

Tilburg University

Structural models of family labor supply

van Soest, A.H.O.

Published in: Journal of Human Resources

Publication date: 1995

Link to publication in Tilburg University Research Portal

Citation for published version (APA): van Soest, A. H. O. (1995). Structural models of family labor supply: A discrete choice approach. *Journal of Human Resources*, *30*(1), 63-88.

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
 You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Structural models of family labor supply: A discrete choice van Soest, Arthur

The Journal of Human Resources; Winter 1995; 30, 1; ABI/INFORM Global pg. 63

Structural Models of Family Labor Supply A Discrete Choice Approach

Arthur van Soest

ABSTRACT

A static neoclassical structural model is presented, explaining labor supply of both spouses in two adults households. Family preferences are described with a direct translog utility function, with the husband's leisure, the wife's leisure, and family income as its arguments. We assume that the choice set of each family is finite. Account is taken of the Dutch tax and benefits system. We allow for hours restrictions and random preferences, and account for unobserved wages of nonworkers. The models are estimated using smooth simulated maximum likelihood. Results based upon Dutch cross-section data from 1987 are illustrated by confidence intervals for elasticities, and by several policy simulations.

I. Introduction

In this paper, we analyze structural models of labor supply of the two spouses in Dutch two adults families. Family utility depends on the husband's leisure, the wife's leisure, and family income. The family members maximize utility subject to a budget constraint, determined by wage rates, nonlabor income, and tax and benefits rules. This model is an extension of the single individual labor supply model, of which numerous applications exist. See, for example, Moffitt (1990), for applications to European and U.S. data. Examples of applications of the two adults model are Hausman and Ruud (1984); Ransom (1987,

Arthur van Soest is a professor of economics at Tilburg University. He is grateful to Stephen Jenkins, Menno Pradhan, and the referees for useful comments. This research was made possible by a fellowship of the Royal Netherlands Academy of Arts and Sciences. The Netherlands Central Bureau of Statistics (CBS) kindly provided the data. The views expressed in this paper do not necessarily reflect those of the CBS. For information on access to the data used in this article, please contact the author at Tilburg University, P.O. Box 90153, Tilburg, The Netherlands. email AVAS@KUB.NL. [Submitted September 1992; accepted December 1993]

THE JOURNAL OF HUMAN RESOURCES • XXX • 1

1989); and Kapteyn, Kooreman, and Van Soest (1990).¹ In these models, hours worked by the two spouses are treated as mixed discrete and continuous random variables. The main distinguishing characteristic of our model is that labor supply is treated as a discrete choice problem. A major advantage of this, is that nonlinear taxes, joint filing, fixed costs of working, unemployment benefits, etc., can easily be incorporated, without affecting model tractability. Secondly, we are able to allow for a richer stochastic specification than usual: we take account of the problem of unobserved wage rates of nonworkers, and can incorporate random preferences. This is feasible because we apply simulated maximum likelihood estimation (Gourieroux and Monfort 1993). Finally, our model avoids problems of model coherency (see, for example, Blundell 1990; Van Soest, Kooreman, and Kapteyn 1993). Our model is fully structural, in the sense that all policy simulations which can be performed in the continuous model, remain feasible. Various specifications are estimated and compared, in terms of the extent to which they fit the data, and in terms of their implications for own and cross-wage and income elasticities of labor supply of the two spouses.

We find that allowing for hours restrictions substantially reduces estimates of labor supply elasticities. Appropriately accounting for wage rate prediction errors affects the elasticities to a much smaller extent. Results are illustrated by several simulations. According to the most general model, the own (before tax) wage elasticities of aggregate labor supply are 0.11 and 0.40 for males and females, respectively. Cross-wage elasticities are much smaller. We find that removing the main disincentive in the tax system for married females to enter the labor market, would lead to an increase of female labor supply by 4.2 percent, and to a decrease of male labor supply by 0.7 percent.

The paper is organized as follows. In Section II, we briefly explain the Dutch labor supply situation, the tax system, the Dutch policy debate on labor supply and labor force participation, and the contribution of our paper. The basic model is presented in Section III. Extensions are discussed in Section IV. Data, estimation results, and illustrating policy simulations, are described in Section V. Section VI concludes.

II. Labor Supply in the Netherlands

A. Facts and Policy

In Table 1, labor force participation (in persons, excluding the unemployed) in the Netherlands is compared to that in the European Community and in the seven major industrialized countries (G7). Male labor supply has decreased substantially during the last thirty years. The Netherlands follows the EC trend in this respect. The main reason for the decrease is that many older workers stop working (WRR 1990). Participation of females in the Netherlands was extremely low in the six-

^{1.} Generalizations in which spouses have separate utility functions and are, for example, assumed to reach some Pareto-efficient leisure consumption allocation, are beyond the scope of this paper. See, for example, Chiappori (1992) for a discussion of the practical value of such models.

1961	1971	1981	1987
91	84	71	72
90	85	75	71
86	83	78	77
27	31	34	42
40	41	43	45
45	46	52	55
	91 90 86 27 40	91 84 90 85 86 83 27 31 40 41	91 84 71 90 85 75 86 83 78 27 31 34 40 41 43

Table 1	
Employed Labor Force, Percentage of Popula	ation
15–64 Years of Age	

Source: CBS (1993).

....

ties, but has largely caught up with the rest of the EC in the eighties. Still, female participation is relatively low. The difference increases if employment is measured in labor years, because of the relatively large numbers of females working part-time. Measured in labor years in 1987, Dutch employment for males and females is 91.2 percent and 73.1 percent of EC average (WRR 1990, p. 68). One of the explanations is the large number of females' jobs of less than 11 hours per week, for example of students. If these jobs are excluded, female employment in persons in 1987 was 34 percent in the Netherlands, compared to 42 percent in the EC (CBS 1993).

In an influential recent report, the Scientific Council for Government Policy (WRR) discusses the desirability of increasing Dutch labor force participation, and provides suggestions for government policy (WRR 1990). The demographic trend of an ageing population implies that, if participation rates per age group remain as they are, an increasingly smaller number of people will have to work and produce for the benefits of the rest of the population. Benefit premiums thus tend to increase, wage costs will increase, and the conservation of the welfare level is endangered. Apart from these economic arguments, the WRR also stresses sociological arguments: employment improves someone's status in family and society. For example, increasing female participation would help emancipation of females.

Increasing employment requires adjustment of labor demand and supply. In this paper, we consider labor supply only. Suggested policy measures focus on females, with attention for specific groups of males only (the elderly and those receiving disablement benefits). Our model allows for an analysis of labor supply responses of both spouses to any change of tax and benefits rules. Main emphasis however is on participation and labor supply of married females.

Policy measures for married females suggested by WRR (1990) can be divided in two categories. The first is summarized by: remove females' disincentives to accept a job from the system of taxes, benefits, premiums, and subsidies. Our structural model can be used to analyze the effects of this type of measures, to the extent that they are reflected in the budget sets. A discussion of the main features of the Dutch tax and benefits system as incorporated in the model is given below. Examples of disincentives that we do not capture, are household income rent subsidies, exemption of health insurance premiums for nonworking partners, and pension arrangements for partners. The second category of policy measures concerns child care facilities. Our model does not directly capture this. Data on child care and its costs were not available. Some indirect indications for the importance of child care facilities may be derived from the effects of family composition on labor supply (Van Praag, Hop, and Eggink 1991).

Apart from increasing total labor supply, many people also pledge for a redistribution of working hours between husband and wife, mainly for emancipation purposes. The structural family labor supply model is obviously very well equipped to analyze the consequences of financial policy measures (wages, taxes, benefits) to equalize male and female labor supply.

B. Taxes and Benefits

The Dutch 1987 tax and premium system for individuals basically consists of eleven tax brackets, with marginal tax rates gradually increasing from 0 to 70 percent. The average and the marginal tax and premium wedge are about 32 percent and 55 percent at the minimum wage, and 43 percent and 58 percent at the mean wage. Some simplifying assumptions are necessary for our purposes, since the data do not contain all necessary information on deductibles, health insurance premiums, etc.

In the tax rules for two adults families, a number of employment disincentives for females have been removed during the last decades. Until 1973, the wife's income was simply added to the husband's income (joint taxation). In 1973, separate taxation was introduced, but the tax free allowance was much lower for wives than for their husbands, and the system of joint premium payment was retained. Since 1984, premium payments are separate, tax free allowance of husband and wife are equal, and most sources of nonlabor income and deductibles of the wife are treated separately.

The remaining employment disincentive for the wife, is the possibility to transfer her tax free amount to her partner, if she does not work. This implies that the width of the husband's tax-free bracket is doubled if his wife does not work (and vice versa). As an implicit consequence, the tax rate on the wife's earnings increases if her husband works. The additional tax rate on the first Dfl 5,000 of her annual earnings, ranges from 33 percent to 47 percent (WRR 1990, p. 218). This creates a disincentive for wives whose husband works, particularly for jobs of only one or two days per week.²

The data contain information on various types of unemployment benefits for those who are actually unemployed. On the other hand, there is no information on what someone would receive if he or she were to become unemployed. Since the level of unemployment benefits strongly depends on someone's labor market

^{2.} The income tax reform in 1990 has simplified the tax and premium rules, and has reduced the number of tax brackets to three for each individual. The transfer possibility of the tax free allowance has been retained.

history, it may very well be correlated with time persistent unobserved individual characteristics. To avoid these problems,³ we have only taken into account the unemployment assistance a family receives when family income, excluding child benefits, is below the official poverty line for a two adults household without children, which is about 50 percent of average after tax earnings of working males in the sample. Child benefits, which do not depend on family income, then make up for the differences between the poverty lines for families with and without children. Unemployment insurance benefits, which generally have limited duration, are thus ignored. This stylized benefits system implies that the first part of someone's budget set is horizontal only if partner's earnings and other income are low or zero.

