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Lessons from Specification Tests for a Labour Supply Model

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ABSTRACT. – This paper investigates the properties of Box-Cox specifications for the labour supply of married women in France, estimated in four stages involving two dichotomous models, a regression with selectivity correction, and the calculation of sample means. Previous estimates implied wage elasticities high enough to be seriously questioned. We re-estimate the model with a more flexible stochastic specification and allow for some variation in the preference parameters across individuals. Furthermore, we account for a certain kind of heteroscedasticity. We submit all steps of the estimation to specification tests using among others LM tests against heteroscedasticity and misspecification of the distribution, information matrix tests, Andrews' χ^2-tests, Vuong's LR-test for non-nested alternatives. Although we do find somewhat lower elasticities the detected heteroscedasticity or parameter stability problems appear to be serious enough to caution against use of these models for policy simulation.

L'apport de tests de spécification pour un modèle d'offre de travail

RÉSUMÉ. – L'article examine les propriétés de spécification de type Box-Cox pour l'offre de travail des femmes mariées en France. L'estimation implique quatre étapes : deux modèles dichotomiques, une régression avec correction du biais de sélecivité, et un calcul de moyennes. Une étude précédente ayant abouti à des élasticités élevées, nous réestimons le modèle avec une spécification stochastique plus souple et enrichissons la modélisation de l'hétérogénéité observée. Toutes les étapes de la procédure sont soumises à des tests de spécification, tests du multiplicateur de Lagrange, tests de la matrice d'information, tests du χ^2 d'Andrews et tests de Vuong du rapport de vraisemblance. Nous aboutissons à des élasticités plus basses, mais les problèmes résiduels d'hétérogénéité non observée paraissent assez sérieux pour recommander la prudence dans l'emploi de tels modèles pour la simulation de politiques économiques.

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1 Introduction

The studies of Blundell and Laisney [1988] and Dagsvik *et al.* [1988] both estimate female labour supply functions for France using the INSEE survey "Budgets des Familles" 1979 and a local criterion approach taking detailed account of the tax and benefit system, but different functional forms. Other important differences are that the model used in the first study is life-cycle consistent under intertemporal separability and that it takes account of job search information. On the other hand, the second study gives a more thorough treatment of the joint estimation of the wage and preference parameters. Both studies find wage elasticities around 2, a value large enough to be seriously questioned and neither reports specification tests.

One obvious problem with the data used is that the distribution of observed weekly hours is strongly concentrated around 40 hours, and to a lesser extent around 20 hours, calling for an explicit treatment of the difference between desired and observed hours. Another potential difficulty concerns the modelling of demographic differences in tastes when using tax variables which also depend on demographics: this leads to identification problems which are studied by Moffitt [1988]. Focusing on alternative treatments of the information contained in observed hours of work and using a larger sample with tax parameter variation, Blundell *et al.* [1991] report wage elasticities substantially lower than 1, and present a range of specification tests. Other differences with their former study concern the exclusion of housing expenditure from the concept of "net dissaving" retained and a change in the variable representing local labour market disequilibrium. [1]

It was thus tempting to re-estimate the model of Dagsvik *et al.* using the same larger sample and the latter new variable (we did not exclude housing expenditure here since our "consumption" concept is after-tax income). Surprisingly, this and changing the treatment of the subsample of job seekers brought little change in the results. The corresponding elasticities are reported in Appendix B with some details on the parameter estimates.

This made us wonder whether differences in the stochastic specification or in the modelling of demographics [2] could be responsible for such diverging results. The investigation of these points with the help of a battery of specification tests, some of which have been introduced recently, is the subject matter of this paper. In section 2 we briefly describe the specifications and the estimation technique used. Section 3 compares the results obtained with two different stochastic specifications, showing no major difference between them. Nevertheless, serious heteroscedasticity and/or coefficient stability problems appear. Section 4 presents heteroscedasticity

1. One further difference concerns relaxing a steady state assumption that we do not wish to mention here in detail: see Blundell and Laisney [1988].
2. Implying differences in the impact of demographics on the elasticities.

corrected estimates. Appendix A gives a short description of the data, the characteristics of which are given in detail in DAGSVIK *et al.* [1988]. Appendix C shows the form of the labour supply curves generated by the model we use. Appendix D gives two examples of the estimated wage equations.

2 The Models

In order to ease and shorten this presentation, we suppose that the after-tax budget line is linear and for details on the treatment of the tax system we refer the reader to the studies already mentioned. However, the estimation results presented below use the full specification.

Let c denote consumption and h the number of hours worked. Household behaviour results from:

$$\text{(1)} \qquad \begin{cases} \max \mathrm{U}(h, c) \\ y + wh = c, \end{cases}$$

where w denote the marginal wage rate and y is some net "unearned income" concept: this is net household income minus net female earnings in the study of DAGSVIK *et al.* (which thus treats disposable income as the relevant measure of consumption) and the difference between household expenditure and net female earnings in the study of BLUNDELL and LAISNEY [1988] (the advantage being that the resulting decisions are consistent with intertemporal decision making).

DAGSVIK *et al.* specify an additively separable Box-Cox utility function:

$$\text{(2)} \qquad \mathrm{U}(h, c) = \mathrm{F}\left(\mathrm{A}\frac{(1-h/\mathrm{T})^{\alpha}-1}{\alpha} + \frac{c^{\beta}-1}{\beta}\right),$$

where T denotes maximum available time, F is an increasing function, A depends on demographics and α and β are parameters. This utility function is concave if α and β are below 1. The CES utility function is the special case $\alpha = \beta$ and $\mathrm{F}(x) = x^{1/\alpha}$. Appendix C discusses the implied labour supply curves over a realistic range of hourly wage rates. The role of the budget constraint is limited to two points $(h, c(h))$ (for h = hours worked and $h=0$) and the corresponding slopes $w(h)$. The gross wage rate W is assumed not to vary with hours, [3] and the net wage rate w is given by

$$\text{(3)} \qquad w = (1-t)\mathrm{W},$$

where t denotes the marginal tax rate.

