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by

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DISCUSSION PAPER

The effect of non-pecuniary job attributes on labour supply

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Abstract

The aim of this paper is to analyse the effect of non-pecuniary job attributes on labour supply. We develop a discrete choice model of labour supply where the choice alternatives are characterised by bundles of hours of work and job insecurity. The parameters of the utility function are obtained using maximum simulated likelihood with Halton sequences to account for unobserved heterogeneity in preferences. We compare the predictive power and labour supply elasticities obtained with our model to those of a more traditional model where only discrete hours choices characterise a job. The results show that once job insecurity is included in the discrete choice alternatives, the predictive power of the model improves significantly. Labour supply elasticities are lower than those obtained by a traditional discrete hours model, but not significantly different. Finally, a decrease of job insecurity at work has a positive and significant effect on participation, implying that policies aimed at improving working conditions could be used to influence labour supply decisions.

Keywords: Discrete choice, labour supply, non-pecuniary.

JEL classification: C25, J22, J81

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1 Introduction

During the last decades, significant progress has been made on issues related to labour supply specification and estimation. However, an important question that has been largely left aside is the effect of working conditions on labour supply. The aim of this paper is to develop a discrete choice model of labour supply which incorporates working conditions in the job choice in order to compare the estimated labour supply responses in this model with those of a model where only a discrete hours set characterises job alternatives.

Discrete choice models of labour supply have become increasingly popular as they overcome most difficulties encountered by the traditional approach based on a continuous set of hours. Most difficulties related to the estimation of continuous labour supply models arise due to non-linearities and non-convexities in the budget sets produced by the presence of complex tax and benefit systems. Further complications arise when the purpose is to estimate labour supply for couples, as the utility function has to be maximised subject to a three dimensional budget constraint, with female leisure, male leisure and total household consumption (see Creedy and Kalb (2005)). Different studies based on the continuous approach have accounted for non-convex budget sets and joint labour supply (see Arrufat and Zabalza (1986), Hausman (1985), Hausman and Ruud (1984)). However, because of the computational difficulties, the specification of the utility function and labour supply functions needs to be restrictively simple. For instance, Hausman and Ruud (1984) calculate estimates of joint labour supply with non-convex budget sets, specifying a flexible functional form of the utility function but remark that the methodology becomes very difficult to apply when other functional forms are used.

Contrary to continuous labour supply models, the idea behind the discrete choice approach is to define a finite number of working hours alternatives and to explicitly specify a utility function characterising the individual's utility at each of the alternatives of the discrete hours set. The estimation of the discrete choice model then provides the parameters defining the shape of the utility function. The main critiques to discrete labour supply models concern the incomplete use of information and the rounding error generated by the discretisation of the choice set. However, this approach offers the main advantage that it facilitates dealing with non-linear and non-convex budget sets as well as accounting for multiple goods in the utility function.

Most studies, using either the discrete or the continuous approach, take income (consumption) and hours of work (leisure) as the only choice variables affecting individuals' labour supply decisions. However, we agree with Dagsvik and Strøm (2004) that "hours of work and income are only two out of several job related attributes, which are important for individual behaviour in the labour market". From literature on job satisfaction we know that adverse working conditions have an important effect on labour market decisions, through their impact on individuals' satisfaction at work. For instance, worker's intentions to quit increase due to low job satisfaction produced by poor working conditions (see Böckerman and Illmakunnas (2005); Böckerman and Illmakunnas (2007)). Adverse working conditions also have an effect on decisions related to absenteeism (Clegg (1983)) as well as on early retirement (Siegrist et al. (2007)). It seems, therefore, reasonable to consider that individuals care about other aspects of work than merely earnings, when they make labour supply decisions.

Within the discrete choice setup, few studies allow for the introduction of non-pecuniary job attributes in the estimation of labour supply. In Dagsvik (1994) and Dagsvik and Strøm (1995) a model of labour supply which accounts for the importance of qualitative factors of jobs is proposed. This model of discrete choice labour supply assumes that the alternatives are characterised by "job packages" which are defined by a bundle of hours of work, wage rates and other non-pecuniary job attributes. Other studies on labour supply such as Aaberge, Dagsvik and Strøm (1995), Aaberge and Colombino (2006) and Dagsvik and Strøm (2004) use a similar methodology. However, to the best of our knowledge, only job sector has been used as a variable representing non-pecuniary job attributes. Dagsvik and Strøm (2004) differentiate, for instance, between private and public sectors, assuming that jobs in these sectors may differ in terms of non-pecuniary attributes. In this paper we follow a similar approach but we extend the framework to variables related to working conditions,in our case job insecurity, using a much simpler specification than that of Dagsvik (1994), Dagsvik and Strøm (1995), and others. We use data from wave 10 of the British Household Panel Survey (BHPS) which corresponds to the years 2000-2001.

The paper is structured as follows. Section 2 presents two different discrete choice models to be used in our labour supply analysis. The conditional logit model is used to estimate the traditional labour supply model where only hours define the choice set. The nested logit model is then used to specify an extended model where the choice set is characterised by bundles of hours of work and job insecurity. Section 3 describes the data and presents some summary statistics. Section 4 presents the estimates of the structural labour supply models. Section 5 discusses the labour responses in terms of wage elasticities and changes in the predicted probabilities from a decrease of job insecurity. Finally, section 6 concludes.

2 Discrete choice models of labour supply

In this section we describe two different types of discrete choice models used to estimate labour supply, namely the conditional logit and nested logit models. Both models are derived under the assumption of utility maximisation. Consider individual i chooses among a finite number of job alternatives, J. The utility obtained from alternative j is U_{ij}, $j = 1, ..., J$. Individual i chooses alternative j if and only if $U_{ij} > U_{ik}$, $\forall k \neq j$. The utility function can be decomposed in a deterministic and a stochastic component[1]: $U_{ij} = V_{ij} + \varepsilon_{ij}$, where the distribution of the random vector $\varepsilon_i = \{\varepsilon_{i1}, ..., \varepsilon_{iJ}\}$ is given by $F(\varepsilon_i)$. The probability that a particular alternative j is chosen is:

$$
\begin{aligned}
P_{ij} \quad &= Prob(U_{ij} > U_{ik}, \forall k \neq j) \\
&= Prob(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}, \forall k \neq j) \\
&= Prob(\varepsilon_{ik} < \varepsilon_{ij} + V_{ij} - V_{ik}, \forall k \neq j)
\end{aligned}
$$

Depending on the specification of the distribution of the random component, different discrete choice models can be obtained. In this paper we focus on two different models. First, a conditional logit model is specified. This model is the most widely used in the analysis of discrete choice labour supply. Second, we develop a nested logit model which corresponds better to the structure of our labour supply model when non-pecuniary job attributes are taken into account.

