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DIW Berlin
German Institute for Economic Research

DIW Berlin

German Institute
for Economic Research

Königin-Luise-Str. 5
14195 Berlin,
Germany

Phone +49-30-897 89-0
Fax +49-30-897 89-200

www.diw.de

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Discrete Choice Labor Supply:
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Peter Haan

Abstract:

Estimating labor supply functions using a discrete rather than a continuous specification has become increasingly popular in recent years. On basis of the German Socioeconomic Panel (GSOEP) I test which specification of discrete choice is the appropriate model for estimating labor supply: the standard conditional logit model or the random coefficient model. To the extent that effect heterogeneity is present in empirical models of labor supply functions, the application of a random coefficient model is necessary to avoid biased estimates. However, because of the complex structure, random coefficient models defy calculating confidence intervals of marginal effects or elasticities. Therefore, if heterogeneity is nonexistent or does not lead to a significant bias in the derived labor supply elasticities, standard discrete choice models provide the more favorable choice. Due to their simple structure, conditional logit models are far less computational intensive providing standard tools to calculate confidence intervals of elasticities. My findings suggest that effect heterogeneity is present when estimating a discrete choice model of labor supply drawing on data of the GSOEP. However, the labor supply elastisities derived form the specifications with and without random effects do not differ significantly. That leads to the conclusion that the standard discrete choice model, attractive for its simple structure, provides an adequate model choice for the analysis of labor supply functions based on the GSOEP.

Keywords: labor supply, discrete choice models, specification test

JEL Classification: C25, C52, J22

Correspondence to:
Peter Haan
DIW Berlin
Köngin-Luise-Straße 5
14195 Berlin
e-mail: phaan@diw.de

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1. Introduction

Estimating labor supply functions using a discrete rather than a continuous specification has become increasingly popular in recent years. The main advantage of the discrete choice approach compared to continuous specifications derives from the possibility to model nonlinearities in budget functions. However, the standard discrete choice approach, the conditional logit model, is based on the restrictive assumption of homogenous error variances. This leads amongst others to the unattractive independence of irrelevant alternatives (McFadden 1973). Econometric literature has suggested more general discrete choice models that relax the iid assumption and that allow for effect heterogeneity, for example the random coefficient model (Revelt and Train 1996). However, these less restrictive specifications have shown to incur very high computational cost, which might obstruct the estimation of confidence intervals of marginal effects or elasticities. It is therefore of particular interest for applied research which approach is more adequate when analyzing discrete choice models: the standard conditional logit model or more general random effect models. To the extent that effect heterogeneity is present in empirical models of labor supply functions, the application of a random effect model is necessary to avoid biased estimates. However, if such heterogeneity is nonexistent or the bias is insignificant standard discrete choice models provide the more favorable choice.

Studies estimating labor supply in the Netherlands (van Soest 1995) and in the UK (Duncan and MacCrae 1999) with several discrete choice models, have found no significant differences between the results of fixed and random specifications. So far, an empirical analysis of different discrete choice labor supply models for German data has not been carried out. There exists a large literature on labor supply in Germany using micro data of the German Socio Economic Panel (GSOEP). Considering the importance of this data set for national and international research on labor supply employing discrete choice (e.g., Beblo et al. 2003, Bonin et al. 2003, Buslei and Steiner 1999, Gustavson 1991), an analysis of the appropriate specification of the discrete choice model on basis of the GSOEP is of particular interest.

The purpose of my paper is twofold. First, I discuss the differences between the standard conditional logit model and random effects discrete choice models. Thereafter, I estimate different model specifications with and without random effect parameters of a household utility function drawing on micro data of the GSOEP. The idea is to test whether the estimation results derived from the specifications with and without random effect parameters differ significantly. Comparing the models, I will focus on two criterions: differences between estimators and differences between labor supply elasticities. Significant differences between estimators imply that heterogeneity is present in the data leading to biased estimators of the conditional logit model. However, this criterion itself is not sufficient to reject the conditional logit model. Significant differences of estimators do not necessarily lead to significant differences of labor supply elasticities, which are central for the analysis of labor supply. Therefore, in order to choose the more adequate model, it is necessary to test for differences of the labor supply elasticities. Considering the Akaike Criterion and (co)variance parameters of random effects, my findings suggest that there exists some evidence for effect heterogeneity in labor supply functions. However, even if heterogeneity is present the implications of the standard discrete choice model and the random coefficient model are the same. Tests based on bootstrapped confidence intervals reject the hypothesis that labor supply elasticities derived from both specifications differ significantly. Therefore, for computational reasons, standard discrete choice models that are more restrictive in their assumptions regarding error variances, seem to represent the adequate model choice for the analysis of labor supply functions on basis of the GSOEP.

