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Alternative Interpretations of Hours Information in an Econometric Model of Labour Supply

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Alternative Interpretations of Hours Information in an Econometric Model of Labour Supply

by

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Abstract

This paper examines the labour supply behaviour of married women in France. Estimating a model with tax parameter variation, careful re-examination of the treatment of the unearned income variable and taking account of education in modelling preferences result in substantially lower elasticities than found in our previous empirical analysis. It turns out that distinguishing between part-time, full-time and long hours gives virtually the same results as treating observed hours as reflecting desired hours. We provide extensive specification diagnostics, including Heckman-Andrews tests, as well as Hausman tests for the comparison of different handlings of the hours information. We also consider different assumptions concerning the perception of the impact of the tax system and provide some evidence in favour of a correct perception.

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1 Introduction

The extent to which observed working hours reflect individual decisions may be important for the reliability of econometric models of labour supply behaviour. Indeed, there has been an increasing awareness of the need to allow for constraints in empirical labour supply models see, among others, Ham (1982, 1986) and Ilmakunnas and Pudney (1989). Where there are also a significant number of individuals who are observed not to participate in the labour market, as is the case for the sample of married women used in this study, a careful treatment of the relationship between desired hours of work and non-participation would seem critical. In particular it is natural to draw a distinction between those individuals who are out of work but actively seeking employment from those who are not involved in active job search (see for example Flinn and Heckman, 1983).

The hours of work of married women in France seem potentially sensitive to these issues as there appears significant bunching of hours at particular points which do not appear to necessarily reflect labour supply preferences. The studies of Bourguignon and Magnac (1990), Blundell and Laisney (1988) and Dagsvik et al. (1988) document these issues while dealing with taxes. Moreover, the latter two studies, using the same subsample of the INSEE survey Budgets des Familles 1979, but rather different behavioural models, find high uncompensated wage elasticities which may be considered unrealistic on a priori grounds. Using the same survey as an illustration, this paper examines the robustness of these results to alternative interpretations of observed hours information.

The next two subsections present the relevant basic ideas and the alternative interpretations of hours information studied here. Section 2 briefly discusses the model specification and the data, and section 3 presents and interprets the estimation results. Section 4 gives the results of the tests. We conclude with directions for future work. Appendix A gives descriptive statistics and some preliminary estimation results. Details on the algebra of the tests are collected in Appendix B.

1.1 A Modelling Framework

We start from an economic model for *desired* hours:

$$h^* = h^*(w, x, z) + \epsilon, \tag{1}$$

where w denotes the net marginal wage rate, x denotes net *full* income and z a vector of household characteristics. The randomness of preferences is assumed to result in the additive error term ϵ. By contrast, the data set we have contains no information on desired hours, but only information on reported *normal* hours of work and, for those reporting zero hours, a distinction is drawn between the individuals presently seeking work (henceforth *seekers*) and the others.

Two distinct sets of questions arise: (i) How should we treat the seekers? As participants? (This is closest to the ILO definition of participation). As non-participants? (This is implicitly assumed in studies where job search information is either not available or ignored). Should they simply be excluded? (This may cause selection bias). (ii) Are the reported normal hours of work for each individual on her supply curve (desired hours)? If not, how are they to be related to desired hours of work? Both sets of questions involve a discussion of demand side conditions and their variation over time. Failure to address them satisfactorily may result in the misspecification of the preference structure.

In the following analysis, we treat the seekers as desiring to supply a positive, but unspecified, number of hours. The possibility for some non seeking non-participants to be in fact *discouraged workers* (see Blundell, Ham and Meghir, 1990) will not be considered. This is equivalent to assuming to assuming negligible search costs. We retain the framework introduced by Blundell and Laisney (1988) of grouping the hours information, and place particular emphasis on the implications of different degrees of grouping. The models considered range from an extended Probit model in which the standard Probit model is extended to account for job-seekers among those not in employment. In this specification participation information alone is utilised. At the other extreme is the extended Tobit model where reported hours are assumed to coincide with desired hours. The grouping model lies in this range and assumes hours of work provide only limited information on desired hours. In fact, given that hours are recorded as integers, there remains some degree of grouping even in the Tobit model, which must be considered as an approximation. However, a look at the distribution of reported hours in our sample, pictured in Figure A1, shows that the Tobit specification does not seem a priori attractive.

1.2 Sample Likelihoods under Different Hours Information

We partition the hours range in intervals I_k, $k = 0, .., K$ and the set of individuals in index sets J_k, $k = 0, .., K$ defined through:

$$i \in J_k \Leftrightarrow h_i \in I_k, \tag{2}$$

where h_i denotes the hours reported by individual i. The set S of seekers is a subset of J_0 and our assumptions are as follows:

$$i \notin S \Rightarrow (h_i^* \in I_k \Leftrightarrow h_i \in I_k), \tag{3}$$

$$i \in S \Rightarrow (h_i \in \bar{I}_0),$$

where an overbar indicates the complement.

The sequence of models we consider are distinguished by the increasing amount of information on hours of work that is exploited in the sample likelihood. The simplest model, termed *Extended Probit,* has the following sample likelihood:

$$L_p^* = \prod_{i \in J_0 - S} P[h_i^* \in I_0] \prod_{i \in S} P[h_i^* \in \bar{I}_0 \wedge i \notin E] \prod_{i \in \bar{J}_0} P[h_i^* \in \bar{I}_0 \wedge i \in E], \quad (4)$$

where E denotes the event of finding a job available when searching. Assuming independence between this event and h^* conditional on the observed regressors, the probabilities $P[i \in E]$ and $1 - P[i \in E]$ will factor out. Indeed, given the absence of parameter restrictions, maximization of (4) will be equivalent to maximization of:

$$L_p = \prod_{i \in J_0 - S} P[h_i^* \in I_0] \prod_{i \in S} P[h_i^* \in \bar{I}_0] \prod_{i \in \bar{J}_0} P[h_i^* \in \bar{I}_0]. \quad (4')$$

Although one could advance a number of reasons casting doubt on the independence assumption, it was tested in the study of Blundell et al. (1987) and was not rejected.

Considering a grouping of hours in K groups leads to the *Extended Grouped* specification which has the sample likelihood:

$$L_g = \prod_{i \in J_0 - S} P[h_i^* \in I_0] \prod_{i \in S} P[h_i^* \in \bar{I}_0] \prod_{k=1}^{K} \prod_{i \in J_k} P[h_i^* \in I_k]. \quad (5)$$

Finally, taking reported hours as desired hours while taking account of the seekers results in the *Extended Tobit* model with sample likelihood:

$$L_t = \prod_{i \in J_0 - S} P[h_i^* \in I_0] \prod_{i \in S} P[h_i^* \in \bar{I}_0] \prod_{i \in \bar{J}_0} f(h_i^*), \quad (6)$$

where f denotes the density of desired hours implied by (1).

1.3 Diagnostic Tests

The first set of diagnostics we consider are versions of Lagrange Multiplier tests suggested by White (1982), and are based on the theory of pseudo maximum likelihood. In the Monte-Carlo results reported in Lechner (1991) the corresponding quasi-Lagrange-multiplier (QLM) version was found to have superior small sample properties in comparison with the standard LM test. Furthermore, the estimator of the asymptotic covariance matrix used is consistent in cases where the ML estimator of the vector of coefficients is consistent, yet not asymptotically efficient. This is important in the present situation since we use non-efficient two-step procedures in estimation. The specific formulas for the grouped, Probit and Tobit models used in this paper are obtained through slight modifications of those given by Chesher and Irish (1987) and are provided in Appendix B.