3. We relax that assumption in Appendix D

The stochastic specification assumes the following joint distribution for log (A/T) and log (W):

$$(4)\qquad \begin{cases} \log(W) = X\,b + \varepsilon_1 \\ \log(A/T) = Z\,a + \varepsilon_2. \end{cases}$$

In the original specification of DAGSVIK *et al.* ε_1 and ε_2 are assumed bivariate extreme value distributed, *i.e.*:

$$(5)\qquad P[\varepsilon_1 \leqslant x,\ \varepsilon_2 \leqslant y] = \exp[-e^{\gamma}(e^{-x/\sigma\theta} + e^{-y/\sigma\theta})^{\theta}].$$

where γ is a constant, and θ and σ are parameters. This results in:

$$(6)\qquad \begin{aligned} &V(\varepsilon_1) = V(\varepsilon_2) = (\sigma^2 \pi^2)/6, \\ &\rho = 1 - \theta^2, \end{aligned}$$

where ρ denotes the correlations between ε_1 and ε_2. The distribution is correctly defined for $0 < \theta < 1$ only, and this points to one of the restrictions implied by this specification for the covariance structure: it enforces positive correlation between ε_1 and ε_2. This restriction was not satisfied by the estimates of DAGSVIK *et al.*, and we shall see that it will be violated here as well. The other unpalatable restriction is of course the equality of variances. Thus, we also consider a bivariate normal distribution as alternative. With either specification, the solution of problem (1) implies:

$$(7)\qquad P[h > 0] = P[\varepsilon \leqslant l(0)],$$

and, for $h > 0$:

$$(8)\qquad l(h) - \sigma^*(\alpha - 1)\log(1 - h/T) = \varepsilon,$$

where:

$$(9)\qquad l(h) = \sigma^* \{\log[1 - t(h)] + X\,b - Z\,a - (1 - \beta)\log[c(h)]\},$$

$$(10)\qquad \varepsilon = (\varepsilon_1 - \varepsilon_2)\,\sigma^*.$$

The bivariate extreme value leads to a logistic distribution for ε and to

$$(11)\qquad \sigma^* = 1/(\theta\sigma),$$

where the bivariate normal leads to a standard normal with:

$$(12)\qquad \sigma^{*2} = 1/V(\varepsilon_1 - \varepsilon_2).$$

Depending on the choice of stochastic specification, we shall call l (0) "the logit" or "the probit".

The model could be estimated by full information maximum likelihood but consistent estimators can be obtained with four simple steps, with the following great advantage over FIML: except in step 4, where α is estimated from statistics of the hours distribution, that distribution has no impact on the estimation results. The first three stages classically consist in a reduced form dichotomous participation model (with log W replaced by the regressors which explain it), the estimation of a wage regression with selectivity correction and, finally, the estimation of the structural form of the dichotomous participation model. The "selectivity correction" regressor will be denoted by λ_1, with expression:

$$\lambda_1 = -\log P(0),$$

with

(13) $$P(0) = [1 + \exp(-l(0))]^{-1},$$

and

$$\lambda_1 = \frac{\varphi(l(0))}{\Phi(l(0))},$$

for logit and probit, respectively, with the usual notations for the density and the cumulative distribution function of the standard normal.

In each case (logit or probit estimation) and under the assumption that the model is correctly specified, we have consistent estimates of a, b, β and σ^* at the end of step 3. By then, the covariance structure of the model can be estimated consistently: for the logit model, we have a homoscedastic variance term: [4]

(14) $$V(\varepsilon_1 \mid h>0) = V(\varepsilon_1) = \sigma^2 \pi^2/6,$$

and hence step 2 gives a consistent estimate of σ and (11) a consistent estimate of θ. For the "probit" model, the situation is slightly more complex since we have: [5]

(15) $$V(\varepsilon_1 \mid h>0) = \sigma_1^2 (1-r^2) + \sigma_1^2 r^2 (1 - l(0)\lambda_1 - \lambda_1^2),$$

where

$$r = \text{corr}(\varepsilon_1, \varepsilon_2 - \varepsilon_1).$$

This variance varies across individuals and thus we should use GLS for efficient estimation of the wage equation. However, since the (consistent) OLS estimate of $\sigma_1^2 r^2$ (squared coefficient of the regressor λ_1) is very small compared to the residual variance, the efficiency gain would be tiny. For the same reason, the upper and lower bounds for $V(\varepsilon_1 \mid h>0)$, σ_1^2 and $\sigma_1^2(1-r^2)$ will be close to each other. [6] In the computations reported below, we use the lower bound in order to retrieve near-consistent estimates of σ_1, σ_2 and ρ.

Taking expectations of both sides of (8), conditional on working, leads to the following consistent estimate for α:

(16) $$\hat{\alpha} = \frac{(1/N)\sum_{i=1}^{N} \hat{l}_i(h_i) - (1/N)\sum_{i=1}^{N} \hat{\lambda}_i}{(\hat{\sigma}^*/N)\sum_{i=1}^{N} \log(1 - h_i/T)}$$

where N is the number of participants in the sample, and a hat over a

4. See DAGSVIK [1987].
5. For details, see HECKMAN [1979].
6. The term in the last parenthesis in (15) lies between 0 and 1 (see HECKMAN [1979]).

function value denotes the consistent estimate resulting from substitution of consistent estimates in place of parameter values; λ is given by:

$$\lambda = l(0) + P(0)^{-1} \log[1 - P(0)]. \tag{17}$$

The expression given in DAGSVIK *et al.* for the variance of $\hat{\alpha}$ in the logit case carries over to the probit case with the following minor change concerning the derivative of the selection bias correction regressor, denoted there by Q_i, which becomes:

$$Q_i = -\lambda_i (l_i + \lambda_i). \tag{18}$$

The Cournot elasticities for the Box-Cox model are given by:

$$e_w = \frac{1 + (\beta - 1)\, wh/c}{(1-\beta)\, wh/c + (1-\alpha)\, h/(T-h)}, \tag{19}$$

and it is clear from this equation that no direct demographic influence will be reflected in the elasticities if α and β are constant across households.[7] Yet it is not difficult to allow for some variation in these parameters within the four-step estimation framework described above. Letting β vary with demographics amounts to introducing interaction terms between these and $\log(c)$ in the dichotomous steps, and α can be made variable by taking the means in (16) over different subsamples.

Finally, equation (8) provides us with estimates of the residuals $\hat{\varepsilon}$ for the participants.

3 Comparison of Logit and Probit Results

Before discussing the results, we would like to stress again that the reason for the comparison presented here lies in the different covariance structures implied by the two underlying bivariate distributions for the wage and the taste shifter. We already mentioned in section 2 that the restrictions of the bivariate extreme value distribution were not satisfied by the estimates of DAGSVIK *et al.*, which questions the validity of the specification. By using the more flexible bivariate normal distribution, and thus relaxing these restrictions, we hoped to increase the quality and reliability of the results.

Tables 1 and 2 give estimation and test results for step 3. Testing this step thoroughly is particularly attractive since, firstly, we can use the classical test procedures designed for the Maximum Likelihood framework,

7. By contrast, BLUNDELL and LAISNEY [1988] specify quasi-homothetic preferences and estimate a labour supply equation where the maximum time available for work and the minimum expenditure on goods are allowed to vary with demographics. This allows for a good deal of variation in the elasticities across households for given wage rate and unearned income.

TABLE 1

Structural Coefficients, log of Likelihood, and Covariance Structure Estimated with β Fixed.