The paper is organized as follows. In a theoretical part I derive the conditional logit model and discuss its limitations. Hereafter, a model is presented that circumvents these limitations: the random coefficient model. In the following, I develop a discrete choice labor supply model that is estimated applying specifications with and without random effects. Considering statistical tests, I draw conclusions in the last section.

2. Theory

The purpose of this section is to present the conditional logit model and to discuss its limitations. Furthermore, I provide an overview of more flexible discrete choice specifications that have been developed to circumvent theses limitations. In particular, I focus on the random coefficient model.[1]

2.1 Conditional logit model

Discrete choice models are based on the assumption of utility maximizing behavior of individuals. An individual i chooses among J alternatives that provide different levels of utility. The utility function consists of an observable part V_{ij} and random elements ε_{ij}:

[1] In this section I mainly draw on Kenneth Train`s textbook, Discrete Choice Methods with Simulation (2003).

(1) $U_{ij} = V_{ij} + \varepsilon_{ij}$.

The probability that individual i chooses alternative k is:

(2) $$\Pr_{ik} = \Pr(U_{ik} > U_{im}; \forall m \neq k)$$
$$= \Pr(V_{ik} + \varepsilon_{ik} > V_{im} + \varepsilon_{im}; \forall m \neq k) .$$

In order to derive an operational model the crucial question is how to treat the unknown part of the utility function. Drawing on Luce (1959), McFadden (1973) showed that if (and only if) each ε_{it} is independently and identically distributed (iid) with type I extreme value (Gumble) distribution $F(\varepsilon_{ij}) = \exp\left(-e^{-\varepsilon_{ij}}\right)$, with fixed variance $\frac{\pi^2}{6}$,[2] the logit choice probability can be derived:[3]

(3) $$\Pr_{ik} = \frac{\exp(V_{ik})}{\sum_{j=1}^{J} \exp(V_{ij})}, k \in J .$$

Assuming that the observed part of the utility function is specified to be linear in parameters, $V_{ij} = X'_{ij}\beta$, the logit probability becomes:

(4) $$\Pr_{ik} = \frac{\exp\left(X'_{ik}\, \beta\right)}{\sum_{j=1}^{J} \exp\left(X'_{ij}\, \beta\right)}, k \in J ,$$

where vector X_{ij} captures K observable variables of individual i in alternative j and vector β is a vector of K coefficients.

In econometric literature conditional logit models are often employed and their desirable properties are discussed in the standard textbooks (e.g. Greene 2003). Therefore, I directly turn to the problems and shortcomings resulting from the restrictive assumption that the error terms are iid with a homogenous variance. Train (2003) names three main limitations of conditional logit, those being repeated choices over time, taste variation, and most prominent, substitution patterns. I focus on the latter two in detail.

Individual taste can be captured in conditional logit models as long as it varies systematically with respect to observed variables. However, if systematic taste variation is unob-

[2] The mean of the extreme value distribution is not zero; yet, the mean is not important since only differences in utility matter and the difference between two random terms that have the same mean has itself a mean of zero. Using the extreme value distribution for the errors is very similar to the assumption of an independent normal distribution of the error terms. In fact, empirically the difference is usually indistinguishable (Train 2003: 39).
[3] For the mathematical proof see McFadden (1973).

served it introduces a random element μ_i in the error term of the above defined utility function (1). Since μ_i is not observable, it becomes part of the error term of the utility function $\varepsilon_{ij}^* = \varepsilon_{ij} + \mu_i$. Therefore, the utility function changes in the following way:

$$(5) \qquad U_{ij} = V_{ij} + \varepsilon_{ij}^* \ .$$

If the unobservable taste variable μ_i correlates with alternatives the error term ε_{ij}^* is also correlated over alternatives. This implies that the required iid assumption does not hold anymore.