2.1 Conditional logit models

Most discrete choice models of labour supply are conditional logit models. The conditional logit model is obtained assuming that the stochastic component, ε_{ij} is independent and identically distributed over alternatives and follows a type-one extreme value distribution, given by:

$$F(\varepsilon_{ij}) = e^{-e^{-\varepsilon_{ij}}}$$

Under the conditional logit setup, the probability that alternative j is chosen is given by[2]:

$$
\begin{aligned}
P_{ij} &= Prob(\varepsilon_{ik} < \varepsilon_{ij} + V_{ij} - V_{ik}, \forall k \neq j) \\
&= \frac{e^{V_{ij}}}{\sum_{k=1}^{J} e^{V_{ik}}}
\end{aligned}
$$

[1] For this reason, these models are known as random utility models.
[2] See McFadden (1974) for a proof.

In our basic model, individuals choose among a finite number of working hours alternatives in order to maximise their utility, defined over net income and hours of work. We assume that the gross wage rates are fixed and independent of the hours of work. The decision is taken given the gross wage rates and the tax and benefit system[3].

More formally, let h_i be the number of hours worked by individual i. We define J discrete hours alternatives so that h_{ij} represents the number of hours worked by individual i under alternative j, with $j = 1, ..., J$. In our model, four alternatives are defined, $J = 4$: inactivity, part-time, full-time, overtime. Let y_{ij} be individual i's net income given the hours choice h_{ij} and x_i a vector of individual characteristics. The net income y_{ij}, when $h_i = h_{ij}$ is chosen, is defined as:

$$y_{ij} = w_i * h_{ij} + \mu_i + T(w_i, h_{ij}, \mu_i, x_i)$$

where w_i are gross hourly wage rates, μ_i is non-labour income and the function $T(w_i, h_{ij}, \mu_i, x_i)$ represents the tax-benefit rules which depend on gross wages, hours of work, non-labour income and individual characteristics. Several functional forms can be used to specify the deterministic part of the utility function. Here, we define it as a second order polynomial:

$$V(y_{ij}, h_{ij}, x_i) = \alpha_1 y_{ij}^2 + \alpha_2 h_{ij}^2 + \alpha_3 y_{ij} h_{ij} + (\beta_1 x_i') y_{ij} + (\beta_2 x_i') h_{ij}$$

The sample likelihood function for the conditional logit model is given by:

$$L = \prod_{i=1}^{N} \prod_{j=1}^{J} \left[P_{ij} \left(y_{ij}, h_{ij}, x_i \right) \right]^{d_{ij}}$$

where d_{ij} is a dummy equal to one if individual i chooses alternative j and zero otherwise.

[3] A tax and benefit microsimulation is performed in order to calculate the individuals' net income from their gross income (see section 4).

2.2 Nested logit models

Nested logit models are appropriate when the set of choice alternatives can be grouped into subsets, called nests. More formally, let the set of alternatives $j = 1, 2, ..., J$ be partitioned into M non-overlapping nests denoted $B_1, B_2, ..., B_M$. The nested logit model is obtained assuming that the stochastic component, $\varepsilon_i = (\varepsilon_{i1}, ..., \varepsilon_{iJ})$ has a cumulative distribution

$$exp\left(-\sum_{m=1}^{M}\left(\sum_{j\in B_m} e^{-\varepsilon_{ij}/\tau_m}\right)^{\tau_m}\right)$$

which is a type of Generalised Extreme Value (GEV) distribution. τ_m is known as the dissimilarity parameter and measures the degree of independence in unobserved utility among alternatives in nest m. The higher the value of τ_m, the greater the degree of independence. For the model to be consistent with utility maximising behaviour, τ_m must lie in the unit interval $(0 < \tau_m \leqslant 1)$ for all m[4] (McFadden (1981)). A value of $\tau_m = 1$ represents complete independence within nest m and in the case $\tau_m = 1$ for all m (no correlation in unobserved utility among all the alternatives in all nests) the standard conditional logit formula is obtained. Values of $\tau_m > 1$, correspond to models consistent with utility maximisation for some values of the explanatory variables only. Kling and Herriges (1995) provide the necessary conditions for local consistency with random utility maximisation of nested logit models. A negative value of τ_m is inconsistent with utility maximisation (McFadden (1981)). Given the distribution of the unobserved part of the utility, the probability of choosing alternative $j \in B_m$ is given by[5]:

$$P_{ij} = \frac{e^{V_{ij}/\tau_m}\left(\sum_{j\in B_m} e^{V_{ij}/\tau_m}\right)^{\tau_m - 1}}{\sum_{l=1}^{M}\left(\sum_{j\in B_l} e^{V_{ij}/\tau_l}\right)^{\tau_l}}$$

Our basic model of labour supply, presented in section 2.1, could well be specified in a nested logit structure. Individuals would first decide whether to work or not. If the choice is to work then they decide whether to work part-time, full-time or overtime. Thus, we have two nests. The first nest, B_1, has only one alternative (inactivity) and the second nest, B_2, three alternatives (work part-time, full-time or over-time); a total of four alternatives, $J = 4$. Under our nested logit structure, the probability of choosing alternative j in the participation nest (B_2) is:

[4] This ensures that the distribution has non-negative density.