	Logit			Probit		
Struc. coef	Estimate	*t*-values	Sign. (%)	Estimate	*t*-values	Sign. (%)
a (Const)......	−1.71725	−3.7337	0.0189	−1.70174	−3.7244	0.0196
a (Z1).......	0.27340	9.0169	0.0000	0.27297	8.9562	0.0000
a (Z2).......	0.08382	3.8499	0.0118	0.08477	3.9289	0.0085
a (Z34)......	0.50599	9.1986	0.0000	0.50673	9.2500	0.0000
a (Z5).......	0.33415	7.8944	0.0000	0.33462	7.8937	0.0000
a (Z6).......	0.23047	9.8708	0.0000	0.23149	9.9483	0.0000
β..........	0.65477	16.0551	0.0000	0.65869	16.2680	0.0000
σ*.........	2.50458	12.6898	0.0000	1.49797	12.9661	0.0000
α..........	−0.76215	−4.54495	0.0005	−0.68191	−3.3838	0.0714
−2* Log L (1)		4178			4174	
−2* Log L (3)		4266			4264	
	σ_1^2	σ_2^2	ρ	σ_1^2	σ_2^2	ρ
	0.16	0.16	−0.69	0.16	0.36	0.16

TABLE 2

Test After Step 3 with β Constant

	Logit			Probit		
	Heteroscedasticity (QLM)					
Variable	Statistic	D.o.f.	Sign. (%)	Statistic	D.o.f.	Sign. (%)
Z1.........	3.507	1	6.113	3.351	1	6.718
Z2.........	0.008	1	92.810	0.010	1	91.963
Z34........	0.129	1	71.946	0.284	1	59.416
Z5.........	1.551	1	21.297	1.355	1	24.435
Z6.........	0.495	1	48.162	0.710	1	39.941
log C0......	0.234	1	62.856	0.098	1	75.406
LMWRO	12.356	1	0.044	13.176	1	0.028
All.........	17.801	7	1.290	18.128	7	1.140
		(Burr II)	Distribution		(Pearson)	
step 1.......	16.223	1	0.006	20.125	2	0.004
step 3.......	4.623	1	3.154	5.592	2	6.106
Indicators			Information Matrix Tests			
All.........	60.424	36	0.658	55.776	35	1.427
Maindiag	16.687	8	3.354	19.256	7	0.742
Const.......	0.038	1	84.351			
Z1.........	0.002	1	96.632	0.009	1	92.282
Z2.........	0.193	1	66.055	0.289	1	59.101
Z34........	0.767	1	38.113	1.864	1	17.212
Z5.........	1.503	1	22.022	0.973	1	32.395
Z6.........	1.390	1	23.845	0.898	1	34.332
log C0......	0.326	1	56.817	0.045	1	83.164
LMWR0.....	7.281	1	0.697	13.382	1	0.025
			Andrews' Chi-square test (X368)			
	21.330	2	0.002	20.692	2	0.003
			Vuong's test: Logit vs. Probit [N (0, 1)]			
	−1.363		8.651			

and secondly, this step provides more efficient estimates of the structural parameters than previous steps do. We do not present detailed results for step 1 to avoid flooding the reader with numbers, but will refer to them where appropriate. It must remain clear that tests performed for step 3 are conditional on previous estimates. The specification of the wage equation is fairly standard (see Table D.1) but since we cannot exclude the possibility of heteroscedasticity, we also estimate WHITE'S [1980] heteroscedasticity-robust covariance matrix. For the bivariate normal another possibility that we have not explored would be to test the distributional assumption for steps 1 and 2 jointly using the tests of LEE [1982, 1984]. [8]

Table 1 gives the structural parameters for logit and probit estimation of the model with constant β. The standard errors reported are derived from the first-order asymptotic expansion of the structural parameters in terms of the estimated parameters. The estimator for the covariance of the latter does not take previous steps into account. The estimated structural coefficients are not dramatically different from the previous results, and there are no big differences between logit and probit estimates. An exception is the parameter σ*, due to the different normalisations of probit and logit. Note that identification is made possible by the the restriction that the coefficient of the marginal wage rate is equal to 1 [see equation (9)]. The table also indicates the covariance structure, which contains the only striking differences between the two specifications: firstly, the logit

TABLE D.1

Wage Equations With and Without Time Dummies

Variable	Estimate	t	Sign. (%)	HR-t	Estimate	t	Sign. (%)	HR-t
CONSTANT . .	2.9143	37.53	0.0	45.08	2.8612	36.45	0.0	41.37
Z1	0.0175	1.44	14.9	1.55	0.0203	1.70	8.0	1.82
Z2	0.0029	0.22	82.5	0.22	−0.0059	−0.45	65.0	−0.47
X31	−0.3356	−6.24	0.0	−8.00	−0.3145	−5.94	0.0	−7.29
X32	−0.2705	−5.26	0.0	−6.95	−0.2528	−5.00	0.0	−6.32
X33	−0.0994	−1.85	6.3	−2.37	−0.0949	−1.80	7.0	−2.21
X34	−0.0183	−0.32	74.6	−0.43	−0.0114	−0.20	83.0	−0.26
X35	0.0880	1.58	11.3	2.13	0.0836	1.53	12.0	1.95
X368	0.1481	2.33	1.9	2.56	0.1553	2.49	1.0	2.63
X379	0.2600	3.99	0.0	5.80	0.2586	4.04	0.0	5.58
X54	0.0971	4.66	0.0	4.82	0.0929	4.54	0.0	4.69
X6.	−2.4572	−2.82	0.5	−3.09	−2.4549	−2.87	0.0	−3.10
X7.	0.1297	5.88	0.0	6.22	0.1154	5.30	0.0	5.60
OTIME					−0.0929	−2.78	0.0	−2.35
NTIME					0.1105	4.40	0.0	4.09
LOGP0	−0.0344	−1.41	15.7	−1.28	−0.0440	−1.82	6.0	−1.68
R^2		0.226				0.254		

F-test (Heteroscedasticity via X368)

Statistic	D.o.f.	Sign. (%)	Statistic	D.o.f.	Sign. (%)
0.7363	1454/82	3.43	0.7072	1452/80	1.75

8. This was pointed out by a referee.

specification appears to be inconsistent since it should result in a positive correlation [see the lines below equation (6)]. Secondly, the restriction of equality of variances appears to be rejected by the probit. The value of $\hat{\alpha}$ is larger in probit than in logit, resulting in higher wage elasticities (see Table 5).