To test for the appropriate degree of hours grouping we employ a sequence of Hausman-Wu tests in which the potential efficiency gains from an increase in the amount of information on hours used in estimation is compared with the likely inconsistency resulting from hours constraints. The idea of the tests conducted is that for two nested groupings, if the assumptions (3) are valid for both, the estimates obtained with the finer grouping will be more efficient than those obtained with the coarser one, whereas they will become inconsistent for the first one if (3) is valid for the second one only.

Finally, we present results of misspecification tests based on the Heckman-Andrews principle (see Andrews, 1988a,b), which is a generalisation of the classical Pearson χ^2 statistic. This test seems to be particularly attractive in our context, since the necessary grouping of endogenous and exogenous variables is naturally suggested by the different models used.

2 Empirical Analysis

2.1 The model specification

The general form of our labour supply model for hours of work h can be written

$$h = \alpha_0 + \alpha_1 \frac{1}{w} + \alpha_2 \frac{m}{w} \tag{7}$$

where w is the net real marginal wage and m , a measure of (real) virtual income that will be discussed below, is constructed using the budget identity $m = e - wh$ in which e is total expenditure (measured directly in the Budgets des Familles) and w is the marginal wage as in (7). Although we did not attempt to correct for the discrepancy between real expenditure and consumption due to infrequency of purchase (as in Kay et al., 1984), we do allow for measurement error and/or endogeneity of m during estimation by the use of instrumental variables (see Keen, 1986).

The attraction of using (7) is twofold. First, it is a simple "three parameter" model but unlike the linear labour supply model it allows Slutsky consistency while permitting negative sloping labour supply behaviour (see Stern, 1986). Second, using our definition of m as in (8) it is life-cycle consistent as defined in Blundell and Walker (1986). A simple rearrangement of (7) generates the following Stone-Geary earnings equation.

$$wh = w\gamma - \beta[x - a(w, p)], \tag{8}$$

with x the *virtual full income* given by $x = e + w(T - h) = m + wT$, where T is the total time available and $a(w, p) = w(T - \gamma) + d$, where d represents the minimum expenditure on goods at prices p. The corresponding labour supply equation is:

$$h = \gamma(1 - \beta) + \beta\frac{d}{w} - \beta\frac{m}{w}. \qquad (9)$$

Note that d is identified from a simple participation Probit since it is computed as the ratio between the coefficients of $1/w$ and m/w and ratios of coefficients are not affected by the lack of identification of the scale parameter in the Probit model.

The budget line resulting from the French tax system is piecewise linear, with kinks at the ends of each of the tax brackets, at the points where the withdrawal of the means-tested child benefit begins and ends, and at the various ceilings for the social insurance contributions. However, for most women in the sample, visual inspection of the budget line reveals no striking deviation from linearity. See Appendix D. For more details on the way the French tax-benefit system is modelled here, see Dagsvik et al. (1988) and our 1988 study. Here the budget line is linearized around the observed point, using the budget identity as explained above. Since m can be suspected of endogeneity on several grounds, it has been instrumented.

As we shall see below, this model passes non-linearity checks, whereas, in spite of our apparently rudimentary treatment of the tax system, disregard of taxes leads to rejection of the linearity[1] of the earnings equation implied by equation (8) (see Appendix C).

While we allow γ and d to vary with demographics, for the purpose of this exercise we treat β as constant. Thus, two direct extensions of this work would consist in letting β vary (i) with demographics (ii) with $\ln w$ (see Blundell and Meghir, 1986). The latter has the advantage of allowing backward bending and forward sloping for a given m, which is not the case for (7) or (9). Note however that (9) does allow both positive and negative wage elasticities, varying directly with demographics through d. In particular, negative uncompensated wage elasticities are more likely to arise when m is small and consequently when hours are large. Simple separability tests are also available with specification (9) when estimating demand for goods equations (see Blundell, Laisney and Ruth, 1989). As we shall see, the results of diagnostics do not suggest a departure from the chosen functional form. The concavity of the cost function is ensured by the condition that $m + w\gamma > d$, which says that the maximum resources should cover the minimum expenditure and guarantees that desired hours will remain below the maximum number of hours available for work γ.

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1 This statement might confuse the reader, after our remark on the near-linearity of the budget constraint. Linearity here concerns the earnings equation implied by the preferences under the assumption of a linear budget restriction.

2.2 Data

Our sample consists of 3658 households. We exclude housing expenditure from total expenditure e since we may consider it to be fixed outside period specific labour supply and consumption choices. Regional unemployment is introduced in the wage equation instead of the tension indicator previously used (see Blundell and Laisney, 1988 and Dagsvik et al., 1988 for details). Indeed, in those earlier studies, we had chosen households facing the same tax parameters resulting in a smaller sample of only 1928 households. For estimation purposes, this may create some identification problems, as pointed out by Moffitt (1988), since both preferences and taxes depend on some demographics: using a sample with tax parameter variation may overcome that problem to some extent. Otherwise using the same selection rule, we have managed to almost double the sample size.

Table A1 in Appendix A gives the means of the variables relevant for equations (8) and (9) for five subsamples: the first three correspond to participants with positive hours falling in the three hours ranges used in estimation, and the last two correspond to seekers and non participants. The seekers represent 5.5% of the total sample (sampling weights have not been used in this study) and 11.4% of all participants. The participation rate is .480 if seekers are considered as participants and .425 if they are considered as non-participants. Note that the characteristics of the seekers do not lie between those of participants and non-participants: on average the seekers are younger, have more children at école maternelle, are less likely to own their housing and have higher predicted marginal wage rates. Their education level pattern is closer to that of participants supplying long hours than to non-seekers. It would be exaggerated to infer from this that they are *not really* searching for work, but it might be more appropriate to view these women as new entrants having spent some time outside the labour market. They probably differ from the standard view of prime aged men who have recently been layed-off.

3 Estimation Results

3.1 The Parameter Estimates

Table 1 shows maximum likelihood estimation results[2] for the extended Probit model (L_p), the extended grouped model (L_g), and the extended Tobit model (L_t). The grouping corresponds to the following partition of the hours range: long hours[3]: $h > 41.5$; full-time: $35.5 < h < 41.5$; part-time: $1.5 < h < 35.5$;

2 Obtained with a Newton-Raphson procedure based on the Hessian matrix for the Probit model and with the BHHH option of the Gauss procedure *maxlik* with analytical gradient and Hessian for the other models. In all cases the last step used Newton-Raphson and the covariance matrix estimate was obtained as combination of inverse of the Hessian and outer product of gradient.

3 We use the term "long hours" rather than "overtime" since the hours information concerns reported hours and long hours do not imply the payment of an overtime premium.

non participation: $h < 1.5$. (Hours are reported as integers on two digits, hence no individual will be observed on the boundary of an interval). The results for the latter two models are given in terms of scaled coefficients and precision for ease of comparison with the probit estimates.

Strictly speaking, the shape of the budget constraint should enter the calculation of the probability for desired hours of being in any given range. However, the examples of budget constraints presented in Appendix D show that approximating the budget constraint with its linearization at observed hours will not lead to gross mistakes with the data set we use.