III. The Basic Model

The usual assumption in structural labor supply models, is that hours worked (per week) can be each positive real number. We refer to this as "the continuous model." The main distinguishing feature of our framework, is that the choice set is discretized: we assume that each family can choose among the alternatives in the choice set of income leisure combinations $\{(y_i, lm_i, lf_i)\}$ $j = 1, 2, \ldots, m$. Here $lm_i = TE - hm_i$ and $lf = TE - hf_i$, where TE is the time endowment, set equal to 80 hours per week,⁴ and hm_i and hf_i are working hours per week of husband and wife, respectively. We only consider numbers of working hours which are multiples of some fixed interval length IL, in other words, $hm_j = jmIL$, for some $jm \in \{0, \ldots, m_{ind} - 1\}$, and $hf_j = jfIL$, with $jf \in \{0, \ldots, m_{ind} - 1\}$. The choice set thus contains $m = m_{ind}^2$ points. In the data, hours worked per week is always an integer, and most integers from 0 to 60 are present. IL = 1 thus seems a natural choice. In the empirical part of the paper however, we choose IL = 12 or IL = 10, in order to limit the computational burden of the estimation procedure. Correspondingly, m_{ind} is set equal to 5 or 6, and the number of choice opportunities is 25 or 36. The nature of the data thus implies that working with a discrete choice set of some 3,600 elements is natural. For practical reasons, the choice set is further discretized to 25 or 36 elements. Drawbacks of this are the rounding error and the incomplete use of available information.

Moreover, y_j denotes the family's after tax income, including husband's and wife's earnings, possible unemployment benefits, unearned family income such as child allowances, etc.⁵ Details on included taxes and benefits are presented in Section II. For the moment, the before tax hourly wage rate is treated as an observed exogenous variable for all individuals, including nonworkers.

^{3.} In principle, the problem of unobserved benefits can be solved in a similar way as the problem of unobserved wages. This is beyond the scope of this paper.

^{4.} TE could be incorporated as a parameter to be estimated. Preliminary results suggested that the estimate of this parameter is imprecise, and that setting TE equal to 80 hardly affects the other results. 5. Due to lack of data, family expenditures (excluding savings) could not be computed. As a consequence, the model is static and inconsistent with two-stage budgeting in a life cycle framework (see, for example, Blundell 1990).

We work with the translog specification of the direct utility function:

$$(1) \quad U(v) = v'Av + b'v$$

where $v = (\log y, \log lm, \log lf)'$ is the vector of logs of commodity quantities, A is a symmetric 3X3 matrix with entries $\alpha_{ij}(i, j = 1, 2, 3)$, and $b = (\beta_1 \beta_2 \beta_3)'$. Preference variation across families through observed characteristics can be incorporated through the parameters:

(2)
$$\beta_i = \sum_k \beta_{ik} x_k, i = 1, 2, 3, \alpha_{ij} = \sum_k \alpha_{ijk} x_k, i, j = 1, 2, 3$$

The $x_k - s$ reflect family characteristics, such as family composition or the husband's or wife's age, and include a constant term. The index indicating the family is suppressed. In the empirical analysis, some of the parameters will be assumed to be constant across families to reduce the computational burden.

U is defined on the whole positive orthant, including noninteger values of hours worked. For given A and b, it is easy to derive the region in (y, lm, lf) space where U is quasi-concave. If U increases with y, it is quasi-concave at (y, lm, lf) if and only if the indifference surface is convex there: HC must be positive definite, where HC is the matrix of second order derivatives of y with respect to lm and lf, along the indifference surface at (y, lm, lf):

(3)
$$HC = -U_y^{-1} \begin{pmatrix} y_{lm} & 1 & 0 \\ y_{lf} & 0 & 1 \end{pmatrix} HU \begin{pmatrix} y_{lm} & 1 & 0 \\ y_{lf} & 0 & 1 \end{pmatrix}'.$$

Here U_y is the partial derivative of U with respect to y, HU denotes the matrix of second order partial derivatives of U, and $y_{lm} = -U_{lm}/U_y$ and $y_{lf} = -U_{lf}/U_y$, the marginal rates of substitution of male and female leisure with family income. Derivatives are evaluated at (y, lm, lf), and easily obtained from (1).

In defining the choice set, interior points of the budget set are a priori excluded. The economic meaning of the model would therefore be lost if the monotonicity condition that, in some "relevant region" of (y, lm, lf) space, (including, for example, all sample observations), U increases with y, is violated. U is increasing in y at (y, lm, lf) if and only if

(4)
$$2(\alpha_{11}\log y + \alpha_{21}\log lm + \alpha_{31}\log lf) + \beta_1 > 0.$$

In the continuous model with nonlinear taxes, conditions like (3) or (4) often have to be imposed a priori to guarantee model coherency. See, for example, MaCurdy, Green, and Paarsch (1990) or Blundell (1990). This involves imposing a number of inequality restrictions on the parameters of the model, limits the flexibility of specification, and makes ML estimation numerically harder. The discretized approach followed in this paper avoids this. The constraints (3) and (4) are not imposed and can be tested ex post.

Random disturbances are added to the utilities of all choice opportunities in the same way as in the multinomial logit model (Maddala 1983):

(5)
$$U_j = U(y_j, lm_j, lf_j) + \varepsilon_j, (j = 1, ..., m)$$

$$\varepsilon_i \sim EV(I)$$
 $(j = 1, ..., m), \varepsilon_1, ..., \varepsilon_m$ independent,

where EV(I) denotes the type I extreme value distribution with cumulative density $\Pr[\varepsilon_j < \varepsilon] = \exp(-\exp(-\varepsilon))(\varepsilon \in \mathbb{R})$. We assume that the family chooses j for which U_j is largest. The probability that j is chosen is then given by

(6)
$$\Pr[U_j > U_k \text{ for all } k \neq j] = \exp(U(y_j, lm_j, lf_j)) / \sum_{k=1}^m \exp(U(y_k, lm_k, lf_k)).$$

Equation (5) implies $E\{\varepsilon_j\} = 0$ and $V\{\varepsilon_j\} = \pi^2/6$. The assumption that $\varepsilon_1, \ldots, \varepsilon_m$ are i.i.d. limits the flexibility of the error structure, but is necessary to obtain simple expressions for the probabilities in (6). The choice of the magnitude of the common variance can be interpreted as a normalisation. Compared to normalising one of the parameters of the utility function, this normalisation has the advantage that the sign of the normalised parameter is known a priori.

The error structure of the model can be compared with that of the more traditional kinked budget constraint continuous models, which usually include random preferences, optimization errors, or both.⁶ In the case of family labor supply, both types of errors would typically be bivariate, with a univariate term for each spouse. Because of the independence of irrelevant alternatives (IIA) assumption, the $\varepsilon_j - s$ strictly cannot be interpreted as reflecting random preferences due to, for example, unobserved family characteristics (see Ben-Akiva and Lerman 1985). Explicit incorporation of random preferences by adding random components to β_2 and β_3 will be discussed below. A natural way to interpret the $\varepsilon_j - s$ is unobserved alternative specific utility components or errors in perception of the alternatives' utilities, in other words, optimisation errors. Because $P[U_i > U_j | U(y_i, lm_i, lf_i), U(y_j, lm_j, lf_j)]$ depends on $U(y_i, lm_i, lf_i) - U(y_j, lm_j, lf_j)$ and not on, for example, lm_i and lm_j , the errors cannot be interpreted as measurement errors on observed working hours.

To compute the probabilities in (6), we need to know how y is determined by hm and hf, in other words, we need to know the family budget set. The shape of the budget set does not matter. This is a major advantage of our approach compared to the continuous approach, since the latter implies that substantial additional computations are necessary for each additional feature of the budget set [nonlinear taxes, nonconvexities due to the possibility of transfer of tax allowance (see Section II), or due to benefits, etc.].

IV. Extended Models

In this section we discuss three extensions of the basic model introduced above. The extensions should meet three shortcomings of the basic model: first, it treats the problem of unobserved wage rates in an unsatisfactory way. Second, it does not fit the data, in the sense that the number of part-time jobs is strongly overpredicted. Third, it does not allow for random preferences.

^{6.} This is discussed in many papers, starting with Burtless and Hausman (1978). See also Moffitt (1986) for an overview.

A. Errors in Wage Rate Predictions

One of the problems with the type of labor supply models discussed above is that before tax wage rates of many individuals, including all nonworkers, are not observed. The usual approach is to replace wage rates of nonworkers by wage rate predictions, whereas for workers, actual wage rates are used (see for example most papers in Moffitt 1990). This approach in principle does not lead to consistent estimates, since it assumes that wage rates of nonworkers are predicted without error (see MaCurdy, Green, and Paarsch 1990).

Another ad hoc alternative is to use predicted wage rates for workers as well as nonworkers. Because of the nonlinearities in the model and the chosen distribution of the error terms, this would only yield consistent estimates if all families based their decision on the econometrician's predictions instead of actual wage rates. This assumption seems implausible, in particular since some variables will be known to the individual and helpful for predicting, but are not present in the data at hand.

We now explicitly take account of the fact that unobserved wage rates are predicted with error. We use wage equation estimates to construct wage rate predictions, but we also use the estimated standard deviations of the errors in these wage equations to account for prediction errors. The labor supply model itself remains that of Section III. We also retain the assumption that the errors in the wage equations and in (5) are independent, and thus do not allow for endogeneity of before tax wage rates (see Section VI).