Table 2 gives tests for heteroscedasticity and for the distributional assumptions. We only report quasi Lagrange Multiplier tests (QLM), based on WHITE'S [1982] correction of the LM test, which combines information from two consistent estimates of the variance matrix used in the outer product of gradient (OPG) and information matrix variants of the tests, because there is evidence of its being more robust than either of these (see LECHNER [1990]). We computed all three variants and found no large difference between them, except for step 1, where the distributional assumption is clearly rejected. In both models, the same heteroscedasticity problem appears, connected with the predicted logarithm of the marginal wage rate when the woman does not work, LMWR0. Results obtained for step 1 show a heteroscedasticity problem concerning variable X368 (*i.e.* highest degree: end of secondary school or more, and no professional degree), and to a lesser extent log C0.

The test for the logistic distribution is a QLM test against a Burr (II) distribution. [9] The density of the latter is:

$$f(x)=\frac{ke^{-x}}{(1+e^{-x})^{k+1}}, \tag{20}$$

and the logit corresponds to $k=1$. For the probit we use the LM test of BERA, JARQUE and LEE [1984] against the Pearson family. The strong rejection of both distributional assumptions in step 1 is striking. The first conclusion to draw is that the results from heteroscedasticity tests for step 1 need not be taken too seriously, since these assume that the distribution is at least nearly correctly specified. The second tentative conclusion is that semi-parametric estimation of step 1 and step 2 might be fruitful. [10] However, given the sample size there is no clear rejection of one or the other distributional assumption in step 3.

Table 2 also gives the results of the information matrix tests (IM) introduced by WHITE [1982]. The original version of this test and even more its simplified version by CHESHER [1983, 1984] and LANCASTER [1984] avoiding the calculation of third derivatives of the likelihod function have been found to have extensive size under the null even in quite large samples. This problem is solved for logit and probit models by the asymptotically equivalent versions of the test proposed by ORME [1988]. These outperform the previous versions in terms of both size and power (see the Monte-Carlo study of LECHNER [1990]). Given our sample size and the small number of exogenous variables in step 3 we expect this statistic to approximate its

9. The Burr (II) distribution is also used in tests by Fry (1987) and Smith (1988), and for heterogeneity characterisation in defining representative production functions by Gouriéroux and Peaucelle (1988). See Lechner (1990) for the properties of the test.

10. For instance, using the approach of Gallant and Nychka (1987).

asymptotic distribution accurately.[11] In the third part of Table 2 the lines corresponding to all indicators and to the indicators on the main diagonal of the information matrix only suggest rejection of the overall specification. Each indicator on the main diagonal corresponds to a single variable and has most power against problems connected with this variable. Here this indicates parameter instability (CHESHER [1983, 1984]) and/or heteroscedasticity for LMWR0, especially for the probit specification. This confirms the results obtained with the heteroscedasticity tests.

The next part of this table reports ANDREWS' [1988 *a*, *b*] χ^2-test. This is based on clustering the (Y, X) space of the dependent and independent variables according to the hypothesis under test. Given the test results for step 1 we cluster the X-space according to the dummy variable X368. The rejection of both models is clear-cut.[12]

Summing up, we now have good reasons to believe that both the logit and the probit models are distant from the *true* model. VUONG [1989] provides a direct test of whether one of these two non-nested models is more distant (in the sense of the Kullback-Leibler information criterion) from the true model than the other is. The statistic used here is the unadjusted difference of the log-likelihoods (here logit minus probit) divided by an estimator of the variance[13] of this difference. It is standard normal under the null of no divergence. Given the way in which we computed the test statistic, a significant negative value would point to superiority of the probit specification. Here this superiority is not significant.

Tables 3 and 4 correspond to Tables 1 and 2, respectively, for a specification with variable β. This results from a preliminary specification search starting from the inclusion of age dummies (below 35 and above 45), youngest child dummies (*i.e.* youngest child not yet at school, at école maternelle (kindergarten), or other) and two education dummies (X31, technical or professional degree only, and X35, same plus degree corresponding to end of lower secondary school). The choice of the latter was guided by the results of LM tests on missing variables given by BLUNDELL *et al.* [1991], whereas the choice of the former is inspired by BLUNDELL and WALKER [1982].[14] Variables LCX31, LCYC2 and LCYC3 correspond to the products of log C0 with the survivors of the specification search. No change appears in the comparison between probit and logit estimates, except that the problem with the covariance structure in the logit has become more severe, and that the difference between the variances has increased, due to

11. In the computation of the IM statistic for the probit we discarded the diagonal indicator connected with the constant term since it does not contain any information: its inclusion would reduce the power of the test. Moreover, since both version of Orme's statistic are very close, we only report his second one (denoted IM_2 in this paper).

12. The results presented are based on the more efficient estimate of the covariance matrix ($\hat{\Sigma}_2$ in Andrew's notation: using $\hat{\Sigma}_3$ rejection appeared even more severe).

13. Vuong suggests two versions of this estimator. We computed both but report only one (based on $\hat{\omega}_n$ in Vuong's notation) since they turned out to be very close.

14. A justification for letting demographics enter twice in this way could be based on the consideration that our "preference" parameters are affected by differences in the household production technology.

TABLE 3

Structural Coefficients, log of Likelihood, and Covariance Structure Estimated with β Fixed.

Struc. coef	Logit			Probit		
	Estimate	t-values	Sign. (%)	Estimate	t-values	Sign. (%)
a (Const)	−2.53174	−3.7959	0.0147	−2.55279	−3.8164	0.0135
a (Z1)	0.29024	7.6866	0.0000	0.29194	7.6264	0.0000
a (Z2)	0.08903	3.4618	0.0537	0.09057	3.5347	0.0408
a (Z34)	0.47077	6.5298	0.0000	0.47387	6.5677	0.0000
a (Z5)	0.43343	5.4827	0.0000	0.43747	5.5221	0.0000
a (Z6)	0.28541	7.9862	0.0000	0.28740	8.0547	0.0000
β	0.58038	9.9579	0.0000	0.58111	9.9521	0.0000
β_1 (LCX31)	−0.01101	−2.1721	2.9848	−0.01131	−2.1962	2.8078
β_2 (LCYC2)	0.01854	1.8965	5.7896	0.01907	1.9555	5.0525
β_3 (LCYC3)	0.01290	2.1660	3.0315	0.01311	2.2071	2.7309
σ^*	2.20967	9.8261	0.0000	1.31666	9.9203	0.0000
α	−0.98891	−4.3207	0.0016	−0.90491	−3.4911	0.0481
−2* Log L (1)		4264			4260	
−2* Log L (3)		4254			4252	
covariance structure	σ_1^2 0.16	σ_2^2 0.16	ρ −1.17	σ_1^2 0.16	σ_2^2 0.5	ρ 0.15

an increase in the variance of log (A/T). The values found for the variable part of β are both small compared with its constant part and not as well determined as the other variables. The interpretation of the education variable is as follows: having only a technical degree lowers the probability of participation. The effect of the other variables must be interpreted in connection with the a coefficients: one more child at école maternelle or above lowers the probability of participation, but this influence is tempered if it is the youngest child. Note that we do not obtain a negative $\hat{\beta}$ for any household, and thus no backward bending arises (see Appendix C). A classical LR test of the restrictions implied by constant β is not possible[15] in step 3 since the wage variable is different for constant and variable β. However, its computation for step 1 yields a χ^2 of 14 both for logit and probit, a clearly significant value for 3 degrees of freedom. A look at Table 5 shows quite a large drop in wage elasticities, at least compared to previous changes (see Appendix D).