The specification presented is the result of a descending specification search operated with the Probit model, the argument being that this yields consistent estimates. The age regressors are self-explanatory. The children variables are counts except for the category "other children" which is split in three dummies. The category "small children" groups children too young for école maternelle, whether they are kept at home or elsewhere. The category "other children" groups children at primary and secondary school. The education variables entering preferences are general education degrees, in contrast with those entering the wage equation (Table A2), which combine general and vocational degrees. The reference category consists of people who failed the lowest exam or did not take it and failed or dropped out at higher stages. This explains the signs in Table A2. The results appear fairly similar across the three models. A number of coefficients on socio-demographic variables are significant. It is difficult to discuss the economic interpretation of those reduced form coefficients.

The structural coefficients are given in Table 2, where the first column contains values for the Probit model obtained by setting $\sigma = 33$. The models now appear to differ somewhat, especially as regards the effects of age and of the children variables. The maximum number of hours available for work has its maximum at age 25.5, 29.2 and 28.8, respectively, for the three models. The maximum number of weekly hours available for work to a 40-years old woman without children is 38.12 in the extended grouped model, and 44.35 if she lives in a suburb. It becomes negative for a woman older than 56. In interpreting these figures it should be remembered that the normal error term added to equation (9) can be given the interpretation of $1 - \beta$ times a random term entering the parameter γ . The latter will thus have a standard deviation of 43.9 for the extended grouped model. The effects of education on preferences, as captured by the chosen regressors, appear to be non-monotonous, with a maximum for lower secondary school. The children variables act as expected and it proved useful to break the linearity implied by a count for the category "other children". The minimum expenditures on goods are not well determined, except for the effect of being in the process of buying a house: this has a positive impact on minimum expenditures and thus on desired hours (see equation (9)).

3.2 The Estimated Labour Supply Elasticities

Table 3 shows much lower elasticities than those obtained in the studies of Blundell and Laisney (1988) and Dagsvik et al. (1988). The first thought was that this came from the use of a sample *with* tax parameter variation, but this does not seem to be the only reason since the same operation (including the change to regional unemployment rates) with the model of the second named study produced no significant change[4]. We also found elasticities to be fairly sensitive to the choice and specification of socio-demographic effects. The maximum absolute values of elasticities are obtained in the part-time group, as expected because of the presence of hours in the denominator. This is at variance with the results from some other country studies reported by Nakamura and Nakamura (1991). Another interesting feature of these results is that we now have some individuals with negative uncompensated wage elasticities. Inspection shows that these are on average either older women or women with more small children or children at école maternelle. The concavity condition is never violated in the sample.

4 The problem there seems to lie in socio-demographic inflexibility of the functional form, which results in elasticities that depend on no socio-demographic characteristic. See Laisney et al. (1991).

Table 1. Results for the extended Probit, Grouped, and Tobit models with full tax system.

Model	Extended Probit			Extended grouped			Extended Tobit		
Variable	coeff.	std.err.	prob. %	coeff.	std.err.	prob. %	coeff.	std.err.	prob. %
intercept	0.8246	0.2487	0.09	0.8694	0.2180	0.02	0.8855	0.2256	0.01
(age-40)/10	-0.3812	0.0330	0.00	-0.3130	0.0269	0.00	-0.3156	0.0260	0.00
same, squared	-0.1310	0.0304	0.00	-0.1458	0.0276	0.00	-0.1403	0.0268	0.00
primary school	0.2909	0.0570	0.00	0.2834	0.0520	0.00	0.2823	0.0512	0.00
lower secondary	0.4548	0.0857	0.00	0.4051	0.0748	0.00	0.4271	0.0759	0.00
end secondary	0.3623	0.1172	0.19	0.3097	0.1025	0.25	0.3209	0.1046	0.21
higher education	0.2863	0.1424	4.43	0.2289	0.1285	7.48	0.2300	0.1299	7.66
small children	-0.6878	0.0658	0.00	-0.5710	0.0564	0.00	-0.5756	0.0555	0.00
école maternelle	-0.4793	0.0515	0.00	-0.4540	0.0453	0.00	-0.4484	0.0443	0.00
one other child	-0.2481	0.0623	0.01	-0.2454	0.0522	0.00	-0.2457	0.0509	0.00
two other children	-0.6666	0.0737	0.00	-0.6483	0.0636	0.00	-0.6512	0.0625	0.00
> 2 other children	-0.9137	0.0903	0.00	-0.8942	0.0851	0.00	-0.9052	0.0844	0.00
suburb dummy	0.1610	0.0481	0.08	0.1421	0.0418	0.06	0.1480	0.0414	0.03
1/marg. wage [1/w]	2.3854	2.5798	35.51	2.8082	2.2546	21.29	2.0920	2.3373	37.08
owner/w	-0.9884	0.9219	28.36	-1.0901	0.8624	20.62	-1.1725	0.8537	16.96
buyer/w	2.1465	0.6247	0.06	1.7249	0.5466	0.16	1.7306	0.5330	0.11
m/w	-1.5684	0.1866	0.00	-1.3945	0.1662	0.00	-1.3317	0.1654	0.00
$1/\sigma$				0.0300	0.0006	0.00	0.0312	0.0004	0.00
-2*Log Likelihood	4397			10238			17877		

Table 2. Structural parameters corresponding to the coefficients reported in Table 1.

Model	Extended Probit		Extended grouped		Extended Tobit	
Parameter	coeff.	t-value	coeff.	t-value	coeff.	t-value
γ_0	37.24	6.19	38.12	6.75	36.39	6.38
γ_age	-17.21	-18.20	-13.73	-18.75	-12.97	-19.22
γ_age^2	-5.92	-7.33	-6.39	-8.57	-5.77	-8.21
γ_prim. school	13.14	8.61	12.43	8.63	11.60	8.43
γ_lower second.	20.54	8.58	17.76	8.50	17.55	8.50
γ_end second.	16.36	5.22	13.58	4.98	13.19	4.84
γ_higher educ.	12.93	3.51	10.04	3.00	9.45	2.84
γ_small child.	-31.06	-16.42	-25.04	-15.68	-23.66	-15.86
γ_école matern.	-21.64	-14.56	-19.91	-15.53	-18.43	-15.47
γ_one other ch.	-11.20	-7.55	-10.76	-8.40	-10.10	-8.23
γ_two other ch.	-30.10	-16.63	-28.43	-18.18	-26.76	-18.28
γ_> 2 other ch.	-41.26	-19.05	-39.21	-20.16	-37.20	-20.19
γ_suburb dummy	7.27	5.85	6.23	5.67	6.08	5.68
β	0.27	8.87	0.24	8.50	0.22	8.20
d_0	292.48	0.96	387.27	1.28	302.10	0.92
d_owner	-121.20	-1.07	-150.34	-1.21	-169.33	-1.31
d_buyer	263.19	3.50	237.88	3.24	249.91	3.32

Table 3. Elasticities.

