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THEORETICAL AND PRACTICAL ARGUMENTS FOR MODELING LABOR SUPPLY AS A CHOICE AMONG LATENT JOBS

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Abstract. Models of labor supply derived from stochastic utility representations and discretized sets of feasible hours of work have gained popularity because they are more practical than the standard approaches based on marginal calculus. In this paper we argue that practicality is not the only feature that can be addressed by means of stochastic choice theory. This theory also offers a powerful framework for developing a more realistic model for labor supply choices, founded on individuals having preferences over jobs and facing restrictions on the choice of jobs and hours of work. We discuss and clarify how this modeling framework deviates from both the conventional discrete approach [Van Soest, A. (1995) Structural models of family labor supply. A discrete choice approach. Journal of Human Resources 30: 63–88), as well as the standard textbook approach based on marginal calculus (Hausman, J.A. (1985) The econometrics of nonlinear budget sets. Econometrica 53: 1255–1282]. We furthermore discuss how the model based on job choice can be applied to simulate effects of alternative restrictions on hours of work.

Keywords. Labor supply; Random utility models; Tax reform

1. Introduction

Discrete choice models of labor supply based on stochastic utility theory have gained widespread popularity, mainly because they are much more practical than the conventional continuous approach based on marginal calculus, see the survey by Creedy and Kalb (2005). The discrete approach differs from the corresponding continuous one in that the set of feasible hours of work is approximated by a suitable finite discrete set. With the discrete choice approach, it is easy to deal with nonlinear and nonconvex economic budget constraints, and to apply rather general functional forms of the utility representation. With particular distributional assumptions about the stochastic disturbances in the utility function one can derive tractable expressions for the distribution of hours of work, such as the multinomial – or the nested multinomial logit model. From a theoretical perspective, however, the conventional discrete choice model is similar to the standard textbook approach to labor supply in that it is essentially a version of the theory of consumer behavior. The only new assumption postulated is that the set of feasible hours of work is finite.[1] Some researchers, such as Keane (2011) for example, essentially ignore the discrete choice approach to labor supply altogether, while others play it down and refer to it only as a somewhat crude approximate approach that makes estimation problems manageable (Blundell *et al.*, 2007; Heim, 2009).[2]

The main message we wish to convey in this paper is that the conventional discrete labor supply model can be extended and re-interpreted as a model that accounts for important but neglected aspects of the labor market, namely that individuals have preferences over jobs, and face restrictions in their choice of jobs and hours of work. For example, a typical feature of the labor market is that most jobs offer only full-time or a fixed fraction of full-time work (part-time). This feature is reflected in the data on the distribution of hours of work in many countries, with peaks at full-time and part-time hours of work. See, for example, Ilmakunnas and Pudney (1990), Kahn and Lang (1991), Dickens and Lundberg (1993) and Stewart and Swaffield (1997). Traditional models of labor supply, including the conventional discrete labor supply model, are silent about these restrictions and fail to reproduce these peaks. To improve the fit to data in the conventional discrete labor supply model, researchers have often resorted to specifications where the systematic term of the utility function has been modified by introducing suitable dummy variables (van Soest, 1995). Unless one interprets these observed peaks as stemming from preferences, this practice is clearly *ad hoc* from a structural point of view. Although one cannot rule out that workers may have stronger preferences for full-time hours of work, for example, than for alternative hours of work schedules, it seems reasonable to assert that observed peaks at full-time and part-time hours are, to a great extent due to institutional regulations. In fact, everyday experience tells us that working hours in most jobs are regulated (typically full-time hours). Consequently, counterfactual policy simulations based on the discrete choice model, adjusted by suitable dummy variables to improve the fit, will be difficult to interpret.

This paper discusses how the notion of ‘job choice’ and restrictions on hours of work can be accounted for within the framework of discrete choice and random utility representations. We discuss and clarify how this modeling framework deviates from both the conventional discrete approach (van Soest, 1995), as well as the standard textbook approach based on marginal calculus (Hausman, 1985). The approach proposed in this paper formalizes the *ad hoc* adjustment of introducing additional dummy variables and provides an interpretation in terms of demand restrictions on the set of available job opportunities. In other words, the job choice formulation provides a theoretical foundation for the modified discrete labor supply model extended with suitable dummy variables. Furthermore, this formulation also widens the basis for simulations of alternative policies. Note that the point we make here is a theoretical one, and consequently, the alternative approach we propose will in general not provide better fit to the data than the conventional modified discrete labor supply model.

It should be noted that the choice of job and the notion of job attributes have been emphasized in other parts of the labor market literature, see for instance Sattinger (1993), van Ophem *et al.* (1993), but the approach we follow in this paper differs from theirs. Here, the modeling approach departs from a formulation of the choice environment where individuals face latent choice sets of jobs. The jobs are characterized by fixed, job-specific hours of work and nonpecuniary attributes, such as the nature of tasks to be performed, location of the work place, working environment, etc. In this approach, observed hours of work and disposable income, are thus interpreted as hours of work and disposable income that follow from the *chosen* job. Although the sets of jobs that are available to the respective workers are latent (to the researcher), the discrete choice methodology enables us to represent the choice sets of available job opportunities in the model. Thus, the type of model presented here is capable of representing the distribution of preferences on one hand, and economic and latent choice restrictions, on the other. Restrictions on for example part-time hours of work will thus in this setting be interpreted as restrictions on the set of part-time jobs that are available to the individual. Similarly to the conventional discrete labor supply model, the alternative job choice model we propose is rather practical and user-friendly, in the sense that it is very easy to simulate behavioral effects from counterfactual policy reforms, such as changes in the tax system or wages. Thus, we believe that our alternative framework offers additional advantages to the conventional discrete choice approach that should be of particular relevance to practitioners. A version of the labor supply model presented here is part of the model system that Statistics Norway have made available for Norwegian policy-makers, see Thoresen *et al.* (2010).

