

Female Labour Supply in Farm Households: Farm and Off-Farm Participation*

TIM CALLAN

The Economic and Social Research Institute

ARTHUR VAN SOEST

Tilburg University

Abstract: Many Irish women in farm households have an input into the running of the farm, while a much smaller proportion are engaged in off-farm employment. Using cross-section household data, we analyse various models in which farm wives choose between farm work, off-farm paid work, and other (home production) activities. The explanatory variables include family characteristics, farm characteristics and the woman's potential wage rate for off-farm employment. We compare probit- and logit-type models and allow for wage rate endogeneity. The main finding according to all models is the very large sensitivity of off-farm participation with respect to the wage.

I INTRODUCTION

A vast literature on female labour supply has grown up in recent decades. But most studies exclude women whose husbands are self-employed or farmers.¹ The main reason for this exclusion is that such women may face different economic opportunities from others. They have an additional option of assisting on the family farm or business. Furthermore, the value of their

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1. See, for example, Killingsworth and Heckman's (1986) summary of the samples used in these various studies: the vast majority exclude women who are themselves self-employed, or whose husband is self-employed or a farmer.

time in this use is not conveniently summarised by a wage: by definition, relatives assisting are family members who do not receive a regular wage. This creates obvious difficulties in modelling the incentives facing them.

In many countries, the proportion of married women who have this additional option is low: their exclusion from studies in the UK or USA, for example, does not greatly affect the overall picture of married women's labour supply in those countries. But in Ireland the size of the self-employed sector, and more especially of the farm sector, is such that the issue is potentially important. Adjustment of farm labour supply to changes in the balance between farm and off-farm opportunities is of considerable relevance in the context of reforms of the Common Agricultural Policy and the reductions in agricultural output likely to be associated with the completion of the Uruguay round of GATT negotiations. It is clear from the general labour supply literature that women's labour supply may be more responsive than that of men, so that particular attention may need to be given to the labour supply of farm wives in this context.

In this paper we examine the influences on farm wives' participation in farm work and off-farm work. The main focus for the paper is to explore the sensitivity of the results to differences in model specification and estimation procedures. In this way we attempt to identify those results which are robust with respect to statistical assumptions and differences in estimation procedure. The paper is structured as follows. Section II briefly reviews the evidence concerning the extent of farm wives' participation as relatives assisting, and outlines the nature of the data used in the present analysis. A model of the decision between participation in farm work, off-farm employment and non-participation is outlined in Section III, together with the estimation procedures. Section IV deals with the results, and considers the sensitivity of wage elasticities with respect to choices made in model specification and estimation. The main conclusions are drawn together in the final section.

II RELATIVES ASSISTING: A DYING BREED OR A HIDDEN ARMY?

Estimates of the incidence of relatives assisting on family farms vary widely, as pointed out by Fahey (1990). The Census of Population uses a "principal economic status" classification (PES). As Fahey points out, "PES data tend to discount the economic activity of women who see their primary rôle in terms of housework" (Fahey, 1990, p. 179). It is not surprising, therefore, that the Census figures show very low numbers of women classified as relatives assisting — around 5,000 in 1981. The Labour Force Survey includes a labour force measure, under which persons who are engaged in activity for "pay, profit or family gain" for more than one hour per week are

classified as economically active. One might expect that this measure would include many women not included by the PES measure. However, the numbers classified as relatives assisting under this definition in the 1987 Labour Force Survey are also about 5,000.

Sectoral studies of agriculture have shown quite different results. The EC Farm Structure survey² of 1979-80, found over 10 times as many women at work in agriculture as the 1981 Census; and over 90,000 married women working as relatives assisting in agriculture alone. Short-term and seasonal participation were included in this measure, but accounted for only a small proportion of the total. The level of participation shown by this data source has fluctuated, giving rise to suspicions of measurement error, but these fluctuations have been at a high level relative to the Census and Labour Force Surveys.