The best-known limitation of conditional logit models resulting from the iid assumption of the error terms is the property called independence of irrelevant alternatives (IIA). This restriction implies that the odds ratio of two alternatives, j and k, does not depend on other alternatives. Employing equation (3), it is straight foreward to demonstrate that the IIA property holds for the conditional logit model:

$$(6) \qquad \frac{\Pr_{ij}}{\Pr_{ik}} = \frac{e^{V_{ij}}}{\sum_{j=1}^{J} e^{V_{ij}}} \Big/ \frac{e^{V_{ik}}}{\sum_{j=1}^{J} e^{V_{ij}}} = \frac{e^{V_{ij}}}{e^{V_{ik}}} \ .$$

The relative odds of choosing alternative j over alternative k are the same, regardless which other alternatives are available. The IIA property occurs since by assumption any correlation of the error terms over alternatives are excluded. Train (2003) points out that if the model is correctly specified, in the sense that the unobserved portion of utility is random, the IIA property can be seen as an ideal rather than a restriction for providing a good representation of reality. In fact, Luce (1959) developed the discrete choice model starting from the IIA axiom on the choice probabilities. However, in many applications the IIA property is certainly not appropriate (e.g. Berry 1994). Considering a discrete choice labor supply model where individuals have the choice of working zero hours, half time or full time, the restriction becomes obvious. IIA implies that when introducing a new alternative, e.g. overtime, the odds ratios of the other alternatives have to remain constant. This would only be the case if the same proportion of individuals in each alternative decides to choose the overtime alternative.

2.2 Random Coefficient Model

In recent years several more general discrete choice models have been developed that relax the iid assumption and circumvent the limitations of conditional logit. Examples are generalized extreme value models, probit discrete choice models and the random coefficient model (Train 2003). The random coefficient model is the most general specification of discrete choice (Greene 2003). Therefore, I focus on this model. The basis for the random coefficient model is the following utility function:

(7) $U_{ij} = X'_{ij}\beta_i + \varepsilon_{ij}$.

Again, the vector of observable variables that vary over the alternatives is denoted by X_{ij} and the error term ε_{ij} follows an iid extreme value distribution. The difference between the conditional logit model and the random coefficient model is captured in the vector of coefficient β_i. This difference becomes obvious when decomposing β_i into a fixed and a random part:

(8) $\beta_i = \beta + \mu_{i,} \mu_i \sim (0, W)$.

The random part μ_i captures non-observable individual effects, such as taste, which is distributed with mean zero and variance-covariance matrix W. If the variance of μ_i turns out to be zero, the random coefficient specification becomes standard logit. In other words, rather than being fixed the coefficients vary over the individuals in the population with density $f(\beta_i|\beta,W)$, which is described by its mean (β) and variance (W). The researcher cannot observe and estimate β_i but knows its distribution $f(\beta_i|\beta,W)$. Hence, the parameters to be estimated in the random coefficient model are mean β, which is the fixed part of β, and the variance-covariance W, which describes the distribution of the random part μ_i. In the random coefficient specification, the probability to choose alternative k is the integral over all possible values of β_i:

(9) $$P_{ik} = \int \left(\frac{\exp(X'_{ik}\beta_i)}{\sum_{j=1}^{J}\exp(X'_{ij}\beta_i)}\right) f(\beta_i) d\beta_i, k \in J$$.

This probability is a weighted average of the logit formula evaluated at different values of β_i, with weights given by the density $f(\beta_i)$. Therefore, the random coefficient model is often referred to as mixed logit model (Train 2003). When applying the random coefficient model to data, the researcher has to specify the distribution of the coefficients $f(\beta_i)$, e.g. a normal distribution $\beta_i \sim N(\beta, W)$. [4] In order to get a better understanding of the intuition behind the random coefficient model, a simple example is helpful. Assume that vector β_i consists of a single random variable that is described by a known density $f(\beta_i|\beta,W)$. Following, for every possible value of β_i the probability is calculated that individual i chooses alternative j. The density

[4] In most applications, discussed in Train (2003) the density of the coefficient vector has been specified to be normal or lognormal. Heckman and Singer (1984) have developed a more flexible approach that allows for unobservable heterogeneity. They suggest a non-parametric method, which does not rely on a restrictive distribution assumption.

$f(\beta_i|\beta,W)$ determines the weight of each calculated probability in the overall likelihood function.

The limitations of conditional logit do not occur under this more flexible specification. Individual taste variation is now captured in the variance W of the coefficient. The IIA property does not hold anymore, as the denominator of the choice probability $\sum_{j=1}^{J}\exp(X'_{ij}\beta_i)$ is inside the integral and does not cancel. Hence, the random coefficient model provides unbiased estimates even if unobserved heterogeneity is present in the data.