[5] See McFadden (1978) and Daly and Zachary (1978) for a proof.

$$P_{ij} = \frac{e^{V_{ij}/\tau}\left(\sum\limits_{j\in B_2} e^{V_{ij}/\tau}\right)^{\tau-1}}{e^{V_{io}} + \left(\sum\limits_{j\in B_2} e^{V_j/\tau}\right)^{\tau}}$$

and the probability of choosing the inactivity alternative (nest B_1) is:

$$P_{i0} = \frac{e^{V_{io}}}{e^{V_{io}} + \left(\sum\limits_{j\in B_2} e^{V_{ij}/\tau}\right)^{\tau}}$$

where V_{io} is the utility of individual i from inactivity and τ is the parameter measuring the degree of independence among the alternatives in the participation nest, B_2. The nested logit structure becomes more appropriate once we take into account non-pecuniary job attributes given that these factors are only observed in the case individuals work. More specifically, individuals first decide whether or not to work. If the individual decides to work then she faces different job alternatives characterised by bundles of hours of work and other non-pecuniary job attributes. In particular, in our extended model we introduce job insecurity as a non-pecuniary job attribute affecting labour supply. Three job insecurity levels are defined and, therefore, there are nine alternatives in the participation nest (B_2) composed of combinations of hours of work and job insecurity levels. More formally, let s_{ij}, represent the level of job insecurity of individual i under alternative j. The deterministic part of the utility function, expressed as a second order polynomial is given by:

$$\begin{aligned} V(y_{ij}, h_{ij}, s_{ij}, x_i) = {} & a_1 y_{ij}^2 + \alpha_2 h_{ij}^2 + \alpha_3 s_{ij}^2 + \alpha_4 y_{ij} * h_{ij} + \alpha_5 y_{ij} * s_{ij} \\ & + \alpha_6 h_{ij} * s_{ij} + (\beta_1 x_i')y_{ij} + (\beta_2 x_i')h_{ij} \\ & + (\beta_3 x_i')s_{ij} \end{aligned}$$

and the sample likelihood function is similar to that of the conditional logit.

2.3 Unobserved heterogeneity in preferences

The models presented above account for differences in preferences but only for observed individual characteristics. However, unobserved individual characteristics might also affect the choice probabilities, in which case the estimates obtained above would be biased. In order to take into account unobserved heterogeneity in preferences, random terms can be introduced in the deterministic part of the utility function. These random terms are not only important because they allow for introduction of unobserved heterogeneity in preferences but also because they relax the assumption of independence from irrelevant alternatives (IIA) resulting from the extreme value distribution of the latent factor. In fact, the unobserved portion of the utility function becomes correlated over alternatives through the common influence of the random terms (see Train (1998) and Train (2003)). Consider, for instance, our conditional logit model; the deterministic part of the utility function can now be written as[6]:

$$V(y_{ij}, h_{ij}, x_i, v_i) = \alpha_1 y_{ij}^2 + \alpha_2 h_{ij}^2 + \alpha_3 y_{ij} * h_{ij} + (\beta_1 x_i' + v_{i1}) y_{ij} + (\beta_2 x_i' + v_{i2}) h_{ij}$$

where v_{i1} and v_{i2} are terms of unobserved individual preferences and are assumed to be independent and normally distributed, with density $\phi(v)$. Due to the fact that unobserved components enter the choice probabilities, it is necessary to integrate over their distributions. The sample likelihood function is then given by:

$$L = \prod_{i=1}^{N} \int_{v} \prod_{j=1}^{J} \left[P_{ij} \left(y_{ij}, h_{ij}, x_i, v_i \right) \right]^{d_{ij}} \phi\left(v\right) d\left(v\right)$$

The likelihood is difficult to calculate since it requires the computation of the two dimensional integral ($v_i = \{v_{i1}, v_{i2}\}$). In order to approximate these integrals we use maximum simulated likelihood. The moments of the distribution of the random terms are estimated within the structural model. Assume that the unobserved heterogeneity component follows a bivariate normal distribution[7]:

$$v \sim N\left(\begin{pmatrix} u_1 \\ u_2 \end{pmatrix}, \begin{pmatrix} \sigma_{1,1}^2 & 0 \\ 0 & \sigma_{2,2}^2 \end{pmatrix} \right),$$

and $v = \{v_1, v_2\}$ can be calculated by:

$$v = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix}$$

where $\begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}$ is the Cholesky decomposition of the variance covariance matrix defined above[8]. It is in fact these Cholesky factors which are estimated within the structural model. The idea behind maximum simulated likelihood is, then, to make R draws for ξ_1 and ξ_2; for each draw the conditional logit probability is calculated and then averaged over the R draws[9]. This average corresponds to the simulated probability:

[6] The specification for our nested logit model with job insecurity is similar but an additional random term is added to represent unobserved heterogeneity in preferences for job insecurity $v_i = \{v_{i1}, v_{i2}, v_{i3}\}$.

[7] For the sake of readibility we suppress the subscript for individuals.

[8] A Cholesky factor L of a matrix W is defined such that $LL' = W$.

[9] In our model, 50 random draws from the Halton sequences are used, $R = 50$.

$$\check{P}_{ij} = \frac{1}{R}\sum_{r=1}^{R} P_{ij}\left(y_{ij}, h_{ij}, x_i, v_i^r\right)$$

and the simulated sample likelihood to be maximised is then given by the following expression[10]:

$$SL = \prod_{i=1}^{N}\prod_{j=1}^{J}(\check{P}_{ij})^{d_{ij}}$$

Here, we follow Train (2003) and instead of using random draws to obtain ξ_1 and ξ_2 we use Halton sequences[11], which generate quasi random draws. Consider for instance the Halton sequence for number 3, illustrated in Train (2003)[12]. The sequence is generated by dividing the unit interval (0,1) into three parts. The first elements of the sequence correspond to the breakpoints: $\frac{1}{3}$ and $\frac{2}{3}$. Then, each of the segments is divided into three parts and the breakpoints of the segments enter the sequence; with the lowest breakpoints in all segments entering before the highest. Each of the nine segments is then divided into three parts, and the dividing points added to the sequence, and so on: $\frac{1}{3}$, $\frac{2}{3}$, $\frac{1}{9}$, $\frac{4}{9}$, $\frac{7}{9}$, $\frac{2}{9}$, $\frac{5}{9}$, $\frac{8}{9}$, $\frac{1}{27}$,... The sequence cycles over the unit interval, providing better coverage than random draws as it progressively fills in the unit interval evenly and more densely (Train (2003)). For a sample of observations, one long Halton sequence is generated and a part of the sequence is used for each observation. This ensures a better coverage since the gaps left by the draws for one observation are filled by the draws of the next one. This induces, as well, a negative correlation over observations which reduces the error in the simulated log-likelihood function (Train (2003)). By construction, Halton draws are for a uniform density. In order to obtain draws from a standard normal density, the inverse cumulative normal is evaluated for each element of the sequence. Finally, for sequences in several dimensions, a prime number for each dimension must be chosen. The initial elements of each Halton sequence are eliminated because they are highly correlated, at least through the first cycle of each sequence. Therefore, the number of discarded elements must be at least equal to the largest prime used. Halton sequences have the advantage of reducing integration error and provide faster convergence compared to random draws. In fact, Bhat (2001) shows that, in the framework of mixed logit models, the simulation error is lower using 100 Halton numbers than 1000 random numbers. Train (2001) confirms this result and attributes the improvement to two reasons. First, Halton numbers provide a better coverage of the domain of integration. Second, the simulated probabilities become negatively correlated over observations which reduces the variance of the log-likelihood function.

[10] The same expression applies for the case of a nested logit model, but where $\check{P}_{ij}$ is calculated using the nested logit formula.

[11] Halton sequences in our estimation are created using the command *mdraws* from Cappelari and Jenkins (2006) in stata and using Train's(2003) program in GAUSS.

[12] Halton sequences are usually defined in terms of a prime number.

3 Data

The data for our analysis comes from wave 10 of the British Household Panel Survey containing information for years 2000 and 2001. The BHPS is a nationally representative survey for the United Kingdom, which provides information about individual and household characteristics, wages, other income sources and working conditions. Wave 10 of the BHPS contains 15,603 individuals, however, we restrict our analysis to non-married and non-cohabitating individuals without children, who gave full interview. This restriction is made for two reasons. First, at this stage, only tax and benefit rules affecting single individuals with no dependent children were programmed in our tax and benefit simulation model. Second, this enables us to neglect interactions within the household in the context of labour supply. As it is usually done in the literature, we further exclude individuals in self-employment because their labour supply decisions may differ considerably from those of salaried workers. Disabled individuals, full-time student and pensioners are also excluded in order to keep only those individuals available for the labour market. This leaves us with a sample of 690 individuals.

Before restricting our analysis to our sample of interest we need to treat the problem of non-observed gross wages for non-workers. We do this by estimating a two-step Heckman selection model for men and women separately, using the whole sample. We use as regressors the usual variables found in the literature: age, education and region dummies are used for the wage equation while non-labour income, being married and having children of different ages are added in the selection equation. The results of the estimation are shown in Table 1. Most variables present the expected signs, both in the selection and in the wage[13] equation. In particular, wages and the probability of participation increase with age at a decreasing rate. The higher the level of education, the higher the probability of participation and the higher the wage. Being married increases the probability of working for men and decreases the probability of participation for women, as expected. Participation is lower with the presence of young children in the household and these variables are significant for women. For men, only having children aged between 5 and 11 has a negative and significant effect on participation. Non-labour income has the expected negative and significant effect on participation. Finally, the coefficient for the inverse Mill's ratio is positive and significant for women, implying a selectivity and therefore that their observed wages are higher than the wage offers of a random sample.

[13] Wages are defined as log-hourly wages.

Table 1: Heckman selection model

	Men		Women	
loghwage				
age	0.0951***	(0.00397)	0.0590***	(0.00367)
age2	-0.00104***	(0.0000522)	-0.000668***	(0.0000482)
cse	0.123***	(0.0327)	0.146***	(0.0321)
olevel	0.222***	(0.0267)	0.224***	(0.0253)
alevel	0.320***	(0.0283)	0.340***	(0.0285)
higher	0.373***	(0.0249)	0.455***	(0.0251)
university	0.652***	(0.0279)	0.818***	(0.0284)
_cons	0.00290	(0.0839)	0.368***	(0.0787)
selection				
age	0.0953***	(0.00751)	0.148***	(0.00733)
age2	-0.00136***	(0.0000877)	-0.00200***	(0.0000861)
cse	0.0923	(0.0758)	0.203**	(0.0682)
olevel	0.204**	(0.0629)	0.442***	(0.0537)
alevel	0.197**	(0.0681)	0.437***	(0.0637)
higher	0.424***	(0.0582)	0.601***	(0.0530)
university	0.514***	(0.0706)	0.573***	(0.0655)
nlab_inc	-0.00148***	(0.0000651)	-0.00142***	(0.0000628)
married	0.226***	(0.0475)	-0.188***	(0.0414)
child0_2	-0.0452	(0.0726)	-0.464***	(0.0613)
child3_4	-0.0513	(0.0764)	-0.381***	(0.0614)
child5_11	-0.180***	(0.0510)	-0.183***	(0.0436)
child12_15	-0.0842	(0.0526)	-0.0334	(0.0456)
_cons	-0.979***	(0.160)	-1.911***	(0.152)
mills				
lambda	-0.0541	(0.0310)	0.0729**	(0.0254)
area dummies	Yes		Yes	
N	6690		8035	

