical in the present context.

Manski (1977) in a paper developing the foundation of discrete choice models introduced the idea of random choice set generation as a formal means of accounting for unobservable differences in the alternatives available to different workers. In this formalism, workers are represented as having a probability distribution over access to all the possible sets which can be generated from the basic list of alternatives. Swait and Ben-Akiva (1986, 1987), building on this work and on an unpublished paper of Ben-Akiva (1977), developed and estimated such a model empirically in a study of transportation mode choices. Their Independent Availability Logit (IAL) model assumes that there is a constant probability across workers that each alternative will be available, and that these probabilities are independent across alternatives. However, though Ben-Akiva (1977) had suggested making the probabilities of the alternative availabilities functions of individual characteristics, and though Andrews and Srinivasan (1994) have recently estimated a model with such individually-varying probabilities in a marketing study, no known studies using random choice set generation have specified the choice set availabilities as dependent on another set of actors, as is done here.²³

²³ The IAL model was unknown to me when I first developed and estimated the TSL model, as was Manski's (1977) theoretical analysis. Though he did not develop a choice set generation formulation which explicitly represented other actors making alternatives available, Manski did suggest the possibility verbally (p. 234).

Swait and Ben-Akiva (1986, p. 76) express reservations about the implication of the IAL model, expressed in its name, that the availabilities of the various alternatives to individuals are statistically independent. Under IAL there should not be an association between, say, the probability of being offered a professional and a managerial job. However, the TSL model does not share this property, even though it is assumed that the disturbance terms are independent across categories. In TSL, the systematic dependence of the offering probabilities on the characteristics of the individuals

Game Theoretic Matching and Job Search Models

The addition of a second set of actors in the random utility matching model produces what can be considered a stochastic specification of a deterministic two-sided game called the college admissions model in the game theoretic literature (see Roth and Sotomayor 1990 for a review of relevant game theory models). However the college admissions model is a centralized matching game, while matches are formed in a decentralized manner in the random utility matching model described above. Formal analysis of the random utility matching model as a game produces new insights into the behavioral characterization of the model, reveals strategies which employers and workers may try to implement, and leads to a related process interpretation which helps justify the TSL estimation method (_____ 1994b).

Game theoretic models have been developed as abstract accounts of behavior in labor markets, with limited comparisons of theoretical predictions to the behavior of real markets (see Mortensen 1988 for an additional review). Various existing refinements of the deterministic college admissions model offer possible directions of extension for the probabilistic random utility matching model. However, the game theoretic literature sometimes tends toward hyperrational analyses in which workers must make difficult calculations of optimal strategies; sociological development of the random utility matching model should avoid such tendencies. The TSL model nonetheless is, so far as I know, the first applied random utility specification of a two-sided game, and could be extended in a hyperrational direction as such. Use of the TSL model allows parameter estimation under the assumption that a formal game is being played.

Economic job-search models closely related to game theoretic matching models (see Mortensen 1986, 1988; Devine and Kiefer 1991) also offer potential directions for extending the random utility matching model. In job search models the quality of matches between employers and workers is assumed to be difficult for the actors to evaluate initially, which leads to the formation of poor initial matches. Explicit models of information flow among actors then lead to plausible

receiving offers can be expected to induce cross-individual correlations among the offers obtained from different categories of employers.

deductions about the rates of match formation and dissolution, and the properties of equilibrium states the market should approach through time. Refinements along these lines could lead to improved random utility matching specifications which still have a bounded rationality character. Estimable parametric job search models with multiple occupational categories have not appeared, to my knowledge.

In many game and job search models a principle resource which employers offer in jobs — namely, wages — is not considered to be a fixed property of the job, but rather to be negotiated between potential employment partners (Roth and Sotomayor 1990, Mortensen 1988). This type of specification is rejected in the sociological random utility matching model for reasons familiar to readers of Thurow (1975) and Sørensen (1983, 1986).

Economic Assignment Models of the Distribution of Earnings

A broad category of economic models, reviewed by Sattinger (1993), considers the problem of individual occupational outcomes by taking the idea of employers negotiating wages to its logical conclusion. In these economic assignment models the distribution of workers into jobs, which are typically classified by industrial sector rather than occupation,²⁴ is assumed to occur not by virtue of any rejections of potential workers by employers, but by employers optimally setting the wages that each individual would be offered to perform each particular job. In Sattinger's words, these models derive "the wage differentials that are consistent with an equilibrium assignment of workers to jobs. The equilibrium wage differentials are those that yield equality between amounts of labor supplied and demanded in each [sectoral] submarket of labor" (p. 832). The models produce predicted distributions of workers across sectors as a function of the preferences and resources of workers and employers, just as the random utility matching model does.²⁵ Some have also been

²⁴ The TSL model could also be estimated with a sectoral classification of employers, but the occupational classification is more relevant to sociological questions.

