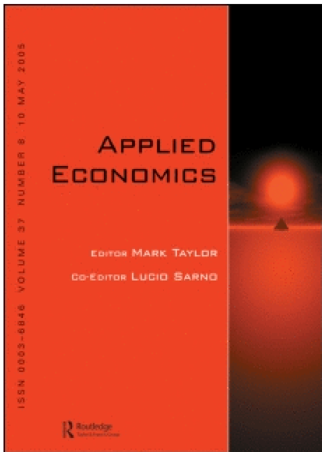

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An analysis of the determinants of job satisfaction when individuals' baseline satisfaction levels may differ

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An analysis of the determinants of job satisfaction when individuals' baseline satisfaction levels may differ

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A growing literature seeks to explain differences in individuals' self-reported satisfaction with their jobs. The evidence so far has mainly been based on cross-sectional data and when panel data have been used, individual unobserved heterogeneity has been modelled as an ordered probit model with random effects. This article makes use of longitudinal data for Denmark, taken from the waves 1995–1999 of the European Community Household Panel, and estimates fixed effects ordered logit models using the estimation methods proposed by Ferrer-i-Carbonel and Frijters (2004) and Das and van Soest (1999). For comparison and testing purposes a random effects ordered probit is also estimated. Estimations are carried out separately on the samples of men and women for individuals' overall satisfaction with the jobs they hold. We find that using the fixed effects approach (that clearly rejects the random effects specification), considerably reduces the number of key explanatory variables. The impact of central economic factors is the same as in previous studies, though. Moreover, the determinants of job satisfaction differ considerably between the genders, in particular once individual fixed effects are allowed for.

I. Introduction

In recent years economists have taken an increasing interest in the analysis of the subjective well-being of individuals; see Frey and Stutzer (2002) for a recent review. In the field of labour economics, following the seminal articles by Hamermesh (1977), Freeman (1978) and Clark and Oswald (1996), this has spawned a growing number of studies of the determinants and consequences of differences in individuals' reported job satisfaction. Work psychologists have for a long time been arguing that for most

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people jobs cannot only be characterized by the pay and hours of work associated with them, as standard economic analysis does, but also by job and workplace features like promotion and other career prospects, job security, job content and interpersonal relationships; see Warr (1999) for a comprehensive survey. In fact, when the employees are asked, as in e.g. the International Social Survey Programme – see Clark (2005) – they typically rank job security and job interest highest, whilst pay and hours of work are found in the opposite end of the ranking.

Economists have a longstanding tradition of viewing subjective measures of individuals' preferences with considerable scepticism. As described by Wansbeek and Kapteyn (1983):

> 'Utility seems to be to economists what the Lord is to theologians. Economists talk about utility all the time, but do not seem to have hope of ever observing it this side of heaven. In microeconomic theory, almost every model is built on utility functions of some kind. In empirical work little attempt is made to measure this all-pervasive concept. The concept is considered to be so esoteric as to defy direct measurement by mortals. Still, in a different role, *viz*., of non-economists, the same mortals are the sole possessors of utility functions and can do incredible things with it.'

The arguments that individuals may differ with respect how they scale feelings and hence communicate their well-being level, that well-being is ordinal (not cardinal), and that subjective feelings may be reflecting their innate personalities are obviously all valid and important objections that should not be swiftly dismissed.[1] This led Stigler and Becker (1977) to conclude: 'economists continue to search for differences in prices or incomes to explain any differences or changes in behaviour' (p. 76).[2] On the other hand, the often made claim that much of economic analysis considers intrinsic motivational factors to be unimportant is obviously wrong. Rather, as is eloquently discussed in Lazear (2000), economic analysis is concerned with the study of situations where the intrinsic motives are taken as given and the aim of the analysis is to examine the influence of extrinsic motives and especially the trade-offs economic agents face at the margin.

And yet, scholars in other social sciences, especially in psychology, have taken individuals' responses to questions about their perceived well-being much more seriously and based much of their empirical evidence on this type of information. A substantial body of research has been built showing that job satisfaction is strongly correlated with several mental physical health indicators. In parallel, a growing number of studies focusing on life satisfaction or financial situation have appeared in economics; see e.g. Bonke and Browning (2003) and Frijters *et al.* (2004a, b).

At the same time, in many countries firms and employers pay close attention to the subjective well-being of their employees and to how these perceive their current jobs. Thus, the European Union has called the member states' attention to the quality aspects of work and has emphasized the importance of improving job quality in order to promote social inclusion and employment (European Commission, 2001, 2002). In Denmark, several of the major companies are regularly carrying out their own worker/job satisfaction surveys, and an employee satisfaction index constructed using identical questionnaires has in recent years been computed for an increasing number of European countries.[3]

The current article is concerned with identifying what lies behind differences in people's subjectively reported job satisfaction and changes therein. For this purpose we make use of data for Denmark from the European Community Household Panel (ECHP), more specifically the five waves from the period 1995 –1999. The waves 1994–1998 have recently been analysed in European Commission's (2002) annual report *Employment in Europe*. Denmark has been shown to have among the most satisfied workers in the world; in Europe only Austria and Ireland have reached as high levels of employee satisfaction (see Sousa-Poza and Sousa-Poza, 2000).