Standard errors in parentheses

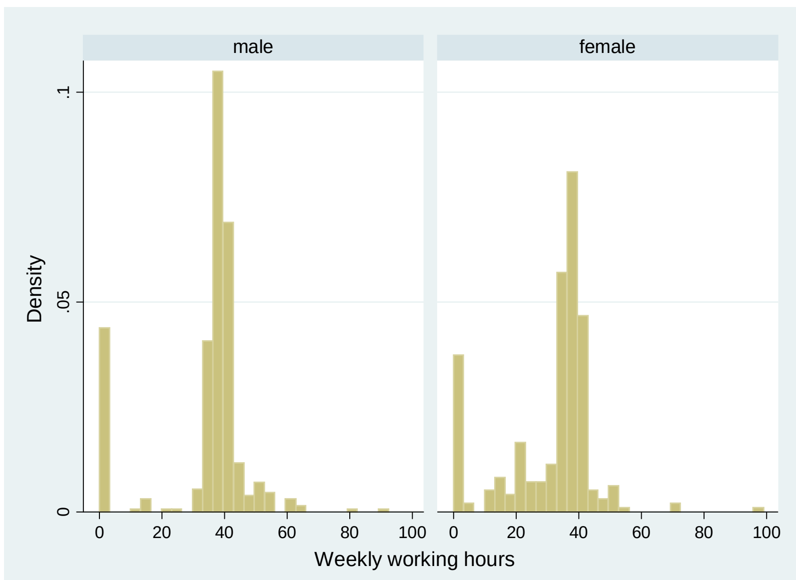
Notes: higher corresponds to higher qualifications; nlab_inc represents non-labour income; and childi_j are dummies for households with children aged between i and j

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Using the results obtained with the Heckman selection model, gross hourly wages are imputed for non-workers. Once the information on gross hourly wages is available for all individuals, we need to calculate the disposable income for each discrete hours alternative. For this, we developed our own tax and benefit microsimulation model for the BHPS[14], based on EUROMOD version 2001 (see Sutherland and Gutierrez (2004)). Seven tax and benefit rules are simulated: minimum wage, national insurance employee contributions[15], contributory job seekers allowance[16], income tax, income support[17], housing benefit[18] and council tax benefit[19]. Other benefits are not simulated but are included in the calculation of disposable income.

Consider now the distribution of weekly hours of work for men and women in our sample, presented in Figure 1.

Figure 1: Distribution of male and female weekly working hours



[14]The description of this tax and benefit microsimulation model is available from the author.
[15]National insurance contributions finance national insurance benefits and national insurance retirement pension. Conditions on previous contributions determine eligibility to contributory benefits.
[16]Contributory job seeker's allowance is a benefit for the unemployed, conditional on active job search. Only those under state pension age are eligible and the duration is up to 6 months.
[17]Income support is a means-tested benefit for those with low income and who are not working.
[18]Housing benefit is a means-tested benefit intended to contribute to the cost of rent for low income households.
[19]Council tax benefit is a means-tested benefit for those with low income who are liable to pay council tax, which is a local tax based on property values.

We observe important peaks for inactivity and full-time work (around 40 hours per week) for both men and women and in the case of women a small peak is observed for part-time work (around 20 hours per week). Taking this into consideration, and given that we estimate the structural labour supply model for men and women together, we define four discrete hours points, characterising inactivity, part-time work, full-time work and over-work: $h = \{0, 20, 40, 55\}$ which correspond to the intervals $0 - 5, 6 - 34, 35 - 45, > 45$. These discrete hours points represent the set of alternatives in our basic model.

In the extended model, job insecurity is used as a non-pecuniary job attribute to be included in the job choice bundle. The BHPS provides information concerning satisfaction with job security at work. Job security takes values between 1 and 7 with 1 representing that the individual is "not satisfied at all" with job security at work and 7, that the individual is "completely satisfied". Despite the subjective nature of this variable, recent studies show that perceived job insecurity is associated with objective indicators of insecure jobs, in particular the type of labour contract: temporary or permanent (see Näswall and De Witte (2003), Deloffre and Rioux (2003), Campbell et al. (2007) and Clark and Postel-Vinay (2009)). Moreover, perceived job insecurity has proved to be a good predictor of future unemployment experiences, implying that such variables provide reliable information concerning individuals' objective job insecurity situation in the labour market (Deloffre and Rioux (2003), Campbell et al. (2007)). For our extended labour supply model, we generate a job insecurity variable taking values 1 to 3, where 1 represents "low job insecurity" (satisfied with job security), 2 represents "middle job insecurity" (neither satisfied nor dissatisfied) and 3 "high job insecurity" (dissatisfied with job security)[20]. Ten discrete choice alternatives are therefore defined for the extended model, representing bundles of hours of work and job insecurity: $(h, insec)$ where $h = \{0, 20, 40, 55\}$ and $insec = \{1, 2, 3\}$.

The remainder of this section provides some summary statistics for our sample of interest and for each discrete hours alternative. Means and standard deviations of the variables used in our labour supply model are presented in Appendix A. Table 2 shows that our sample is composed of slightly more men than women. Average age and the percentage of individuals with higher education is rather close for both groups. Men work, on average, more hours than women and receive, on average, a higher net income. Finally, the percentage of individuals dissatisfied with their job security situation is rather similar for both groups. Concerning the different discrete hours alternatives, Table 3 confirms that the two main groups are full-time work and inactivity. Average age is much higher in the part-time work group and this group together with the inactivity group present the lowest percentage of individuals with higher education. In particular, only 28.72% of the inactive individuals have higher education, com-

[20] The seven original values of satisfaction with job security were regrouped in such a way in order to save computational time in the estimation of the structural labour supply model.

pared to 54.35%, in full-time work. In terms of job insecurity, the percentage of individuals dissatisfied is the highest for part-time jobs.

Table 2: Summary Statistics per gender

	Obs.	Age	Higher education (%)	Hours worked per week	Net income per week	Job insecurity (% dissatisfied)
Men	390	38.51	50.00	33.48	259.04	15.57
Women	300	41.72	50.67	30.50	233.44	16.23
All	690	39.90	50.29	32.38	248.06	15.86

Table 3: Discrete employment statistics

Alternatives	Share (%)	Hours worked per week	Age	Higher education (%)	Net income per week	Job insecurity (% dissatisfied)
1	13.62	0	41.82	28.72	143.57	-
2	11.01	20	48.61	44.74	192.85	19.74
3	66.67	40	37.99	54.35	274.02	15.65
4	8.70	55	40.55	60.00	284.17	13.33

4 Empirical results

This section presents the results of the structural labour supply estimation. Three models are estimated. The first model is the conditional logit model traditionally used in the discrete choice literature to estimate labour supply when only discrete hours alternatives define the choice set. The second model also only takes hours into account as the variable defining the choice alternatives, however, a nested logit specification is used to estimate the parameters of the utility function. Finally, the third model is a nested logit model where the choice set is defined by bundles of hours of work and job insecurity levels, in the case individuals choose to work. In all cases, age and education[21] are used as regressors to account for observed heterogeneity in preferences and we account for unobserved heterogeneity by using Halton sequences. Table 4 presents the estimated parameters for these three models.