²⁵ The terminology, "preference" and "resource," is my characterization, and not the economists', who use a much more detailed and theoretically grounded terminology.

developed statistically so that the preferences of workers and employers (classified by sector) can be estimated, as in the TSL model.

The key difference between these models and the random utility matching model is the assumption that employers adjust wages to clear the market, as workers engage in wage competition for jobs. That is, to make employment in a sector just sufficiently remunerative to attract the necessary number of workers, and no more, employers raise or lower wages. In contrast, the random utility matching model assumes that the demand for employment in an occupation at prevailing wages *may* exceed the supply of jobs, and that employers may choose among an excess of willing candidates rather than lower wages until the supply of labor just balances demand. As a result, queuing and job competition, as in Thurow (1975) and Sørensen (1983, 1986), may be induced. It is perhaps worth saying that such an exercise of choice by employers seems rather common, even though it is removed by assumption from the economic assignment models.

Sattinger nominates Heckman and Sedlacek's (1985, 1990) development of Roy's (1950) model as the most promising route to estimating assignment models (1993: 873). Heckman and Sedlacek, following Roy, handle the demand side of the assignment problem by introducing separate wage equations for each sector. These equations estimate the wage that each individual would be paid to work in each sector, leaving the workers formally free to choose a job in any sector, and to choose in practice the sector offering them the highest wage. In contrast, the random utility matching model handles the demand side of the assignment problem by directly representing each employer's *decision* whether or not to offer a job to each individual. Sattinger (1993, p. 842, n. 13) nicely differentiates the type of model I am proposing from the economic models he reviews, as he refers the reader to another article: "Dale Mortensen (1988) reviews matching problems related to the assignment problem. In this literature, matches are formed through the voluntary actions of agents rather than as the solution to an aggregate maximization problem." He also (p. 834) distinguishes the economic assignment models from "structuralist theories in sociology . . . [which] do not assume competitive access to jobs," citing Granovetter (1981) and Kalleberg and Berg (1987) as examples. The random utility matching model underlying TSL is a structuralist model in

this sense, since it excludes (wage-) competitive access to jobs; TSL is proposed as suitable for use in empirical studies of ideas developed in sociological structuralist theories.

Actor-Oriented Sociological Models

A relatively formal research tradition has mathematically modeled the competition of workers for advancement within systems of opportunity structured either according to the needs of employers or as a result of power struggles between workers and employers. White's (1970) vacancy chains, Boudon's box model (1974), Thurow's (1975) job competition, Sorensen's (1977) vacancy competition, and Stewman and Konda's (1983) venturi models are examples. The theorizing underlying these models is actor-oriented, and systemic properties of the theorized systems are clearly retained in the translation to mathematics. A key idea is that opportunities for employment or advancement are contingent on the dispositions or needs of employers, often discussed in terms of vacancies in fixed job positions. Certain of these models have been faulted for providing too rigid a representation of structure, in which nothing but a vacancy can lead to increased achievement (Rosenbaum 1984),²⁶ but a main practical drawback has been a lack of a flexible statistical technique suitable for weighing the relative importance of measured variables in the allocations of jobs.

Coleman (1991) developed a model which represents occupational outcomes as a system result of the distributions of preferences and resources among employers and workers, as does the random utility matching model. He emphasizes the importance of a system approach to opportunity, in which outcomes are determined "by the resources of the person, relative to those of other persons in the market, the resources of the job, relative to those of other jobs, the interest of the employer in the person's resources, and the interest of the person in the job's resources" (p. 3), and discusses very lucidly the advantages of such an approach in making calculations of expected changes in occupational distributions when demographic or other presumptively exogenous changes in circumstances occur. These sorts of calculations can also be made with the random utility matching

²⁶ This criticism does not apply to TSL.

model underlying TSL.