The novelty in our article is the application of the methodology proposed by Das and van Soest (1999) and Ferrer-i-Carbonel and Frijters (2004) to estimate

[1] Scholars of subjective well-being seem to disagree about the importance of personality as a determinant of life satisfaction; see Diener and Lucas (1999) for a survey.
[2] For a recent, useful discussion and summary of the experimental and field data literature on the meaningfulness of answers to subjective questions, see Bertrand and Mullainathan (2001).
[3] See www.europeanemployeeindex.com

the determinants of job satisfaction. In doing so we use fixed effects ordered logit models on Danish data. Unlike previous analyses we make use of longitudinal job satisfaction data while simultaneously preserving the ordered nature of the information in the fixed effects approach. The models are estimated on samples of male and female workers, separately. For comparison and testing purposes we also estimate two other models: a random effects ordered probit model and an ordered probit that explicitly accounts for the correlation between time-invariant unobservables and time-varying observables.

We find that using the fixed effects approach (which clearly outperforms the random effects specification), considerably reduces the number of key explanatory variables, especially for women. The key economic variables, wages and hours of work, survive the introduction of fixed effects, though. The coefficient estimates obtained using the Das and van Soest (1999) and the Ferrer-i-Carbonel and Frijters (2004) estimation strategies are relatively similar. For males there are two differences; the Das and van Soest estimation yields insignificant and significant estimates for poor health and public sector employment, respectively. For females, none of the estimated coefficients with the Das and van Soest procedure differ significantly from zero. Consequently, the determinants of reported job satisfaction clearly differ between the genders.

The remainder of the article is organized as follows. Section II briefly discusses the earlier literature on the topic of the article. Section III outlines the data used and Section IV discusses the empirical strategy adopted. Section V gives the results. The VI Section summarizes our conclusions.

II. Previous Research

As was already mentioned above, economists' interest in job satisfaction is of relatively recent date, whereas sociologists and work psychologists have a considerably longer and hence more extensive experience of examinations of the determinants and impact of job satisfaction; for an excellent summary; see Warr (1999). This literature differs in at least three respects from how economists have approached essentially the same data sets and closely related questions. First, the dependent variable in analyses aiming at understanding the factors underlying differences in job satisfaction across individuals has usually been constructed by averaging the ordinal responses to the questions concerning satisfaction. Thus, satisfaction is implicitly assumed to be cardinal.

Second, the vast majority of the noneconomists' investigations employ ordinary least squares (OLS) as their estimation technique. This follows naturally from the implicit assumption that the job satisfaction responses are cardinal. Moreover, they do not account for the fact that the dependent variable is bounded. Typically, the literature has little discussion both of measurement errors in the dependent variable and of what is subsumed in the error term. Most of the psychological as well as the economic research have been based on cross-sections. As a consequence, little attention has been paid to the importance of individual differences in baseline job satisfaction levels, which in a longitudinal framework could be modelled as individual-specific fixed effects. Clark and Oswald (2002) discuss the role of fixed effects in studies of well-being. The method used in their application is however OLS, that is, cardinality is implicitly assumed. A previous study recognizing the potential importance of controlling for fixed effects is Winkelmann and Winkelmann (1998), in which the effects of changes in labour force status on life satisfaction are examined. But in order to enter fixed effects, they collapsed the satisfaction variable into a binary variable and used Chamberlain's (1980) conditional logit estimation technique. The same approach is adopted by Hamermesh (2001). Third, unlike economists, scholars in psychology and related fields do not enter working hours as an explanatory variable.

The early contributions to the economic job satisfaction literature are from the late 70s. Hamermesh (1977) is the first to develop and test a theory of overall job satisfaction, whereas Freeman (1978) and Borjas (1979) examined the relationship between unionism and job satisfaction where the latter is adopted with the motivation that it is a measure that captures other aspects of the workplace, which are not reflected by conventional objective variables.

The 1990s witnessed a renewed interest in job satisfaction research among economists spawned by a series of articles in particular by Andrew Clark and Andrew Oswald. Four of their first articles (Clark, 1996, 1997; Clark and Oswald, 1996; Clark *et al.*, 1996) made use of (three) different measures of job satisfaction obtained from the first wave of the British Household Panel Survey (BHPS) and carried out an ordered probit analysis of the importance of individual and workplace characteristics in explaining reported differences. Most of the other articles (see e.g. Blanchflower and Oswald, 1998; Lydon and Chevalier, 2002) on the determinants of job satisfaction that have used other data sources have also been based on one or several cross-sections and continued to use ordered probit as their estimation method. Three notable exceptions are Gardiner and Oswald (2001), Employment in Europe (2002) and Sanz de Galdeano (2002) which are based on panel data. However, they do little to exploit the longitudinal nature of their data.