[21] Three education dummies are included in the model: high education corresponds to higher education or qualifications; middle education corresponds to a-levels or o-levels; and low education corresponds to education below o-levels.

Table 4: Estimated parameters of the structural model

variable			Conditional logit coef.	Conditional logit st.error	Nested logit coef.	Nested logit st.error	Nested logit insecurity coef.	Nested logit insecurity st. error
y^2			-5.026	(72.719)	-3.015	(8.5613)	-0.239	(1.6047)
h^2			-0.606***	(0.1627)	-0.139***	(0.0143)	-3.468**	(1.3228)
y x h			-6.762***	(1.6931)	-0.917***	(0.2060)	-1.332*	(0.5273)
$insec^2$							0.299	(0.2631)
h x $insec$							-0.0005	(0.0466)
y x $insec$							-0.090	(0.5567)
y			68.834***	(18.902)	11.418***	(2.7934)	16.085**	(6.2054)
	x	age	-0.335	(0.2132)	-0.0603	(0.0371)	-0.123	(0.0757)
	x	high edu	-9.879	(8.0950)	-3.386*	(1.7103)	-3.569	(2.9083)
	x	mid. edu	-0.543	(8.7536)	-1.585	(1.7942)	-1.216	(3.0462)
	x	low edu	-2.285	(13.005)	-2.095	(3.0078)	0.4388	(5.9093)
	x	random1	-0.112	(0.7466)	-0.112	(0.7466)	0.194	(1.2654)
h			2.989**	(0.9283)	0.881***	(0.1255)	2.476*	(1.0305)
	x	age	0.0028	(0.0104)	-0.0002	(0.0020)	-0.0026	(0.0040)
	x	high edu	1.910**	(0.5801)	0.315***	(0.0859)	0.476**	(0.1696)
	x	mid. edu	1.235**	(0.4829)	0.194*	(0.0822)	0.305*	(0.1458)
	x	low edu	1.272**	(0.6242)	0.216	(0.1311)	0.175	(0.2391)
	x	random2	-1.788**	(0.5905)	0.109	(0.1256)	-0.106	(0.1487)
$insec$							-4.064*	(1.9409)
	x	age					0.0216	(0.0181)
	x	high edu					0.478	(0.5311)
	x	mid. edu					0.514	(0.5594)
	x	low edu					1.211	(1.0179)
	x	random3					1.480	(1.2654)
τ					0.246***	(0.0572)	0.587**	(0.2325)

Standard errors in parentheses; *p<0.05,**p<0.01,***p<0.001

In general our results are in line with economic theory. Concerning the conditional logit model, marginal utility of income[22] is positive in around 97% of the cases and as the coefficient of income square is negative, concavity in income for the utility function is respected for these observations. Marginal utility of hours of work is negative in 54% of the cases, however, hours square presents a negative coefficient, contrary to what is expected.

[22] In order to obtain the marginal utility of income, the first derivative of the utility function with respect to income is calculated. The estimated parameters and the information of each variable is then used to obtain the value of the first derivative for each observation. Then the percentage of observations with a positive first derivative is calculated.

Turning to the nested logit models, the first thing to remark is that in both cases, τ, the parameter of independence among the alternatives in the participation nest is significant. Additionally, in both cases τ is between 0 and 1. Our nested logit models are therefore consistent with utility maximisation and seem more appropriate than a conditional logit model, as τ is different from unity. Marginal utility of income is positive in around 80% of cases in the basic nested logit model and 90% of cases in the extended model. Moreover, income square presents a negative coefficient in both cases, as it is required to obtain concavity in income for the utility function. Marginal utility of hours is negative only in 48% of cases in the basic nested logit model, however, when job insecurity is introduced in the job choice, marginal utility of hours becomes negative for 90% of cases. Our labour supply model incorporating non-pecuniary job attributes produces, therefore, results which are more consistent with economic theory. In both models the coefficient of hours square is negative and significant. As expected job insecurity has a negative and significant effect on individuals' utility, confirming the importance of non-pecuniary job attributes on labour supply. In particular, marginal utility of job insecurity is negative for around 86% of cases. Finally, it is interesting to observe that unobserved heterogeneity is significant only for hours of work in the conditional logit model. This is explained by the fact that, under the nested logit structure, the parameter τ captures the correlation in unobserved utility among alternatives in the participation nest. τ is significant and different from 1, implying an important correlation among these alternatives. In the absence of the nested logit structure, this correlation is captured by the unobserved heterogeneity terms. Table B.1 in the Appendix presents the three models estimated here, without random terms in preferences. The estimated coefficients of the conditional logit model are quite different than those presented in Table 4, as a result of the unobserved heterogeneity terms.

The ability of our model to fit the data can be tested by comparing predicted and observed frequencies. Predicted frequencies are obtained by averaging up individual probabilities for each discrete hours alternative over the whole sample, while observed frequencies are simply the frequencies of each observed choice over the whole sample. It can be seen in Table 5 that the nested logit model fits better the data than the conditional logit. Moreover, once job insecurity is included, the nested logit model performs even better. In fact, almost a perfect fit is obtained for our sample of single and childless individuals. However, once we compare the fit for men and women separately, we observe that our model underpredicts part-time work for females and overpredicts part-time for males. We believe that this problem is related to the estimation of the parameters for men and women together, rather than to a model misspecification. In fact, it is most likely that differences in preferences exist among both groups, although we consider a rather homogenous group of only single and childless individuals. Nevertheless, a separate estimation for men and women was not possible due to the reduced size of our sample[23]. The nested logit model with job insecurity

[23]In order to take into account, in some way, gender differences, we reestimated the parameters including a female dummy in the preferences but this did not improve the predictive

produces better predictions than the conditional logit, also in the absence of random terms in preferences, as can be seen in Table B.2 in the Appendix.