However, Coleman makes very different assumptions in order to achieve a model, assumptions which are economic in flavor. He assumes a perfect market with an equal number of jobs and workers, discarding the possibility of unemployment. He assumes that all resources held by workers and employers have an equilibrium, per-unit, monetary, market value which prevails for all members of the system. Thus, unlike the random utility matching model and Heckman and Sedlacek's (1985, 1990) model, there is no possibility of different valuations of resources by employers or workers in different occupational or sectoral markets. Because Coleman's model assumes a perfect market, and therefore a lack of sociological structuralist or even frictional explanations of inter-market differences in the values of resources, it is hard to see how it might be developed into a more differentiated and structural model. It is also unclear how Coleman's model could be used to generate a proper statistical estimation procedure useful for hypothesis testing, rather than the ad hoc procedure demonstrated in Coleman and Hao (1989).

Eliason (1995) proposed a model to test some of Sørensen and Kalleberg's (1981) propositions concerning differences in the allocations of workers in open and closed systems. Eliason's basic conception is identical to the random utility matching model proposed here: "workers are assumed to prefer that position which maximizes his or her perceived utility ... [and] employers are assumed to prefer a specific worker if that worker maximizes the employer's perceived utility" (p. 249). However, the steps taken to achieve an estimable model are quite different. Eliason posits the existence of a "joint utility function" which is maximized by "the matching process in the labor market," and which he calls "the labor market matching function" (p. 250). Workers gain access to positions, he says, "only when the joint distribution of the perceived utilities is maximized," by which he means only when the "joint utility function" is maximized, since some *function* of the separate utilities must be defined for a maximum to exist. This assumption of a labor market matching function whose maximum determines the allocation of workers to jobs is the primary technical basis of Eliason's claim to have extended Sørensen's and Kalleberg's theory, as he says in his conclusion (p. 266).

Though it may seem plausible that some labor market matching function is maximized in the allocation of workers to jobs, game theory shows the situation is too complex for such an assertion to be accepted uncritically. There are in general many possible stable matchings in systems of workers and employers who freely enter employment relationships, rather than only one. Which particular stable matching is achieved depends on informational and strategic conditions which are not implied by the utility functions. So if it is stated that a particular function attains a maximum at a stable matching, it must be explained why this function would have the same value at each of the possible outcomes. Otherwise it would not necessarily be true that the particular stable matching actually achieved in any instance corresponded to the maximum.

Game theory does establish one result which is somewhat similar to Eliason's requirement. When the preferences of actors are exclusively monetary, and when each employer negotiates salaries with all its workers individually rather than offering fixed salaries for positions, it can be shown (in a simple assignment model) that the sum of the monetary returns received by each matched pair of employers and workers achieves the same, maximum value across all stable matchings (Roth and Sotomayor 1990, corollary 8.8). This result does not apply to utilities in general, however. Even if all actors have utility functions which weight money heavily enough that any nonmonetary influences could be offset (the assumption that "everything is for sale," which is dubious), there is no reason to believe that the sums or other reasonable functions of the individual utilities of matched workers and employers would be the same at all stable matches. Furthermore, in the situation, closer to the concept of a closed system (Sørensen 1983), in which employers offer fixed salaries for positions it is easy to construct examples of multiple, stable matches which differ in any plausible function of the employers' and workers' utilities.²⁷ There is therefore no reason to

²⁷ A simplified example consists of three employers, E_1 , E_2 and E_3 , and three workers, w_1 , w_2 and w_3 . Assume each employer has a hiring quota of one worker, which cannot be exceeded, and that all actors would prefer a match to any partner over the possibility of not being matched at all. If the actors' orders of preferences are $P(E_1) = w_1, w_2, w_3$; $P(E_2) = w_1, w_2, w_3$; $P(E_3) = w_1, w_3, w_2$; $P(w_1) = E_1, E_2, E_3$; $P(w_2) = E_1, E_3, E_2$; $P(w_3) = E_1, E_2, E_3$; then two matchings are stable. These are

accept Eliason's assertion of a single function whose value is maximized by labor market matching processes in general. The complexity of the matching problem is not reducible to the maximization of a single function (except in the special case just mentioned), no matter how convenient this would be for modeling.