The paper is organized as follows: The next section discusses briefly the main features of other approaches that have appeared in the literature. In Section 3 we describe in detail our alternative job choice model. Section 4 discusses identification, empirical specification and model assessment, as well as some aspects related to policy simulations.

2. Main Features of Previous Approaches

This paper focuses solely on structural analysis of labor supply in a static setting, that is, analysis based on theories with explicit representations of preferences and budget restrictions, as well as other choice restrictions. Structural models enable the researcher to quantify behavioral effects from counterfactual policy interventions, which are at the core of discussions on welfare effects of policy changes.[3]

An overwhelming majority of approaches in the literature on static structural labor supply are based on variations of the standard textbook theory of consumer demand (standard approach). In this approach the individual agent is assumed to have preferences over total consumption and leisure, and is assumed to maximize utility under the economic budget constraint determined by the wage, nonlabor income and the tax system, see early contributions on econometric modeling and empirical analyses by Heckman (1974, 1979).

Recent surveys on structural labor supply modeling focus almost entirely on contributions based on the standard approach, see Blundell and MaCurdy (1999), Blundell *et al.* (2007), Keane (2011) and Meghir and Phillips (2010). As mentioned in the introduction, the obvious fact that agents have preferences over qualitative job attributes, and face important quantitative restrictions when making labor market decisions, is typically neglected. A number of researchers have extended the standard labor supply model to the case with nonlinear (piece-wise linear) budget constraints that possibly imply non-convex budget sets. This type of budget sets follows from tax systems found in many countries, where deduction rules for different types of taxes imply that marginal taxes may not be monotonously increasing with income, but may in fact decrease in specific income intervals. Burtless and Hausman (1978) and Hausman (1979, 1980, 1985), Blomquist (1983), MaCurdy *et al.* (1990), Triest (1990), and others, have made important contributions to the modeling of labor supply in this type of situations.[4] Blundell *et al.* (1998) is also based on a continuous approach, but relies on an identification strategy based on comparing labor supply over time (covering several tax reforms) for different groups defined by cohort and education level.[5]

Unfortunately, standard labor supply models based on marginal criteria, as well as the conventional discrete choice models applied in the studies referred to above, are silent about the potential importance of job attributes for labor supply behavior. There are, however, important modifications of the standard labor supply models in the literature that address the problem of restrictions on labor market choices, such as Altonji and Paxson (1988), Ilmakunnas and Pudney (1990), van Soest *et al.* (1990), Tummers and Woittiez (1991), Dickens and Lundberg (1993), and Bloemen (2000; 2008).[6] Early attempts to model constraints on hours of work have taken different forms. For instance, in the model of Ilmakunnas and Pudney (1990) individuals are restricted in various degrees in their opportunities of choosing part-time and full-time work. They utilize actual information on person specific constraints in the labor market, and conduct policy simulations with and without constraints. Dickens and Lundberg (1993) assume a standard labor supply model with a particular rationing device that is somewhat similar in spirit to the one of Ilmakunnas and Pudney (1990), although the final empirical specification of the model is entirely different. Similarly, Bloemen (2000), van Soest *et al.* (1990) and Tummers and Woittiez (1991) apply various specifications to account for hours of work restrictions. However, despite these earlier attempts to account for important labor market characteristics, there are few recent studies that accommodate choice restrictions in the analysis of labor supply.

2.1 *The Standard Textbook Approach*

Typically, the standard approach to labor supply modeling, see Blundell and MaCurdy (1999), is to choose a specification of an individual labor supply function (hours of work function) consistent with the maximization of a quasi-concave utility function in disposable income and leisure, subject to the economic budget constraint. For simplicity, consider the case with convex budget sets with constraint approximated by a suitable smooth representation. Suppose, for example, that the chosen labor supply function has the structure

$$h = \alpha + \beta \tilde{w}(h) + X\gamma + \delta \tilde{I}(h) + \varepsilon. \tag{1}$$

when

$$\alpha + \beta \tilde{w}(0) + X\gamma + \delta \tilde{I}(0) + \varepsilon > 0 \tag{2}$$

and $h = 0$ otherwise. Here $\tilde{w}(h)$ is the marginal wage, $\tilde{I}(h)$ is so-called virtual nonlabor income, X is a vector of individual characteristics that affect preferences, ε is a random error term, α, β, γ and δ are unknown parameters. The inequality in (2) represents the condition for working. In general, when the tax system is nonlinear, the marginal wage rate and virtual income depend on hours of work and are therefore endogenous. As a result, one cannot estimate the model by using the ordinary least squares method based on (1), and have to rely on appropriate instruments, which are not always easy to find. Additional complications follow from the fact that the wage is not observed for those who do not work (the selection problem).

After the parameters of this labor supply function have been estimated, one needs to solve for h (conditional on wage and nonlabor income) in the nonlinear equations given by (1) and (2), which may – or may not – be cumbersome. A more serious concern is that the linear relation in (1) may at best be a rather crude approximation of the ‘true’ labor supply function. In fact, the linear functional form of the supply function is clearly *ad hoc* from a theoretical perspective. It is, however, possible to formulate and estimate more complicated labor supply functions in the case where the budget set is convex and smooth. However, in the presence of nonconvex and kinked budget sets, which are quite typical in many countries, the analysis becomes very complicated in the case when more general and flexible model specifications are used, see Bloemen and Kapteyn (2008).

Thus, to summarize, the traditional textbook approach based on marginal calculus, including the extension proposed by Hausman (1985), has the following weaknesses. First, it becomes intractable to estimate except cases with rather simple specifications. Second, empirical results obtained by this approach seem to be far from robust with respect to different specifications of functional form and distributional assumptions. The wide variation in labor supply estimates found in the literature testifies to this (Blundell and MaCurdy, 1999). Third, this approach is silent about other important aspects of the labor market, namely that workers have preferences over job types and may face important constraints in their labor market choices.