Summarizing briefly the more recent literature[4] one can say that it has typically found that pay and work hours to be positively and negatively, respectively related to job satisfaction. Other important contributing factors are individual traits, such as age and gender and some features characterizing the individuals' workplaces and jobs. As we have seen, the studies have mainly been based on cross-sectional data, and even when researchers have had access to panel data on employees' job satisfaction levels, the longitudinal nature of the data has only been exploited to a limited extent.

III. Econometric Analysis

We analyse overall job satisfaction by means of the random effects ordered probit model (Butler and Moffitt, 1982) and the fixed effects ordered logit estimator recently proposed by Ferrer-i-Carbonel and Frijters (2004).[5] For comparison purposes and as a robustness check we also use the estimator proposed by Das and van Soest (1999).

Logit and probit models have often been used with cross-sectional data in analyses about well-being and satisfaction. The ordered probit model has also been applied in longitudinal studies. In that case unobserved heterogeneity has been dealt within the random effects approach. The fixed effects approach has rarely been implemented owing to the lack of suitable econometric methods. However, some authors (e.g. Winkelmann and Winkelmann, 1987) have adopted it by transforming the ordinal variable into a binary one that takes the value of one above (or under) a specific threshold. Assuming that the error term is logistic yields the ordinary logit model that can be estimated using standard likelihood methods (see Rasch, 1960, 1966; Andersen, 1970; Chamberlain, 1980).

Two recent studies have proposed new estimations methods that can handle the original rankings of the dependent variable in the fixed effects approach (Das and van Soest, 1999; Ferrer-i-Carbonel and Frijters, 2004).[6] The proposed models have the particularly appealing property that no particular correlation is assumed between the fixed individual effects and the error term. Moreover, while the random effects ordered probit model assumes 'ordinal comparability', i.e. that satisfaction is interpersonally comparable, implying that if $S_i > S_j$ then $W_i > W_j$ (S, standing for 'satisfaction' and W, standing for 'well-being'), the fixed effects ordered logit does not.

In our approach, we assume that (Ferrer-i-Carbonel and Frijters, 2004)

(1) Job satisfaction (JS) is a positive monotonic transformation of an underlying concept called well-being: if $JS_{it} > JS_{is}$ then $W_{it} > W_{is}$ $(t \neq s)$.
(2) Both time-invariant, υ_i, and time-varying unobserved factors, ε_{it}, are present. However, while the former are related to observed factors, the latter are not, i.e. $\mathrm{cov}(\varepsilon_{it}, x_{it}) = \mathrm{cov}(\upsilon_i, \Delta x_{it})$ and $\mathrm{cov}(\upsilon_i, x_{it}) \neq 0$.

The first assumption implies that there is a correspondence between what is measured, JS_{it} (for an individual $i = 1, \ldots, N$ and for a time period $t = 1, \ldots, T$) and what we are interested in, namely a form of well-being, i.e. W_{it}. Several studies have shown that reported general satisfaction levels perform well in predicting the underlying concept of welfare. This in turn implies that self-reported job satisfaction levels can be used as proxies for the well-being in the job sphere. The second assumption is more strictly related to the statistical properties of our model. It implies all relevant time-varying factors are observed and the remaining fixed unobserved factors affect the levels of other variables and not their changes. An example of such factors is 'personality traits' like extraversion, optimism and neuroticism; see Diener and Lucas (1999).

Our dependent variable JS – job satisfaction – $\in \{1, \ldots, 6\}$ is an ordinal indicator of the individual's overall satisfaction in his/her main activity. Since the data available are longitudinal, we dispose of this measure for a number of individuals $i = 1, \ldots, N$ over a given time-period indexed by $t = 1, \ldots, T$. More precisely, we observe a sample of Danish workers over the years 1995–1999. In addition to

[4] In the longer working article version of this article, we provide a more detailed survey of this literature.
[5] The fixed effects ordered logit model is used also in the companion articles by Frijters *et al.* (2004a, b).
[6] See also Frijters *et al.* (2004) and Ejrnaes and Pörtner (2002).

their self-reported job satisfaction levels, the data set includes many individual and job-related characteristics for each survey year, some of which will be used as explanatory variables in our analysis.