However, the picture is marred by the test results of Table 4: while no big change appears in the heteroscedasticity tests, the distributional assumptions become much more dubious. The IM test also points to a more clear-cut rejection of the overall specification.[16] Although this might

15. VUONG [1989] also presents LR-tests for overlapping models but we have not implemented them here [ars longa, vita brevis].

16. Seven indicators had to be deleted to resolve the singularity of the estimated covariance matrix of the test. The degrees of freedom have been adjusted accordingly (59 instead of 66 for the logit, for instance).

TABLE 4

Tests After Step 3 with β Variable

	Logit			Probit		
			Heteroscedasticity (QLM)			
Variable	Statistic	D.o.f.	Sign. (%)	Statistic	D.o.f.	Sign. (%)
Z1	3.025	1	8.200	2.991	1	8.371
Z2	0.301	1	58.298	0.406	1	52.383
Z34	0.081	1	77.552	0.188	1	66.485
Z5	0.693	1	40.511	0.444	1	50.502
Z6	3.374	1	6.622	4.198	1	4.047
log C0	0.190	1	66.253	0.068	1	79.393
LMWR0	13.637	1	0.022	14.871	1	0.012
LCX31	3.928	1	4.750	3.904	1	4.817
LCYC2	0.694	1	40.487	0.580	1	44.643
LCYC3	0.002	1	96.657	0.002	1	96.186
All.	23.948	10	0.774	25.578	10	0.435
		(Burr II)	Distribution		(Pearson)	
step 1	19.887	1	0.000	25.994	2	0.000
step 3.	7.984	1	0.472	10.740	2	0.465
Indicators			Information Matrix Tests			
All.	115.760	59	0.001	109.263	58	0.005
Maindiag	23.731	11	1.392	21.869	10	1.578
Const.	0.154	1	69.492			
Z1	0.061	1	80.504	0.358	1	54.962
Z2	0.345	1	55.710	0.642	1	42.284
Z34	0.308	1	57.887	0.710	1	39.928
Z5	0.908	1	34.053	0.430	1	51.204
Z6	5.829	1	1.576	3.907	1	4.809
log C0	0.004	1	94.888	0.023	1	88.013
LMWR0	6.066	1	1.378	14.747	1	0.012
LCX31	5.419	1	1.992	3.795	1	5.419
LCYC2	0.638	1	42.441	0.480	1	48.828
LCYC3	0.006	1	94.009	0.001	1	97.665
			Andrews' Chi-square test (X368)			
	19.545	2	0.006	18.573	2	0.009
			Vuong's test: Logit vs. Probit [N (0, 1)]			
	−1.062		14.436			

be attributed mainly to the large increase in the number of indicators, note that the White and Chesher and Lancaster versions of the IM test would be much more prone to this difficulty than Orme's version. Individual indicators show that the problem with LMWR0 remains. In the logit model there now appears to be a problem with variables Z6 and LCX31, but none of the corresponding statistics is overly significant. Andrews' and Vuong's test statistics remain more or less unaffected. These consequences of the introduction of three otherwise seemingly not very influential variables came as a surprise to us.

TABLE 5

Unweighted Individual Elasticities

		Logit β cst.	Probit β cst.	Logit β var.	Probit β var.	Logit β cst. h.c.X368	Logit β var. h.c.X368
Cournot	min	0.61	0.64	0.50	0.52	0.44	0.35
	mean	1.86	1.94	1.60	1.65	1.76	1.48
	max	25.52	26.58	22.41	23.22	24.66	21.25
Slutsky	min	0.82	0.85	0.72	0.74	0.60	0.51
	mean	2.05	2.13	1.80	1.86	1.96	1.68
	max	25.71	26.76	22.60	23.41	24.84	21.44
Total Income . .	min	−0.60	−0.60	−0.61	−0.62	−0.60	−0.61
	mean	−0.19	−0.20	−0.20	−0.21	−0.19	−0.19
	max	−0.02	−0.02	−0.03	−0.03	−0.02	−0.02
Virtual Income	min	−8.70	−8.95	−9.01	−9.31	−8.80	−9.10
	mean	−0.52	−0.53	−0.54	−0.56	−0.51	−0.54
	max	−0.06	−0.06	−0.06	−0.06	−0.06	−0.06
Frisch.	min	0.88	0.92	0.78	0.82	0.71	0.62
	mean	2.61	2.74	2.31	2.42	2.49	2.17
	max	31.30	32.79	27.73	28.95	30.32	26.36

TABLE 6

Additional Heteroscedasticity Tests

	Constant β			Variable β		
Variable	Statistic	D.o.f.	Sign. (%)	Statistic	D.o.f.	Sign. (%)
LCX31	1.250	1	26.354			
LCYC2.	1.278	1	25.820			
LCYC3.	0.140	1	70.842			
X31	1.675	1	19.565	4.401	1	3.591
X32	2.310	1	12.858	1.202	1	27.298
X33	0.009	1	92.513	0.046	1	83.010
X34	2.518	1	11.258	2.086	1	14.867
X35	1.599	1	20.612	1.692	1	19.336
X368	5.152	1	2.322	6.947	1	0.840
X379	0.888	1	34.613	1.831	1	17.599
X54	2.622	1	10.542	2.921	1	8.741
X6.	0.472	1	49.194	0.763	1	38.229
X7.	2.007	1	15.654	1.818	1	17.761
Log $t(0)$	0.081	1	77.627	0.079	1	77.844

4 Further Results: Correction for Heteroscedasticity

We now turn to an explicit modelling of the heteroscedasticity detected above, for the logit model only. More precisely, in step 3 we estimate the

TABLE 7

Structural Coefficients, log of Likelihood, and Covariance Structure Estimated with Logit and Correction for Heteroscedasticity (with $d = X368$)