2.2 *The Conventional Discrete Choice Model*

During the last 15 years the adaptation of discrete choice models has become increasingly popular, mainly because this approach simplifies drastically the implementation of complicated nonlinear budget constraints. The work of Bingley and Walker (1997), Blundell *et al*. (2000), van Soest *et al*. (2002), Creedy *et al*. (2004), Haan and Steiner (2005), Labeaga *et al*. (2007) and Blundell and Shepard (2012) are examples of how empirical discrete choice labor supply models can be conveniently estimated and simulated for the purpose of assessing the effect of counterfactual tax reforms. The ability of discrete choice models to handle rather complex decision processes is also substantiated by the use of such models to analyze labor supply jointly with for example welfare programme participation or use of nonparental care services. Examples of this type of work are provided by Hoynes (1996), Keane and Moffitt (1998), Brewer *et al.* (2006) and Kornstad and Thoresen (2007).

The discrete choice labor supply model departs from the theory of random utility models (see McFadden, 1984). We shall next give a summary description. Let $U(C, h)$ denote the agent's utility function of real disposable income and hours of work (C, h), and assume that

$$U(C, h) = v(C, h) + \eta(C, h) \tag{3}$$

where $v(C, h)$ is a positive deterministic term that represents the mean utility across observationally identical agents and $\eta(C, h)$ is a random term that is not correlated with the structural term $v(C, h)$ and with c.d.f. $\exp(-\exp(-x))$, defined for real x.[7] Moreover, $\eta(C, h)$ and $\eta(C', h')$ are independent for $(C, h) \neq (C', h')$.The budget constraint is given by

$$C = f(hw, I) \tag{4}$$

where w and I are the wage and nonlabor income, respectively, and $f(\cdot)$ is the function that transforms gross income into after-tax household income. The function $f(\cdot)$ can in principle capture all details of the tax and benefit system. Furthermore, the set D of feasible hours of work is a finite set. If (4) is inserted into (3), we obtain

$$\tilde{U}(h) \equiv U(f(hw, I), h) = v(f(hw, I), h) + \eta(f(hw, I), h) = \psi(h) + \tilde{\eta}(h) \tag{5}$$

where $\psi(h) = v(f(hw, I), h)$, and $\tilde{\eta}(h) = \eta(f(hw, I), h)$. For simplicity we have suppressed wage and nonlabor income in the notation. By well-known results from the theory of discrete choice (McFadden, 1984) it now follows that the probability $p(h)$, that the agent will supply h hours of work, given D, the budget constraint in (4) and the wage rate and nonlabor income (w, I), is equal to

$$p(h) = P(\tilde{U}(h) = \max_{x \in D} \tilde{U}(x)) = \frac{\exp(\psi(h))}{\exp(\psi(0)) + \sum_{x \in D} \exp(\psi(x))} \tag{6}$$

In empirical applications, the structural part of the utility function, $v(C, h)$, is assumed to have a convenient functional form and is allowed to depend on individual covariates, see for example van Soest (1995) and van Soest *et al.* (2002). Unfortunately, and similarly to the standard model above, the model given in (6) is unable to fit the data well in most cases due to observed peaks at full-time and part-time hours of work. Researchers have therefore replaced the systematic utility term $v(C, h)$ by a 'modified' utility term $v(C, h) + \gamma(h)$, where $\gamma(h)$ is equal to one for hours of work different from part-time and full-time hours of work. For example, $\gamma(h) = a$ for h equal to full-time hours and $\gamma(h) = b$, for h equal to part-time hours, and zero otherwise, where a and b are constants that are estimated from data. Under the modified specification the choice model takes the form

$$p(h) = \frac{\exp(\psi(h) + \gamma(h))}{\exp(\psi(0)) + \sum_{x \in D} \exp(\psi(x) + \gamma(x))} \tag{7}$$

After the introduction of the modified systematic term of the utility function, the model can be made to fit the data quite well. However, the problem of how this practice should be justified remains. One possibility is to interpret $v(C, h) + \gamma(h)$ as 'true' representation of the systematic part of the utility function, but this implies that one believes that agents may have nonmonotone utility in hours of work.

In particular, this means that agents will have higher utility for part-time and full-time hours of work than for other hours. Although it cannot be ruled out that individuals may have particular preferences for full-time and part-time hours of work, for example, due to social conventions and habits, it seems more plausible to interpret the peaks found in the data as resulting from restrictions on hours of work. Indeed, some researchers have focussed on this latter interpretation. Unfortunately, this interpretation lacks foundation because the modeling framework above has no theoretical rationing device that can rationalize quantity restrictions. This is because the conventional discrete labor supply model differs from the continuous one only on the assumption that the set of possible hours is discrete and finite. Thus, the ad hoc practice of introducing dummy variables into the conventional discrete labor supply model to improve the fit to the data has the unfortunate implication that the model will no longer be structural. As a consequence, it will be problematic how counterfactual policy simulations should be interpreted.

The discrete approximation of the set of feasible hours (D) of what is believed to be the ideal continuous choice set is not essential here because it does not change the basic theoretical setting, namely that the worker is assumed to be able to choose combinations of hours of work and consumption freely, as long as the budget constraint is met.

Among some researchers there seems to be a belief that the use of discrete choice models in the context of labor supply represents a somewhat crude approximation (Blundell *et al.*, 2007; Heim, 2009). The reason is that the 'true' choice setting is viewed as a continuous one, and consequently the discretization of the choice set of hours of work that follows by implementing a discrete choice model will induce approximation (measurement) errors. In our opinion, such an attitude is unjustified. The discrete approximation to what is believed to be the true continuous setting is hardly an important point. First, it may be argued (as we do) that the true choice setting is in fact a discrete one. Second, with today's computer capacity one may use a very fine-meshed partition: there is hardly any limit to the number of discrete alternatives that can be applied.[8]

3. The Job Choice Model

We shall now review essential features of our maintained job choice model. A more rigorous exposition and further details are found in Dagsvik and Strøm (2006) and Dagsvik and Jia (2012a).[9] As mentioned in the introduction, this model departs in an essential way from previous approaches in that we focus on a more comprehensive description of the choice environment in which job choice is the fundamental decision variable.