Random-effects ordered probit

Our reference model is the ordered probit model with individual random effects:

$$\begin{aligned} JS_{i,t}^{j^*} &= x'_{i,t}\beta + v_i + \omega_{it} \quad \text{or} \\ JS_{i,t}^{j^*} &= x'_{i,t}\beta + \varepsilon_{it} \quad \text{with} \quad \varepsilon_{it} = v_i + \omega_{it} \end{aligned} \tag{1}$$

where JS_{it}^* is latent overall satisfaction in job while JS_{it} is the observed satisfaction level declared at the survey's date; x_{it} are observable individual characteristics; v_i is an individual random characteristic, normally-distributed, fixed over time and orthogonal to x with unknown variance; and finally ω_{it} is a time-varying error-term, normally-distributed, orthogonal to v_i; both v_i and ω_{it} are distributed independently of all x. The assumption of normality of the error terms yields an ordered probit model. The model is again built around a latent regression model with some cut-off points (λ) that are estimated along with the β. Individual heterogeneity is unobserved; therefore to obtain the unconditional log-likelihood we need to integrate the conditional log-likelihood. The integration is done with the Gauss-Hermite quadrature (25 points were chosen); see Butler and Moffit (1982).

In addition to (1), we also estimate a model where we explicitly account for correlation between the time-invariant unobservables and the time-varying observables. Following Mundlak (1978) we specify this correlation as a linear function of the time-varying observables. Thus, the model becomes

$$\begin{aligned} JS_{i,t}^{j*} &= x'_{i,t}\beta + v_i + \theta x_i + \omega_{it} \quad \text{or} \\ JS_{i,t}^{j*} &= x'_{i,t}\beta + \varepsilon_{it} \quad \text{with} \quad \varepsilon_{it} = v_i + \theta x_i + \omega_{it} \end{aligned} \tag{2}$$

Fixed-effects ordered logit

The Ferrer-i-Carbonel and Frijters (2004) estimator. Some unobserved individual characteristics may affect a particular job dimension. In that case a spurious correlation between that dimension and those unobserved characteristics may arise and thereby bias the estimated coefficients. While the random effects ordered probit in (1) can to a certain extent indicate the direction of the effects of some determinants of job satisfaction, the above-mentioned spurious correlation is most likely to be present. Although with the approach of Mundlak (1978) an attempt is made to control for this correlation, in the current analysis the outcome is likely to be rather poor, since we have only one continuous time-varying variable of interest. Moreover, in modelling the correlated random effects a particular form of the correlation is imposed. Consequently, in our case a fixed effects approach seems to be more appropriate.

The estimator proposed by Ferrer-i-Carbonel and Frijters (2004) derives from an extension of the idea of Chamberlain (1980) to a fixed-effect ordered logit framework. The model is:

$$\begin{aligned} JS_{it}^* &= x_{it}\beta + f_i + \varepsilon_{it} \\ JS_{it} &= k \Leftrightarrow JS_{it}^{j^*} \in [\lambda_k^i, \lambda_{k+1}^i) \end{aligned} \tag{3}$$

where again JS_{it}^* is latent overall job satisfaction; JS_{it} is the observed satisfaction level; f_i is an individual fixed effect; ε_{it} is the error term with logistic CDF; $k = 0, \ldots, K$; $t = 1, \ldots, T$. This is an ordered logit model with fixed individual effects and individual specific thresholds λ_k^i. The model assumes that the intercepts are increasing i.e. $\lambda_k^i < \lambda_{k+1}^i$. However, it does not assume ordinal comparability.

The statistic of interest is:

$$\begin{aligned} &\Pr\left[I(\mathbf{JS}_{i1} > k_i), \ldots, I(\mathbf{JS}_{iT} > k_i) \middle| \sum_t I(JS_{it} > k_i) = c \right] \\ &= \frac{\prod_{t=1}^{T} \left\{ 1 + I(\mathbf{JS}_{it} > k_i)(e^{-\lambda_{k_i}^i + (x_{it}\beta + f_i)} - 1) \right\} / \prod_{t=1}^{T} \left\{ 1 + e^{-\lambda_{k_i}^i + (x_{it}\beta + f_i)} \right\}}{\sum_{JS \in S(k_i, c)} \left(\prod_{t=1}^{T} \left\{ 1 + I(\mathbf{JS}_{it} > k_i)(e^{-\lambda_{k_i}^i + (x_{it}\beta + f_i)} - 1) \right\} / \prod_{t=1}^{T} \left\{ 1 + e^{-\lambda_{k_i}^i + (x_{it}\beta + f_i)} \right\} \right)} \\ &= \frac{e^{\sum_{t=1}^{T} I(\mathbf{JS}_{it}^j > k_i) x_{it}\beta}}{\sum_{JS \in S(k_i, c)} e^{\sum_{t=1}^{T} I(\mathbf{JS}_{it}^j > k_i) x_{it}\beta}} \end{aligned} \tag{4}$$

This statistic implies that all the individuals whose satisfaction scores vary over time are included in the estimation procedure (Frijters *et al.*, 2004a, b). Note that the last expression in (4) is the likelihood of observing the job satisfaction levels that are above the cut-off point, given that there are c satisfaction levels that are higher than k for each individual i. Thus, $S(k_i, c)$ represents the set of all possible combinations of job satisfaction (in each of the j dimensions considered) that satisfy:

$$\sum_t I(JS_{it} > k_i) = c_i$$

and c_i denotes the number of times over the observation period that job satisfaction is higher than the bound k_i.[7] Evidently, one advantage of this estimation method is that it avoids loosing a huge amount of information: information about all individuals, whose job satisfaction level changes, is used.