	β constant			β variable		
Variable	Estimate	t-values	Sign. (%)	Estimate	t-values	Sign. (%)
a (Const)	−1.89400	−4.0269	0.0057	−2.83041	−4.0427	0.0053
a (Z1)	0.27921	8.9255	0.0000	0.29887	7.5424	0.0000
(Z2)	0.08634	3.8567	0.0115	0.09161	3.4211	0.0624
a (Z34)......	0.52502	9.2169	0.0000	0.49150	6.5051	0.0000
a (Z5)	0.33608	7.7323	0.0000	0.43983	5.3657	0.0000
a (Z6)	0.23454	9.7315	0.0000	0.29634	7.8454	0.0000
β..........	0.63863	15.3507	0.0000	0.55306	9.0569	0.0000
β_1 (LCX31)...	–	–	–	−0.01233	−2.2646	2.3540
β_2 (LCYC2) ..	–	–	–	0.01979	1.9494	5.1252
β_3 (LCYC3) ..	–	–	–	0.01445	2.3198	2.0351
σ_0^* ($d=0$)	2.38157	12.4219	0.0000	2.06573	9.5348	0.0000
σ_1^* ($d=1$)	1.70244	5.9118	0.0000	1.41674	5.4769	0.0000
ψ	−0.33570	−2.4344	1.4916	−0.37712	−2.7537	0.5893
α_0 ($d=0$).....	−0.81881	−4.5382	0.0009	−1.09183	−4.3230	0.0032
α_1 ($d=1$).....	−1.54081	−5.1416	0.0000	−1.93111	−4.3530	0.0028
−2* Log L (1)		4166			4153	
−2* Log L (3)		4261			4246	
	σ_1^2	σ_2^2	ρ	σ_1^2	σ_2^2	ρ
($d=0$)	0.15	0.15	−0.91	0.15	0.15	−1.53
($d=1$)	0.21	0.21	−1.74	0.21	0.21	−2.96
Andrews' test	Statistic	D.o.f.	Sign. (%)	Statistic	D.o.f.	Sign. (%)
(X368)	26.320	2	0.000	24.325	2	0.001

model with the following distribution function:

$$F(X\varphi;\, z\psi) = \frac{1}{1+\exp[-X\varphi/\exp(z\psi)]}. \tag{21}$$

The corresponding log-likelihood function is no longer concave, but different starting values invariably led to the same optimum for all estimations.

Specifying z to be the log marginal wage rate (at $h=0$) the estimates for ψ are -0.734 (-3.67) for constant β and -0.779 (-3.84) for variable β (t-values). The high t-values obtained confirm the previous results of the QLM tests. But due to the form of our model, there is no consistent way of deriving the corresponding preference parameters. Fortunately, it turns out that there is a natural way out of this dilemma. In the heteroscedasticity tests reported above we always restricted attention to the variables appearing as regressors in the equation under test. Table 6, presenting heteroscedasticity tests based on a wider range of variables for the logit model, shows that this was a bad idea indeed, since it made us overlook the fact that the detected heteroscedasticity appearing through LMWR0 is channelled through X368, the dummy for higher education (baccalauréat or above) with no professional or technical degree. This becomes even more compelling when considering the high values of Andrews' test based on clustering according to that variable.

Correcting for heteroscedasticity with z specified as a dummy in (21) can be reconciled with the structure of the model in the following way: calling τ the coefficient of LMWR0 in the model based on (21) we identify two different values of σ^*:

(22) $$\sigma_0^* = \tau \qquad \text{for} \quad z=0$$

and

$$\sigma_1^* = \tau \, exp(\psi) \qquad \text{for} \quad z=1,$$

and these lead to the same structural parameters a and β for the two groups of households defined by the dummy. Of course, this procedure could also be applied with a continuous z variable. However, it would then result in a different value of σ^* for each household, which would make estimation of α problematic.[17]

For a dummy variable this procedure leads to a very natural parameterization of α in the form:

(23) $$\alpha = \alpha_0 (1-z) + \alpha_1 z,$$

where the α_i $(i=0,1)$ can be estimated through (16) by replacing N and σ^* by the relevant values N_i and σ_i^* and summing over the relevant sample.

Table 7 shows the estimation results obtained for step 3 with heteroscedasticity correction applied in all steps. Whereas in steps 1 and 3 we used the ML procedure described above, in step 2 we use EGLS by estimating the two different variances over the two subsamples generated by X368. Comparison with Tables 1 and 3 reveals no big difference in the structural parameters estimated, except for the covariance structure and $\hat{\alpha}$: the subgroup corresponding to X368 (6.81% of the sample) has higher variances of log wage and taste shifter than the rest of the sample, and lower values of $\hat{\alpha}$ leading to lower wage elasticities of labour supply for that group. A possible interpretation is that this subgroup contains individuals who did not have the intention to work after completing their education.[18] The overall distribution of the elasticities reflects this: the elasticities are smaller. This would be an encouraging result if this specification proved statistically better than the previous ones. However, this is not the case, as the following discussion shows.

The increase in Andrews' statistic is surprising at first sight. Yet one can understand that the more complicated structure of the model with heteroscedasticity correction implies a lower quality of the approximation

17. Unless one would be prepared to use (8) to simulate a value of α for each household by using the relevant value of $\hat{\sigma}^* (= \hat{\tau} \exp(z \hat{\psi}))$ and drawing a value of ε in the logistic distribution. A more appealing alternative (inspired from Heckman and MaCurdy, 1980) would be to regress $\hat{\sigma}$ on a set of dummies and make α dependent on these.

18. Recall that most women in the sample have completed their education in the sixties or before.

of the asymptotic distribution of the test. $\hat{\psi}$ is significant in the first step and the variances are different in the second step (see Appendix D). But $\hat{\psi}$ remains significant in step 3, against the expectation that taking account of heteroscedasticity in the first two steps might have removed the problem detected for the estimated value of LMWR0. Tests conducted for an ordinary logit estimation of step 3 following heteroscedasticity-corrected steps 1 and 2 show no major change in comparison with the relevant parts of Tables 2, 4 and 6.

We also looked at the consequences of introducing time dummies in the wage equation following a suggestion by John Ermisch. We used two dummies, called OTIME and NTIME, corresponding to "long hours" (over 41.5 weekly hours) and "full-time" (between 35.5 and 41.5). The estimates reported in Table D.1 show that these result in a non-convexity in the budget line. However, the premium for full time does not seem high enough, given the curvature of the indifference curves, to give rise to the situation where an individual would become indifferent between working full time and not working. Thus the local criterion used here probably retains its validity. The results show no significant departure from those reported above, whether we allow β to vary or not, and whether or not we correct for heteroscedasticity.

A final manifestation of the overall misspecification, taking account of the estimation of α, is given by looking at the estimated residuals obtained for the participants from equation (8). The expectation of each such residual conditional on participation should be positive, and hence we expect their average over participants to be positive. However, this average is negative for all models, with values around -0.4 for the probit and -0.8 for the logit.