Eliason's model contains other questionable specifications. For example, it is remarkable that no job characteristics appear in the empirical estimation of the supposed joint utility function (his equation 2) even though the function was introduced as reflecting workers' as well as employers' perceived utilities of matches (p. 250). In addition, the linkage between his matching and wage functions is neither an assumed correlation of error terms (representing unmeasured characteristics shared across equations) nor a dependence of one function on the outcome of the other, but is instead a correlation between the *systematic* part of the matching function and the error term of the wage function. The z_{i3} used to define the linking correlation is a deterministic function only of the w_i and γ_j vectors in the matching function, and does not depend on the values of the function's disturbance term, η_{ij} , nor on the values of its outcome, v_{ij} .²⁸ This makes the derivation of

$(E_1:w_1, E_2:w_2, E_3:w_3)$ and $(E_1:w_1, E_2:w_3, E_3:w_2)$, in an obvious notation (Roth and Sotomayor 1990: 31). Any utilities which satisfy the stated preference orders can produce either stable matching, depending on the details of the matching process. If the utility function for worker 2, say, is defined so that it is very negatively affected by some characteristic of employer 2 which is not present in employer 3 (say employer 2 produces an immoral good, which matters greatly to worker 2 but not much at all to the other workers), then it is not hard to see that a reasonable joint function of the utilities of the employers and workers could have a higher value at the second matching compared with the first, though either matching would be stable. The basic problem is that the maximum of a joint function of the utilities is a numerical quantity, while the matchings depend only on the rank ordering of the utilities; any difference in utilities which preserves the rank orders will affect the maximum but not the matching.

²⁸ See his equation A-2 and the sentence which follows it, while recalling that $\Phi^{-1}(\bullet)$ is a deterministic function, not a stochastic transformation, and that the probability of an outcome is not

his equation (4), the supposed effect of the wage process on the matching process, meaningless: the w_i have been declared to be exogenous, not endogenous (p. 252), and the γ_j are fixed population parameters. No effect of the *wage* process can operate on the matching process through the z_{is} , since they are deterministic functions of w_i and γ_j , which are exogenous and fixed quantities in the *matching* function itself.

Though Eliason's intention of looking for differential effects of workers' qualifications in closed and open systems of positions is well-considered and important, the key assumption of a labor market matching function on which his model is based, the improper linkage of the two basic equations, and other problems, make it hard to accept the empirical results at face value. The TSL model, by contrast, is not based on any assumed maximization of a joint function of workers' and employers' utilities, but is a direct expression of the basic game theoretic matching situation in stochastic form (_____ 1994b).

DISCUSSION

The mechanism by which the preferences and resources of employers and workers determine the allocation of workers to jobs in a free economy is this: workers choose the jobs whose resources they prefer from the sets available to them; and employers choose the workers whose resources they prefer from the sets they find available. To transform such a truism into a useful model, the preferences of both types of actors have been represented here by utility functions containing measured and unmeasured characteristics. A direct development of this simple idea leads to a two-sided logit, or TSL, model which provides joint estimates of the preferences of both workers and employers, using data only on the characteristics of individuals and the jobs they hold.

The TSL model considers the basic problem of occupational attainment from a point of view different from prevailing approaches. By mathematically describing the matching process which determines outcomes, it has been possible to break into interrelated pieces an estimation problem which prevailing techniques have considered unitary. Instead of directly predicting outcomes from

the outcome itself.

the characteristics of individuals, as in regression, the TSL model tries first to explain the rankings which employers have over workers, and the rankings which workers have over types of jobs.²⁹ These rankings are functions of unobserved utilities whose systematic parameters are estimated. The actual outcomes, the assignments of workers to jobs, cannot be predicted by the model without external information on the level of demand for jobs of different types, represented by the demand intercepts in each category. Since the estimation of preferences is separated analytically from the estimation of demand effects, TSL estimates of preferences are insensitive to changes in demand, unlike regression estimates, and, as simulation with the model shows (_____ 1992), also unlike log-linear/multinomial estimates, if the simple matching process is granted to be a reasonable mechanism. TSL estimation attempts to find constancy or change in preferences over time (or, potentially, place), net of changes in demand.

Application of the model to General Social Survey data did indeed show constancy of preferences of both employers and workers over the seventies and eighties, at least according to the BIC criterion, which is more conservative than the corresponding likelihood ratio tests. For women, only levels of demand in occupations seem to have changed between the decades; there were large positive changes in the demand intercepts for women in professional, managerial, and clerical/service occupations, but there was little evidence of change in the standards of women's employers with respect to education, age or race. Nor was there much evidence of changes in women's evaluations of prestige and autonomy. For men, the situation was simpler still: there was no evidence of change, period. Even the demand intercept estimates for men showed little evidence of change. The implication of these results is that the opportunity of men, defined as the chances of employment in the various occupations, stayed stable over the period, while the opportunity of women increased in ways which did not reflect changing valuations of education, age or race.