In order to describe the way in which the prediction errors are incorporated, we rewrite the model in rather general terms. The labor supply model yields probabilities of working hours combinations of husband and wife as a function of before tax wage rates of husband and wife (Wbm and Wbf) and family characteristics (X, including other family income):

(7)
$$\Pr[(hm, hf) = (hm_j, hf_j)] = F_j(Wbm, Wbf, X)(j = 1, ..., m),$$

where F_j is given by (6). The index indicating the family is suppressed. The likelihood contribution in case of observed Wbm^o and Wbf^o and choice (hm_{job}, hf_{job}) is given by

(8)
$$L = F_{iob}(Wbm^o, Wbf^o, X)$$
.

· ·

....

Measurement errors in Wbm^{o} and Wbf^{o} are thus ignored. The wage equations for males and females are given by

(9)
$$\log Wbs = Z'_s \pi_s + \eta_s$$
 $(s = m, f)$

where Z_m and Z_f are vectors of individual characteristics and η_m and η_f are unobserved errors, assumed to be normally distributed, independent of Z. The standard approach is to replace Wbm^o and Wbf^o in (8), if not observed, by Wbm^p $= \exp(Z'_m \pi_m)$ and $Wbf^p = \exp(Z'_f \pi_f)$, ignoring η_m and η_f . However, for given density p of (Wbm, Wbf), conditional on Z_m and Z_f and determined by π_m and π_f and the density of (η_m, η_f) , the correct likelihood contribution if both wage rates are unobserved is given by

(10)
$$L = \int_0^\infty \int_0^\infty F_{job}(Wbm, Wbf, X) p(Wbm, Wbf) dWbm dWbf.$$

Similar expressions, involving a single integral, can be given if either Wbm or Wbf is unobserved.

In general, (10) cannot be written as a sum of normal probabilities, and computation of L requires numerical integration. There are various ways in which this can be avoided. The first is to derive a simulated moment estimator, generalizing the estimator of McFadden (1989) for the multinomial probit model. This implies that in the first order conditions corresponding to maximizing the likelihood, scores must be replaced by fixed instruments, and that probabilities or partial derivatives of probabilities are replaced by smooth unbiased simulators. McFadden shows that the resulting estimator is consistent, irrespective of the number of replications per individual on which the simulators are based.

An easier alternative, also based on replacing expectations by simulated means, is to approximate the integral in (10) by

(11)
$$L_R = \frac{1}{R} \sum_{r=1}^{R} F_{job}(Wbm_r, Wbf_r, X)$$

where $(Wbm_1, Wbf_1), \ldots, (Wbm_R, Wbf_R)$ and R independent draws from the distribution of (Wbm, Wbf) (conditional on Z_m and Z_f). Similarly, if only the husband's wage rate is unobserved, L is replaced by

(12)
$$L_R = \frac{1}{R} \sum_{r=1}^{R} F_{job}(Wbm_r, Wbf^o, X)$$

and an analogous expression can be given if only Wbf is observed. The approximate likelihood function is maximized, in which, for nonworkers, L is replaced by L_R (see Lerman and Manski 1981; Gourieroux and Monfort 1993). The resulting estimator is inconsistent for fixed R but will be consistent if R tends to infinity with the number of observations (n). If R tends to infinity at a large enough rate (to be precise, if $\sqrt{n/R} \rightarrow 0$), the approximate ML and exact ML estimator are asymptotically equivalent. For fixed n, the estimator converges to the MLestimator if $R \rightarrow \infty$.

B. Hours Restrictions

The basic model appears not to capture the data, in the sense that the number of part-time jobs is strongly overpredicted. The same problem was noted by, for example, Dickens and Lundberg (1985) and by Tummers and Woittiez (1991). A possible explanation is that it does not account for the lack of available part-time jobs. Several explanations for the lack of part-time jobs can be given. Because of fixed costs of hiring workers, or, equivalently, increasing returns to scale of the worker's production, employers may be reluctant to hire part-time workers. This may be an incentive to offer lower wages to part-time workers. Results of Tummers and Woittiez (1991) suggest that this is indeed the case to some extent,

but that this is not enough to explain the lack of part-time jobs. The reason may be the fact that, at least in the Netherlands, most wages are determined by collective bargaining between unions and employer organizations in sectors, and generally do not allow to discriminate between full-time and part-time workers. In this paper, we have assumed that before tax wage rates do not depend on hours worked.

Employers may also simply not offer part-time jobs or refuse to hire workers desiring to work part-time. As a consequence, part-time jobs will be scarce and average search costs for a part-time job will be relatively high. Dickens and Lundberg (1985) have incorporated this idea explicitly into a model of labor supply in a framework with a limited number of job offers, in which most people are restricted in the choice of their working hours. It has been shown (Tummers and Woittiez 1991; Van Soest, Woittiez, and Kapteyn 1990) that such a model fits Dutch data much better than the standard model. Still, with no information on the actual number of job offers or the restrictions individuals actually face, estimation of the job offer mechanism is based upon indirect information (on actual working hours) only. The question then arises whether explaining the phenomena in the data requires this whole extra branch of the model.

The multinomial logit framework in this paper allows for a much simpler ad hoc approach: We include alternative specific constant terms for the alternatives in which either the male or the female works part-time. These constants reflect monetary or nonmonetary drawbacks of working part-time, for example, search costs of part-time jobs (which, in our static framework, cannot be incorporated explicitly), or unattractive job characteristics. If $m_{ind} = 6$ and IL = 10, this leads to six additional parameters. Equation (5) is replaced by

(13)
$$U_j = U(c_j, lm_j, lf_j) + \gamma_m(lm_j) + \gamma_f(lf_j) + \varepsilon_i$$
 $(j = 1, ..., 36),$

where, for s = m, f,

(14)
$$\gamma_s(ls) = \gamma_{sk}$$
 if $hs = 80 - ls = 10k, k = 1, 2, 3$

 $\gamma_s(ls) = 0$ otherwise.

The $\gamma_{sk} - s(s = m, f, k = 1, 2, 3)$ are expected to be negative.

As in the Dickens and Lundberg model, the assumptions that the extra parameters do not depend on characteristics such as wage rates, education level, family composition, etc., implicitly reflects the assumption that hours restrictions are homogeneous across the labor market. It implies that the relative lack of part-time jobs is uncorrelated with these characteristics. We come back to this in Section VI.

A drawback of introducing the alternative specific parameters is that the parameterization depends on the chosen discretization of the choice set. For different values of m_{ind} and IL, different parameters must be used, and results for various values of m_{ind} can no longer be compared. The same drawback is present in the Dickens and Lundberg model. If m_{ind} is large, it may be worthwhile to circumvent this by further parameterizing the $\gamma_{sk} - s$.

C. Random Preferences

Because of the assumption in the multinomial logit model, the $\varepsilon_j - s$ in (5) cannot be interpreted as random preferences due to unobserved family characteristics. Random preferences can be incorporated explicitly by adding error terms to some of the parameters, for example β_2 and β_3 , corresponding to the log-linear terms of male and female leisure in the direct utility function. We thus replace the expressions for β_2 and β_3 in (2) by

(15)
$$\beta_i = \sum_k \beta_{ik} x_k + \zeta_i, i = 2, 3.$$

We assume that ζ_2 and ζ_3 are mutually independent, independent of other errors in the model and of all covariates, and normally distributed with mean 0. Conditional on ζ_2 and ζ_3 , we retain the same labor supply model as before, including the IIA assumption. The probabilities unconditional on ζ_2 and ζ_3 (but for given wage rates) are given by

(16)
$$\Pr[(hm, hf) = (hm_j, hf_j)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Pr[(hm, hf)]$$

= $(hm_j, hf_j) | (\zeta_2, \zeta_3)] p_{\zeta}(\zeta_2, \zeta_3) d\zeta_2 d\zeta_3$

where p_{ζ} is the density of (ζ_2, ζ_3) .

Unobserved random preferences thus complicate ML estimation in a similar way as unobserved wage rate components. Expressions for the likelihood involve a complicated bivariate integral if both wage rates are observed. If both wage rates are unobserved, combining (10) and (16) leads to the following expression for the likelihood contribution:

(17)
$$L = \int_0^\infty \int_0^\infty \int_{-\infty}^\infty \int_{-\infty}^\infty F_{job}(Wbm, Wbf, X|\zeta_2, \zeta_3) p_{\zeta}(\zeta_2, \zeta_3)$$
$$\times p(Wbm, Wbf) d\zeta_2 d\zeta_3 dWbm dWbf$$

where $F_{job}(Wbm, Wbf, X|\zeta_2, \zeta_3)$ is defined as before, but now conditional on (ζ_2, ζ_3) . The integral in (17) can, as before, be approximated by

(18)
$$L_R = \frac{1}{R} \sum_{r=1}^{R} F_{job}(Wbm_r, Wbf_r, X | \zeta_{2r}, \zeta_{3r}).$$

Here $(Wbm_r, Wbf_r, \zeta_{2r}, \zeta_{3r})$, $r = 1, \ldots, R$, are independent draws from the distribution of $(Wbm, Wbf, \zeta_2, \zeta_3)$ (conditional on Z_m and Z_f). Similar expressions can be given for the case that one wage rate is observed.