When comparing specifications with and without random coefficients it remains an empirical question whether the implications, e.g., labor supply elasticties, of the unbiased specification are significantly different from those, derived from the biased results of the conditional logit model. If the differences are not significant, the conditional logit estimator is the more favorable approach as the flexibility of the random coefficient model causes very high computational costs. Considering equation (9) this becomes evident since for each random coefficient an integral has to be calculated. As the number of random coefficients increases, the likelihood function has no longer a closed form solution. Econometric and statistic literature has suggested several simulation and numerical integration techniques to deal with this problem. The choice probabilities have been estimated by using Monte Carlo simulation techniques to approximate the integrals, and then by maximizing the resulting simulated log-likelihood function. According to Bronstein and Train (1999) approximately 250 draws are necessary in order to get unbiased results.[5] A more efficient simulation method has been derived by Train (1999). He suggests using draws from a Halton sequence rather than random draws. This method is superior to the Monte Carlo simulation as the error terms of the simulation decrease at a higher speed (Train 2003). Numerical integration techniques are another possibility to solve multiple integrals. Rabe-Hesketh et al. (2002) employ numerical integration by adaptive Gauss-Hermite quadrature. The authors demonstrated that this method is computationally more efficient than Monte Carlo simulation techniques or ordinary numerical integration. Although these routines reduce the computational cost of flexible discrete choice models significantly, it remains cumbersome and very time consuming to employ these esti-

[5] Halton sequences are created by dividing a unit interval into N even parts. The N-1 dividing points become the first elements in the Halton sequence. Each of the N portions of the unit interval are divided again in N parts, and so on. Hence, Halton sequences provide an even distribution of points across the unit interval (Train 1999).

mation techniques. This constraint makes the estimation of confidences intervals of marginal effects or elasticities impractical.[6]

3. Discrete Choice Labor Supply

In this section I develop a discrete choice labor supply model that serves as basis for estimations of the above-described discrete choice specifications. Estimating labor supply using a discrete rather than a continuous specification has several advantages. A discrete choice approach takes into account the fact that hours of work are heavily concentrated at particular hours, such as zero hours, half time or full time. Furthermore, the specification of hours categories reduces measurement errors in the number of hours actually worked. The main advantage of the discrete choice approach compared to continuous specifications derives from the possibility to model nonlinearities in budget functions (e.g. Duncan and MacCrae 1999).

In my application, I focus on a household labor supply function where both spouses jointly maximize a utility function. The household's labor supply decision is modeled by a utility function, which is assumed to depend on the leisure time of the male (L_m) and the female (L_f) spouse as well as on real net household income (Y). Following van Soest (1995), I assume that a household's utility U_i in alternative j, can be described by the following translog function:

$$(10) \qquad U_{ij}(x_{ij}) = x'_{ij}Ax_{ij} + \beta' x_{ij} + \varepsilon_{ij},$$

where $x = (y, l_m, l_f)'$. The components of x are the (natural) logs of net household income, leisure of the husband and the wife, respectively. These components enter the utility function (10) with linear, quadratic and cross terms between the spouses' leisure terms and household income. The matrix A, with elements α_{mn}, m,n = (1, 2, 3), contains the coefficients referring to the non-linear terms, the vector β_k, k = (1, 2, 3), the corresponding coefficients of the linear terms. ε_{ij} is a stochastic error term accounting for unobservable factors that affect the household's utility. As demonstrated above, if the error terms follow an iid extreme value distribu-

[6] As an example, in the following empirical application of the random coefficient model the estimation of the simplest specification (only one coefficient is assumed to vary randomly) takes approximately 6 hours employing a standard computer. Hence, the estimation of confidence intervals using the bootstrap with 100 random draws would last for more than 3 weeks. Additional random coefficients increase the computing time exponentially.

tion, the probability that household i chooses alternative k can be described by a conditional logit model:

$$(11) \qquad P_{ik} = \frac{\exp\left(x'_{ik} A x_{ik} + \beta' x_{ik}\right)}{\sum_{j=1}^{j} \exp\left(x'_{ij} A x_{ij} + \beta' x_{ij}\right)}, \text{ k} \in J \quad .$$

When assuming all coefficients to be random, this probability becomes:

$$(12) \qquad \text{P}_{ik} = \int_{-\infty}^{\infty} \left(\frac{\exp\left(x'_{ik} A_i x_{ik} + \beta_i' x_{ik}\right)}{\sum_{j=1}^{j} \exp\left(x'_{ij} A_i x_{ij} + \beta_i' x_{ij}\right)}\right) f(\beta_i) f(A_i) d\beta_i dA_i \quad .$$

Drawing on previous studies on household labor supply based on the GSOEP[7] that employ a discrete choice approach (Steiner and Wrohlich 2003), I specify 13 alternatives of working hours, among which households have the choice. The definition of the hours' categories is motivated by both economic considerations and the actual distribution of hours in the sample.