Within this general pattern of stability there are still interesting comparisons to be made across occupational categories. In general, education was valued most highly by professional

²⁹ However, the rankings of types of jobs by workers has been de-emphasized in this presentation, for the sake of simplicity.

employers, then managerial and clerical/service employers, while blue collar employers appeared to value years of education negatively. This is an indication that blue collar offers (not outcomes) become *less* likely with more education. Apparent discrimination against nonwhites was localized in managerial occupations for men, with very strong evidence for the effect by the BIC criterion. For women there was strong evidence of this effect in the eighties, but not the seventies. In no other category besides management was there strong evidence of such discrimination, net of other characteristics, against either nonwhite men or women. Age appeared to be a factor in obtaining employment offers only for men, and then only for managerial jobs. The positive valuation of age for managerial offers may reflect the time it usually takes to obtain relevant experience and/or capital. These findings of differences in the determinants of opportunity across occupations (which are generally replicated across the independent samples from the two periods) give insights into the structure of opportunity which are not available from linear regression or log-linear/multinomial models.

In evaluating the results obtained here, and the potential usefulness of TSL methods in other studies, certain limitations which exist at this stage of development should be considered. The use of occupational category means to represent the characteristics of all jobs within a category has three drawbacks. The detailed information on the jobs held by each individual in the sample is discarded, leading to a loss in efficiency and power. The use of mean data also downwardly biases the estimates of the individuals' preference coefficients, as mentioned above. Finally, using means reduces the number of job characteristic variables which can be used in estimation, since there are only $J - 1$ data points for each variable, rather than the much larger $N - 1$ observations in the sample. However, against these points it can also be said that using job characteristics at the level of occupational categories has proved useful in such a well-regarded effort as Hout's SAT model (1984, 1988). The above analysis suggests that even with category means TSL is able to produce useful (and qualitatively quite different) results as well.

A second main concern which the TSL method presents is the computational burden of estimation. Although a convenient, special-purpose estimation program is available for other

researchers' use, the amount of time required to obtain estimates is not negligible. Even on a very fast workstation, turnaround times were on the order of an hour for the analyses presented here. On slower machines, the estimations could each have taken many days. This lack of speed is due both to the combinatorial complexity of the likelihood and the slowness of EM estimation techniques in general.

A third problem is a question of basic realism. The model assumes that workers and employers are each in possession of information about the relevant characteristics of all potential partners. This is impossible. It can be argued, though, that the characteristics of the partners that actors finally choose is a good enough indicator, for the purpose of estimation, of the characteristics they would have chosen had they had perfect knowledge. On the other hand, the model as now constituted contains no way to represent the importance of differential access to information about partners in the actual matching process.

Each of these concerns is a matter of research I am pursuing. It seems very likely that a method for using individual-level job characteristic information rather than occupational means will soon prove practical; this will solve the three subsidiary problems mentioned three paragraphs ago. Estimation speed can be improved with standard EM acceleration techniques, and possibly with a consistent estimation method involving a simplification of the likelihood. Results have been derived on the effects of information flow and the related effects of the sizes of local labor markets, and should soon be incorporated in the estimation program. These improvements will increase the practical capabilities of the TSL method without fundamentally altering the basic theoretical approach proposed here.

The basic theoretical approach itself should be considered in evaluating the TSL model, and merits some closing comments. It is evident that TSL is based on a model of choice, but it may be less clear whether this is a "rational choice model," as this term is commonly applied. Rational choice has connotations which many sociologists find unpalatable as a basic characterization of behavior. Though this is not the place to develop the point, rational choice is not a single concept (see Sen 1987 for a concise review). The idea of rational choice begins with the idea of consistency

of choice, but often proceeds to include the self-interested, calculating behavior associated with "economic man" and the idea of optimization (though in fact neither consistency nor self-interest implies the other, as Sen points out).

TSL stops at consistency of choice as the basic characterization of behavior which is necessary to estimate preferences. Clearly, without some consistency of choice across similar circumstances, no estimation would be possible. But there is no implication in the model that the choices are made on account of any self-interested calculations; instead, the choice behavior may result for moral or normative reasons, to satisfy collective rather than individual goals, because of habit, or through the operation of the rules (Giddens 1984) or schemas (Sewell 1992) which theorists have persuasively argued may structure action for reasons lying outside the immediate situations of apparently atomistic actors making isolated choices.

By contrast, economic models of choice often assume some self-interested calculation in their subjects, and are often then able to simplify the inferential problem as a result. Heckman and Sedlacek's (1985, 1990) model is a good example. By assuming that employers will optimally adjust wage offers for each individual, it is possible to pretend that individuals choose among jobs which are freely available to them in all sectors, just as they would in a simple multinomial conditional logit model. Though Heckman and Sedlacek's model is still difficult to estimate, the simplifying assumption of this optimal behavior on the part of employers has removed the choice behavior of the employers (replacing it with optimal wage setting), and has thus sidestepped the natural complexity of modeling interrelated choices on both sides of the market.