The Das and van Soest (1999) estimator. Das and van Soest (1999) have developed another method that exploits the Chamberlain estimator to build a fixed effects ordered logit model. Their estimator is based on a weighted average of the Chamberlain estimator for each k. In their framework, an estimate of k is obtained for those individuals for which $T > \sum_{t=1}^{T} I(JS_{it} > k) > 0$ for each $0 < k < K$. The clear advantage of this estimator is that it accounts for all possible individuals' k's and hence uses more information. Its disadvantage is that there may not be enough data in each category k in order to estimate β_k. This implies that when there is not enough variation over the categories, those thresholds cannot be used, and the corresponding categories have to be dropped. This happens in our estimation for the low satisfaction values reported by men (only values higher than 2 could be used for them). It should be noted that this estimator requires stricter regularity conditions than the one examined in the previous section since the weight matrix depends on the joint probability of being in the data more than once.

The Das and van Soest estimator is based on the following procedure. First one transforms each individual's satisfaction vector $\{JS_{i1}, \ldots, JS_{iT}\}$' into a set of K vectors, such that $\{(JS_{i1} > k); ::::; (JS_{iT} > k)\}'$ for $k = 0$ to $K-1$ with K being the number of values that the ordinal variable may take. For each k, one estimates the parameters of interest applying the Chamberlain estimator to data for the individuals for whom $T > \sum_{t=1}^{T} I(JS_{it} > k) > 0$. This allows us to obtain a consistent estimator implying $\sqrt{n_k}(\beta_k - \beta) \to N(0, \sum_{kk}^{-1})$ $k = 0, \ldots, K-1$. The final Das and van Soest estimator is obtained through a minimum distance step

$$\widehat{\beta} = \arg\min_{\beta} \frac{1}{2} \times \left[\begin{pmatrix} \beta_0 \\ \cdots \\ \beta_K \end{pmatrix} - \begin{pmatrix} \beta \\ \cdots \\ \beta \end{pmatrix} \right]' \Omega^{-1} \left[\begin{pmatrix} \beta_0 \\ \cdots \\ \beta_K \end{pmatrix} - \begin{pmatrix} \beta \\ \cdots \\ \beta \end{pmatrix} \right]$$

with Ω being the weighting matrix with entries $\omega_{a,b} = \Sigma_{aa}^{-1} \Sigma_{ab}^{-1} \Sigma_{bb}^{-1}$ with $a, b = 0, \ldots, K-1$. In order to make the estimator operational, the unknown matrices are replaced with their sample analogues.

Specification testing: random or fixed-effects

To assess the comparative advantage of estimating a fixed-effects ordered logit model relative to a random effects ordered probit, we implement the test presented in Frijters *et al.* (2004). For this we use the variables that at the same time are present in both the fixed effects and the random effects models.

We define $\tilde{\beta}_{RE}$ to be the coefficients of the variables that are present in both models but resulting from the estimation of the random effects ordered probit. In the absence of effects related to fixed individual characteristics, we expect that the coefficients should be very similar. Under the null-hypothesis that there are no *FE*, therefore

$$\text{H0:}\ \beta^{\text{FE}} = \alpha\, \tilde{\beta}_{RE}$$

where α is an unknown positive constant originating from the different normalizations assumed in the estimation of the *FE* and *RE* models.[8] Notice that the β_{RE} only contains the coefficients of those variables that are present at the same time in both the fixed effects and the random effects models. To simplify the exposition, we write $\gamma_{RE} = \alpha\, \beta_{RE}$.

Under the null hypothesis, we can use the following standard likelihood ratio test:

$$-2 * \left[L(\tilde{\beta}_{ML}^{FE}) - L(\tilde{\gamma}_{ML}^{RE}) \right] \sim \chi(k) \tag{5}$$

[7] Further details regarding both the estimation procedure and the properties of the estimator can be found in Ferrer-i-Carbonel and Frijters (2004).