[Table I]

Because of the small number of men in part-time employment in the sample, only three categories could be specified for them, namely: non-employment (unemployment and non-participation in the labor force), 1-40 hours, and more than 40 hours (overtime). Table 1 shows that about a third (34.2%) of all wives living in couple households do not work, 40.2 % work part-time (defined as working less than 35 hours a week), and less than a third (25.6%) work more than 35 hours a week, i.e. full-time. About 10% of all husbands in household have no work. At the same time, approximately a third (32.3%) of all husbands work overtime (more than 40 hours). In only 2.3 % of all couple households both spouses work overtime.

To generate net incomes I use a microsimulation model for Germany, which is based on data of the GSOEP.[8] The microsimulation model calculates tax amounts and benefit enti-

[7] A description of the GSOEP can be downloaded from www.diw.de/soep; see also Haisken-DeNew and Frick (2001).
[8] Buslei and Steiner (1999) provide a detailed overview of the microsimulation model.

tlements and simulates the household net income at each defined alternative of working hours. For workers, I use their observed wage. For non-workers, wages are estimated controlling for selection bias (Blundell and MaCurdy 1999). Leisure time of both spouses is calculated by subtracting the weekly working hours in each category from the total time, which is assumed to amount to 80 hours per week. Household specific variables that are constant over alternatives are taken from the GSOEP as well. I focus only on married couples with both spouses having a flexible labor supply. That implies all couples are excluded in which either spouse is a civil servant, self-employed, student, on maternity leave, or retired. Only persons between 20 and 65 years of age are considered. After dropping observations due to missing variables, 2812 households remain. The year of analysis is 2001.

4. Estimation

The question that is addressed in the empirical part is whether the theoretical differences between the random and the fixed specification matter when applying these models to data. In other words, I test whether the implications of the models with and without random coefficients differ significantly. As mentioned above, I focus on tow criterions: differences in the estimators and differences in the labor supply elasticites.

Standard conditional logit estimation of the above derived labor supply model serves as the benchmark specification. In addition to the variables that depend on alternatives, income and both spouses' leisure, I introduce interaction terms between these variables and household specific characteristics, such as age, number of children, nationality, disability and region. By defining dummy variables for the alternatives, in which women work part time, I take account for the lack of available part time jobs. This procedure has been suggested by van Soest (1995) to control for hours restrictions.

[Table 2]

The results are presented in the first column of table 2. Regarding the significance of the estimated coefficients, the model is well specified. In a discrete choice specification, it is difficult to interpret the estimated coefficients, because in a non-linear setting the coefficients are not directly tied to the marginal effects. The impact of continuous variables on the household's utility can be obtained by differentiating equation (10). As for 95% of the sample the first derivative with respect to income and both leisure terms is positive while the second is negative, the theoretical assumption of a concave utility function holds. The quantitative implications of the labor supply model can best be described by deriving hours and participation elasticities with respect to given percentage change in the gross wage rate. Although a closed-form expression of elasticities is not available for the utility function estimated here, elasticities can be calculated from the simulated change in estimated hours and participation rates to an exogenous change in the gross wage rate. At given gross wages, the expected number of hours worked as well as the labor force participation rate can be calculated for each sample observation. Comparing these values to the simulated hours and participation rates resulting from a given percentage change in gross wages yields hours and participation elasticities. It is important to stress that these elasticities have to be interpreted carefully. First of all, they are not directly comparable to elasticities of previous studies derived from continuous specifications of labor supply. Furthermore, gross wage enters the utility function only indirectly via the net income. Because a one percentage increase in the gross wage of women has on average a lower impact on the household income than a one percentage increase of male`s gross wage the calculated elasticities are on a different scale for both sexes. In table 2, I summarize different elasticity estimates for various population groups resulting from a one percentage increase in either the wife's or the husband's gross wage.