V. Data and Estimation Results

The data we use stem from the Socio Economic Panel (SEP) wave drawn in October 1987 by the Netherlands Central Bureau of Statistics. We only use observations concerning families with at least husband and wife, with both partners between 16 and 65 years of age. After eliminating a few observations with missing values, 2,859 families remained. In 13.0 percent of these, neither spouse has a paid job. In 3.1 percent of all cases, only the wife works. In 49.7 percent of the families, only the husband works, and in the remaining 34.1 percent, both spouses have a paid job. Working hours include regular overtime if it is paid, as well as hours worked in secondary jobs. They refer to the usual working week and thus do not correct for the number of holidays, etc.⁷ For 20 males and 17 females in 33 families, it is known that they have a paid job, but the number of working hours could not be retrieved. These families are retained in the sample; their likelihood contributions are adjusted to account for the missing information.

After tax earnings include allowances for shift work, paid overtime, tips, etc. Before tax wage rates are computed from after tax earnings and hours worked, inverting the tax function described in Section II. For about 8 percent of working males and 6 percent of working females, no wage rate could be computed. Most of these people did not answer the earnings questions, not being salaried employees.

We distinguish two types of (after tax) family income other than spouses' earnings: Child benefits and other income, mainly capital income. Income of other household members is not included. It is thus assumed that, for example, earnings of children do not affect the husband's and wife's labor supply decisions. Unemployment benefits are also excluded from the other income measure. Sample statistics on the major variables are mentioned in Table 2. There is significantly negative correlation between other family income (excluding child benefits) and male and female working hours and participation.

In constructing family budget sets, we assume that before tax wage rates do not depend on hours worked. Thus, due to the tax system, average after tax wage rates are decreasing. The generalization of Moffitt (1984) and Tummers and Woittiez (1991), who find lower before tax wage rates for part-time jobs, is beyond the scope of our paper.

To obtain wage rate predictions for nonworkers, we have estimated wage equations for males and females. Selection bias was taken into account in the usual way, adding a reduced form participation equation and allowing for nonzero correlation between the two equations (Heckman 1979).⁸ The two equations model was then estimated by maximum likelihood, for males and females separately. The endogenous variable is the log of before tax hourly earnings. Explanatory variables include dummies for the education levels, age variables, the minimum wage, and the regional unemployment rate. Estimation results are mentioned in Table A1 in the appendix.

We find a significantly negative correlation coefficient for males. This is unexpected and may indicate misspecification of the reduced form model. The correlation coefficient is insignificant for females. Estimated slope coefficients are gener-

^{7.} The hours question in the survey is, for those who have one paid job: "How many hours per week do you usually spend on this job?" and for those with more than one paid job: "How many hours per week do you usually spend in total on these jobs?"

^{8.} We thus assumed joint normality of the errors. Results of Melenberg and Van Soest (1993) suggest that this has no significant impact on the wage equation estimates.

Table 2	
Sample	Statistics

Variable (De	escription)			Mean	Standard Deviation	Number
NCH	(number c	of children)		1.09	1.12	2859
DCH < 6	(dummy c	hildren younger t	han 6)	0.28	0.45	2859
AGEM	(age husb	and)		41.13	11.05	2859
AGEF	(age wife)			38.63	11.02	2859
EDLM	(education	n level, husband;	1:low, 5:high)	2.72	1.08	2859
EDLF	(education	n level, wife)		2.34	0.97	2859
СНВ	(child ben	efits; Dfl per wee	k)	33.55	47.65	2859
OFI	(other fam	nily income; Dfl p	per week)	39.47	147.90	2859
WBM	(before ta	x hourly wage rat	e, husband; Dfl)	26.71	17.35	2176
WBF	(before ta	x hourly wage rat	e, wife; Dfl)	18.46	8.83	989
HM	(working	hours per week, l	nusband ^a)	35.42	17.88	2839
HF	(working	hours per week, v	wife ^a)	9.68	14.66	2842
DEM	(dummy e	mployed, husban	d)	0.84	0.36	2859
DEF	(dummy e	mployed, wife)		0.40	0.49	2859
Pearson Cor	relation Coef	ficients				
	HF	WBM	WBF	DEM	DEF	OFI
НМ	0.14	-0.12	0.03	0.86	0.14	-0.28
HF		-0.04	0.03	0.15	0.82	-0.08
WBM			0.23		-0.02	0.10
WBF				0.03		0.06
DEM					0.16	- 0.34
DEF						-0.10

a. Including nonworkers.

ally in line with common findings. The wage rate increases with education and age and, according to the product terms, the increase with age is strongest for the highest education levels. The impact of the minimum wage rate on the wage rate is quite high, particularly for females. However, the legal minimum wage varies with age only, so this regressor may simply correct for the imperfect fit of the log quadratic age pattern.

A. Results Basic Model

The model introduced in Section III (Model I) has been estimated by maximum likelihood. Unobserved wage rates were replaced by predictions based upon the estimates in Table A1, without taking account of the error in the wage equation. Included family characteristics in (2) are the number of children (*NCH*), a dummy for children younger than six (*DCH* < 6), the male's log age (*LAGE*) and log age squared (*L2AGE*) (in β_2), and the female's log age and log age squared (in β_3 and α_{23}). β_1 and the α_{ij} 's other than α_{23} are assumed not to depend on family

characteristics.⁹ Estimation results are mentioned in the appendix (Table A2), both for IL = 12 and $m_{ind} = 5$ (25 choice opportunities), and for IL = 10 and $m_{ind} = 6$ (36 opportunities).

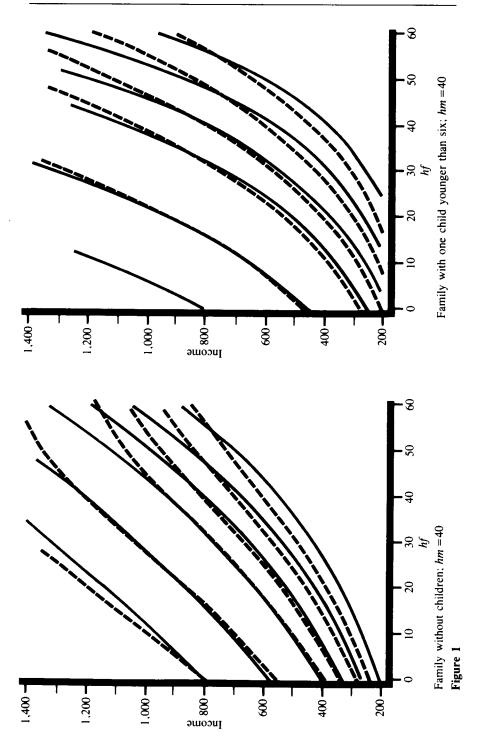
Most of the parameter estimates for the two cases are similar, in particular the slope parameters including family characteristics. There are some significant differences between the estimated $\alpha - s$. In general, estimated standard errors are remarkably small, and many parameters are significantly different from zero. Since parameters by themselves are not very informative here, some auxiliary calculations are used to illustrate the results.

It is easy to check that (4) is satisfied for all sample observations, in other words, utility increases with consumption. Equation (3) is satisfied for most sample observations: According to the estimates based on $m_{ind} = 5$ and $m_{ind} = 6$, the utility function is not quasi-concave at 0.8 percent and 6.3 percent of all sample points, respectively. These observations are high income families in which the wife has a full-time job. In the continuous model, this finding would not have been possible, since quasi-concavity of U would have been imposed a priori to guarantee coherency (see MaCurdy, Green, and Paarsch 1990, for example).

The parameters of *NCH* and *DCH* < 6 imply a negative impact on female labor supply. Labor supply decreases with age for most males and females. In figure 1, some indifference curves are drawn, for fixed working hours of the partner. Solid lines refer to $m_{ind} = 5$, dashed lines to $m_{ind} = 6$. Comparison of the curves gives some idea about the importance of discretizing the budget set, in other words, going from 36 to 25 points. Differences between curves for families of different composition confirm the stylized fact that family composition affects the wife's labor supply more than the husband's. Moreover, the difference between the shapes of the curves for the two spouses suggests that the elasticity of substitution is larger for females than for males, implying larger own wage rate elasticities of females than of males. Elasticities will be discussed below in more detail for several models. Finally, the concave parts of some of the dashed curves are in line with the fact that according to the $m_{ind} = 6$ estimates, quasi-concavity is violated at some sample points.

Although results discussed so far seem satisfactory, Table 3 shows that the model hardly fits the data at all. The table presents actual and simulated marginal frequencies of male and female labor supply, using the $m_{ind} = 6$ discretization. For both sexes, the rate of nonparticipation is underpredicted, as well as the number of people working 31-42 hours a week, the interval which includes the common full-time working week in the Netherlands. The number of part-time workers is strongly overpredicted, as well as the number of people working more than 42 hours per week. The misfit of the model is confirmed by chi-squared diagnostic tests (Andrews 1988): The explained sum of squares of a regression of a vector $(1, \ldots, 1)' \in \mathbb{R}^n$, where *n* is the number of observations, on the vectors of differences between observed and predicted cell frequencies and the score

^{9.} There is no theoretical reason for not incorporating these characteristics in, for example, α_{12} and α_{13} as well. The usual approach is to let them enter in two places, in the constant term of each spouse's hours equation (as in Hausman and Ruud 1984). In that sense our choice is already more flexible.



	Males			Females	8
hm	Actual	Predicted	hf	Actual	Predicted
0	15.959	6.605	0	61.783	53.700
10	0.637	6.119	10	8.988	20.723
20	2.052	8.922	20	11.253	10.744
30	2.654	18.294	30	5.909	6.081
40	58.033	29.205	40	10.510	4.269
50	20.665	30.854	50	1.557	4.482

Table	3		
~ .			