[8] This vector of coefficients is obtained through the estimation of the random effects ordered probit on the whole sample and has var(ε_{it})=1. Conversely, when using the fixed-effects estimator only a sub-sample of individuals is used. Thereby, these two models do not share the same normalization. See Frijters *et al.* (2004).

where ($\tilde{\beta}^{FE}_{ML}$) is the coefficients vector obtained from the maximum likelihood estimation of the unrestricted fixed-effects ordered logit and $L(\tilde{\beta}^{FE}_{ML})$ the value of the corresponding (log) likelihood; k denotes the number of restricted parameters; $L(\tilde{\gamma}^{RE}_{ML})$ is the likelihood of the fixed-effects model when the value of the parameters are equal to $\alpha\,\beta_{RE}$. As pointed out by Frijters *et al.* (2004), there are at least two problems that make this testing procedure harder than it seems at first glance. First, one needs to re-estimate the model to re-fit the unrestricted parameters of the model. Second, and not less important, α is unknown. To avoid the last problem notice that

$$2L(\tilde{\beta}^{FE}_{ML}) - 2L(\alpha\tilde{\beta}^{RE}) > 2L(\tilde{\beta}^{FE}_{ML}) - \max_{\hat{\alpha}}\{2L(\hat{\alpha}\tilde{\beta}^{RE})\} \tag{6}$$

The inequality (6) implies that a lower bound for $2L(\tilde{\beta}^{FE}_{ML}) - 2L(\alpha\tilde{\beta}^{RE})$ is attained by using the $\hat{\alpha}$'s, which maximize $L(\hat{\alpha}\tilde{\beta}^{RE})$. Consequently, rejecting the null at the lower bound implies that the true statistic will also reject it.

IV. Data Description

The data used in this article are extracted from the European Community Household Panel (ECHP) waves 1995–1999. The data were collected annually on several issues regarding family structure, family and family members' incomes and employment and provide unique information about the dynamics of social change and individual behaviour.[9]

The job satisfaction questions in the ECHP ask the individuals to give an integer response on a scale from 1 to 6 which best describes how satisfied (or dissatisfied) they are with specific job facets: wages, job security, type of work, working hours, working time, working conditions and commuting time. In addition, they are asked about the overall ('all things considered') satisfaction in their main job or activity. For those working, this variable may be thus interpreted as the 'overall job satisfaction' and this will be the dependent variable in our empirical analysis. The reported 'overall' job satisfaction is not merely the average of the already reported satisfaction levels for the different aspects of jobs, but captures some additional aspects of the jobs held or reflects the differences in the weights each employee attaches to the individual job facets.[10] A response of one represents the lowest level of satisfaction and six the highest.

Table 1. Mean job satisfaction by year and gender

	Average job satisfaction	
Year	Men	Women
1995	4.990	4.999
1996	4.927	4.905
1997	4.935	4.993
1998	4.967	4.939
1999	4.865	4.853
Total	4.937	4.938

Table 1 shows the annual means of the dependent variable for men and women, separately. We may note that the means are remarkably constant during the 5 year-period under study. Furthermore, the scores are high: close to or slightly below five.

The high persistency in mean job satisfaction levels masks the fact that there are quite frequent year to year changes in individuals' reported levels of job satisfaction; see Table 2. In each year, only about 38 (35)% of the male (female) respondents report the same levels as in the preceding year. Though the period considered – 5 years – is too short to shed light on whether changes are temporary blips or dips, or of a more permanent character, this result is especially noteworthy in view of the fact that our subsequent econometric analysis exploits the longitudinal aspects of the data. While there is no trend in the average satisfaction levels, in each year the proportion of individuals whose satisfaction level has increased relative to the previous year is higher than the proportion whose satisfaction level has decreased compared to the year before. Finally, we can see that the patterns are very similar for male and female employees.

Only time-varying variables have been introduced in the fixed effects ordered logit. More specifically they are: the square of the respondents' age, an indicator for health (as measured by number of nights in hospital as in-patient during past 12 months), holding a temporary job, having a 'newborn child', working part-time, working in the public sector, having received training provided by the employer,

[9] Concerning nonresponse and attrition the reader is referred to the article by Nicoletti and Peracchi (2002). The nonresponse rates in the satisfaction question are found to be very low.

[10] We have carried out some simple cross-tabulations of 'overall satisfaction' and the seven different facets of jobs. These show indeed that they are positively correlated, but the correlations are far from perfect.

Table 2. Changes in job satisfaction levels compared to previous year (shares in %)

	Men			Women		
Year	Lower	Higher	Same	Lower	Higher	Same
1996	0.273	0.281	0.446	0.269	0.305	0.426
1997	0.234	0.346	0.420	0.216	0.377	0.408
1998	0.241	0.268	0.491	0.295	0.276	0.429
1999	0.286	0.163	0.551	0.290	0.201	0.509

Table 3. Fixed effects ordered logit estimates – Men

	Ferrer-i-Carbonel and Frijters (2004)		Das and van Soest (1999)	
	Coeff.	SE	Coeff.	SE
Age squared	0.002	0.001	−0.000	0.001
Part-time work	−1.049**	0.501	−0.320*	0.135
Health proxy	−0.035***	0.020	−0.009	0.010
Employer provided training	0.258**	0.101	0.181*	0.081
Newborn child	0.165	0.172	0.170	0.137
Temporary contract	0.255	0.190	0.206	0.148
Log of gross hourly wage	0.662**	0.302	0.531*	0.266
Public sector	0.009	0.288	0.570*	0.214
Time-effects	Yes		Yes	
α	1.419**			
Log-likelihood ratio test	−42.064			

Note: Significance levels (*) 10%, (**) 5%, (***) 1%.

log of current gross hourly wage and time-specific dummies.