A job is characterized with fixed (job-specific) working hours, wages and other nonpecuniary attributes. Let $U(C, h, z)$ be the (ordinal) utility function of the household, where (C, h) denotes disposable income and hours of work and the positive indices, $z = 1, 2, \ldots,$ refer to labor market opportunities (jobs) and $z = 0$ refers to the nonmarket alternative. For a market opportunity (job) z, associated hours of work is assumed fixed and equal to $H(z)$. In this paper, we shall assume that the hours of work take only a finite number of values, represented by the set D. For simplicity, we shall only consider the special case where the wage only depends on individual qualifications and do not vary across jobs. See Dagsvik and Jia (2012a) for a treatment of the more general case with job-specific wages. The utility function is assumed to have the additive separable structure

$$U(C, h, z) = v(C, h) + \varepsilon(z) \tag{8}$$

where $\varepsilon(z)$ is a term that captures the agent's utility of the unobservable nonpecuniary aspects of job z.[10] Similarly to the previous section we assume that $\varepsilon(z)$, $z = 0, 1, 2, \ldots,$ are iid random variables with c.d.f. $\exp(-\exp(-x))$. This assumption is consistent with the property that the choice of jobs satisfies the property of Independence from Irrelevant Alternatives (IIA), (Luce, 1959).[11] It is sometimes argued that commonly maintained assumptions about the error term of the utility function, yielding labor supply choice probabilities that satisfy the IIA property, are unrealistic. The central property that yields IIA is the assumption of i.i.d. error terms of the utility function. However, the job choice model can easily be extended to a more flexible empirical framework by using nested multinomial logit specifications or specifications with random effects. See Dagsvik and Jia (2012a) for a discussion of these cases and similar ones. For example, it may be argued that the error terms associated with the utility of positive hours of work may be correlated, whereas they are independent of the error term of the utility of not working, due to the effect of a latent variable which we may coin 'taste for work'.

For given hours and wage, h and w, the economic budget constraint is given by (4). With the same notation as in the previous section, we realize that the term $\psi(h) = v(f(hw, I), h)$ is now to be interpreted as the representative utility of jobs with hours of work h, given the wage w and nonlabor income I.

Agents in the labor market are likely to face restrictions on the set of available market opportunities. This is because there are job types for which the worker is not qualified and there may be variations in the set of job opportunities for which he or she is qualified. In addition, due to competition in the labor market, the most preferred type of job for which a worker is qualified may not necessarily be available to her or him. Let $B(h)$ denote the agent's set of available jobs with hours of work h; that is, this set contains those jobs z for which $H(z) = h$. Let $m(h)$ be the number of jobs in $B(h)$. There is only one nonmarket alternative, so that $m(0) = 1$. The choice sets $\{B(h)\}$ are unobserved to the researcher. So far we treat the terms $\{m(h)\}$ as deterministic. We shall return to this issue below.

Further, let $\varphi(h)$ denote the probability that the agent chooses a job with offered hours h, given wage, nonlabor income and individual characteristics.

Analogously to the previous section it follows from standard results in discrete choice theory that the agent will choose job z in $B(h)$ if the utility of this job, $v(f(hw, I), h) + \varepsilon(z)$, is higher than, or equal to the utility of all other jobs that are available, or, what is equivalent, equal to the highest utility that can be attained, given the choice restrictions. The corresponding probability that the agent shall choose this job can then be expressed as

$$P\Big(v(f(hw, I), h) + \varepsilon(z) = \max_{x \in D \cup \{0\},\, k \in B(x)} (v(f(xw, I), x) + \varepsilon(k))\Big)$$

$$= \frac{\exp(\psi(h))}{\sum_{x \in D,} \sum_{z \in B(x)} \exp(\psi(x)) + \exp(\psi(0))} \tag{9}$$

We recognize the expression on the right hand side as the representative utility of job z divided by the sum of the representative utilities across all available alternatives. However, we are not particularly interested in this probability. Instead we want to derive an expression for the probability that the agent shall choose *any* job with hours of work and wage $\varphi(h)$, that is, the probability that the agent shall choose any job within $B(h)$. This probability is therefore obtained by summing the choice probability above over all alternatives within $B(h)$, that is,

$$\varphi(h) = \sum_{z \in B(h)} \frac{\exp(\psi(h))}{\sum_{x \in D,} \sum_{z \in B(x)} \exp(\psi(x)) + \exp(\psi(0))} = \frac{\exp(\psi(h))m(h)}{\exp(\psi(0)) + \sum_{x \in D} \exp(\psi(x))m(x)} \tag{10}$$

for positive h. When $h = 0$, we get

$$\varphi(0) = \frac{\exp(\psi(0))}{\exp(\psi(0)) + \sum_{x \in D} \exp(\psi(x))m(x)} \tag{11}$$

Equations (10) and (11) yield choice probabilities that are analogous to multinomial logit ones with representative utility terms $\{\psi(h)\}$, weighted by the frequencies of available jobs, $\{m(h)\}$. Note that a consequence of our distributional assumptions about the random error terms in the utility function, given in (8), is that the respective numbers of available latent jobs, $\{m(h)\}$, represents a set of *sufficient* statistics for the corresponding choice sets. Unfortunately, $\{m(h)\}$ is not directly observable, but under specific assumptions, one can identify $m(h)$ and $\psi(h)$ and estimate their parameters. For the sake of interpretation, and with no loss of generality, let

$$\theta = \sum_{x \in D} m(x) \quad \text{and} \quad g(h) = m(h)/\theta$$

One can interpret $g(h)$ as the fraction of jobs available to the agent with offered hours of work equal to h, whereas the parameter θ is the total number of jobs available to the agent. We shall call $\theta g(h)$ the *opportunity measure* and $g(h)$ the *opportunity distribution*.

The interpretation of θ can be extended to include fixed cost; see Cogan (1981). To realize this, assume that a positive parameter c, representing the utility (disutility) of fixed cost, enters additively in the utility function given in (8) for positive hours of work. Then, evidently, the structure of the choice probabilities above remains the same, apart from θ which now transforms to $\theta \exp(c)$.