Model	Extended Probit					Extended grouped					Extended Tobit				
Subsample	1%	25%	50%	75%	99%	1%	25%	50%	75%	99%	1%	25%	50%	75%	99%
Part-time															
wage	-0.02	0.46	0.74	1.18	6.25	-0.09	0.34	0.58	0.96	5.27	-0.03	0.38	0.61	0.97	5.27
income[5]	-8.10	-1.64	-1.11	-0.79	-0.23	-7.26	-1.47	-1.00	-0.71	-0.21	-6.67	-1.35	-0.92	-0.65	-0.19
Slutsky	0.25	0.73	1.01	1.45	6.52	0.14	0.58	0.82	1.21	5.51	0.20	0.60	0.83	1.20	5.54
Full-time															
wage	0.002	0.23	0.34	0.46	0.89	-0.04	0.17	0.27	0.38	0.76	-.002	0.19	0.28	0.38	0.76
income	-1.16	-0.67	-0.56	-0.44	-0.23	-1.04	-0.59	-0.50	-0.40	-0.21	-0.96	-0.55	-0.46	-0.37	-0.19
Slutsky	0.27	0.50	0.61	0.73	1.16	0.20	0.41	0.51	0.62	1.00	0.22	0.41	0.50	0.60	0.98
Long hours															
wage	-.003	0.18	0.30	0.42	0.76	-0.05	0.13	0.23	0.34	0.65	-.007	0.15	0.24	0.34	0.64
income	-0.94	-0.59	-0.49	-0.39	-0.18	-0.85	-0.53	-0.44	-0.35	-0.16	-0.78	-0.49	-0.40	-0.32	-0.15
Slutsky	0.27	0.45	0.57	0.69	1.03	0.19	0.37	0.47	0.58	0.89	0.21	0.37	0.46	0.56	0.86
all participants															
wage	0.002	0.25	0.37	0.55	2.77	-0.05	0.18	0.30	0.45	2.24	-.003	0.20	0.31	0.45	2.28
income	-3.96	-0.78	-0.59	-0.47	-0.22	-3.54	-0.69	-0.53	-0.42	-0.20	-3.26	-0.64	-0.49	-0.38	-0.18
Slutsky	0.27	0.52	0.64	0.82	3.03	0.20	0.42	0.54	0.69	2.48	0.22	0.42	0.53	0.67	2.50
seekers															
particip/wage	0.09	0.46	0.82	1.27	3.74	0.04	0.33	0.62	0.98	2.98	0.07	0.37	0.66	1.01	2.95
non-participants															
particip/wage	0.11	0.78	1.20	1.81	4.76	0.09	0.63	0.90	1.40	3.64	0.08	0.63	0.95	1.44	3.67

5 This is the virtual income m.

Table 4. Diagnostics: empirical significance levels (%).

Model		Extd. Probit	Extd. Grouped	Extd. Tobit
QLM - Test	d.o.f.			
linearity	3	35.965	12.164	14.825
m^2	1	36.322	10.743	17.293
w^2	1	15.829	9.342	7.830
ln$w$	1	20.083	11.571	9.386
homoscedasticity	16	0.012	0.000	0.000
(age-40)/10	1	1.275	0.000	0.000
same, squared	1	8.241	78.918	85.372
lower secondary school	1	24.193	0.264	0.007
end secondary school	1	0.011	0.046	0.002
école maternelle	1	6.841	31.005	4.820
one other child	1	49.576	2.316	1.969
two other children	1	10.241	0.168	1.693
>2 other children	1	80.761	0.000	0.010
suburb dummy	1	24.479	2.648	1.848
1/marginal wage [1/w]	1	0.464	0.164	0.000
owner/w	1	71.933	0.006	0.084
buyer/w	1	2.985	0.067	0.096
m/w	1	23.190	0.000	0.000
normality	2	20.645	0.000	0.000
skewness	1	8.283	0.000	0.000
kurtosis	1	80.828	0.000	0.000
Heckman-Andrews tests				
participation	1	18.633	0.000	0.000
predicted hours	4	8.093	0.000	0.000
marginal wage	5	38.015	0.000	0.000
m	5	12.024	0.000	0.000
end secondary school	2	38.880	0.000	0.000

4 Model Evaluation and Predictive Performance

Table 4 shows the results of diagnostic tests[6]. The first series of tests concerns non-linearity tests: we test separately and jointly against m^2, w^2 and $\ln w$ missing in the earnings equation (8). The second series concerns heteroscedasticity: we test against a special form of heteroscedasticity, namely with the logarithm of variance linear in all non-constant model regressors. (We have deleted entries consistently above the 5% empirical significance level, including the models reported in Appendix C). The third series concerns non-normality: we test separately against skewness and kurtosis and jointly against both.

Linearity is passed easily (except for the models with incomplete treatment of the tax system, see Appendix C: this is no surprise since one can expect a tradeoff between non-linearity in the budget restriction and non-linearity in the preferences).

For the probit model, heteroscedasticity appears only through the dummy variable "education = end of secondary school". The similarity with Laisney et al. (1991) on this point is striking. Since this questions consistency, we have estimated a model explicitly allowing for this type of heteroscedasticity. Although heterogeneity appears between the subsample defined by this dummy (which represents 6.8% of the total) and the rest of the sample, the coefficients for the latter are only slightly altered, suggesting that inconsistency is not a problem for most of the sample.

The normality check is passed easily by the probit model, (and this is confirmed by testing against an SNP alternative, see Gabler et al., 1990) but non-normality, as reflected in QLM statistics, becomes a problem when more information on hours is used. This is a familiar phenomenon, which is documented in Monte-Carlo experiments by Blundell, Peters and Smith (1989). There is yet another interpretation: since all these tests are consistent, they will reject the null of a valid grouping of hours which is maintained when testing for non-normality, in case the invalidity of the grouping leads to inconsistency of the estimator. This interpretation is also suggested by the Hausman tests reported below. Heteroscedasticity becomes also more stringent and the same comment applies.

The Heckman-Andrews tests reported are based on clustering the endogenous variable according to participation (2 classes), and the exogenous variables according to (a) nothing (1 class), (b) predicted hours (4 classes corresponding to the groups used in the estimation of the extended grouped model), (c) predicted marginal wage rate (5 classes), (d) predicted virtual income (5 classes) and (e) "end of secondary school" (2 classes), and forming the corresponding cartesian

6 Since all test statistics are asymptotically χ^2 we only indicate the corresponding degrees of freedom and the empirical significance level.

products[7]. No rejection occurs for the Probit models, whereas the specification is constantly rejected when using hours information. The same interpretation as above can be drawn here. However, we should also note that the small sample properties of these Heckman-Andrews tests have yet to be investigated.

Table 5. Hausman tests.

Null	Extended Tobit			Extended Grouped		
Alternative	statistic	d.o.f.	sign. %	statistic	d.o.f.	sign. %
Probit	26.63	13	1.48	34.47	13	0.10
	28.37	14	1.26	36.28	14	0.09
	69.07	15	0.00	134.55	15	0.00
Extended Grouped	17.41	9	4.27			
	42.30	10	0.00			
	42.76	11	0.00			

Table 5 presents the results of Hausman tests for the overall validity of each alternative treatment of the hours information. The results are presented in matrix form where the intersection of line i and column j corresponds to the test of the validity of model j when model i is assumed correct. Each row is repeated three times, to take account of problems with the failure of positive semi-definiteness of the difference between the covariance matrices, which are revealed by comparison of the standard errors reported in Table 1. We drop the negative eigenvalues, which amounts to restricting attention to a subspace where positive semi-definiteness holds. In a further step we also investigate the effect of distrusting small positive eigenvalues, which is valid as well for the same reason. In this way we find that the extended Tobit specification is mildly rejected when tested against the extended grouped, but that both are severely rejected when tested against the probit. That is no real surprise given the previous discussion. Rather more surprising is the fact that the extended grouped specification is more severely rejected than the extended Tobit.