5 Conclusions

The first, obvious, conclusion concerns the need for testing. This is trivial but our own example shows that this has not quite become standard practice yet. Secondly, it appears that, although the extreme value specification is not internally consistent (leading to a negative estimate of the correlation between the error terms whereas it implies a positive value) the probit specification does not fare better in specification tests. Among the problems affecting the present specifications, we have privileged the treatment of heteroscedasticity and to a lesser extent coefficient variation, which commonly plague cross-section studies. Other potential problems deserving attention are non-separability between leisure and consumption, measurement errors, endogeneity (e. g. of children) etc. In particular, the persistent differences between the elasticities obtained here and those obtained by BLUNDELL *et al.* [1991] might come from endogeneity of the unearned income variable, on top of the bias generated if the life cycle hypothesis holds. Another possible source of divergence may lie in a different treatment of variables correlated with fixed costs of work.[21] An obvious candidate would be the "suburbs" dummy X54 but it might be rewarding to explore this idea more thoroughly. Yet none of the extensions just mentioned is straightforwardly implementable in the very tight specification studied in this paper. This suggests moving to a different specification altogether in order to obtain a model that could be used confidently for policy simulation.

Summing up, at this stage the only definite result we have obtained is that the preference parameters presented here are still dubious. However, after this specification search, where first and second moment specifications turned out to be more closely related than we had first realized, we feel that we have a much better understanding of both the model and the data.

21. This was suggested to us by Jim Heckman.

APPENDIX A

Data

From the survey Budgets des Familles 1979, we selected 3658 households with the following characteristics:

- The main cell of the household is a married couple.
- The male is either working, or, if presently out of work, has already had a job and is looking for a new one.
- The female is neither at school nor is a student or a pensioner or an 'aide familiale' (*i.e.* working in family business).
- She is not self-employed, except perhaps as a farmer.
- She is neither a teacher nor an artist nor a member of the clergy, army or police.
- Her reported normal weekly hours of work do not exceed 69 hours.
- The household has no wage earner other than husband or wife.
- The wife's age is between 26 and 65 years.

Table A1 gives the means and ranges of the variables used. The first

TABLE A1

General Data Description

Symbol	Description	Min	Mean	Max
PART	Indicator for participation	0	0.4254	1
SEEK	Indicator for seeking	0	0.0547	1
Z1=X1	(Age-40)/10 of female	-1.4	-0.0404	2.5
Z2=X2	Z1 squared	0	0.9074	6.25
Z34	Number of children not yet at school	0	0.1777	3
Z5	Number of children at école maternelle	0	0.2195	3
Z6	Number of other children in the household	0	1.1946	10
X31	No general education degree; professional degree (P.D.)	0	0.2384	1
X32	Degree of primary school (BEP); no P.D.	0	0.2898	1
X33	Same plus P.D.	0	0.1378	1
X34	Degree end of lower secondary school (BEPC); no P.D.	0	0.0927	1
X35	Same plus P.D.	0	0.0921	1
X368	Baccalauréat and above; no P.D.	0	0.0681	1
X379	Same plus P.D.	0	0.0426	1
X54	Suburbs town dummy	0	0.3876	1
X6	Regional unemployment rate	0.0002	0.064	0.0966
X7	Telephone dummy	0	0.63	1
C	Consumption of household	3794	70653	989928
C0	Consumption of household, computed, as if female does not work	3225	59486	960848
TMARG	Marginal tax rate	0.0919	0.2323	0.4977
TMARG0	Marginal tax rate, computed as if female does not work	0.0919	0.2104	0.4977
WF	Gross hourly wage of the female	0	7.5375	56.6
HF	Normal hours worked by the female grossed up to yearly hours	0	810.25	3432

two variables are a participation dummy (defined as weekly hours below 1.5) and a "seeking" dummy (corresponding to the female's own declaration). Female age is modelled quadratically, through (age-40)/10 and its square. Variables Z34, Z5 and Z6 count children in categories based on schooling rather than directly on age. Variable Z34 is the number of children not yet at any form of school, Z5 children at "école maternelle" (kindergarten), and Z6 is the number of other chidren. The education dummies X31-X379 combine information on the highest general education and professional degrees obtained. The odd endings correspond to the presence of a professional degree, the even endings to its absence. The default is no degree whatsoever: this would correspond to notation X30 (for the female), whereas X31 denotes a professional degree and absence of general education degree. For general education, three levels are distinguished: end of primary school X32, end of lower secondary school X34, baccalauréat and above X368. X6 is the regional unemployment at the time of the interview and X7 is a telephone dummy. The other variables relate do the treatment of the tax system explained by Dagsvik *et al.* and to the transitions from step 1 to step 3.

APPENDIX B

Preliminary Results (co-authored by Annette Niedergesäß[22])

Table B1 summarizes the salient features of the logit estimations corresponding to the three different treatments of the seekers and Table B2 gives the corresponding elasticities.

TABLE B1

Preliminary Estimation Results: Variations in the Treatment of the Seekers

Seekers treated as:	Participants		Non participants		Excluded		DAGSVIK *et al.* [1988]	
Intercept	4.43	(4.6)	4.44	(4.5)	4.63	(4.5)	2.47	(1.8)
Z1 = X1.	−.69	(−12.9)	−.58	(−11.2)	−.68	(−12.3)	−.56	(−7.7)
Z2 = X2.	−.21	(−4.0)	−.27	(−5.1)	−.23	(−4.3)	−.35	(−4.8)
Z34	−1.27	(−11.6)	−1.15	(−10.6)	−1.32	(−11.5)	−1.32	(−8.7)
Z5	−.84	(−9.4)	−.88	(−9.7)	−.93	(−9.8)	−.74	(−6.0)
Z6	−.58	(−13.9)	−.57	(−13.5)	−.61	(−13.9)	−.63	(−10.8)
LMRW0	2.45	(12.6)	2.37	(12.3)	2.61	(12.8)	2.55	(8.9)
LOGC0	−.86	(−9.9)	−.87	(−9.8)	−.92	(−10.1)	−.71	(−6.0)
beta	.65	(8.2)	.63	(7.8)	.65	(8.4)	.72	(5.0)
alpha	−.81		−.67		−.58		−.63	

TABLE B2

Elasticities

Seekers treated as:	Participants			Non participants			Excluded			DAGSVIK *et al.* [1988]		
	min	mean	max	min	mean	max	min	mean	max	min	mean	max
Cournot	.45	1.89	26.9	.46	1.99	28.7	.49	2.03	30.1	.03	1.94	19.5
Slutsky	.73	2.07	27.0	.76	2.19	28.8	.79	2.23	30.3	.68	2.15	19.8
Tot. Inc.	−.46	−.18	−.04	−.49	−.20	−.04	−.50	−.21	−.05	−.65	−.21	−.03
Frisch	.86	2.60	30.6	.93	2.81	33.0	.98	2.91	34.9	.95	2.72	25.2

The column on the right hand side of each table corresponds to the results of DAGSVIK *et al.*, who treated the seekers as non-participants. The new results are obtained with a larger sample with variation in tax parameters. The estimated parameters are now better determined, with the intercept becoming significant. A comparison of the original estimates

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with the new ones when seekers are treated in the same way reveals no change in the coefficients that could point to better identification of the effect of the effect of children on the preferences: the biggest differences between the two sets of coefficients appear for age squared, children at école maternelle and the log of consumption when the woman does not work.