Table 5: Predicted vs observed frequencies

		Observed	Predicted		
			Conditional logit	Nested logit	Nested logit insecurity
All	Inactivity	13.19	11.72	12.39	13.79
	Part-time	11.01	22.10	12.57	11.04
	Full-time	66.81	52.30	65.78	66.55
	Overtime	8.99	13.88	9.26	8.61
Men					
	Inactivity	13.85	11.19	11.86	13.20
	Part-time	3.85	20.81	11.29	10.09
	Full-time	72.56	53.92	67.39	67.88
	Overtime	9.74	14.08	9.47	8.83
Women					
	Inactivity	12.33	12.41	13.08	14.56
	Part-time	20.33	23.78	14.24	12.28
	Full-time	59.33	50.20	63.69	64.83
	Overtime	8.00	13.60	8.99	8.33

5 Labour supply elasticities and responses to changes in job insecurity

The parameter estimates obtained in the previous section can be used to calculate labour supply elasticities and to analyse the effects of policy reforms on participation and labour supply. The aim of this section is twofold. First, wage elasticities obtained with our extended nested logit model are compared to those of the traditional conditional logit model. Then, using our extended model, we analyse the effect of a change in job insecurity on labour suppy.

Labour supply elasticities in discrete choice models are calculated numerically using the estimated parameters of the utility function (see Creedy and Kalb (2005)). First, we increase gross hourly wages by 1% and compute the

power of the model.

new disposable income for each alternative using our tax and benefit microsimulation model. Then, with the parameters from the utility function, obtained in the previous estimation, we calculate the average simulated probability of being at each alternative for both the old and the new value of disposable income[24]. These probabilities are then used to compute the expected value of labour supply before and after the wage increase, following:

$$E[h|y,x] = \sum_{j=1}^{J} \check{P}_{ij} * h_j$$

Finally, labour supply elasticities are computed numerically by dividing the percentage change in expected labour supply by the percentage change in wages, 1% in this case. Table 6 shows the elasticities obtained for men and women with both the conditional logit and the nested logit models.

Table 6: Labour supply elasticities by gender

		Conditional logit	Nested logit	Nested logit insecurity
Men		0.0446	0.04012	0.0375
	low job insecurity			0.0148
	middle job insecurity			0.0505
	high job insecurity			0.0295
Women		0.0482	0.0260	0.0370
	low job insecurity			0.0132
	middle job insecurity			0.0221
	high job insecurity			0.0356
All		0.0461	0.0341	0.0373

The three models estimated provide labour supply elasticities which are quite in line with previous studies. In fact, elasticities for childless single individuals are in general very small, between 0 and 0.3 and there is no systematic difference between men and women. Our basic conditional logit model provides a labour supply elasticity of 0.0461 and the elasticities do not differ significantly between men and women. When the nested logit structure is used, labour supply elasticities decrease, both in the case when only hours enter the choice set and when

[24]Individual subscripts are omited for ease of readability.

job insecurity is taken into account. In order to test whether these differences are significant, we created bootstrapped confidence intervals for the conditional logit elasticities using 1000 repetitions. Elasticities of the three models turned out to be not significantly different, as both nested logit elasticities fall within the calculated confidence intervals of the conditional logit. In our extended nested logit model, a further distinction can be made between different levels of job insecurity. We observe that female labour supply elasticities increase with the level of job insecurity. This result suggests that wage increases would have a stronger effect when people face adverse conditions at work. In the case of men, the results are less clear. Elasticities are higher for men in high job insecurity jobs compared to those with low job insecurity. However, labour supply elasticities of the middle group are considerably higher than for the other groups.

In addition to the calculation of labour supply elasticities, our extended nested logit model allows us to analyse the effect of non-pecuniary job attributes, job insecurity in our case, on labour supply. However, because of the qualitative nature of our job insecurity variable, the same methodology used to calculate wage elasticities cannot be applied. Here we simulate the effect of a decrease of job insecurity by observing the change in predicted probabilities calculated by our model. We decrease levels of job insecurity for all individuals; this means that those individuals who presented high job insecurity are now attributed a medium level of job insecurity and those who reported a medium level of job insecurity are now attributed a low level of job insecurity. Table 7 presents the predicted probabilities calculated with our model before and after the decrease in job insecurity.

Table 7. The effect of a decrease in job insecurity

	Predicted probabilities		
	before	after	difference
Inactivity	13.79	10.87	-2.92
Part-time	11.04	11.52	0.48
Full-time	66.55	68.71	2.16
Overtime	8.61	8.89	0.28

Our results show that a decrease in job insecurity has a positive and significant effect on participation. In fact, the probability of inactivity decreases by 2.92% after the improvement of job security conditions. All working alternatives present an increase with the most important being that of full-time work (2.16%). This result is particularly interesting in terms of policy because objectives aimed at providing incentives for participation could also be achieved through the channel of improving non-pecuniary job attributes, and not only through monetary incentives. In order to have an idea of the magnitude that the decrease in inactivity represents, we calculated the increase in overall gross wages necessary to obtain an equivalent decrease in inactivity. An increase in overall gross wages of more than 30% would be needed in order to obtain a similar decrease in the probability of inactivity. These results provide an interesting insight into the effect of non-pecuniary job attributes on labour supply, however, it is important to remark that this labour supply model doesn't take into account the reaction of firms to policies aimed at improving working conditions. In fact, from the demand side, providing better working conditions might represent extra costs which could be linked to a decrease in wages. This would result in a negative effect of labour supply and therefore the total effect would be ambiguous. The incorporation of labour demand within our setting is an important step for further research.