7 We report only results based on the Σ_3 estimate of the covariance matrix, due to numerical problems with the use of Σ_2. (See Andrews, 1988a,b for details).

Finally, in Table 6 we present an assessment of within sample predictive performance. Table 6(a) gives the sum of estimated probabilities for each cell using the estimates from each model specification. In the case of the Probit the variance is set as in Table 2. It is noticeable that the impact of using more hours information is to increase over-prediction of participation. Table 6(b) focuses on the participants and in particular on the ability of the models to replicate the observed hours distribution. The results are disappointing and confirm the impression from 6(a), that even conditional on participation the model predicts too many part-time workers. To some extent this may reflect the importance of fixed costs which suggest a bimodal distribution between non-participation and full-time. This would also go some way towards explaining the low forecast non-participation rate in 6(a).

Table 6: Within Sample Simulation Performance

Model	non-part.	part-time	full-time	long hours
(a) Unconditional Expectations				
Probit	1860	1030	124	444
Grouped	1692	1102	140	525
Tobit	1602	1134	140	489
Actual	1902	342	986	228
(b) Conditional Expectations (on participation)				
Probit		998	121	438
Grouped		952	124	479
Tobit		983	125	448
Actual		342	986	228

Given the limited hours variation in our sample it proved impossible to obtain sensible fixed costs estimates, that is a generalised selectivity model of the Cogan (1981) type could not be identified. This confirms the overall suspicion that the results on labour supply are driven by the participation decision itself. However, it may also reflect a more important consideration relating to the pay-off to retaining full-time employment even where part-time employment would yield short-run benefits.

5 Conclusions

This paper has concerned the detailed examination of information over hours of work and job search in the estimation of labour supply models for married women in the French data set Budgets des Familles. Although normal hours of work for those women in employment are available, this information may not reflect desired hours of work. Moreover, for those not in employment but searching for work it would seem unreliable to assume their desired hours of work are non-positive. As a result we treat job seekers as participants and consider various degrees of grouping on hours of work.

A discrete choice model which treats job seekers as participants and which acknowledges the full implications of the French tax and benefit system appears to produce most plausible results. Utilising information on hours in grouped form or in actual hours form appeared to add little to this specification and no model could explain satisfactorily the observed distribution of hours between part-time and full-time. However, relaxing information over the tax and benefit system appeared to result in inferior model estimates. Our preferred model displayed significantly smaller wage elasticity estimates than those obtained in previous studies. Even there we found some indication of distributional misspecification, most especially with heteroscedasticity, but obtained some evidence that this may not affect consistency for the largest part of the sample.

Clearly these results are heavily influenced by the lack of significant variation in observed hours. Nevertheless there does appear to be an important distinction between the participation and hours decision (see also the results of Bourguignon and Magnac, 1990). However, with the recent availability of the 1985 data source, which is known to indicate an increase in the proportion of women working part-time, it may become possible to identify a more precise and separate process for hours of work conditional on participation. Our conjecture is that correct treatment of reported hours and job-seekers should result in more stability of preference parameters over time and our intention is to test this hypothesis.

Appendix A: Data and wage equation

Figure A1. Distribution of "normal" hours of work per week for working married women, France 1979.

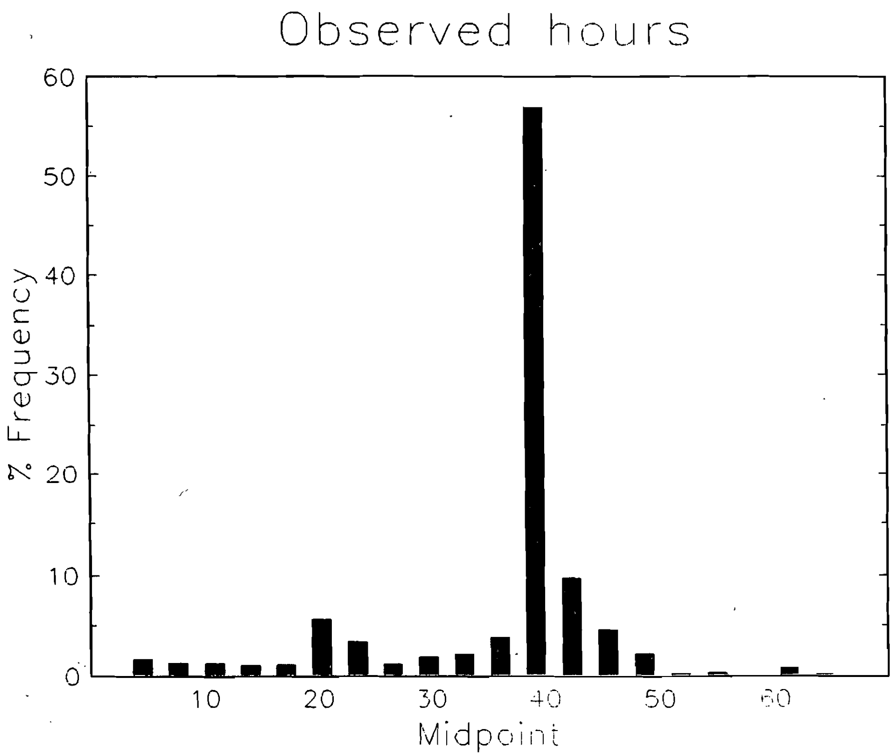

Table A1. Descriptive statistics.

INSEE survey Budgets des Familles 1978-1979, 3658 households based on a married couple.[8]

Subsample	Participants			Part-time			Full-time			Long hours			Seekers			Non seekers		
# Observ.	1556			342			986			228			200			1902		
Variable	min	mean	max	min	mean	max	min	mean	max	min	mean	max	min	mean	max	min	mean	max
age	26	37.997	60	26	38.854	58	26	37.588	60	26	38.825	60	26	36.910	59	26	41.146	65
suburbs	0	0.420	1	0	0.380	1	0	0.442	1	0	0.386	1	0	0.390	1	0	0.361	1
prim.school	0	0.438	1	0	0.415	1	0	0.432	1	0	0.496	1	0	0.515	1	0	0.410	1
lower second	0	0.228	1	0	0.193	1	0	0.255	1	0	0.167	1	0	0.165	1	0	0.151	1
end second.	0	0.077	1	0	0.058	1	0	0.089	1	0	0.053	1	0	0.065	1	0	0.068	1
higher educ.	0	0.031	1	0	0.035	1	0	0.031	1	0	0.026	1	0	0.070	1	0	0.042	1
small child	0	0.148	3	0	0.096	2	0	0.166	3	0	0.145	2	0	0.175	2	0	0.202	3
ec. matern.	0	0.184	2	0	0.234	2	0	0.177	2	0	0.136	2	0	0.310	2	0	0.239	3
other child	0	0.931	5	0	1.301	5	0	0.816	5	0	0.868	4	0	1.080	5	0	1.423	10
all children	0	1.262	5	0	1.632	5	0	1.160	5	0	1.149	5	0	1.565	5	0	1.864	12
owner	0	0.106	1	0	0.114	1	0	0.102	1	0	0.110	1	0	0.095	1	0	0.174	1
buyer	0	0.454	1	0	0.436	1	0	0.474	1	0	0.395	1	0	0.430	1	0	0.400	1
marg.wage*[9]	8.065	13.028	22.728	9.119	12.880	22.072	8.065	13.208	22.728	8.656	12.470	21.906	8.874	13.300	20.634	7.434	12.831	23.305
m*	9011	57711	163524	9011	59878	163524	11202	57545	123614	14975	55180	131862	23983	59890	139255	-740	68268	251955
expend.*[10]	22046	82565	187884	22026	74184	187884	22026	84923	158543	22026	84936	172819						
hours	3	36.630	66	3	21.196	35	36	39.862	41	42	45.807	66						

8 For further indications on the selection rule, see Blundell and Laisney (1988).

9 * = predicted. Nominal values in 1979 Francs, hourly wage rate.