The point of retaining this complexity in the TSL model is to avoid introducing any *assumptions* of self-interested calculation on the part either of employers or workers, though without denying that such calculation often occurs. The lack of such rationality assumptions, in any sense going beyond consistency, is from the sociological point of view a positive achievement rather than an omission, undertaken for theoretical reasons just as economists have for their own theoretical reasons taken the opposite tack. The TSL model is designed to measure the determinants of choice among employers and workers, whether the choices are economically rational or

sociologically structured, or some combination of both. It is expected that further development and application of the model will produce new information concerning the varied and socially structured determinants of opportunity and choice in the labor market, and in other situations in which the choices of two types of actors are mutually constraining.

Appendix: Derivation of the Null-Model Log-Likelihood

In the null model, all parameters are set to zero in equations (5) and (9) of the text. This implies that the probability of selecting a job from any given category is simply $1/N_i$, where N_i is the number of categories from which individual i has obtained offers, *including* the unemployment category; and that the probability of obtaining an offer from any category except unemployment is $\exp(0)/[1 + \exp(0)] = 1/2$ for all individuals. (The probability of an "unemployment offer" remains 1.0.) The probability that i accepts a job in category 0, unemployment, is then given by reformulating equation (10) in the text to reflect the simplifying role of N_i in the null case:

$$\begin{aligned} \Pr(A_{i0}) &= \sum_{N_i=1}^{J+1} \Pr(A_{i0}|N_i)\Pr(N_i) \\ &= \sum_{N_i=1}^{J+1} \frac{1}{N_i} \binom{J}{N_i-1} \left(\frac{1}{2}\right)^J \\ &= \left(\frac{1}{2}\right)^J \frac{1}{J+1} \sum_{N_i=1}^{J+1} \frac{(J+1)!}{N_i![(J+1)-N_i]!} \\ &= \frac{2^{J+1} - 1}{2^J(J+1)}, \end{aligned}$$

using the identity $\sum_{k=0}^n \binom{n}{k} = 2^n$. This null model $\Pr(A_{i0})$ is the value called p_0 in the text. By

symmetry, the probabilities of selecting any categories besides unemployment must all be equal to one another, and thus equal to $(1 - p_0)/J$. The log-likelihood in the text follows from substituting p_0 and $(1 - p_0)/J$, respectively, for the probabilities of cases observed in unemployment and the employed categories.

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TABLE 1. DESCRIPTIVE STATISTICS

	Profes- sional	Mana- gerial	Sales/ Clerical/ Service	Mfg. Blue Collar	Other Blue Collar	Not Employed	Total
Women, 1972-1980							
Education	15.57	13.35	12.33	10.78	11.10	11.83	12.40
std. dev.:	1.99	2.27	1.84	1.88	2.56	2.52	2.58
Age	32.96	34.36	33.54	34.44	34.00	33.56	33.58
std. dev.:	6.03	5.27	5.78	5.79	5.52	5.57	5.69
Nonwhite	0.12	0.04	0.17	0.13	0.16	0.12	0.13
std. dev.:	0.32	0.20	0.37	0.34	0.37	0.33	0.34
Prestige	58.19	49.33	35.43	28.86	29.90	38.70	40.04
std. dev.:	7.30	10.15	10.64	5.40	8.78	12.58	13.57
Supervisor	0.13	0.28	0.13	0.04	0.21	0.21	0.17
std. dev.:	0.34	0.45	0.34	0.19	0.42	0.41	0.37
Total cases	316	118	691	153	58	1296	2632
percent:	12.0	4.5	26.3	5.8	2.2	49.2	100.0
Women, 1982-1990							
Education	15.76	14.23	12.73	11.42	12.41	12.32	13.25
std. dev.:	2.23	2.21	1.90	1.66	2.05	2.57	2.57
Age	33.68	34.50	33.62	34.11	33.31	33.30	33.65
std. dev.:	5.53	5.51	5.61	5.53	5.76	5.60	5.59
Nonwhite	0.12	0.09	0.19	0.32	0.15	0.20	0.17
std. dev.:	0.33	0.28	0.39	0.47	0.35	0.40	0.38
Prestige	57.75	49.84	36.80	29.20	29.93	37.87	42.01
std. dev.:	8.62	8.74	9.59	7.30	9.46	13.69	13.78
Supervisor	0.09	0.27	0.18	0.07	0.20	0.23	0.18
std. dev.:	0.29	0.44	0.39	0.25	0.41	0.42	0.38
Total cases	586	373	1098	159	96	971	3283
percent:	17.8	11.4	33.4	4.8	2.9	29.6	100.0