When inserting the opportunity measure into the expressions for the choice probabilities, we obtain

$$\varphi(h) = \frac{\exp(\psi(h))g(h)\theta}{\exp(\psi(0)) + \theta \sum_{x \in D} \exp(\psi(x))g(x)} \tag{12}$$

and

$$\varphi(0) = \frac{\exp(\psi(0))}{\exp(\psi(0)) + \theta \sum_{x \in D} \exp(\psi(x))g(x)} \tag{13}$$

The expressions for the labor supply choice probabilities given in (12) and (13) form the point of departure for the corresponding empirical specification. Note that (12) can, alternatively be written as

$$\varphi(h) = \frac{\exp(\psi(h) + \log(\theta g(h)))}{\exp(\psi(0)) + \sum_{x \in D} \exp(\psi(x) + \log(\theta g(x))).} \tag{14}$$

The expression in (14) has the same structure as the expression in (7). There is, however, an essential difference between (7) and (14) because $\log g(h) + \log \theta$ in (14) is no longer a term that is added in an *ad hoc* manner but is given an explicit representation of choice restrictions that stem from the demand side of the labor market.[12]

The approach above corresponds to a similar formulation by Dickens and Lundberg (1993), and extensions thereof, see Tummers and Woittiez (1991), and Bloemen (2000). However, the approach by Dickens and Lundberg (1993) does not allow for nonpecuniary attributes of jobs, and it is fairly complicated compared to the simplicity of the job choice model above. In one sense the approach of Dickens and Lundberg (1993) is, however, more general than the job choice model discussed so far, in that it allows for stochastic choice sets and thereby accommodates unobserved heterogeneity in job opportunities. One can, however, interpret the job choice model as a model with stochastic choice sets of available job opportunities. See Dagsvik (1994), Dagsvik and Strøm (2006) and Dagsvik and Jia (2006) for discussions on how the approach can accommodate stochastic choice sets.[13]

An issue we have avoided so far is how the opportunity measure is determined in equilibrium. In Dagsvik (2000) and Dagsvik and Jia (2012b) it is demonstrated that the framework above can be interpreted as a particular two-sided matching equilibrium model. In particular, it is shown how the opportunity measure depends on the utilities of the firms (cost-or production functions). It is, however, beyond the scope of this paper to discuss the equilibrium setting, and we shall in the following resort to a reduced form representation.[14]

It seems reasonable to assume that the opportunity density $g(h)$ is fixed in the short run, at least as a first approximation. Institutional restrictions, such as centralized negotiations between labor unions and employers' associations, may corroborate to this assumption. Moreover, in many firms it may be desirable to require the workforce to have more or less the same working hours because the production process requires workers to be present at the workplace simultaneously. The parameter θ, however, will, in addition to depending on individual qualifications, depend on business cycle variations.

Introducing random effects in the wage equation loosens the somewhat restrictive form of the model that follows from the IIA property. In fact, IIA will be relaxed in typical empirical applications, without introducing additional random effects, because the wage is replaced by a wage equation that includes a stochastic error term, and thus a mixed multinomial logit model follows (McFadden and Train, 2000). See also Haan (2006) on this issue. This type of random effect specification, to account for unobserved inter-individual heterogeneity in wages, has been used by Dagsvik and Strøm (2006), Dagsvik and Jia (2012a), and Kornstad and Thoresen (2007).

4. Model Specification and Assessment

4.1 *Empirical Specification*

This section contains a brief discussion on empirical specification and assessment. Note first that without further assumptions about the distribution of unknown parameters across the population econometric models are nonparametrically unidentified. To achieve identification one typically assumes that after controlling for some individual characteristics at hand the parameters are constant across the population. However, this procedure may be questionable because many studies indicate that there is often unobserved variation in parameters across individuals (given functional form specifications of the utility function). The parameters may even be correlated with observed variables in the model. In general, there will be a trade off between functional form assumptions for the structural part of the utility function and random effect assumptions.[15] Recall that for any reasonable functional form one can obtain a perfect fit to cross-section data by choosing a sufficiently flexible distribution of random effects. In our opinion it is therefore better to rely on a functional form with reasonable theoretical properties and allow a flexible random effect specification instead of insisting on an *ad hoc* flexible functional form specification with limited variation of parameters across the population. This state of affairs calls for specifications and functional form assumptions that can be justified on *a priori* theoretical grounds.

We shall now discuss assumptions that will ensure identification of the job choice model. As indicated above, we believe it is important to provide plausible theoretical arguments in support of the choice of mathematical specification of the model. As regards functional form of the systematic part of the utility function, Dagsvik and Strøm (2006), Dagsvik and Røine Hoff (2011) and Dagsvik (2012) discuss a theoretical approach to this end based on particular invariance principles. These invariance assumptions imply that the systematic term $v(C, h)$ is of a generalized Box-Cox functional form that allow for particular interaction terms in order to accommodate nonseparability features, see Dagsvik and Røine Hoff (2011) and Dagsvik (2012) for details. Specifically, they show that the resulting nonseparable functional form is given by

$$v(C, h) = \frac{\gamma(C^{\alpha} - 1)}{\alpha} + \frac{\delta((M - h)^{\beta} - 1)}{\beta} + \frac{\mu(C^{\alpha} - 1)((M - h)^{\beta} - 1)}{\alpha\beta} \tag{15}$$

where $\alpha, \beta, \gamma, \delta$ and μ are constants and M is maximum feasible hours of work. When $\alpha < 1, \beta < 1, \gamma > 0$ and $\delta > 0$, and μ satisfies suitable constraints, then the function given in (15) is strictly concave. With the functional form given in (15) one can show that the model is identified.