Observed and Predicted Frequencies Basic Model; $m_{ind} = 6$

Explanation

hm, hf: hours categories males and females:

0: 0-5, 10: 6-15, 20: 16-25, 30: 26-35, 40: 36-45, 50: > 45.

actual: sample fraction (percentage)

predicted: predicted fraction (percentage), using the estimates in Table A2.

vectors, follows, under the null hypothesis of no misspecification, a chi-squared distribution with m degrees of freedom.

The finding that the standard model cannot explain the peaks in the hours distribution is not new and has motivated incorporating explicit hours restrictions in the individual labor supply model (Dickens and Lundberg 1985; Tummers and Woittiez 1991). Empirical results with these suggest that there are too few part-time jobs. Apparently, our approach of grouping working hours into rather broad intervals of 10 or 12 hours per week does not solve this problem.

B. Estimation Results Extended Models

Table A2 also contains the estimation results of various extensions of the model. These are based upon $m_{ind} = 6$ and IL = 10, in other words, a choice set of 36 elements. Model II refers to the basic model with additional parameters reflecting hours restrictions [see especially (13) and (14)]. The error structure is the same as in the basic model. The *ML* estimates for β_1 and for the $\alpha_{ij} - s$ not depending on family characteristics, strongly differ from those of Model I. Parameters related to family characteristics however are similar to earlier findings. The estimates imply that utility (the $\gamma_{sk} - s$, s = m, f, k = 1, 2, 3, not taken into account) increases with family income for all observations. U is quasi-concave at 99.9 percent of all observations.

All estimates for the $\gamma_{sk} - s(s = m, f, k = 1, 2, 3)$ are significantly negative. This confirms the interpretation that they reflect hours restrictions and that Model II is a significant improvement of the basic model. This is also confirmed using familiar tests for the null that all $\gamma_{sk} - s$ are equal to zero (*LM*, Wald, or *LR* test; the null is strongly rejected by either of these). As to be expected, introducing the $\gamma_{sk} - s$ solves the problem of Table 3: predicted frequencies are now very similar

to actual frequencies, with a maximum difference of 0.29 percentage point for hf = 0. It should however be admitted, that the model specification can still be rejected by chi-squared diagnostic tests similar to those discussed above, if these tests are based upon a bivariate cell partition, considering *hm* and *hf* simultaneously.

Model III estimates in Table A2 refer to the model in which not only hours restrictions are included, but also wage prediction errors are taken into account for persons with unobserved wage rate. The likelihood function is approximated using (11) and (12), with R = 5 (Model IIIa) and R = 10 (Model IIIb). We used the wage equation estimates in Table A1, and assumed that the error terms in the two equations are independent.¹⁰ The fact that parameters in the wage equation are estimated is not taken into account in computing the standard errors of the labor supply model estimates. These standard errors might therefore be underestimated.¹¹ The two sets of parameter estimates are very similar, suggesting that R = 5 already yields reasonable accuracy, even though consistency of approximate ML requires $R \rightarrow \infty$. Due to insufficient memory space for storing large matrices in Fortran, we were not able to obtain estimates for larger R. Differences with Model II seem substantial and significant, at least for the α_{ii} – s and β_1 . Estimates of the slope coefficients of family characteristics are again very well in line with previous results, and so are the estimates of the $\gamma_{sk} - s$, reflecting hours constraints. The estimates of Model IIIa imply that U would be decreasing with income at 3.3 percent of all sample points. For these observations, the microeconomic foundation of the model is lost. At 0.4 percent of sample points, indifference surfaces are not convex. Predicted marginal frequencies appear to be virtually identical to those of Model II.

Finally, Table A2 presents results for Model III extended with explicit random preferences [ζ_2 and ζ_3 in (15); Model IV]. We assume that ζ_2 and ζ_3 are independent and normal. Approximate ML was used, based upon (17) and similar likelihood contributions in case of observed wage rates. Again, results obtained with R = 5 and R = 10 are virtually identical. We present those for R = 10. Differences with Model III results are minor. The estimates for the standard deviations of the random preference terms seem rather inaccurate, and the importance of incorporating these errors is not confirmed.¹²

C. Elasticities

Elasticities for the average family, in other words, the family with average characteristics, wage rates and other income, are presented in Table 4. We present six

^{10.} In principle, it is possible to estimate wage rate equations and labor supply model simultaneously. This requires a small adjustment of the likelihood function only. The number of parameters to be estimated substantially increases. Earlier results with the single individual model (see especially, Van Soest and Kooreman 1991) suggest that coefficients in the wage equations hardly change.

^{11.} Again, results in Van Soest and Kooreman (1991) suggest that this problem is of no practical importance. In a simultaneous model for a single individual, the correlation matrix between the estimator for wage equation and labor supply parameters, is quite small.

^{12.} Standard tests (*LR*, *LR*, Wald) are in principle invalid due to the one-sided nature of the alternative. Still, any bivariate confidence region for $((\sqrt{\{z\}}, (\sqrt{\{z\}})))$ with a reasonable size contains (0,0).

Table 4

Elasticities for the Average Family

	Wage Rate Male			Wag	Wage Rate Female			Other Family Income		
	Median	Q10	Q90	Median	Q10	Q90	Median	Q10	Q90	
Model	I (basic n	nodel: m _{ine}	f = 6):							
hm	0.153	0.136	0.172	-0.036	-0.042	-0.030	-0.034	-0.037	- 0.030	
hf	-0.171	-0.237	-0.116	1.027	0.961	1.078	-0.009	-0.018	0.001	
Model	II (hours	restriction	is included)							
hm	0.104	0.078	0.122	-0.015	-0.023	-0.010	-0.026	-0.031	-0.022	
hf	0.051	-0.049	0.122	0.524	0.470	0.599	0.016	0.004	0.029	
Model	III (hours	restrictio	ns and wage	prediction	errors incl	uded: $R =$	10)			
hm	0.076	0.053	0.093	-0.017	-0.025	-0.012	-0.030	-0.035	-0.026	
hf	0.005	-0.093	0.072	0.472	0.417	0.543	0.008	-0.005	0.019	

Explanation:

hm: working hours males; hf: working hours females

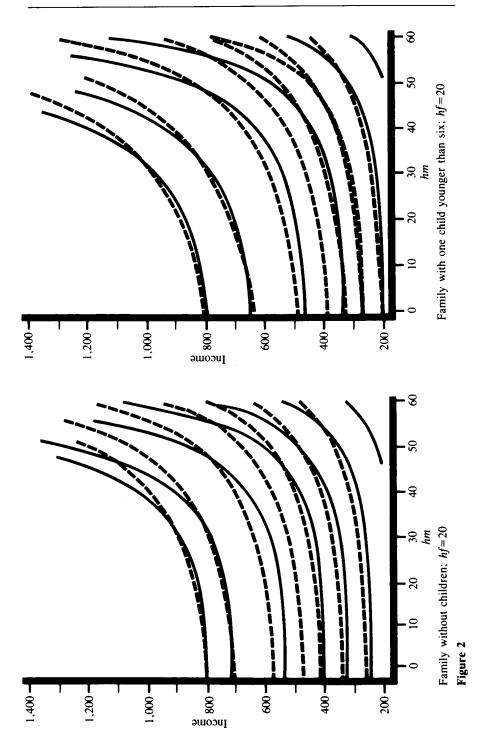
Q10: first decile; Q90: ninth decile; [Q10;Q90]: 80 percent confidence interval.

elasticities: of husband's and wife's expected hours worked,¹³ with respect to before tax wage rates of husband and wife, and with respect to other family income. The tax and benefits system described in Section II is fully taken into account.

To judge the accuracy of the estimates, the elasticities are calculated 100 times, for 100 independent draws of the parameters from the estimated asymptotic distribution of their estimator. We present median elasticities, and the first and ninth deciles. The latter two are the bounds of a two sided confidence interval of approximately 80 percent.

For the basic model, we present the results for the discretization with $m_{ind} = 6$ only. The confidence intervals based on $m_{ind} = 5$ always overlap with these, again indicating that discretizing into 25 or 36 points does not make too much difference. The elasticity estimates for the basic model seem very precise. Own wage elasticities are significantly positive at the 10 percent level. Corresponding to earlier findings for the Netherlands, the own wage elasticity of females is larger than for males. A closer look at the calculations reveals that, for both spouses, the effect of an own wage increase on expected hours is largely due to an increasing participation probability. Both cross-wage elasticities of hours worked are significantly negative, suggesting that male and female leisure are substitutes. Cross-wage sensitivity is much smaller than own wage sensitivity. The elasticity of the husband's hours with respect to other family income is small but significantly negative. For the wife's hours, it is even smaller and insignificant.

^{13.} In spite of the discretization, the expected number of hours worked, taking account of the random errors in (5), is a continuously differentiable function of wages and nonlabor income, so the elasticities are well defined.



In the Model II elasticities, hours restrictions parameters are fully taken into account. The female's own wage rate elasticity is significantly smaller than in Model I. Cross-wage elasticities also decrease in absolute value, the effect of the husband's wage rate on the wife's hours no longer being significant. Elasticities with respect to other family income remain very small. Surprisingly, the impact of other income on the wife's working hours is now significantly positive.

For Model III, we only present results based upon R = 10 draws per observation, since results with R = 5 are virtually identical. The confidence intervals overlap with those of Model II. The point estimates of own wage elasticities are somewhat smaller than in Model II. The husband's labor supply elasticity with respect to other family income is significantly negative but small, whereas the wife's is now again insignificant. Allowing for random preferences hardly changes the elasticity estimates. We therefore have omitted the results for Model IV.¹⁴

We thus conclude that own wage elasticities tend to decrease if the model is further extended, particularly if hours restrictions are incorporated. This conclusion remains valid for other families, with, for example, a different family composition. The main differences between elasticities for families with different characteristics are due to differences in expected hours. For example, the wife's expected hours decrease with family size, while her own wage elasticity increases with family size.