To account for potential differences across genders all the estimations have been carried out for males and females, separately. The two samples include 3936 women and 4227 men, respectively.

V. Results

Turning now to the estimates, which are set out in Tables 3 and 4 for males and females, respectively, we may first note that the test of random effects *versus* fixed effects described in Section IV, decisively rejects the former. As can be seen from the statistics α and the likelihood ratio test reported at the bottom of Tables 3 and 4, the null hypothesis is rejected at the lower bound,. The random effects ordered probit estimates are in Table A1 in the appendix. A comparison of these with the preferred fixed effects model estimates reveals some interesting patterns.

The first thing worth noting is that the key economic explanatory variables like income from work, training, poor health and temporary jobs attach similar coefficient estimates.[11] Thus, previous job satisfaction models have not been far from the mark in this respect. It is worth remarking, however, that the coefficient to wage income for women is positive albeit insignificant in all specifications. As the data on working hours are crude, making a distinction between full- and part-time work only, the insignificant signs to this dummy variable should not worry us much.[12] Other similarities are found for those explanatory variables the estimated coefficients of which are insignificant; i.e. when a variable does not differ from zero in the random effects model, it does not in the fixed effects models, either. There is one exception, however. According to the fixed effects estimations, for females employment in the public sector increases their job satisfaction. This is not completely unexpected as there is a negative wage premium for Danish public sector employees (Pedersen *et al.*, 1990) but at the same time more working time flexibility and less pressure on doing overtime work in the public sector.[13]

[11] More precisely, the magnitudes of the coefficients differ but their statistical significance does not.
[12] Still, for males the part-time work dummy carries a statistically significant, negative coefficient in the fixed effects model.
[13] In corresponding estimations for six different facets of job satisfaction for males and females separately (but not reported here), we find that public sector employees are more satisfied with their working times and working hours but less satisfied with their earnings than private sector employees.

Table 4. Fixed effects ordered logit estimates – Women

	Ferrer-i-Carbonel and Frijters (2004)		Das and van Soest (1999)	
	Coeff.	SE	Coeff.	SE
Age squared	−0.0010	0.001	−0.002	0.002
Part-time work	−0.004	0.185	−0.076	0.222
Health proxy	0.005	0.010	0.015	0.016
Employer provided training	0.141	0.105	0.199	0.138
Newborn child	0.247	0.176	0.010	0.254
Temporary contract	0.280	0.191	0.167	0.243
Log of gross hourly wage	0.177	0.349	0.331	0.426
Public sector	0.667*	0.315	0.410	0.352
Time-effects	Yes		Yes	
α	2.418**			
Log-likelihood ratio test	−22.82			

Note: Significance levels (*) 10%, (**) 5%.

With one exception the Mundlak approach (see Equation 2) led to only minor changes in the estimates for males. The exception is the coefficient to the hourly wage which is clearly larger when correlation between time-invariant unobservables and time-varying observables are accounted for. For females the estimates using the two approaches are virtually identical.

A second noteworthy observation is that there are substantially fewer explanatory variables that differ from zero for female employees and that this is in particular the case in the fixed effects estimations. In fact in the latter, there is only one, public sector employment, and as we will see below this is not robust.

The coefficients estimates obtained using on one hand the Ferrer-i-Carbonel and Frijters (2004) and on the other hand the Das and van Soest (1999) estimation strategy are relatively similar. For males there are two differences; the Das and van Soest estimation yields insignificant and significant estimates for poor health and public sector employment, respectively. The key economic variables – the hourly wage and hours (part-time work) – remain significant, albeit the precision of the Das and van Soest estimates is lower. For females, none of the estimated coefficients with the Das and van Soest procedure differ significantly from zero. Thus, the determinants of reported job satisfaction clearly differ between the genders.

For male employees the number of nights spent in hospital and employer provided training obtained negative and positive coefficients, respectively. The first variable is a proxy for health status which is plausibly negatively related to job satisfaction as individuals in a good physical and psychic condition are likely to be able to earn more, to feel relatively more certain of their continued employment, to be more able to choose and carry out the type of work they like, and to have less difficulties with the number of working hours, placement of working hours or with working conditions. The second observation is also plausible as training provided by the employer implies both improved future career prospects and increased job security. The estimates do not lend support to notions that temporary, fixed-term contract jobs are considered as bad.