10 Computed as $e = m + wh$ using observed hours and predicted values for m and w.

Table A2. Wage equation.

Dependent variable: log (gross wage), 1556 observations, R^2 = .244

Variable	estimate	std. err.	t-value[1]
intercept	2.8613	.0798	35.844
(age-40)/10	.0315	.0118	2.671
same squared	.0037	.0132	0.279
no gen.education degree[2]	-.2928	.0534	-5.486
end of primary school	-.2498	.0510	-4.900
" plus professional degree	-.0968	.0530	-1.828
lower secondary school	-.0263	.0561	-.468
" plus professional degree	.0692	.0548	1.263
baccalauréat or higher	.1325	.0631	2.100
" plus professional degree	.2318	.0646	3.590
suburb dummy	.0607	.0221	2.751
regional unemployment rate	-.7658	.0907	-.844
telephone dummy	.1079	.0222	4.858
Greater Paris	.0936	.0272	3.445
no car	-.0333	.0434	-.769
two cars or more	.0753	.0225	3.345
selectivity regressor	.0832	.0211	3.941

1 These are computed under homoscedasticity.

2 The reference category corresponds to no professional (or vocational) degree *and* no general education degree.

Appendix B: Formulas used in the computation of test statistics

Denote the score vector under $H^0 : \theta = (\theta_1', \theta_2^{0}')'$ by s, the OPG matrix by I and the information matrix by J. Partitioning s and J accordingly, the QLM test statistic is given by

$$\text{QLM} = s_2'(J_{22} - J_{21}J_{11}^{-1}J_{12})^{-1}([J^{-1}IJ^{-1}]_{22})^{-1}(J_{22} - J_{21}J_{11}^{-1}J_{12})^{-1}s_2 .$$

See White (1982, 1983) or Gouriéroux and Monfort (1989) for details. Estimates of I and J under H^0 are given by the empirical covariance of the score and by the evaluation of the information matrix at the estimated (restricted) vector of parameters $(\hat{\theta}_1^{0}', \theta_2^{0}')'$.

It is convenient to express all these elements using generalised residuals (see Chester and Irish, 1987). Denoting by x the regressors, by t the variables used for the variance (homoscedasticity test) and by z the potentially omitted variables, the elements of the score needed are:

$$h\sum_{i=1}^{N} e^{(1)}x, \quad \frac{h^2}{2}\sum e^{(2)}, \quad \frac{h^2}{2}\sum e^{(2)}t, \quad \frac{h^3}{2}\sum e^{(3)}, \quad \frac{h^4}{4}\sum e^{(4)}, \quad h\sum e^{(1)}z$$

where h denotes $1/\sigma$ and $e^{(n)}$ the (centered) nth generalized residual. The first two elements appear in s_1 in the notation above, whereas s_2 consists of a selection from the other elements, depending on the precise nature of the test. The third element will be used in heteroscedasticity tests, the fourth and fifth for skewness and kurtosis, and the sixth for missing variables. The information matrix can be written in terms of the second moments of the generalized residuals: denoting $E_{ij} = \mathrm{E}(e^{(i)}e^{(j)})$ and including all potential elements of the score, we have:

$$J_{11} = \begin{bmatrix} h^2\sum E_{11}xx' & \\ \frac{h^2}{2}\sum E_{12}x' & \frac{h^4}{4}\sum E_{22} \end{bmatrix}$$

$$J_{12} = \begin{bmatrix} \frac{h^3}{2}\sum E_{11}xx' & \frac{h^4}{4}\sum E_{13}x & \frac{h^5}{4}\sum E_{14}x & h^2\sum E_{11}xz' \\ \frac{h^4}{4}\sum E_{22}t' & \frac{h^5}{4}\sum E_{23} & \frac{h^6}{8}\sum E_{24} & \frac{h^2}{2}\sum E_{12}z' \end{bmatrix}$$

$$J_{22} = \begin{bmatrix} \frac{h^4}{4}\sum E_{22}tt' & & & \\ \frac{h^5}{4}\sum E_{23}t' & \frac{h^6}{4}\sum E_{33} & & \\ \frac{h^6}{8}\sum E_{24}t' & \frac{h^7}{8}\sum E_{34} & \frac{h^8}{16}\sum E_{44} & \\ \frac{h^3}{2}\sum E_{12}zt' & \frac{h^4}{2}\sum E_{13}z & \frac{h^5}{4}\sum E_{14}z & h^2\sum E_{11}zz' \end{bmatrix}$$

For the probit model, the second element of the score, that corresponding to h, must be discarded, and consequently the last line and last column of J_{11}, as well as the last line of J_{12}.

For the computation of the generalized residuals and their second moments we must distinguish between the three models. See Chesher and Irish (1987, 41) for details.

(1) Probit: let $w = xc$, $p = \Phi(w)$ and $f = \phi(w)$. Then:

$$e^{(1)} = \frac{f}{p(1-p)}(y-p),$$

$$e^{(2)} = -we^{(1)},$$

$$e^{(3)} = (2+w^2)e^{(1)},$$

$$e^{(4)} = -w(3+w^2)e^{(1)}$$

and

$$E = \frac{f^2}{p(1-p)}\begin{bmatrix} 1 & & & \\ -w & w^2 & & \\ 2+w^2 & -w(2+w^2) & (2+w^2)^2 & \\ -w(3+w^2) & w^2(3+w^2) & -w(2+w^2)(3+w^2) & w^2(3+w^2)^2 \end{bmatrix}$$

(2) Extended Tobit: let y denote hours worked, d_1, d_2, d_3 denote three dummies corresponding to non-participants, seekers and participants, respectively, let $t = hy - w$ and $e = -d_1 f/(1-p) + d_2 f/p$. Then:

$$e^{(1)} = e + d_3 t,$$

$$e^{(2)} = -we + d_3(t^2 - 1),$$

$$e^{(3)} = (2 + w^2)e + d_3 t^3,$$

$$e^{(4)} = -w(3 + w^2)e + d_3(t^4 - 3)$$

and the E matrix is given on the next page, after the E matrix for the extended grouped model.