(TABLE 1 CONTINUED)

	Profes- sional	Mana- gerial	Sales/ Clerical/ Service	Mfg. Blue Collar	Other Blue Collar	Not Employed	Total
Men, 1972-1980							
Education	16.14	14.05	12.96	11.36	11.41	12.63	13.10
std. dev.:	2.37	2.66	2.36	2.32	2.56	3.20	3.11
Age	33.22	34.76	32.54	33.76	33.58	32.31	33.52
std. dev.:	5.60	5.57	5.89	5.95	5.45	5.84	5.72
Nonwhite	0.07	0.03	0.16	0.15	0.14	0.18	0.11
std. dev.:	0.25	0.18	0.36	0.36	0.35	0.38	0.32
Prestige	59.71	48.15	34.58	34.33	34.04	36.71	42.02
std. dev.:	10.35	8.56	10.50	8.31	9.32	12.90	13.99
Supervisor	0.17	0.44	0.10	0.07	0.17	0.02	0.20
std. dev.:	0.37	0.50	0.30	0.26	0.38	0.15	0.40
Total cases	400	423	231	332	530	233	2149
percent:	18.6	19.7	10.7	15.4	24.7	10.8	100.0
Men, 1982-1990							
Education	16.45	14.41	13.38	11.82	12.14	12.24	13.58
std. dev.:	2.36	2.30	2.37	2.08	2.29	2.92	2.88
Age	34.52	34.93	33.17	33.64	33.29	33.35	33.90
std. dev.:	5.54	5.64	5.60	5.56	5.65	5.90	5.67
Nonwhite	0.09	0.05	0.20	0.11	0.16	0.21	0.13
std. dev.:	0.29	0.21	0.40	0.31	0.37	0.41	0.33
Prestige	60.72	47.72	32.34	33.90	34.21	34.34	41.83
std. dev.:	10.94	7.96	11.32	7.74	9.24	12.45	14.51
Supervisor	0.24	0.39	0.07	0.03	0.22	0.17	0.21
std. dev.:	0.43	0.49	0.25	0.16	0.41	0.38	0.41
Total cases	502	560	369	325	658	237	2651
percent:	18.9	21.1	13.9	12.3	24.8	8.9	100.0

TABLE 2. TWO-SIDED LOGIT ESTIMATES OF EMPLOYERS' AND WORKERS' PREFERENCES

EMPLOYERS' PREFERENCES										
	Women, 1972-1980 (N = 2,632)					Women, 1982-1990 (N = 3,283)				
	Prof	Mgmt	Clerical/ Service	Mfg. Blue	Other Blue	Prof	Mgmt	Clerical/ Service	Mfg. Blue	Other Blue
Intercept	-2.605** (15.87)	-2.570** (20.19)	.304 (1.86)	-.174 (0.47)	-3.078** (18.41)	-1.563** (13.45)	-1.477** (16.05)	1.669** (5.43)	-0.679 (1.88)	-2.401** (18.71)
Education	.988** (12.23)	.228** (5.46)	.242* (4.19)	-1.068** (4.25)	-.140 (2.59)	.791** (16.53)	.311** (9.96)	.370** (4.41)	-.691** (4.50)	-.023 (0.49)
Age	.011 (0.65)	.036 (2.05)	.011 (0.81)	.007 (0.16)	.005 (0.21)	.005 (0.40)	.039 (3.34)	.039 (1.97)	.053 (1.33)	-.005 (0.26)
Nonwhite	.214 (0.72)	-1.155 (-2.46)	.723 (2.82)	1.382 (1.19)	.174 (0.45)	-.422 (2.18)	-.864* (4.22)	-.144 (0.61)	1.656 (2.46)	-.401 (1.31)
R^2_U	.795	.235	.179	.801	.069	.716	.324	.311	.674	.016
\hat{C}	5.987	7.247	44.214	5.029	11.955	25.533	24.618	51.438	11.739	9.034
Men, 1972-1980 (N = 2,149)										
Intercept	-1.831** (15.82)	-.622** (5.10)	-.524* (4.02)	1.123 (2.23)	1.011 (3.56)	-1.683** (13.95)	-.248 (1.50)	.191 (1.05)	1.460 (2.41)	1.712 (2.47)
Education	.674** (14.87)	.349** (9.91)	.138 (3.21)	-.735** (4.58)	-.449** (4.64)	.723** (16.57)	.431** (9.51)	.267** (4.79)	-.894** (4.32)	-.501 (2.31)
Age	.027 (1.87)	.091** (6.64)	-.005 (0.28)	.032 (0.69)	.007 (0.20)	.016 (1.16)	.069** (5.07)	.011 (0.54)	.138 (1.98)	.038 (0.59)
Nonwhite	-.529 (1.90)	-1.570** (5.02)	.096 (0.36)	-.228 (0.39)	-.819 (2.15)	-.285 (1.21)	-1.693** (6.25)	.815 (2.23)	-1.196 (1.73)	.357 (0.46)
R^2_U	.728	.479	.085	.719	.497	.727	.541	.247	.787	.515
\hat{C}	10.889	15.465	10.427	7.964	3.672	10.574	6.410	11.009	8.960	3.487
WORKERS' PREFERENCES										
	Women		Men							
	1972-80	1982-90	1972-80	1982-90						
Prestige	.037** (5.22)	.059** (9.08)	.099** (9.95)	.094** (10.78)						
Autonomy	.143** (11.64)	.136** (10.12)	.034 (3.21)	.037 (3.60)						