VI. Concluding Remarks

In recent years data on employees' satisfaction with their jobs, and various aspects of these, have become increasingly available to researchers. This information is typically of ordered character and some of the more frequently used data sets are panels. So far relatively few analyses have, however, actually exploited the longitudinal character of the data. This is particularly surprising as not only the levels of, but also the changes in job satisfaction, and factors underlying these, are potentially very interesting. Prior to this article another weakness of the literature has been that the possibility that individuals differ with respect to their baseline satisfaction levels – or in the jargon of panel data econometrics: individual fixed effects – are not allowed for in the estimations. The main novel feature of this article is that we apply new statistical methods for estimating an ordered logit model with fixed effects to panel data on job satisfaction.

Entering individual fixed effects does indeed make a difference: both the estimated coefficients of time-varying explanatory variables, and their significance, change as we allow for individuals to have different baseline satisfaction levels. This is in particular true for female employees, and the results suggest that different factors are important determinants of men's and women's reported job satisfaction. For men, accounting for fixed effects does not give rise to major changes with respect to explanatory variables like wages and hours of work. Consequently, previous work appears not to have been far from the mark in this respect.

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Appendix

Table A1. Random effects and correlated random effects ordered probit

	Men				Women			
	RE		CRE		RE		CRE	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Individual traits								
Age	−0.098**	0.022	−0.097**	0.022	−0.047	0.025	−0.047	0.025
Age × Age	0.001**	0.000	0.001**	0.000	0.001*	0.000	0.001*	0.000
Part-time	−0.094	0.176	−0.117	0.179	0.095	0.066	0.095	0.067
Health proxy	−0.022**	0.007	−0.022**	0.007	0.010	0.004	0.001	0.004
Married or cohabiting	0.093	0.066	0.097	0.066	0.131	0.070	0.131	0.070
Experience squared	0.039**	0.020	0.036	0.020	−0.002	0.022	−0.003	0.022
Newborn child	−0.064	0.084	−0.064	0.084	0.079	0.094	0.079	0.095
Job characteristics								
Training provided by the employer	0.129**	0.045	0.132**	0.045	0.098*	0.049	0.098*	0.049
Temporary contract	−0.202**	0.069	−0.206**	0.069	0.104	0.082	0.104	0.082
Public sector	0.045	0.072	0.034	0.072	0.032	0.0711	0.032	0.071
(Ln) hourly wage	0.268**	0.101	0.452**	0.150	0.113	0.110	0.123	0.169
Sector								
Agriculture	0.322	0.221	0.309	0.222	0.342	0.421	0.341	0.421
Services	−0.120	0.074	−0.123	0.074	−0.031	0.110	−0.031	0.111
Occupation								
Legislators	0.445**	0.152	0.477**	0.155	0.228	0.215	0.228	0.215
Professionals	0.294**	0.131	0.326**	0.133	0.128	0.111	0.129	0.111
Technicians	0.278**	0.126	0.296**	0.128	0.038	0.091	0.038	0.091
Service workers	0.352**	0.142	0.357**	0.145	0.146	0.098	0.145	0.098
Skilled agricultural	0.669**	0.308	0.667*	0.310	−0.478	0.322	−0.478	0.322
Craft and trade workers	0.094	0.137	0.095	0.137	−0.206	0.326	−0.206	0.326
Assemblers	0.142	0.140	0.133	0.141	0.059	0.177	0.058	0.179
Elementary tasks	0.188	0.128	0.184	0.128	−0.290*	0.132	−0.291*	0.134
Education								
Higher	−0.004	0.099	0.003	0.099	−0.001	0.098	−0.000	0.098
Secondary	0.015	0.078	0.018	0.078	0.010	0.087	0.010	0.087
Job status								
Supervisory	−0.067	0.071	−0.061	0.071	0.350**	0.098	0.350**	0.098
Intermediate	−0.169**	0.067	−0.168**	0.067	−0.047	0.072	−0.047	0.072
$\lambda(1)$	0.573**	0.066	0.573**	0.067	0.759**	0.086	0.759**	0.086
$\lambda(2)$	1.269**	0.075	1.269**	0.076	1.514**	0.089	1.514**	0.090
$\lambda(3)$	2.325**	0.078	2.325**	0.078	2.556**	0.091	2.556**	0.091
$\lambda(4)$	4.007**	0.079	4.008**	0.080	4.091**	0.094	4.091**	0.094
$\lambda(5)$	4.217**	0.502	4.141**	0.542	3.618**	0.512	3.633**	0.543
Time-effects	Yes		Yes		Yes		Yes	
Random effects	Yes		Yes		Yes		Yes	
Averages	No		Yes (age and wage)		No		Yes (age and wage)	

Notes: *Significant at 5%; **significant at 1%.