Several researchers have applied a polynomial specification in leisure and disposable income, whereas others have applied translog specifications or Box-Cox type of functional forms. As is well known, the translog and the polynomial functional form do not imply that the deterministic part of the utility function is globally concave. Dagsvik and Strøm (2006), Dagsvik *et al.* (2010), Mastrogiacomo *et al.* (2011) and Dagsvik and Jia (2012a) show that the Box-Cox functional form yields more or less the same fit as quadratic specifications. In some cases, however, the quadratic specification has the undesirable feature of not increasing in leisure (Dagsvik and Jia, 2012a). Since the Box-Cox functional form is nonlinear in parameters, it is more complicated to estimate than the corresponding quadratic one. Mastrogiacomo *et al.* (2011) report difficulties with estimating Box-Cox utility specifications in some cases. Blundell and Shepard (2012) found that their Box-Cox utility specification resulted in an unacceptable estimate of one parameter.

Consider next identification in the case with no parametric functional form assumptions. If the offered wage depends on hours of work one cannot obtain identification in the nonparametric case without further assumptions. Assume therfore that the offered wage does not depend on hours of work. Provided the parameters are constant across the population, then Dagsvik and Jia (2012a) show that one can identify $v(C, h)$ apart from an additive term $d(h)$, say, that depends on h. This means that one can only separate preferences and the opportunity distribution up to an additive term depending on h. This is evident from the structure of the choice probabilities in (12) and (13), because

$$\psi(h) + \log g(h) = v(f(hw, I), h) + \log g(h)$$

for positive h. To obtain full identification one must therefore make functional form assumptions. Alternatively, if data on preferred hours are available, one would evidently be able to identify and estimate the utility function: see Euwals and van Soest (1999) and Bloemen (2008) for studies exploiting data on desired hours of work. It is, however, important to note that for policy simulations that consist in changes in the economic budget constraint, represented by the function f, there is no need to separate $v_2(h)$ from $g(h)$ because $v_2(h)$ and $g(h)$ do not depend on f. Recall that here we are only concerned with supply effects under given assumptions about job restrictions, represented by the job opportunity measure and *not* about the corresponding equilibrium opportunity measure.

One type of specification of the opportunity distribution that seems reasonable and has been used in several empirical applications is to assume that $g(h)$ is uniform apart from peaks at full-time and part-time hours: that is, $g(h)$ is assumed to be constant apart from peaks at full-time and part-time hours.

Since the opportunity distribution of hours and the opportunity measure of the total amount of available jobs appear in the model as $\theta g(h)$, one does not have to impose the restriction that the sum of $g(h)$ should be equal to one when estimating the model, because one can easily obtain the desired normalization after the model has been estimated. Thus, the empirical specification of the job choice model is similar to the model of van Soest (1995), extended to include suitable dummy variables to account for hours constraints. The parameter, θ, representing the total amount of job opportunities available, can be allowed to depend on education (and a constant), and is estimated simultaneously with the choice model. Thus, more precisely, under the assumptions just discussed, one may conveniently represent $\log(\theta g(h)) = \log \theta + \log g(h)$ as a linear function in length of schooling and dummies for part-time and full-time hours of work. The parameter δ in (15) is typically specified as a function of age and number of children at different ages (in the case of female labor supply). Furthermore, a wage equation is estimated to allow prediction of wages for those who do not work. Once the wage equation, the choice probabilities and the opportunity measure have been fully specified one can easily form the likelihood function, see for example Dagsvik and Jia (2006).

In the model version presented in this paper the jobs are latent and thus job characteristics do not appear in the analysis. However, job characteristics can be introduced by classifying jobs into observable sectors. See Dagsvik and Strøm (2006) who have formulated and estimated a version of the model with two observable sectors (public and private).

4.2 *Model Simulations and Performance*

A much debated issue is how structural models should be assessed; see for example Hausman (1992). The problem is that the researcher usually does not have much information about model performance apart from goodness-of-fit measures. One key test of model performance is to examine how the model predicts out of sample labor supply behavior. To this end we shall present two examples taken from Dagsvik and Jia (2012a), where a job choice model for married couples is estimated on Norwegian data for 1997. The estimated model is then used to illustrate the model performance of the alternative discrete labor supply model. In particular, model predictions are compared with results from a 'naive' prediction procedure, where labor supply behavior is assumed to be the same over time, namely, remains as the 1997 level.

In a first example, model predictions are compared with data from the same data source as used in the estimation of the model, that is the Labor Force Survey, but for a year a significant distance to the year used in the estimation of the model, namely 2006. In 2006 a tax reform was introduced that implies a substantial realignment of dividend income and wage income taxation. In addition to a higher effective tax on dividends, there was a substantial reduction in the maximum marginal tax rate, from 55.3% to 47.8%, which was expected to increase labor supply.

In Figures 1 and 2 the distributions of working hours in the data are compared to the results of model simulations for eight discrete hours intervals for married males and married females, respectively: the medians of the intervals for positive working hours are 260, 780, 1040, 1560, 1960, 2340 and 2600. We see that the distributions of working hours[17] for married females (Figure 2) is closer to the actual frequencies for 2006 than to 1997, whereas the move to higher working hours for males, as suggested by the model simulation results, does not seem to be reproduced in the data. Thus, the model predictions are not perfect as regards the responses of the males. However, the responses of the females seem to be well captured by the model simulations.

In a second example, income tax return data for 2003 are used. In contrast to the Labor Force Survey, this dataset covers many more households but unfortunately does not contain information on hours of work. This example is interesting because it provides an indication on how the model is able to predict the out of sample income distribution. Figure 3 displays the observed and predicted disposable income distributions for married couples (adjusted to 1997 prices). Again, we see rather close correspondence between the actual distribution of 2003 and the model prediction.