Notes: Absolute values of $t = (\text{est./s.e.})$ in parentheses. * = strong evidence of effect: $|t| \geq \sqrt{(\ln N + 6)}$; ** = very strong evidence: $|t| \geq \sqrt{(\ln N + 10)}$.

TABLE 3. RELATIVE FIT STATISTICS FOR VARIABLE SELECTION

Model	Preference Coefficients Included in Model	Demand Intercepts?	Estimated Parameters	Test Within Model	LR							
					Women			Men				
					1972-80	1982-90	1972-80	1982-90	1972-80	1982-90		
	Workers' Employers'			2LL	BIC'	2LL	BIC'	2LL	BIC'	2LL	BIC'	
				(+ 6380)	(+ 1850)	(+ 9210)	(+ 2320)	(+ 7010)	(+ 1520)	(+ 8710)	(+ 2030)	
1	prestige, autonomy	yes	22	—	99.1	52.7	234.9	28.2	478.6	9.6	685.8	9.1
2	prestige	yes	21	1	68.4 *	75.5	210.6 *	44.4	469.4 *	11.2	674.4 *	12.5
3	autonomy	yes	21	1	31.6 *	112.3	39.1 *	215.9	4.6 *	475.9	6.8 *	680.1
4	none	yes	20	2	10.0 *	126.0	2.9 *	244.0	3.8 *	469.1	5.4 *	673.7
5	prestige, autonomy	yes	17	1	78.3 *	34.2	198.0 *	24.6	438.7 *	11.2	619.8 *	35.6
6	prestige, autonomy	yes	17	1	94.0	18.4	218.3 *	4.3	426.3 *	23.6	651.7 *	3.7
7	prestige, autonomy	yes	12	6	73.0 *	0.1	179.2 *	2.9	379.8 *	31.7	586.8 *	29.2
8	none	no	0	7	-1871.4 *	1850.0	-2235.0 *	2320.0	-1200.6 *	1520.0	-1508.6 *	2030.0

* Likelihood ratio chi-square probability of fit within nesting model is ≤ 0.05 .

TABLE 4. RELATIVE FIT STATISTICS FOR TESTS OF STRUCTURAL CHANGE

Model	Period Interactions		Estimated Parameters	Women		Men	
	With These Coefficients			2LL	BIC'	2LL	BIC'
	Workers'	Employers'		(+15500)	(+4170)	(+14600)	(+3650)
9	none	none	22	8.9	155.7	1.7	5.6
10	none	intercepts	27	203.8	4.3	27.7	22.0
11	prestige	intercepts	28	211.5	5.3	27.7	30.4
12	prestige, autonomy	intercepts	29	212.4	13.0	27.8	38.9
13	prestige	intercepts, education	33	230.3	29.8	32.7	67.8
14	prestige	intercepts, education, nonwhite	38	241.7	61.9	40.0	102.9
15	prestige	intercepts, education, nonwhite, age	43	243.9	103.1	44.3	141.0
16	prestige, autonomy	intercepts, education, nonwhite, age	44	244.0	111.7	44.4	149.4

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