6 Conclusion

The aim of this paper was to provide an insight into the effect of non-pecuniary job attributes on labour supply. Two different types of discrete choice models were used. We first estimated a conditional logit model where the choice set is defined only by discrete hours alternatives. This is the approach most widely used to estimate discrete choice labour supply. Then, we specified a nested logit model where the choice set is still defined only by hours alternatives but where individuals first decide whether to work or not and then choose among the alternatives of part-time, full-time or overtime. Finally, we proposed a nested logit model where the choice set is defined by bundles of hours of work and job insecurity, for those individuals who choose to work. The estimation of these structural labour supply models was done using maximum simulated likelihood with Halton sequences in order to account for unobserved heterogeneity in preferences.

Different observations can be drawn from our work. First of all, the nested logit structure seems appropriate for the analysis of labour supply. In fact, the dissimilarity paramater among the alternatives in the participation nest is significant and smaller than one, as required. Second, as expected, job insecurity has a negative effect on individuals' utility, with a calculated marginal utility which is negative for around 86% of the observations. Moreover, the specification of the model is more consistent with economic theory as the marginal utility of hours turns also negative in around 90% of cases, while it attained only around 50% with the two other models. Third, the predictive power of the model improves considerably for our whole sample when job insecurity is included in the nested logit model. Fourth, labour supply elasticities calculated with the extended model are lower than those of a conditional logit model, although these differences are not significant. Moreover, elasticities for individuals working in high job insecurity jobs are higher than for those in low insecurity jobs implying that people working under adverse job security conditions respond more to wage changes. Finally, a decrease of job insecurity decreases the probability of inactivity by 2.92%, suggesting that policies aimed at improving working conditions could be used to influence labour supply decisions.

Several extensions can be considered for the analysis presented in this paper. First of all, the analysis of the effect of job insecurity could be extended to other groups, such as lone parents or couples with children. Second, at this stage we did not take into consideration the relationship between wages and job security, nevertheless, in the case some sort of trade-off exists, this needs to be accounted for in our labour supply estimation. Another important aspect is the incorporation of other non-pecuniary job attributes in the analysis. Here we only included job insecurity, however, many other factors at work may have an effect on labour supply decisions. Finally, a comparative analysis of the effect of policy reforms on labour supply and income distribution can be performed for the basic and the extended labour supply model.

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A Variables and summary statistics

Table A.1. Descriptive statistics

	mean	std. dev.
Net income	247.31	139.37
Hours of work	32.20	15.129
Age	39.90	12.447
Female	0.435	0.4961
Education		
No qualification	0.165	0.3716
Secondary education(cse)	0.064	0.2445
Olevels	0.151	0.3580
Alevels	0.117	0.3221
Higher qualification	0.280	0.4492
University	0.223	0.4167
Job security		
1 (Not satisfied at all)	0.0384	0.1923
2	0.0284	0.1662
3	0.0918	0.2890
4 (Not satis./dissatis.)	0.0785	0.2691
5	0.180	0.3848
6	0.397	0.4898
7 (Completely satisfied)	0.185	0.3889

B Discrete choice labour supply without unobserved heterogeneity in preferences

Table B.1: Estimated parameters of the structural model

			Conditional logit		Nested logit		Nested logit insecurity	
variable			coef.	st.error	coef.	st.error	coef.	st. error
y^2			-12.096	(23.814)	-3.423	(8.1890)	-0.098	(1.1968)
h^2			-0.193***	(0.0192)	-0.134***	(0.0101)	-3.058***	(0.4729)
y x h			-2.806***	(0.3805)	-0.901***	(0.1977)	-1.045***	(0.2637)
$insec^2$							0.762***	(0.1720)
h x $insec$							-0.014	(0.0336)
y x $insec$							0.066	(0.2166)
y			27.935***	(4.5363)	11.131***	(2.6184)	13.403***	(3.4323)
	x	age	-0.115	(0.0733)	-0.059	(0.0357)	-0.118*	(0.0554)
	x	high edu	-3.705	(3.1311)	-3.213*	(1.6191)	-3.210	(2.2212)
	x	mid. edu	-1.327	(3.3758)	-1.482	(1.7275)	-0.932	(2.4217)
	x	low edu	-1.953	(5.2913)	-2.006	(2.9073)	-1.712	(4.3283)
h			1.031**	(0.1925)	0.863***	(0.1120)	2.119***	(0.3489)
	x	age	-0.00002	(0.0034)	-0.0003	(0.0019)	-0.0009	(0.0027)
	x	high edu	0.623***	(0.1144)	0.296***	(0.0712)	0.440***	(0.0977)
	x	mid. edu	0.435***	(0.1233)	0.180*	(0.0733)	0.281**	(0.1007)
	x	low edu	0.459*	(0.1947)	0.203	(0.1222)	0.280	(0.1746)
$insec$							-3.748***	(0.8368)
	x	age					0.007*	(0.0027)
	x	high edu					0.035	(0.0951)
	x	mid. edu					0.065	(0.0996)
	x	low edu					0.296*	(0.1241)
τ					0.269***	(0.0247)	0.520***	(0.0840)

Standard errors in parentheses; *p<0.05,**p<0.01,***p<0.001

Table B.2: Predicted vs observed frequencies

		Observed	Predicted		
			Conditional logit	Nested logit	Nested logit insecurity
All	Inactivity	13.19	8.85	12.41	13.71
	Part-time	11.01	24.65	12.55	10.99
	Full-time	66.81	50.90	65.80	66.69
	Overtime	8.99	15.60	9.24	8.61
Men					
	Inactivity	13.85	8.15	11.85	12.99
	Part-time	3.85	23.45	11.23	10.20
	Full-time	72.56	52.48	67.45	67.99
	Overtime	9.74	15.91	9.47	8.82
Women					
	Inactivity	12.33	9.76	13.13	14.64
	Part-time	20.33	26.20	14.28	12.02
	Full-time	59.33	48.86	63.65	64.99
	Overtime	8.00	15.18	8.94	8.34

Table B.3: Labour supply elasticities by gender

		Conditional logit	Nested logit	Nested logit insecurity
Men		0.0329	0.0416	0.0305
	low job insecurity			0.0083
	middle job insecurity			0.0462
	high job insecurity			0.0150
Women		0.0435	0.0268	0.0348
	low job insecurity			0.0155
	middle job insecurity			0.0152
	high job insecurity			0.0258
All		0.0374	0.0353	0.0323