Fahey's conclusion, based on comparisons within and between the relevant surveys, is that the Labour Force Survey (and *a fortiori* the Census of Population) underestimates the numbers of farm wives engaged in farm work, while the figures in the Farm Structures Survey may be somewhat on the high side. Differences in concepts may play some rôle in creating the gap between the different estimates, but it is clear that there are also substantial biases involved. The reasons for such biases are outside the scope of the present paper; suffice it to say that difficulties in establishing the boundaries between farm work and other work, the preconceptions of enumerators, interviewers and respondents, shaped by general societal attitudes and the relative prestige accorded to different statuses have all been identified as possible contributors.³

The data used in the present study were drawn from the ESRI Survey of Income Distribution, Poverty and Usage of State Services, conducted in 1987. Respondents answered questions about their main economic status in a way similar to that for the Labour Force Survey. But they were also asked separate questions about extent of farm work, irrespective of their answer to the question on principal economic status.⁴ Those who stated that their principal status was home duties, but reported working more than an hour a week on the farm were reclassified to the status of relatives assisting.⁵ This

2. For a more detailed assessment of this data source see Fahey (1990) and O'Neill (1985).

3. Shortall (1990), for example, argues that the concentration on traditionally defined farm work obscures women's rôle.

4. The key question, asked of every respondent, was "Do you own or operate any farm land, or assist with the running of a farm owned by a member of your family?" Follow-up questions included the number of weeks of full-time work, and for part-time work, the number of weeks and weekly hours.

5. Most of those reclassified in this way worked substantially more than the minimum of one hour.

definition of "relatives assisting" on farms in the ESRI survey produces a figure of just under 40,000 married women in this status. This lies between that of the Farm Structure survey, which is suspected of being an overestimate, and those of the Census of Population and Labour Force Surveys, which are suspected of being underestimates.

The ESRI survey contains a total of 511 farm households, but only 418 of these contained a woman aged under 65 and married to the person mainly responsible for the farm. Missing data led to the exclusion of a further 23 cases, leaving a sample of 395 cases for analysis. Of these cases, 44 women (11 per cent) were engaged in paid off-farm employment, 159 (40 per cent) were classified as relatives assisting with farm work, with the remaining 192 (49 per cent) engaged in neither of these activities. A description of the variables used in the analysis is given in Appendix A, with sample statistics in Appendix B.

More detailed information on weeks and hours of work is available for about 85 per cent of those classified as relatives assisting. Of these, about 80 per cent were found to have worked for 40 weeks or more in the year; and less than 8 per cent worked fewer than 13 weeks. Combining information on weeks worked and hours worked per week, we constructed a measure of annual labour input. Taking a value of 48 weeks at 40 hours as a measure of a full year's work, we found that 11 per cent worked as relatives assisting for a full year, 26 per cent worked between a half-year and a full year, and a further 38 per cent worked the equivalent of between a quarter-year and a half-year. Thus, for the vast majority of those classified as relatives assisting, their rôle involved a substantial time commitment rather than simply a seasonal one.⁶ As a result, the extent of participation as a relative assisting would not be substantially changed by raising the threshold from one hour per week of farm work.

Of the 44 women working in paid employment, only 1 worked for less than 20 hours per week, and over 70 per cent worked for at least 30 hours per week. This suggests that either the opportunities for part-time work were extremely limited, or the fixed costs associated with employment (such as travel to work, and some element of childcare costs) discouraged the choice of such arrangements. Half of the 44 women were in professional or technical jobs, including 18 in teaching or nursing — a higher proportion than for the full population of employed married women.

6. Interviews were conducted between February and September 1987. Some women who had only a short, seasonal involvement in farm work may not have classified themselves as relatives assisting because of the timing of the interview; but the group identified here, as indicated by the extra information on weeks of work, does not include many such women.