[Table 3]

Overall, estimated own wage elasticities are rather small: measured by hours worked a 1% wage increase raises labor supply by about 0.3% for wives and by about 0.2% for husbands. Estimated elasticities for men and women living in West Germany are markedly larger than for East German women. These regional differences could be related to the greater importance of demand-side restrictions on labor supply as a result of the still very depressed situation on the labor market in East Germany. However, it could also be related to a different preference structure of East Germans due to their previous work experience in the GDR, or to institutional differences. Similar differences are also observed with respect to participation elasticities. Cross-wage elasticities between wives and husbands are negligible in both regions and for all household groups considered here. This holds for hours worked as well as for labor force participation rates.

When employing a random coefficient model, the crucial question is which parameters to assume to be random. In my analysis, I employ specifications of previous studies estimating labor supply with a random coefficient model. I define the most flexible model, with random coefficients in the linear terms of income (β_y) and both leisure terms (β_{lf}, β_{lf}). This approach has been employed by Duncan and MacCrae (1999).[9] In this specification, the choice probability (12) has the following form:

$$(13) \qquad P_{ik} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\frac{\exp\left(x'_k A x_k + \beta' x_k\right)}{\sum_{j=1}^{j} \exp\left(x'_j A x_j + \beta' x_j\right)} \right) f(\beta_Y) f(\beta_{lf}) f(\beta_{lm}) d\beta_Y d\beta_{lf} d\beta_{lm} .$$

Van Soest (1995) extended the conditional logit model by assuming both leisure terms (β_{lf}, β_{lm}) to vary between individuals. By contrast, in an analysis of Leu and Gerfin (2003), only the income parameter (β_y) is assumed to be random. Drawing on that, I estimate three different random coefficient models: Model I with the leisure terms being random (β_{lf}, β_{lm}), model II where only β_y is random, and model III with the most flexible specification (β_{lf}, β_{lf}, β_y). The estimations are performed using the routine gllamm (Generalized linear latent and mixed models) that has been developed by Rabe-Hesketh et al. (2001). [10]

The estimation results are presented in the columns 2-4 in Table 2. Considering the derivations with respect to income and both leisure term, again, the assumption of concavity in the utility function holds for 95% of the households in all three specification. The estimation results of the most flexible specification, model III, suggest that unobserved heterogeneity is present in the model. First of all, estimates of the (co)-variances of all random parameters are significant. Furthermore, the Akaike Information Criterion (AIC) indicates that the random specification of model III is superior to the specification of the standard logit model.[11] That implies that the variances of the error terms are not constant, and thus the IIA assumption in the standard logit model is violated. This implication is supported by a test proposed by Hausman and McFadden (Greene 2003), as the hypothesis of the validity of the independ-

[9] In general, in the most flexible specification all coefficients should be varying randomly. However, as the previous studies indicate (e.g. Duncan and MacCrae 1999) it is reasonable to assume only the linear terms to be random.
[10] More information about gllamm can be obtained at www.gllamm.org. I would like to thank Sophia Rabe-Hesketh for helping me using gllamm.
[11] The model with the smallest AIC is the preferred, as AIC= -2(lnL/T)+2(k/T).

ence assumption is rejected.[12] The AIC for model I and model II exceeds the criterion of model III. Following, within the random coefficient models, the specification of model III is the preferred.

These results suggest that unobserved heterogeneity is existent in the discrete choice models of labor supply estimated here. Thus, conditional logit leads to biased estimators. However, as mentioned above, this criterion is not sufficient to reject the conditional logit model. The question remains whether accounting for heterogeneity changes the quantitative implications of the estimation significantly. Therefore, I turn to the labor supply elasticities.[13] Using the above-described method, I simulate elasticities for the models with random effects. The idea is to test whether the elasticities of the specifications with and with out random effects differ significantly. Significant difference is rejected if the elasticities derived from the random coefficient estimation lie within the 95% confidence interval of the elasticities derived from the standard logit model.

[Table 4]

In parentheses I present the bootstrapped confidence intervals of the elasticities derived from the standard logit model (table 3). It becomes obvious that the implications of all random specifications do not differ significantly from those derived from the conditional logit model. All simulated elasticities are within the 95% confidence interval of the standard logit estimation. This holds even for model III where unobservable heterogeneity is present in all three coefficients.