(3) Extended grouped: let d_1, d_2, d_3, d_4, d_5 denote dummies for non participants, part-time, long hours and seekers, respectively, and v denote the vector $(-\infty, 1.5, 35.5, 41.5, +\infty)$. Further denote by z the vector with components $z_i = hv_i - w$. Then:

$$e^{(1)} = -\sum_{i=1}^{4} d_i \frac{\phi(z_{i+1}) - \phi(z_i)}{\Phi(z_{i+1}) - \Phi(z_i)} + d_5 \frac{\phi(z_2)}{1 - \Phi(z_2)}$$

$$e^{(2)} = -\sum_{i=1}^{4} d_i \frac{z_{i+1}\phi(z_{i+1}) - z_i\phi(z_i)}{\Phi(z_{i+1}) - \Phi(z_i)} + d_5 \frac{z_2\phi(z_2)}{1 - \Phi(z_2)}$$

$$e^{(3)} = 2e^{(1)} - \sum_{i=1}^{4} d_i \frac{z_{i+1}^2\phi(z_{i+1}) - z_i^2\phi(z_i)}{\Phi(z_{i+1}) - \Phi(z_i)} + d_5 \frac{z_2^2\phi(z_2)}{1 - \Phi(z_2)}$$

$$e^{(4)} = 3e^{(2)} - \sum_{i=1}^{4} d_i \frac{z_{i+1}^3\phi(z_{i+1}) - z_i^3\phi(z_i)}{\Phi(z_{i+1}) - \Phi(z_i)} + d_5 \frac{z_2^3\phi(z_2)}{1 - \Phi(z_2)}$$

and using the abbreviations $\Delta x_i = x_i - x_{i-1}$ and $\phi_i = \phi(z_i)$, $\Phi_i = \Phi(z_i)$,

$$F = \begin{bmatrix} \sum_{i=2}^{5} \frac{[\Delta\phi_i]^2}{\Delta\Phi_i} & & & \\ \sum_{i=2}^{5} \frac{[\Delta z_i\phi_i][\Delta\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i\phi_i]^2}{\Delta\Phi_i} & & \\ \sum_{i=2}^{5} \frac{[\Delta z_i^2\phi_i + 2\Delta\phi_i][\Delta\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i^2\phi_i + 2\Delta\phi_i][\Delta z_i\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i^2\phi_i + 2\Delta\phi_i]^2}{\Delta\Phi_i} & \\ \sum_{i=2}^{5} \frac{[\Delta z_i^3\phi_i + 3\Delta z_i\phi_i][\Delta\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i^3\phi_i + 3\Delta z_i\phi_i][\Delta z_i\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i^3\phi_i + 3\Delta z_i\phi_i][\Delta z_i^2\phi_i + 2\Delta\phi_i]}{\Delta\Phi_i} & \sum_{i=2}^{5} \frac{[\Delta z_i^3\phi_i + 3\Delta\phi_i]^2}{\Delta\Phi_i} \end{bmatrix}$$

E matrix for the extended Tobit model:

$$E = \begin{bmatrix} -wf + p + \frac{f^2}{1-p} & & & \\ (1+w^2)f - w\frac{f^2}{1-p} & -w(1+w^2)f + 2p + w^2\frac{f^2}{1-p} & & \\ -w(3+w^2)f + 3p + (2+w^2)\frac{f^2}{1-p} & (6+3w^2+w^4)f - w(2+w^2)\frac{f^2}{1-p} & -w(15+5w^2+w^4)f + 15p + (4+4w^2+w^4)\frac{f^2}{1-p} & \\ (5+4w^2+w^4)f - w(3+w^2)\frac{f^2}{1-p} & -w(9+4w^2+w^4)f + 12p + w^2(3+w^2)\frac{f^2}{1-p} & (42+21w^2+6w^4+w^6)f - w(6+5w^2+w^4)\frac{f^2}{1-p} & E_{44} \end{bmatrix}$$

$$E_{44} = -w(87+29w^2+7w^4+w^6)f + 96p + w^2(9+6w^2+w^4)\frac{f^2}{1-p}$$

Appendix C: Perception of the tax system

Table C1 shows estimation results for probit models with different assumptions on how the tax system affects the decisions of the households through its impact on the marginal tax rate and on the virtual unearned income: the first one considers the complete tax system, including benefits and social security contributions, the second considers only taxes in a restricted sense, ignoring benefits and contributions, and the third one sets the marginal tax rate to zero and corresponds to a linear budget constraint. Given the comments in subsection 2.1, the differences between the three specifications will lie more in overall differences in marginal wage rates than in the way the latter *change* over the range of feasible working hours. See also Appendix D.

The model that differs most from the others is the Probit model where taxes are ignored. This leads to much stronger wage *and* income effects than the other models (see Blomquist, 1988, for a theoretical investigation of the problems resulting from disregarding the tax system in labour supply studies). The values reported in Table C2 for corresponding structural coefficients, that is, the coefficients of equation (9), were obtained by setting the scale parameter σ at a value of 33. The value of .70 obtained for the marginal value of time β when ignoring taxes is clearly theoretically unacceptable. Of course one could argue that the arbitrary value of σ chosen is not suited to that model. Choosing $\sigma = 10$, which yields a value of .21 for β, leads to a value of 38.4 for the maximum number of weekly hours available for work to a childless 40 year old woman with no general education degree, which is near to the other results. But note the reversal on the impact of education on labour supply, and the very different estimates for the minimum expenditures, which are scale-invariant. By contrast, considering taxes in the restricted sense only does not lead to dramatic changes in the structural coefficients.

Table C3 tells a different story and shows clearly the trade-off between the specification of the marginal tax rate and non-linearity in the preferences: linearity is passed easily for the model with complete treatment of the tax system only. The deterioration of the heteroscedasticity diagnostic for the inverse of the marginal wage reinforces this finding, which is no surprise since that diagnostic picks a special type of non-linearity. Note that a naive application of the Akaike information criterion would have led to prefer the model without taxes to the others and the model with taxes in restricted sense to the model with the full tax system. We hope that we have persuasively documented the danger of that procedure.

Table C1. Results of binary Probit estimation with different treatments of the perception of the tax system.

Model	Probit: Full tax system			Probit: Taxes in restricted sense			Probit: No tax		
Variable	coeff.	std.err.	prob. %	coeff.	std.err.	prob. %	coeff.	std.err.	prob. %
intercept	0.8246	0.2487	0.09	0.5821	0.2565	2.32	2.7082	0.2505	0.00
(age-40)/10	-0.3812	0.0330	0.00	-0.3654	0.0331	0.00	-0.3601	0.0341	0.00
same, squared	-0.1310	0.0304	0.00	-0.1318	0.0305	0.00	-0.1237	0.0308	0.00
primary school	0.2909	0.0570	0.00	0.3057	0.0573	0.00	0.1941	0.0590	0.10
lower secondary	0.4548	0.0857	0.00	0.5130	0.0869	0.00	-0.0412	0.0922	65.48
end secondary	0.3623	0.1172	0.19	0.4488	0.1192	0.01	-0.3322	0.1253	0.79
higher education	0.2863	0.1424	4.43	0.3901	0.1441	0.67	-0.3482	0.1470	1.78
small children	-0.6878	0.0658	0.00	-0.6624	0.0655	0.00	-0.5634	0.0685	0.00
école maternelle	-0.4793	0.0515	0.00	-0.4597	0.0516	0.00	-0.3599	0.0540	0.00
one other child	-0.2481	0.0623	0.01	-0.2207	0.0623	0.03	-0.1018	0.0634	10.80
two other children	-0.6666	0.0737	0.00	-0.6173	0.0739	0.00	-0.3657	0.0769	0.00
> 2 other children	-0.9137	0.0903	0.00	-0.8374	0.0911	0.00	-0.3510	0.0995	0.04
suburb dummy	0.1610	0.0481	0.08	0.1795	0.0483	0.02	0.0008	0.0493	98.62
1/marg. wage [1/w]	2.3854	2.5798	35.51	6.0182	2.9988	4.47	-16.7075	3.1280	0.00
owner/w	-0.9884	0.9219	28.36	-0.8725	1.0504	40.61	0.2224	1.2185	85.51
buyer/w	2.1465	0.6247	0.06	2.6599	0.7104	0.01	2.8566	0.8271	0.05
m/w	-1.5684	0.1866	0.00	-1.9893	0.2149	0.00	-4.0566	0.2886	0.00
-2*Log Likelihood	4397			4352			4182		

Table C2. Structural parameters corresponding to the coefficients reported in Table C1.