III ANALYSIS OF FEMALE LABOUR SUPPLY IN FARM HOUSEHOLDS

Basic Model

Our focus in this section is on the labour supply behaviour of farm wives. As noted earlier, the labour supply of this group is rendered more complex by the fact that they may allocate time to farm activities, as well as to off-farm employment, home production and leisure. The data collected in the ESRI survey are not sufficiently detailed to support a full structural model along the lines of the household production models surveyed by Gronau (1986). A structural model would include a production function (in this case, for farm output), with the time spent by a farm wife as relative assisting figuring as one form of labour input, substitutable against other labour and non-labour inputs. Here a simpler approach is adopted, with farm characteristics (farm size, soil type and farm system) being treated as factors which shift the productivity of labour inputs. These factors are treated as exogenous, as well as the off-farm labour supply of the husband. The main endogenous variable is an index D indicating the woman's type of economic activity:

D=1: the woman has a formal job and receives a wage (employed)

D=2: the woman works on the farm (relative assisting)

D=0: the woman is neither an employee, nor a relative assisting (non-participant).

The value of D indicates the main activity. In principle, it is possible that individuals might combine farm work and off-farm employment. But the data show that very few women combine farm work and off-farm work. This may reflect the lack of suitable part-time jobs. In principle, a model similar to that set out below, but of a multivariate rather than multinomial nature, could be used to allow for this possibility. Given the very small number of women combining outside work with work as a relative assisting, estimation of such a model would be infeasible, so instead D is treated here as having one and only one value. A wage rate is observed if and only if D=1. The natural logarithm of the wife's gross (i.e., pre-tax) hourly wage rate is denoted by W.

We want to find out what determines D, with emphasis on economic factors such as W. W is treated separately from the other variables, because of the observability problem (it is not observed unless D=1) and because of possible endogeneity. We therefore also include a wage equation. A so-called "random utility" model can capture the main features of interest. The complete model for individual i is as follows:

$$U_{ij} = A_{ij} + u_{ij} \quad (j = 0, 1, 2) \quad (1)$$

$$D_i = j \text{ if and only if } U_{ij} \geq U_{ik}, \quad k = 0, 1, 2 \quad (2)$$

$$A_{ij} = X_i' \beta_j + \gamma_j W_i \quad (j = 1, 2); \quad A_{i0} = 0 \quad (3)$$

$$W_i = Z_i' \alpha + v_i \quad (4)$$

$$u_{i0} = 0; \quad (u_{i1}, u_{i2}, v_i | X_i, Z_i) \sim N_3(0, \Sigma) \quad (5)$$

Thus, if $\gamma_1 = \gamma_2 = 0$, (1) through (3) yield the familiar multinomial probit model with three alternatives (see, for example, Maddala, 1983). By means of normalisation, $\Sigma(1,1) = \Sigma(2,2) = 1$. Because only the differences $U_{ij} - U_{ik}$ are identified, the normalisation $U_{i0} = 0$ is necessary for identification.

The covariance matrix Σ can be a full matrix. There seems to be no economic reasons for setting $\Sigma(1,2)$ equal to zero. In particular, if we imposed $\Sigma(1,2) = 0$ and then rewrite the model with a different normalisation such as $U_{i1} = 0$, we would obtain a transformed covariance matrix with a non-zero element in place of $\Sigma(1,2)$ (the covariance between $-u_{i1}$ and $u_{i2} - u_{i1}$ is non-zero if the covariance between u_{i1} and u_{i2} is zero).

If we ignore labour market constraints leading to involuntary unemployment, U_{i1} can be interpreted as the difference between utility of employment and utility of non-participation. The term $\gamma_1 W_i$ thus reflects the impact on utility of the difference between earnings and returns of non-participation (i.e. home production). It might also pick up some taste-shifter effect, however. Since the wife's contribution to farm output is not observed, returns to activity as a relative assisting are not measured. The term $\gamma_2 W_i$ may to some extent pick up the part of difference between farm earnings and returns of home production not captured by other regressors such as farm size and type. Again it may also reflect a pure taste-shifter effect. Given the information in the data, the two cannot be disentangled.

Setting $\Sigma(1,3) = \Sigma(2,3) = 0$ boils down to assuming that W is exogenous. Unobserved characteristics not included in X or Z may however lead to correlation between v_i and the u_{ij} 's. Therefore, we shall at least try to estimate the model with a full covariance matrix Σ , although, for practical purposes, it may still be necessary to impose zero restrictions.