D. Policy Simulations

As discussed in Section II, our model can be used to predict the consequences of financial policy measures affecting family budget sets on labor supply of both spouses. To illustrate this, some simulation results are presented in Table 5. Results refer to sample averages. The first row contains sample averages of hours worked and the sample fractions of families in which no spouse works, in which one spouse works, and in which both spouses work. The second row is based upon the basic model (Model I), and again reveals that this model does not capture the data. The other rows are therefore based upon the Model III estimates (Table A2, Column 3b), allowing for hours constraints and wage rate prediction errors. Comparing Rows 1 and 3 shows that this model captures sample participation rates reasonably well.

In Rows 4 and 5, before tax wage rates of all males and females, respectively, have been increased by 10 percent. Resulting own wage elasticities of average hours worked are 0.11 and 0.40, respectively. These are comparable to the corresponding elasticity estimates for the average family.¹⁵

The last two rows refer to changing the tax and benefits system described in Section II. Row 6 shows the effect of abolishing the transfer possibility of the tax free amount. One earner families will thus face a tax increase, and a disincentive of female participation is removed. The estimated effects are an increase of

^{14.} Allowing α_{12} and α_{13} to vary with family characteristics, hardly affects the elasticity estimates in any of the models.

^{15.} Elasticities vary substantially across subgroups. For example, for the subsample of families with and without young children, the wives' own wage elasticities are 0.36 (change from 11.71 to 12.13 hours per week) and 0.58 (from 5.55 to 5.87), respectively.

Table 5	
Simulation	Results

	Average Hours		Participation Rates (percentage)			
	hm	hf	hm = 0 $hf = 0$	hm = 0 $hf > 0$	hm > 0 $hf = 0$	hm > 0 hf > 0
1. Sample 2,826 (observations)	34.82	9.90	12.85	3.11	48.94	35.10
2. Simulation Model I	34.88	10.33	7.53	1.34	47.40	43.73
3. Simulation Model III	34.98	10.00	12.11	3.46	49.26	35.17
4. Wage rates males * 1.10	35.36	10.03	11.29	3.23	50.07	35.41
5. Wage rates females * 1.10	34.92	10.40	11.88	3.76	48.34	36.02
6. Separate taxation (no transfers)	34.72	10.42	12.65	3.59	46.95	36.80
7. Separate taxes and benefits	34.10	9.29	11.40	5.73	52,86	30.01

female labor supply by 4.2 percent, but also a decrease of male labor supply by 0.7 percent. Total hours of both spouses would thus increase by 0.4 percent only. The effect is thus more a redistribution of hours worked than just an increase of female labor supply. The number of families in which only the husband works, would decrease by 4.7 percent, and the number of two earner families would increase by 4.6 percent. The final row shows what could happen if the whole system of taxes and benefits were individualized. Individual benefits are then assumed to be at most Dfl 167 per week, in other words, 50 percent of the official family poverty line. This creates a disincentive for wives of working husbands, since the wife will receive benefits if she does not work, no matter what her husband earns. This effect would dominate the separate taxation effect: Female labor supply decreases by 7.1 percent, and the number of two earner households decreases by 14.5 percent. Obviously, the results of this final simulation are merely an illustration, because of the strongly stylized benefit system incorporated.

VI. Conclusions

We have considered models of family labor supply characterized by a discretized budget set. The main advantage of these models is that they allow in a computationally tractable way for all kinds of nonlinearities and nonconvexities in the budget set. This makes them a fruitful instrument for the analysis of policy measures related to taxes and benefits. In our view, this is more important than the possible drawback: Since hours are categorized into groups, we make a rounding error, and do not use the sample information to its full extent.

Extensions of the basic model show that the fit improves substantially if hours restrictions are accounted for, even though this happens in an ad hoc way. Allowing for hours restrictions substantially reduces estimated own wage elastici-

ties. Extensions with more random terms are handled by using approximate ML, based upon simulated probabilities. We thus treat the problem of unobserved wage rates in a satisfactory way, and we can explicitly allow for random preferences. Incorporating these two features, however, does not substantially affect the elasticity estimates. The policy value of one of the extended models is illustrated by several simulations of tax and benefits changes suggested in policy discussions to stimulate female participation in the Netherlands. Because we model family labor supply, these simulations reveal labor supply effects not only for females, but also for their husbands.

Because misspecification is still present, calculated elasticities and policy simulations must be interpreted with some reservation. The sensitivities of labor supply with respect to own and partner's wage rates are rather small compared to other findings for the Netherlands (see, for example, Theeuwes and Woittiez 1992), and tend to become smaller the more general and realistic the model becomes. This suggests that the true elasticities may also be rather small. Results of a final example of an extension confirm this: We extended Model III, allowing $\gamma_{fk}(k = 1, 2, 3)$, the hours restrictions parameters for females, to depend on the wife's characteristics (*LAGE*, *L2AGE*, *NCH*, *DCH6*). The 80 percent confidence bounds for the average male's and female's own wage elasticities of expected hours worked, are [-0.005, 0.048] and [0.269, 0.362], respectively. Income elasticities slightly increase (in absolute value), but remain very small.

Appendix 1

Estimation Results

Table A1

Wage Rates and Participation Model

	Mal	es	Fema	les
	Parameter	t-value	Parameter	t-value
Participation Equation				
Constant	-73.82	- 11.53	- 34.81	-6.39
DED2	0.36	3.78	0.21	2.89
DED3	-0.01	-0.01	1.12	1.41
DED4	-2.67	-2.13	0.69	0.54
DED5	-2.48	- 1.99	0.83	0.62
$LAGE (= \log age)$	45.66	11.42	21.15	6.24
L2AGE (= LAGE squared)	-6.48	- 11.93	-3.16	-6.77
DED3 * LAGE	0.19	0.76	-0.17	-0.76
(DED4 + DED5) * LAGE	0.92	2.79	0.05	0.14
DWEST	0.11	1.38	0.13	2.17
UNEMPR	-0.84	0.51	-1.31	-0.90
WMIN	-2.12	-2.89	-0.02	-0.03
NCH (no. of children)	0.08	1.89	-0.26	-8.32
DCH < 6 (dummy child < 6 yrs)	-0.29	-2.68	-0.77	- 10.51
Log Wage Rate Equation				
Constant	-10.56	-6.82	-1.17	-0.59
DED2	0.07	2.74	0.05	1.45
DED3	-0.51	-2.00	-0.42	-1.23
DED4	-2.03	-6.17	-1.33	-2.85
DED5	- 1.86	- 5.57	-1.21	-2.57
LAGE	6.70	7.02	1.02	0.81
L2AGE	-0.92	-6.94	-0.14	-0.82
DED3 * LAGE	0.20	2.83	0.15	1.62
(DED4 + DED5) * LAGE	0.68	7.68	0.47	3.65
DWEST	0.08	4.85	0.09	3.67
UNEMPR	-0.73	-1.66	0.34	0.51
WMIN	0.57	3.67	0.84	3.21
σ(η)	0.35	95.83	0.33	61.56
ρ	-0.54	-9.78	0.11	0.94

Explanation:

Wage variable: log before tax hourly wage rate (Dfl per hour).

The education variable ED ranges from 1 (primary school) to 5 (university level). The variables DED2, DED3, DED4, and DED5 are dummies for the corresponding levels (DED3 = 1 if ED = 3; DED3 = 0 otherwise, etc.).

DWEST: dummy variable; *DWEST* = 1 if the family lives in the western part of The Netherlands (with largest population and industrial density); DWEST = 0 otherwise.

UNEMPR: unemployment rate (males and females jointly) in the region; 11 regions (provinces) are distinguished.

WMIN: log of before tax minimum wage (in DFL/hour) fixed by law.

 $\sigma(\eta)$: standard deviation of the error term in the wage equation.

ρ: correlation coefficient between the error terms in the participation equation and the wage equation.