5. Conclusion

It was the purpose of my analysis to discuss the theoretical and empirical differences between discrete choice models with and without random effects, namely the conditional logit model and the random coefficient model. From a theoretical perspective the differences are obvious. Due to less restrictive assumptions in the distribution of the error terms, the random coefficient model circumvents the limitations of conditional logit such as the IIA property and provides unbiased estimates even if unobserved heterogeneity is present in the data. However, as

[12] The test is rejected as the test statistic ($\chi^2(33)=668.89$) exceeds the critical value of the chi-squared distribution.
[13] Since cross elasticities are negligible (table 3), I focus only on own wage elasticities.

simulation or numerical integration is required to estimate the more flexible models, they have very high computational costs.

Therefore, when applying these models to data the key question is which discrete choice specification is more adequate: the standard logit model or the random coefficient model. The Akaike Criterion and (co)variance parameters of random effects provide evidence that effect heterogeneity is present in the data. However, when turning to labor supply elasticities derived from fixed and random specifications, the implications of the models do not differ significantly.

That leads to the conclusion that the standard discrete choice model, attractive for its simple structure, provides an adequate model choice for the analysis of labor supply functions based on the GSOEP.

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Table 1: Distribution of households across hours categories

Hours		Men: 0		Men: 1 – 40		Men: > 40	
Women	0	160	(5.7)	471	(16.8)	328	(11.7)
	1 – 15	78	(2.8)	253	(9.0)	129	(4.6)
	16 – 34			436	(15.5)	233	(8.3)
	35 – 40	85	(3.0)	357	(12.7)	152	(5.4)
	> 40			66	(2.4)	64	(2.3)

Notes: The first number refers to the absolute frequency in the sample, (in parentheses) relative frequency in percent.

Table 2: Estimation results

	CLOGIT		MODEL I		MODEL II		MODEL III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
income	-8,571	4,399	-10,629	5,144	-8,571	4,406	4,609	7,246
$income^2$	1,240	0,256	1,427	0,309	1,240	0,256	0,718	0,423
income*lm	-0,963	0,314	-1,006	0,366	-0,963	0,314	-1,325	0,417
income*lf	-0,602	0,322	-0,655	0,336	-0,602	0,322	-1,111	0,378
lm	59,224	5,509	72,439	10,934	59,224	5,511	74,102	9,267
lm^2	-4,379	0,334	-5,399	0,885	-4,379	0,334	-5,188	0,611
lf	82,239	6,498	87,069	7,797	82,239	6,496	93,197	8,497
lf^2	-7,154	0,543	-7,271	0,585	-7,154	0,543	-7,431	0,628
lf*lm	-1,986	0,431	-2,707	0,659	-1,986	0,432	-2,772	0,648
income*ger	7,896	3,376	-1,282	0,438	-1,072	0,341	-1,208	0,414
$income^2$*ger	-0,590	0,256	-0,262	0,383	-0,218	0,358	-0,289	0,398
lm*ger	-1,072	0,341	-0,109	0,145	-0,102	0,127	0,013	0,157
lf*ger	-0,218	0,358	9,476	3,963	7,896	3,382	7,984	5,632
lm*lf*ger	-0,102	0,127	-0,699	0,296	-0,590	0,256	-0,549	0,402
lm*east	-11,517	2,378	-11,909	2,461	-11,517	2,378	-11,463	2,628
lf*east	-13,334	2,219	-13,666	2,298	-13,334	2,219	-13,295	2,448
lm*lf*east	2,646	0,584	2,689	0,606	2,646	0,584	2,505	0,643
income*east	4,095	1,714	4,265	1,954	4,095	1,714	4,003	2,260
$income^2$*east	-0,365	0,138	-0,390	0,155	-0,365	0,138	-0,399	0,178
lm*age	-0,396	0,070	-0,497	0,105	-0,396	0,070	-0,494	0,098
lm*age^2	0,518	0,076	0,643	0,122	0,518	0,076	0,638	0,111
lf*age	-0,616	0,090	-0,647	0,096	-0,616	0,090	-0,677	0,104
lf*age^2	0,843	0,105	0,885	0,113	0,843	0,105	0,922	0,124
lm*disabled	2,100	0,484	2,501	0,661	2,100	0,484	2,526	0,640
lf*disabled	2,830	0,791	2,837	0,808	2,830	0,791	3,126	0,889
lz*child6	4,215	0,269	4,276	0,283	4,215	0,269	4,472	0,311
lz*child16	2,136	0,191	2,145	0,200	2,136	0,191	2,198	0,214
lz*child17	0,512	0,187	0,521	0,191	0,512	0,187	0,539	0,202
d2	-1,051	0,146	-1,042	0,147	-1,051	0,146	-0,937	0,151
d11	-0,982	0,081	-0,988	0,081	-0,982	0,081	-1,032	0,083
d12	-0,492	0,087	-0,495	0,087	-0,492	0,087	-0,558	0,088
d16	-1,208	0,105	-1,212	0,105	-1,208	0,105	-1,225	0,106
d17	-0,551	0,102	-0,551	0,102	-0,551	0,102	-0,516	0,103
Var(income)	-	-	-	-	2,123	0,803	32,583	6,848
Var(lf)	-	-	0,337	0,466	-	-	9,420	2,579
Var(lm)	-	-	2,546	2,215	-	-	14,834	3,931
Cov(lm, lf)	-	-	0,927	0,720	-	-	11,812	2,868
Cov(lm, income)	-	-	-	-	-	-	21,520	4,605
Cov(y, lf)	-	-	-	-	-	-	17,274	3,969
Log-Likelihhod	-6044,168		-6042,357		-6038,694		-6014,7904	
Akaike Criterion	4,3230		4,3238		4,3186		4,30639	