The vectors of exogenous variables X and Z may partly overlap. Throughout the paper, we shall assume that X contains at least one variable which is not in Z (e.g. characteristics of the farm or family composition) and that Z contains at least one variable which is not in X (e.g. the woman's education level). These two conditions are sufficient for (non-parametric) identification of the model, even if no restrictions on Σ are imposed. It is clear that the

latter of the two, which is the hardest to defend from an economic point of view, cannot be omitted, unless restrictions on Σ are imposed instead.

Alternative Models

A number of variants and generalisations of the basic model described above are possible. In order to determine the sensitivity of the results with respect to distributional and functional form assumptions, we estimate some of these alternatives. The relatively small number of observations makes a more general treatment, such as semi-non-parametric estimation, infeasible. The alternatives which we shall consider are the following:

(A) Multinomial Logit, exogenous wage rates

Replace (5) by:

$$u_{ij} \sim \text{EV}, (j=0,1,2); v_i \sim N(0, \sigma_v^2), u_{i0}, u_{i1}, u_{i2}, v_i \text{ independent} \quad (5')$$

Here EV denotes the (standard) extreme value distribution underlying the multinomial logit model (cf. McFadden, 1974). For given W , the choice probabilities are the familiar multinomial logit probabilities:

$$P(D_i = j | X_i, Z_i, W_i) = \frac{\exp(A_{ij})}{\sum_k \exp(A_{ik})} \quad (6)$$

(B) Multinomial Logit, endogenous wage rates

The specification given above does not allow for endogeneity of W . It can however easily be generalised such that it does, without essentially complicating the estimation procedure. This is achieved by replacing (5') by:

$$v_i \sim N(0, \sigma_v^2) \quad (7)$$

$$u_{ij} - \mu_j v_i | v_i \sim \text{EV}, j=0,1,2, \mu_0 = 0 \quad (8)$$

$$u_{i0} | v_i, u_{i1} | v_i, u_{i2} | v_i \text{ independent} \quad (9)$$

If $\mu_j \neq 0$, μ_{ij} and v_i are not independent. μ_1 and μ_2 are parameters to be estimated. The expression for the conditional choice probabilities which generalises the ordinary multinomial logit:

$$P(D = j | X, Z, W) = \frac{\exp(A_j + \mu_j v)}{\sum_k \exp(A_k + \mu_k v)} \text{ with } v = W - Z' \alpha \quad (6')$$

This thus boils down to adding the residual of the wage equation to the systematic part of the U_{ij} 's, with coefficients μ_j .

(C) Non-linearities

The impact of exogenous variables and W on U_{ij} may be non-linear. Obviously, if this only concerns observed exogenous variables, it is straightforward to allow for, including non-linear transformations of these variables in X . The situation is slightly more complicated if the impact of W is non-linear. We may, for example, want to use a Box-Cox transformation and replace (3) by:

$$A_{ij} = X_i' \beta_j + \gamma_j \frac{(\exp(\lambda W) - 1)}{\lambda} \quad (j=1,2); \quad A_{i0} = 0 \quad (3')$$

For $\lambda \rightarrow 0$ we again get the model with the log wage W . For $\lambda = 1$ the wage itself is included. In general, any $\lambda \in \mathfrak{R}$ is possible, although it is often assumed that $\lambda \in [0,1]$. This generalisation can be incorporated in the basic multinomial probit model, as well as in the multinomial logit variants. As will be seen below, the non-linearities make ML-estimation more difficult, but does not complicate a simulation-based estimation procedure.

Estimation Procedures

The basic model can be estimated in several ways. Apart from ML-estimation, we discuss some alternative estimators, which can also be used to estimate the alternative models.

(1) ML-estimation of the Basic Model

This is straightforward. The likelihood contributions can be written as follows, distinguishing the case that W is observed ($D=1$) and the case that W is not observed ($D=2$ or $D=0$). The index i is suppressed.