Table A2

Estimation Results Structural Models

					Ia (m _{ine}	1 = 5)	Ib (m _{ind}	= 6)
					Parameter	t-value	Parameter	t-value
α ₁₁	$(\log^2 y)$				-0.850	- 3.20	- 1.084	- 3.82
x ₂₂	$(\log^2 lm)$				- 3.030	-8.25	-1.808	- 5.12
x 33	$(\log^2 lf)$				0.125	0.31	1.593	4.42
¥ 12	$(\log y \times \log y)$				0.145	0.61	-0.307	-1.2
¥ ₁₃	$(\log y \times \log y)$	g lf)			-2.226	-9.54	-2.318	- 10.16
230	$(\log lm \times 1)$	og lf)			5.319	2.47	5.019	2.53
t ₂₃₁	$(\log lm \times 1)$				-2.585	-2.14	- 2.582	- 2.32
1 ₂₃₂	$(\log lm \times 1)$	og lf \times L2	AGE)		0.361	2.14	0.364	2.33
233	$(\log lm \times 1)$,		-0.500	-2.46	-0.438	- 2.30
234	$(\log lm \times 1)$	og $lf \times De$	CH < 6)		- 1.655	- 3.56	- 1.765	-4.22
1	$(\log y)$				33.472	5.11	41.158	6.02
20	(log <i>lm</i>)				158.440	6.87	146.341	6.96
21	$(\log lm \times I)$	· · · ·			- 80.688	-6.72	- 74.904	-6.81
22	$(\log lm \times I)$,			11.509	6.98	10.693	7.07
23	$(\log lm \times N)$				3.681	2.12	3.209	1.97
24	$(\log lm \times I)$	OCH < 6)			14.850	3.76	15.809	4.46
30	(log <i>lf</i>)				106.523	4.04	82.866	3.40
					52,102		10 010	
	$(\log lf \times L)$	· · ·			-52.182	-3.60	-42.818	- 3.19
32	$(\log lf \times L2)$	AGE)			- 52.182 8.434	-3.60 4.14	-42.818 7.046	
2	$(\log lf \times L2) \\ (\log lf \times N)$	2AGE) CH)						3.74
32 33	$(\log lf \times L2)$	2AGE) CH)			8.434	4.14	7.046	3.74 3.27
32 33	$(\log lf \times L2) \\ (\log lf \times N)$	2AGE) CH)	IIIa (R	= 5)	8.434 5.201	4.14 3.42 4.51	7.046 4.589	- 3.19 3.74 3.27 5.24 = 10)
32 33	$(\log lf \times L2) \\ (\log lf \times N) \\ (\log lf \times D) \\$	2AGE) CH)	IIIa (<i>R</i> Parameter	= 5) <i>t</i> -value	8.434 5.201 15.854	4.14 3.42 4.51	7.046 4.589 16.364	3.74 3.27 5.24
32 33 34	$(\log lf \times L2) \\ (\log lf \times N) \\ (\log lf \times D) \\ \hline \\ II$	2AGE) CH) CH < 6)	·	t-value	8.434 5.201 15.854 IIIb (<i>R</i> Parameter	4.14 3.42 4.51 = 10) <i>t</i> -value	7.046 4.589 16.364 IV (<i>R</i> = Parameter	3.74 3.27 5.24 = 10) <i>t</i> -value
32 33 34	$(\log lf \times L2)$ $(\log lf \times N)$ $(\log lf \times D)$ II Parameter	2AGE) CH) CH < 6) t-value	Parameter		8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99	7.046 4.589 16.364 IV (<i>R</i> = Parameter - 1.415	3.74 3.27 5.24 = 10) <i>t</i> -value - 4.08
32 33 34 11 22	$(\log lf \times L2)$ $(\log lf \times N)$ $(\log lf \times D)$ II Parameter 0.189	2AGE) CH) CH < 6) <i>t</i> -value 0.64	Parameter - 1.342	<i>t</i> -value - 3.97	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977	4.14 3.42 4.51 = 10) t-value - 3.99 - 13.03	$\frac{7.046}{4.589}$ $\frac{4.589}{16.364}$ $\frac{1V (R = -1.415)}{-5.118}$	3.74 3.27 5.24 = 10) <i>t</i> -value - 4.08 - 13.17
11 11 12 13 11	$\frac{(\log lf \times L2)}{(\log lf \times N)}$ $\frac{(\log lf \times N)}{(\log lf \times D)}$ $\frac{11}{11}$ Parameter 0.189 -4.003	2AGE) CH) CH < 6) t-value 0.64 - 11.05	Parameter - 1.342 - 5.038	<i>t</i> -value - 3.97 - 13.25	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380	4.14 3.42 4.51 = 10) t-value - 3.99 - 13.03 - 10.50	7.046 4.589 16.364 IV (<i>R</i> = Parameter - 1.415 - 5.118 - 7.030	3.74 3.27 5.24 = 10) <i>I</i> -value - 4.08 - 13.17 - 10.55
11 11 12 12	$(\log lf \times L2)$ $(\log lf \times N)$ $(\log lf \times D)$ II Parameter 0.189 -4.003 -6.618	2AGE) CH) CH < 6) t-value 0.64 - 11.05 - 10.00	Parameter - 1.342 - 5.038 - 6.970	<i>t</i> -value - 3.97 - 13.25 - 10.53	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957	4.14 3.42 4.51 = 10) t-value - 3.99 - 13.03	$\frac{7.046}{4.589}$ $\frac{4.589}{16.364}$ $\frac{1V (R = -1.415)}{-5.118}$	3.74 3.27 5.24 = 10) <i>t</i> -value - 4.08 - 13.17
11 11 12 13 12 13	$(\log lf \times L2)$ $(\log lf \times N0)$ $(\log lf \times D0)$ II II $Parameter$ 0.189 -4.003 -6.618 1.248	2AGE) CH) CH < 6) t-value 0.64 -11.05 -10.00 4.80	Parameter - 1.342 - 5.038 - 6.970 0.087	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46	7.046 4.589 16.364 $IV (R =$ $Parameter$ -1.415 -5.118 -7.030 0.016 -1.668	3.74 3.27 5.24 = 10) <i>t</i> -value - 4.08 - 13.17 - 10.55 0.06 - 6.74
11 12 13 11 12 13 230	$(\log lf \times L2) \\ (\log lf \times N) \\ (\log lf \times N) \\ (\log lf \times D) \\ \hline \\ II \\ \hline \\ Parameter \\ \hline \\ 0.189 \\ -4.003 \\ -6.618 \\ 1.248 \\ -0.733 \\ \hline \\ \end{cases}$	2AGE) CH) CH < 6) t-value 0.64 - 11.05 - 10.00 4.80 - 3.03	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170	4.14 3.42 4.51 = 10) t-value -3.99 -13.03 -10.50 0.34 -6.46 2.00	7.046 4.589 16.364 IV (<i>R</i> = Parameter - 1.415 - 5.118 - 7.030 0.016 - 1.668 4.143	3.74 3.27 5.24 = 10) 4.08 13.17 10.55 0.06 6.74 1.97
11 11 12 12 13 12 13 13 12 13 13 12 13 13	$(\log lf \times L2) (\log lf \times N) (\log lf \times N) (\log lf \times D) (\log lf \times $	2AGE) CH) CH < 6) t-value 0.64 - 11.05 - 10.00 4.80 - 3.03 2.47	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75	7.046 4.589 16.364 IV (<i>R</i> = Parameter -1.415 -5.118 -7.030 0.016 -1.668 4.143 -2.070	3.74 3.27 5.24 = 10) <i>I</i> -value - 4.08 - 13.17 - 10.55 0.06 - 6.74 1.97 - 1.75
11 11 12 13 13 13 13 13 13 13 13 13 13 13 13 13	$(\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) (\log l$	2AGE) CH) CH < 6) t-value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044	4.14 3.42 4.51 = 10) t-value -3.99 -13.03 -10.50 0.34 -6.46 2.00	7.046 4.589 16.364 $IV (R = -1.415$ -5.118 -7.030 0.016 -1.668 4.143 -2.070 0.278	3.74 3.27 5.24 = 10) -4.08 -13.17 -10.55 0.06 -6.74 1.97 -1.75 1.68
1 1 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) (\log l$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044 0.275	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75 1.68	7.046 4.589 16.364 IV (<i>R</i> = Parameter -1.415 -5.118 -7.030 0.016 -1.668 4.143 -2.070	3.74 3.27 5.24 = 10) -4.08 -13.17 -10.55 0.06 -6.74 1.97 -1.75 1.68
11 11 12 13 13 13 13 13 13 13 13 13 13	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) = -100 (\log lf \times D0) (\log lf \times D$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76 -2.61	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274 - 0.481	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68 - 2.50	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044 0.275 - 0.471	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75 1.68 - 2.45	7.046 4.589 16.364 IV (<i>R</i> = Parameter -1.415 -5.118 -7.030 0.016 -1.668 4.143 -2.070 0.278 -0.476 -1.443	3.74 3.27 5.24 = 10) - 4.08 - 13.17 - 10.55 0.06 - 6.74 1.97 - 1.75 1.68 - 2.47 - 3.43
11 12 13 13 14 11 12 13 13 13 13 13 13 13 13 13 13 13 13 13	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times D0) (\log l$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76 -2.61 -3.76	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274 - 0.481 - 1.459	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68 - 2.50 - 3.47	8.434 5.201 15.854 Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044 0.275 - 0.471 - 1.468	4.14 3.42 4.51 $= 10)$ $t-value$ -3.99 -13.03 -10.50 0.34 -6.46 2.00 -1.75 1.68 -2.45 -3.49 4.11	7.046 4.589 16.364 IV (R = Parameter - 1.415 - 5.118 - 7.030 0.016 - 1.668 4.143 - 2.070 0.278 - 0.476 - 1.443 34.468	3.74 3.27 5.24 = 10) - 4.08 - 13.17 - 10.55 0.06 - 6.74 1.97 - 1.75 1.68 - 2.47 - 3.43 4.29
11 11 12 13 12 13 12 13 12 13 12 13 13 13 14 15 16 16 16 16 16 16 16 16 16 16	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) (\log l$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76 -2.61 -3.76 -0.50	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274 - 0.481 - 1.459 32.021	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68 - 2.50 - 3.47 4.09	8.434 5.201 15.854 Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044 0.275 - 0.471 - 1.468 32.931	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75 1.68 - 2.45 - 3.49 4.11 6.68	7.046 4.589 16.364 $IV (R = -1.415$ -5.118 -7.030 0.016 -1.668 4.143 -2.070 0.278 -0.476 -1.443 34.468 152.496	3.74 3.27 5.24 = 10) 4.08 -13.17 -10.55 0.06 -6.74 1.97 -1.75 1.68 -2.47 -3.43 4.29 6.71
11 11 12 23 33 12 13 230 231 232 233 234 235 236 237 238 239 231 232 233 234 235 236 237 238 238 239 239 239 239 239 239 239 239	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) = 0.000 (\log lf \times D0) = 0.000 (\log lf \times D0) (\log lf \times D0) = 0.000 (\log lf \times D0) (\log l$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76 -2.61 -3.76 -0.50 5.78	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274 - 0.481 - 1.459 32.021 148.631	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68 - 2.50 - 3.47 4.09 6.67	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 0.094 - 1.601 4.170 - 2.044 0.275 - 0.471 - 1.468 32.931 150.631	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75 1.68 - 2.45 - 3.49 4.11 6.68 - 5.66	7.046 4.589 16.364 IV (R = Parameter - 1.415 - 5.118 - 7.030 0.016 - 1.668 4.143 - 2.070 0.278 - 0.476 - 1.443 34.468 152.496 - 65.546	3.74 3.27 5.24 = 10) <i>i</i> -value - 4.08 - 13.17 - 10.55 0.06 - 6.74 1.97 - 1.75 1.68 - 2.47 - 3.43 4.29 6.71 - 5.57
31 32 33 33 34 11 22 33 34 230 231 232 233 234 20 20 21 22 23 33	$(\log lf \times L2) (\log lf \times L2) (\log lf \times N0) (\log lf \times N0) (\log lf \times N0) (\log lf \times D0) = 0.189 - 4.003 - 6.618 - 0.733 - 6.618 - 0.733 - 5.126 - 2.148 - 0.733 - 5.126 - 2.148 - 0.733 - 5.126 - 2.148 - 0.286 - 0.497 - 1.574 - 3.605 - 125.474 - 67.945 - 0.945 -$	2AGE) CH) CH < 6) <i>t</i> -value 0.64 -11.05 -10.00 4.80 -3.03 2.47 -1.86 1.76 -2.61 -3.76 -0.50 5.78 -5.96	Parameter - 1.342 - 5.038 - 6.970 0.087 - 1.558 4.187 - 2.038 0.274 - 0.481 - 1.459 32.021 148.631 - 64.698	<i>t</i> -value - 3.97 - 13.25 - 10.53 0.32 - 6.40 2.02 - 1.75 1.68 - 2.50 - 3.47 4.09 6.67 - 5.59	8.434 5.201 15.854 HIIb (<i>R</i> Parameter - 1.380 - 4.977 - 6.957 - 0.094 - 1.601 4.170 - 2.044 0.275 - 0.471 - 1.468 32.931 150.631 - 65.938	4.14 3.42 4.51 = 10) <i>t</i> -value - 3.99 - 13.03 - 10.50 0.34 - 6.46 2.00 - 1.75 1.68 - 2.45 - 3.49 4.11 6.68	7.046 4.589 16.364 $IV (R = -1.415$ -5.118 -7.030 0.016 -1.668 4.143 -2.070 0.278 -0.476 -1.443 34.468 152.496	3.74 3.27 5.24 = 10) 4.08 -13.17 -10.55 0.06 -6.74 1.97 -1.75 1.68 -2.47 -3.43 4.29 6.71