Explanation:

Income (net monthly household income) and the male and female leisure terms (lm, lf) are in logarithms. East and ger are dummy variables indicating whether households live in East-Germany and are German citizens. Dummy variables d2-d17 =1 if one spouse if working part time. The sample consists of 2812 observations drawn from the GSOEP.

Table 3: Estimated labor supply elasticities for married spouses – Conditional Logit Model

	Male gross hourly wage +1%		*Female gross hourly wage* +1%	
	Men	Women	Men	Women
	Change in participation rates (in percentage points)			
All married couples	0.14	-0.01	0.01	0.13
	(0.11 – 0.17)	*(-0.03 – 0.02)*	*(0.00 – 0.02)*	*(0.11 – 0.15)*
West, all	0.15	-0.02	0.00	0.15
	(0.13 – 0.18)	*(-0.04 – 0.01)*	*(0.00 – 0.01)*	*(0.12 – 0.17)*
East, all	0.09	0.03	0.02	0.07
	(0.04 – 0.14)	*(0.01 – 0.05)*	*(0.01 – 0.04)*	*(0.03 – 0.10)*
	Change in hours (in percent)			
All married couples	0.22	-0.05	0.01	0.34
	(0.18 – 0.26)	*(-0.11 – 0.01)*	*(0.00 – 0.03)*	*(0.28 – 0.40)*
West, all	0.24	-0.08	0.004	0.39
	(0.20 – 0.27)	*(-0.15 – 0.01)*	*(0.00 – 0.02)*	*(0.33 – 0.46)*
East, all	0.14	0.04	0.03	0.16
	(0,07 – 0,21)	*(0.00 – 0.08)*	*(0.01 – 0.06)*	*(0.07 – 0.25)*

(Numbers in parentheses are 95% bootstrap-confidence intervals (percentile method) based on 1,000 replications)

Table 4: Estimated labor supply elasticities for married spouses – Random Specifications

	Male gross hourly wage +1%			*Female gross hourly wage* +1%		
		Men			Women	
	Model I	Model II	Model III	Model I	Model II	Model III
	Change in participation rates (in percentage points)					
All married couples	0.12	0.13	0,13	0.13	0.13	0.14
		(0.11 – 0.17)			*(0.11 – 0.15)*	
West, all	0.13	0.14	0,13	0.16	0.15	0.17
		(0.13 – 0.18)			*(0.12 – 0.17)*	
East, all	0.07	0.09	0,1	0.06	0.07	0.07
		(0.04 – 0.14)			*(0.03 – 0.10)*	
	Change in hours (in percent)					
All married couples	0.18	0.20	0,19	0.36	0.34	0.40
		(0.18 – 0.26)			*(0.28 – 0.40)*	
West, all	0.20	0.22	0,21	0.42	0.39	0.46
		(0.20 – 0.27)			*(0.33 – 0.46)*	
East, all	0.10	0.13	0,15	0.16	0.16	0.19
		(0,07 – 0,21)			*(0.07 – 0.25)*	

(Numbers in parentheses are 95% bootstrap-confidence intervals (percentile method) based on 1,000 replications, which are derived from the conditional logit estimation).