Both the traditional discrete labor supply model and the job choice model presented in this paper are well suited for simulating the effects of changes in the economic budget constraint, determined by the tax system, wages and nonlabor income. A particular feature of the job choice model is that it can also be used to study the effects of changes in the opportunity distribution of offered hours of work as well as the total number of job offers without introducing ad hoc modifications, as discussed above.[18]

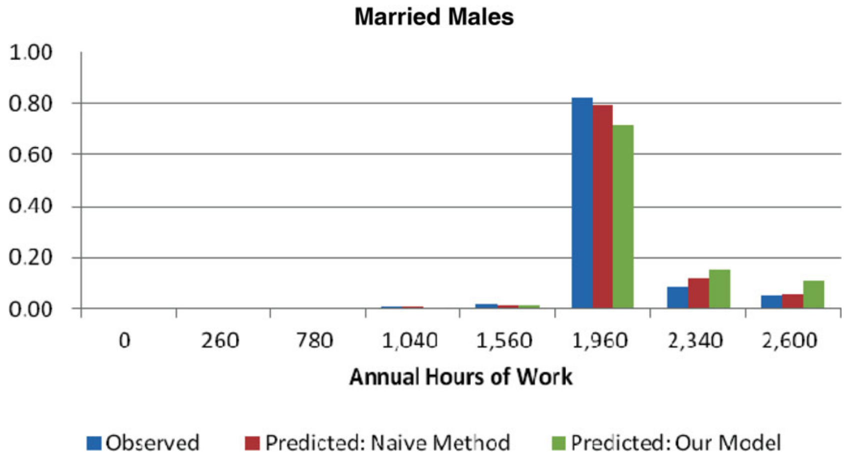

Figure 1. Predicted and Observed Distributions of Hours of Work for Married Men.

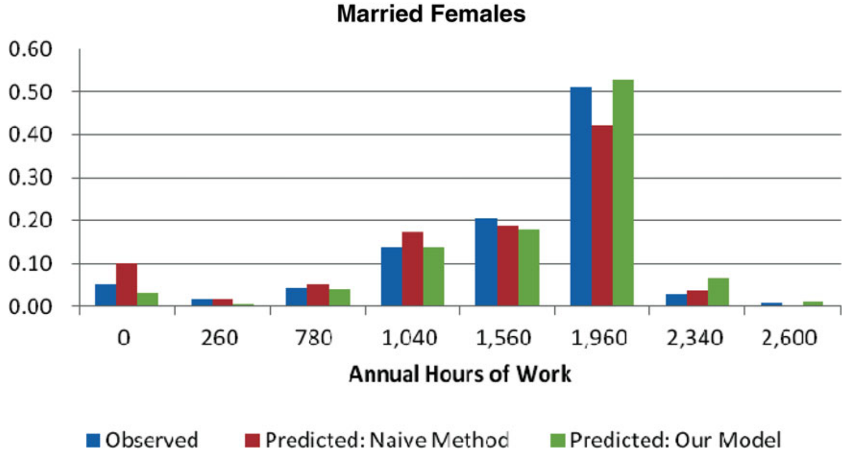

Figure 2. Predicted and Observed Distributions of Hours of Work for Married Women.

Recently, there has been heated discussion among politicians and labor unions about introducing a reform in which part-time positions are replaced by full-time positions. Within our framework one can readily simulate the effect of this reform on labor supply by changing the opportunity distribution of hours, see Dagsvik and Jia (2012a) for more details on the simulation of this type of reform. In contrast, the conventional discrete choice framework cannot simulate the effect of this type of reform because the quantitative choice restrictions are not explicitly represented in the model.

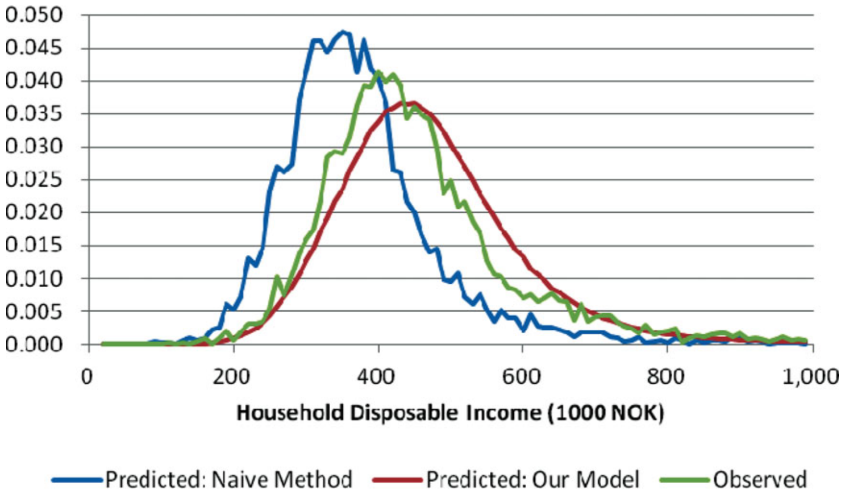

Figure 3. Observed and Predicted Distributions of Disposable Income for Married Couples.

4.3 *Wage Elasticities*

One cannot compute wage elasticities in the usual manner for discrete choice models choice models because the supply function is a stochastic function. Instead it is convenient to calculate elasticities that accommodate the effect of both the systematic terms and the unobservables in the model. This means that one takes into account how the mean of the *distribution* of labor supply is affected by changes in, say, wage levels.

The elasticities that follow from the estimated model for married couples are of moderate magnitude, with married females more responsive than males, and they are more or less of the same magnitudes as in several other labor supply studies found in the literature. See Blundell and MaCurdy (1999) and Meghir and Phillips (2010) for a summary of elasticities from other studies. It is, however, a delicate issue how elasticities should be compared. One complication is that there is variation across studies depending on whether after-tax or pre-tax wage elasticity estimates are produced. It is the post-tax wage that is used the conventional approach (such as the Hausman model)[19] and is therefore the main focus in that part of the literature, whereas the discrete choice literature (including the present study) often report gross wage elasticities; see details in van Soest and Das (2001) and Bargain *et al*. (2011). Another difficulty is that models are nonlinear. As also emphasized by van Soest and Das (2001) it is likely that results will depend on aggregation methods: for instance, whether elasticity estimates are based on average elasticities or elasticities of the average.