Model	Probit: Full tax system		Probit: Restricted taxes		Probit: No tax	
Parameter	coeff.	t-value	coeff.	t-value	coeff.	t-value
γ_0	37.24	6.19	29.17	5.16	294.11	6.39
γ_age	-17.21	-18.20	-18.31	-17.24	-39.11	-6.56
γ_age^2	-5.92	-7.33	-6.61	-8.43	-13.44	-6.38
γ_prim. school	13.14	8.61	15.32	9.90	21.08	6.34
γ_lower second.	20.54	8.58	25.71	10.25	-4.48	-3.76
γ_end second.	16.36	5.22	22.49	7.24	-36.09	-6.24
γ_higher educ.	12.93	3.51	19.55	5.49	-37.81	-6.30
γ_small child.	-31.06	-16.42	-33.19	-15.84	-61.19	-6.56
γ_école matern.	-21.64	-14.56	-23.04	-14.57	-39.09	-6.57
γ_one other ch.	-11.20	-7.55	-11.06	-8.11	-11.06	-6.67
γ_two other ch.	-30.10	-16.63	-30.93	-16.53	-39.71	-6.80
γ_> 2 other ch.	-41.26	-19.05	-41.96	-18.58	-38.13	-7.09
γ_suburb dummy	7.27	5.85	9.00	7.48	0.09	0.18
β	0.27	8.87	0.34	9.83	0.70	14.89
d_0	292.48	0.96	581.76	2.11	-792.03	-4.99
d_owner	-121.20	-1.07	-84.35	-0.83	10.55	0.19
d_buyer	263.19	3.50	257.13	3.81	135.42	3.53

Table C3. Diagnostics: empirical significance levels (%).

Model: Probit		Full tax system	Restricted taxes	No tax
QLM - Test	d.o.f.			
linearity	3	35.965	0.000	0.000
m^2	1	36.322	15.924	0.000
w^2	1	15.829	0.019	0.000
$\ln w$	1	20.083	0.000	0.000
homoscedasticity	16	0.012	0.009	0.012
(age-40)/10	1	1.275	0.759	39.852
same, squared	1	8.241	5.832	2.940
lower secondary	1	24.193	24.564	3.861
end secondary	1	0.011	0.010	0.003
école maternelle	1	6.841	7.245	73.683
one other child	1	49.576	49.846	54.388
two other children	1	10.241	10.798	3.532
>2 other children	1	80.761	93.096	40.096
suburb dummy	1	24.479	30.511	3.859
1/marginal wage [1/w]	1	0.464	0.486	0.051
owner/w	1	71.933	86.762	88.148
buyer/w	1	2.985	4.574	30.921
m/w	1	23.190	12.523	7.768
normality	2	20.645	16.738	6.997
skewness	1	8.283	6.014	10.900
kurtosis	1	80.828	64.701	3.936
Heckman-Andrews tests				
participation	1	18.633	15.348	19.328
predicted hours	4	8.093	5.255	10.358
marginal wage	5	38.015	22.019	46.938
m	5	12.024	11.432	16.533
end second.[x367]	2	38.880	29.113	40.032

Appendix D: Shape of budget restrictions

Figures D1 and D2 show the shape of budget restrictions for taxes in the restricted sense mentioned in Appendix C. The only further non-linearity entailed in the "full tax system" is caused by the ceiling on social security contributions. Figure D1 shows hypothetical budget lines for a household with two children and a capital income of 10 francs per week where the male works 40 hours per week at an hourly wage of 30 francs. For an hourly gross wage of 12 francs, the woman remains within the same tax bracket regardless of the number of weekly hours supplied. She moves through three brackets if she earns 60 francs per hours, and thus belongs to the upper decile of the gross wage distribution. But only for the extreme case of an hourly wage of 120 francs is there a visible departure from linearity. Figure D2 illustrates the impact of the number of children on disposable income through the "quotient familial" mechanism (see Dagsvik et al., 1988 for details).

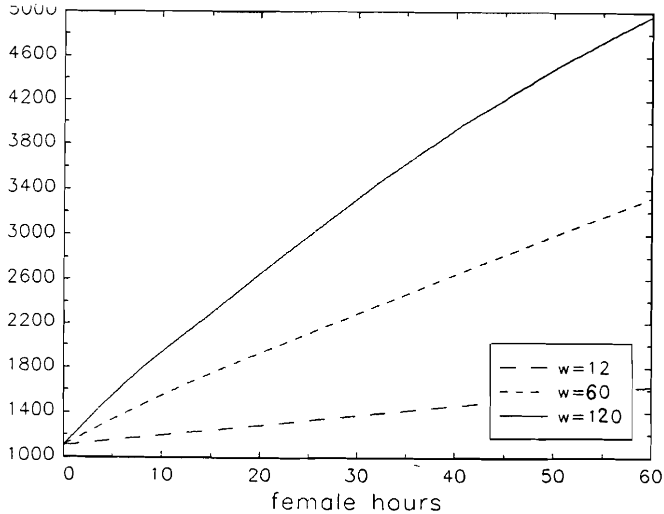

Figure D1. After Tax Budget Constraints for a Woman with two Children and Various Gross Wage Rates.

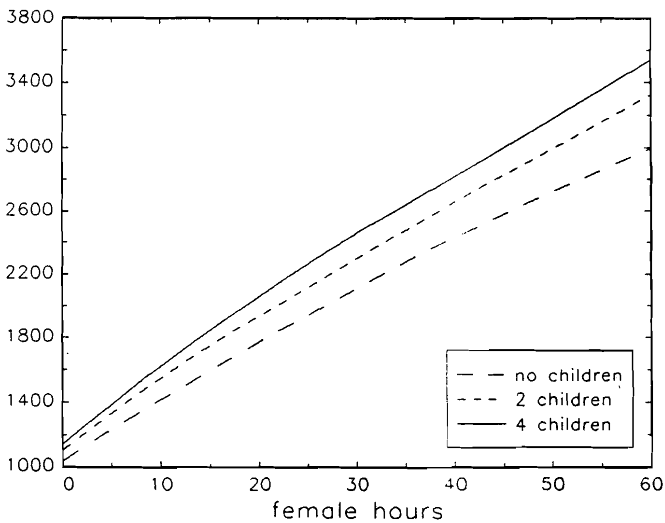

Figure D2. After Tax Budget Constraints for a Woman with a Gross Hourly Wage Rate of 60 Francs and Various numbers of Children.

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