Table A2 (continued)

	II		IIIa $(R = 5)$		IIIb $(R = 10)$		IV (R = 10)	
	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
β ₃₀	131.329	5.17	152.627	5.97	151.613	5.94	153.957	5.98
β3ι	49.787	-3.64	- 50.880	-3.71	- 49.912	- 3.64	- 50.127	- 3.63
β ₃₂	8.066	4.21	8.195	4.26	8.061	4.19	8.099	4.17
β33	5.066	3.60	4.932	3.47	4.856	3.42	4.899	3.45
β ₃₄	14.430	4.61	13.640	4.35	13.704	4.36	13.539	4.31
Ym1	-3.742	- 14.81	-3.740	- 15.02	- 3.734	- 14.99	-3.738	- 15.01
Ym2	-3.143	-22.67	- 3.133	-22.52	-3.131	-22.45	-3.130	-22.48
Ym3	-3.256	-26.26	- 3.238	- 26.05	-3.237	-26.03	-3.235	-25.99
Yrı	- 1.805	- 20.14	- 1.801	-20.21	-1.800	-20.19	- 1.798	- 20.09
Y ₅₂	- 1.365	-11.74	-1.358	- 11.73	-1.358	-11.74	-1.354	- 11.67
Y ₁ 3	-1.522	-11.90	-1.521	- 11.92	- 1.521	-11.93	- 1.519	-11.90
$\sqrt{V\{\zeta_m\}}$							0.254	1.18
$\sqrt{V\{\zeta_f\}}$							0.064	0.22

Explanation:

I: Basic model

II: Model with parameters reflecting hours restrictions ((13)-(14)); imputed wage rates for non-workers

III: Model with hours restrictions and wage rate prediction errors taken into account; approximate ML-estimates using Equations (11)-(12)

IV: III extended with random preferences; approximate ML-estimates using Equations (15)-(16).

y: family income; lm: leisure husband; lf: leisure wife

Definition of explanatory variables: See Table 2.

Definition of parameters: See Equations (1), (2), (13), (14), (15).

References

- Andrews, Donald. 1988. "Chi-Square Diagnostic Tests for Econometric Models." Journal of Econometrics 37(1):135-56.
- Ben-Akiva, Moshe, and Steven Lerman. 1985. Discrete Choice Analysis. Cambridge: MIT Press.

Blundell, Richard. 1990. "Evaluating Structural Microeconometric Models of Labor Supply." Working paper. London: University College.

Burtless, Gary, and Jerry Hausman. 1978. "The Effect of Taxation on Labor Supply: Evaluating the Gary Income Maintenance Experiment." *Journal of Political Economy* 86(6):1103-30.

CBS. 1993. "Arbeidsdeelname in Nederland vanaf 1961 in Internationaal Perspectief." Supplement Sociaal-economische Maandstatistiek 1993(2):13-19.

Chiappori, Pierre-André. 1992. "Collective Labor Supply and Welfare." Journal of Political Economy 100(3):437-67.

Dickens, William, and Shelly Lundberg. 1985. "Hours Restrictions and Labor Supply." NBER working paper No. 1638.

Gourieroux, Christian, and Alain Monfort. 1993. "Simulation Based Inference: A Survey with Special Reference to Panel Data Models." *Journal of Econometrics Annals* 59(1/2):5-34.

- Hajivassiliou, Vassilis. 1993. "Simulation Estimation Methods for Limited Dependent Variable models." In *Handbook of Statistics*, Vol. 11, ed. G. S. Maddala et al., 519-44. Amsterdam: North-Holland.
- Hausman, Jerry, and Paul Ruud. 1984. "Family Labor Supply with Taxes." American Economic Review 74(2):242-48.
- Heckman, James. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1):153-61.

Kapteyn, Arie, Peter Kooreman and Arthur van Soest. 1990. "Quantity Rationing and Concavity in a Flexible Household Labor Supply Model." *Review of Economics and Statistics* 70(1):55-62.

Lerman, Steven, and Charles Manski. 1981. "On the Use of Simulated Frequencies to Approximate Choice Probabilities." In *Structural Analysis of Discrete Data with Econometric Applications*, ed. Charles Manski and Daniel McFadden, 305–19. Cambridge: MIT Press.

Maddala, G. S. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

MaCurdy, Thomas, David Green, and Harry Paarsch. 1990. "Assessing Empirical Approaches for Analyzing Taxes and Labor Supply." *Journal of Human Resources* 25(3):415–90.

McFadden, Daniel. 1989. "A Method of Simulated Moments for Estimation of Multinomial Probits Without Numerical Integration." Econometrica 57(5):995-1026.

Melenberg, Bertrand, and Arthur van Soest. 1993. "Semiparametric Estimation of the Sample Selection Model." Center discussion paper 9334. Tilburg: Tilburg University.

Moffitt, Robert. 1984. "The Estimation of a Joint Wage Hours Labor Supply Model." Journal of Labor Economics 2(4):550-66.

- ——. 1986. "The Econometrics of Piecewise Linear Budget Constraints." Journal of Business and Economic Statistics 4(3):317–28.
- ——. 1990. "Taxation and Labor Supply in Industrial Countries." Journal of Human Resources 25(3).
- Ransom, Michael. 1987. "An Empirical Model of Discrete and Continuous Choice in Family Labor Supply." *Review of Economics and Statistics* 59(3):465–72.

———. 1989. "The Added Worker Effect in a Microeconomic Model of the Family with Market Rationing." Working paper. Salt Lake City: Brigham Young University.

Theeuwes, Jules, and Isolde Woittiez. 1992. "Advising the Minister on the Elasticity of Labour Supply." Leyden: Leyden University. Mimeo.

Tummers, Martijn, and Isolde Woittiez. 1991. "A Simultaneous Wage and Labor Supply Model with Hours Restrictions." Journal of Human Resources 26(3):393-423.

Van Praag, Bernard, J. Peter Hop, and Evelien Eggink. 1991. "A Symmetric Approach to the Labour Market." Working paper. Rotterdam: Erasmus University.

Van Soest, Arthur, Isolde Woittiez, and Arie Kapteyn. 1990. "Labor Supply, Income Taxes, and Hours Restrictions in the Netherlands." *Journal of Human Resources* 25(3):517-58.

Van Soest, Arthur, and Peter Kooreman. 1991. "On the Optimal Degree of Sophistication of a Labour Supply Model." Working paper. Tilburg: Tilburg University.

Van Soest, Arthur, Peter Kooreman, and Arie Kapteyn. 1993. "Coherency and Regularity of Demand Systems with Equality and Inequality Constraints." *Journal of Econometrics* 57(1):161-88.

WRR. 1990. "Een Werkend Perspectief; Arbeidsparticipatie in de Jaren '90''. The Hague: Wetenschappelijke Raad voor het Regeringsbeleid.