Moreover, in nonlinear models the same model may produce very different elasticities on different samples. This stems from the inherent nonlinear properties of this kind of model. To illustrate this point, consider a simple logit model of working/not working, given by

$$P(w, X) = \frac{1}{1 + \exp(-\alpha \log w - X\beta)}$$

where $P(w, X)$ is the probability of working, w is the wage and X is a vector of individual characteristics. This model implies that the wage elasticity of the probability of working is given by

$$\frac{\partial \log P(w, X)}{\partial \log w} = (1 - P(w, X))\alpha$$

Thus, in this model the wage elasticity depends crucially on the level of labor force participation, $P(w, X)$. For example, if the combination of wage and characteristics is such that $P(w, X) = 0.6$, the corresponding wage elasticity becomes 0.4α, whereas if $P(w, X) = 0.80$, the corresponding wage elasticity becomes 0.2α. Thus, when the fraction of individuals who work is 60%, the wage elasticity is twice as high as the wage elasticity when the fraction who work is 80%. Note that the parameters α and β are kept constant across these two examples.

5. Summary

Specification of labor supply models continues to be a controversial issue, and there is no common consensus in the literature of what should be the preferred strategy. Theoretical labor supply models discussed in the literature are often highly stylized and the theory provides little guidance for specifying the empirical counterparts of the theoretical models. Moreover, there is a tendency to play down the importance of specification issues related to functional form and distribution of unobservables. Since with few exceptions economic theory is silent about such issues, researchers have resorted to various *ad hoc* specifications in practical empirical research. As a result, there seems to be no consensus in the research community as to what should be the ‘right’ specification, and consequently there is a large variety of specifications in the literature. This may be one important reason why labor supply wage elasticities in previous work are found to vary all over the map, see Blundell and MaCurdy (1999).

In this paper we have discussed a particular approach based on the notion of choice among job types. Concerns of practicality have often been the dominating motivation for applying the conventional discrete choice labor supply model derived from a particular random utility specification. Here we have discussed arguments for an alternative discrete choice formulation, which accommodates other important aspects of labor market behavior hitherto neglected, namely that individuals care about the nature and content of jobs, and that the set of perceived jobs available to them may be limited. Although we as researchers do not observe the choice of jobs, or the choice restrictions, we have demonstrated how one can still derive the corresponding model for the *observed* choice variables (hours of work of the chosen jobs and corresponding disposable income). Specifically, we have shown how our particular approach accommodates accounting for restrictions on hours of work in a convenient way. Also, the job choice model provides a theoretical rationale for introducing dummy variables to allow for peaks in the data at, for example, full-time and part-time hours of work.

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Notes

1. In addition, the random components of the utility function have c.d.f. which implies a tractable empirical model.
2. Discrete choice approaches are also seen as useful in order to include program participation in models, along the lines of Keane and Moffitt (1998) and Brewer *et al.* (2006).

3. With respect to analyses employing reduced form specifications and exploiting some type of exogenously induced variation, the literature has recently witnessed a number of analyses using tax reform as 'natural experiments' and obtaining measures of elasticities of taxable income, following Feldstein (1995); see the survey by Saez *et al*. (2012). Chetty (2009) argues that such studies very efficiently provide information about welfare effects of taxation and therefore cannot simply be discarded for not addressing key questions.
4. MaCurdy *et al*. (1990) show that the econometric model may impose parametric restrictions that constrain estimates of substitution and income effects in applied work. Mroz (1987) also reviews the specifications employed in the (early) literature and finds that results are sensitive to the methodological choices, such as the measurement of wages. Similarly, Bloemen and Kapteyn (2008) report rather mixed experiences with the Hausman approach: even in the single agent case it is almost impossible to write down the true likelihood function of the empirical model given standard assumptions about unobservables, and considerable expertise and computer time are required to estimate this type of model.
5. To overcome the integrability problem at kinks, Blundell *et al*. (1998) condition on the subsample where observations close to kinks are removed.
6. The issue of indivisibility of labor and constraints on labor market choices has also received some attention in the macro literature, see for example Chang *et al*. (2011).
7. In the terminology of Resnick (1987) this c.d.f. is called the type III (standard) extreme value distribution, or Gumbel distribution. Other authors call this c.d.f. the type I extreme value distribution.
8. From a theoretical point of view, it is interesting to note that in the case when the set of discrete alternatives is infinite, the corresponding choice probability distribution will be a continuous one, see Dagsvik and Strøm (2006).
9. Early versions of this approach are Dagsvik and Strøm (1994), Aaberge *et al*. (1995) and Aaberge *et al*. (1999).
10. The random error term in the utility function can be interpreted as $\varepsilon(z) = \tilde{\varepsilon}(X(z))$, where $X(z)$ is a latent vector of attributes of job z.
11. Here it is assumed that the total set of possible attributes is large, or alternatively, that tastes may vary from one moment to the next for a given agent. In either case it is assumed that the variation in tastes can be approximated by a continuous distribution.
12. The parameter θ can be given an interpretation that is linked to the unemployment rate, see Dagsvik and Strøm (1997).
13. There may several reasons for treating choice sets as random, for instance that choice sets are unobserved to the researcher and that the agent has limited capacity to identify and take choice sets into account (a type of bounded rationality).
14. Peichl and Siegloch (2012) establish an equilibrium model by linking a labor demand model to the conventional discrete choice labor supply model.
15. With several observations for each individual, for example from Stated preference surveys, one would in principle be able to test functional form assumptions without relying on particular assumptions about the distribution of parameters across the population. Another approach suggested by Dagsvik and Røine Hoff (2011) is to carry out nonparametric testing of axioms that imply a particular functional form, provided of course that such an axiomatization exists.
16. The simulated probability distributions in Figures 1 and 2 are derived by calculating the average probability in each state across individual probability distributions.
17. Here it is assumed that the observed peaks at part-time and full-time hours of work are due to choice constraints.
18. The net-of-tax rate is also the key measure in the literature founded on data analysis of tax reforms, referred to in footnote 4.

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