When treating the seekers as participants we expected the results to be closer to those obtained when excluding them than to the results obtained by treating them as non-participants. This is not the case and it is best seen by looking at the elasticities: the largest Cournot elasticities are obtained when seekers are excluded, while they are smallest with seekers as participants. However, there is not a big range of variation, neither between the new results nor compared to the original ones.

APPENDIX C

Aspect of the labour supply curves

The plots shown on Figure C.1 have been obtained by solving

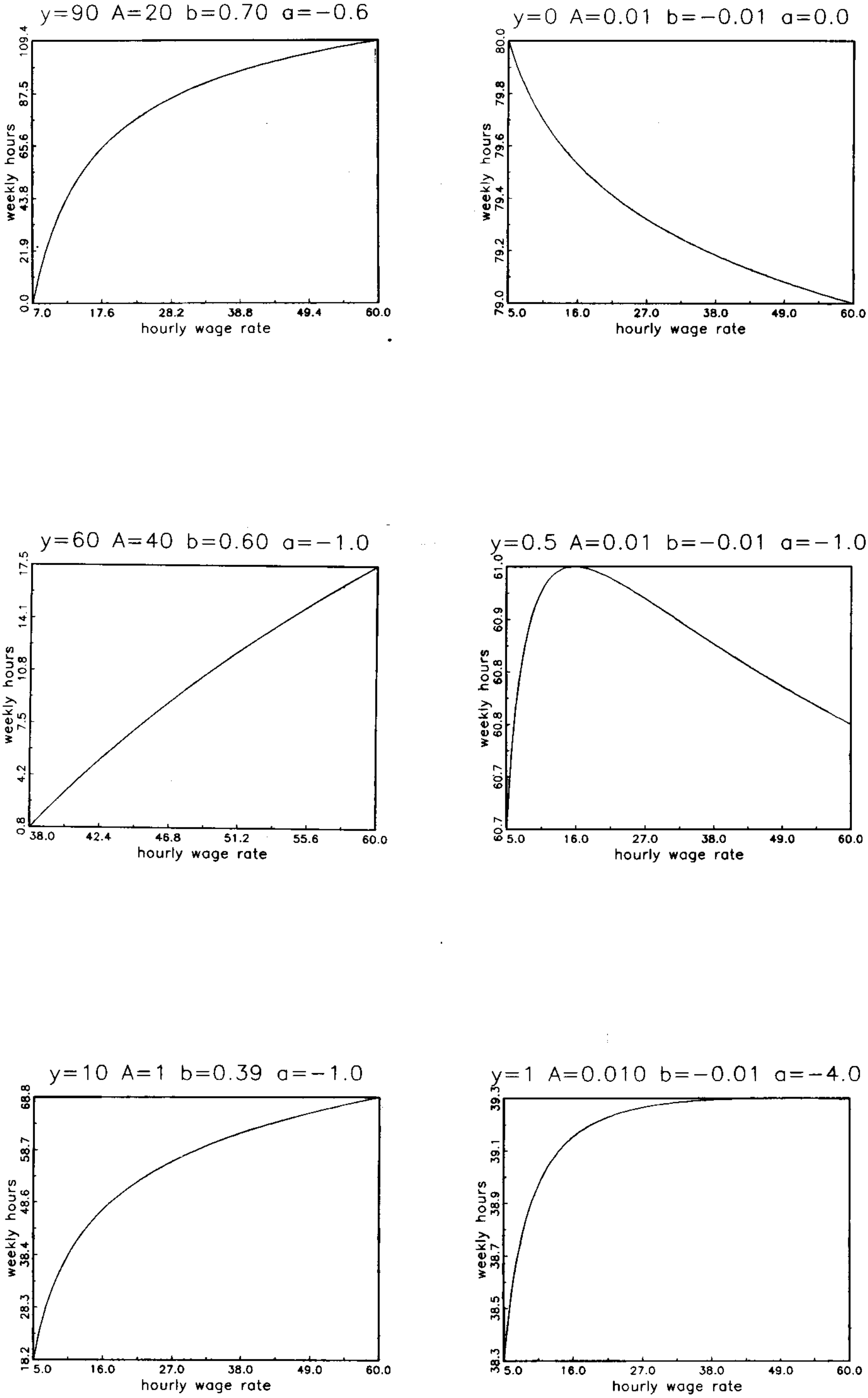
$$\text{(C.1)} \quad \log w - \log(\mathrm{A}/\mathrm{T}) - (1-\beta)\log(y+wh) - (\alpha-1)\log(1-h/\mathrm{T}) = 0$$

numerically for a maximum number of hours of $\mathrm{T} = 8{,}760$ hours, a net hourly wage rate w varying between 5 and 60 F (1969), a fairly realistic range, and for values of the remaining parameters and exogenous variables as shown over each plot. The income variable y is expressed in thousands of francs. It is convenient to think of A as being expressed in hours; the figures reported are in hundreds of hours.

Since A does not appear in the expression of $\partial h/\partial w$ obtained through total differentiation of (C.1), A only acts on the range of desired hours and not on the shape of the supply curve. The impact of α is similar although it does affect the curvature of the schedule. The crucial parameter in determining the shape of the labour supply curve is β. Starting from a parameter and exogenous variables constellation which is close to that reported by DAGSVIK *et al.* the plots have been obtained by pushing β further and further down, adjusting the other parameters and variables so that the range of desired hours remains somewhat realistic (the model uses annual hours but these have been converted to weekly hours for ease of interpretation). Negative desired hours have been cut off. Note that for $\beta = 0$, w disappears from the equation (C.1) if $y = 0$, which determines a horizontal labour supply curve. This indicates why the curves for $\beta = -.01$ are so flat. A look at the corresponding y and A values shows under what extreme conditions the possibility of backward bending, or indeed even simply of a negative slope, does arise.

FIGURE C1

Aspects of Labour Supply Curves from the Box-Cox Specification for Selected Constellations of Parameters and Exogenous Variables



Wage Equations

Table D.1 presents a selection of two of the numerous wage equations which had to be estimated for the different models. They concern the logit model with constant β and no heteroscedasticity correction. See Dagsvik *et al.* for a discussion of the estimated coefficients. The reported F-tests are computed by re-estimating these models over the subsamples defined by X368 and taking the ratio of the two estimated variances. The last column in each panel reports the heteroscedasticity robust *t*-values.

No drastic change arises when we correct for heteroscedasticity in steps 1 and 2.

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