$D=1$, observed log wage W :

$$L = f_v(v) P(-u_1 < -A_1, u_2 - u_1 < A_1 - A_2 | v), \quad (10)$$

where $v = W - Z'\alpha$ and $A_j = X_i'\beta_j + \gamma_j W$.

Here f_v denotes the marginal density of v , which is univariate normal $N(0, \sigma_v^2)$. The conditional probability in (10) is bivariate normal and therefore easy to compute, because of the simultaneous normality of (u_1, u_2, v) .

D=2, wage rate not observed:

$$L = P[u_2 + \gamma_2 v > -X'\beta_2 - \gamma_2 Z'\alpha, u_2 - u_1 + (\gamma_2 - \gamma_1)v > X'(\beta_1 - \beta_2) + (\gamma_1 - \gamma_2)Z'\alpha] \quad (11)$$

Again, this is a bivariate normal probability which can easily be computed. For D=0, an analogous expression can be given.

ML-estimation of the full model, not imposing restrictions on Σ , yields estimates of all the parameters, including those in Σ . If restrictions on Σ are imposed, the estimates of α, β and γ will only be consistent under the null that the restrictions are true. Thus, accounting for simultaneity implies the need to estimate more parameters. In this type of model, this can sometimes be avoided using a two-step estimation procedure:

(2) Two-step Estimation of the Basic Model

Step 1: Estimate α , using the familiar Heckman procedure (add a reduced form participation equation to the wage equation to correct for selectivity bias). This yields an estimate a of α . In principle, the estimate of α will not be consistent given the complete model: according to the complete model, participation is determined by two separate equations, and this is approximated by one reduced form participation equation. However, in practice the asymptotic bias will be quite small.

Step 2: Replace W_i in (3) by its prediction $Z_i'a$ and estimate the resulting multinomial probit model. This solves the problem that W_i is sometimes unobserved. Moreover, although W_i may be correlated with u_{ij} , its predicted systematic part $Z_i'a$ will in general be (asymptotically) uncorrelated with u_{ij} . Thus, the estimator remains consistent if there is simultaneity.

Although this may seem a feasible and computationally attractive procedure, it also creates a new problem: it implies a normalisation different from the original one ($\Sigma(1,1) = \Sigma(2,2) = 1$). The estimates of β thus have to be rescaled, which in general requires estimation of $\text{Cov}\{v_i, u_{ij}\}$. The two-step procedure thus suffers from several drawbacks. The assumptions needed for consistency are just as strong as for ML. Obtaining consistent estimates of the standard errors, taking into account that α is replaced by a , requires extra computations.

(3) Simulated Maximum Likelihood

Exact ML-estimation of the basic model is straightforward because the probabilities in (10) and (11) are bivariate normal. In the alternative models, (11) contains either a convolution of a normal and an extreme value

distribution (the multinomial logit case), or a non-linear function of two normals (in case of non-linearity). In both cases, it remains easy to compute the probability in (10), since the second factor treats v as known. Problems arise with (11). Note that (11) can be replaced by:

$$\begin{aligned} L &= \int_{-\infty}^{\infty} f_v(v) P[u_2 > -X'\beta_2 - \gamma_2(Z'\alpha + v), u_2 - u_1 > X'(\beta_1 - \beta_2) \\ &\quad + (\gamma_1 - \gamma_2)(Z'\alpha + v) | v] dv \\ &= E\{P[D = 2 | v]\} \end{aligned} \quad (11')$$

where the expectation is taken with respect to v . In all variants of the model, $P[D = 2 | v]$ is easy to compute, but the expectation is not, except for the basic model. One way to approximate the expectation in (11') is to replace it by a simulated mean, using R independent draws of v :

$$L_a = \frac{1}{R} \sum_{r=1}^R P[D = 2 | v_r] \quad (12)$$

For large R , L_a approximates L , because of the law of large numbers. Instead of maximising the exact likelihood, the approximate likelihood can be maximised, in which for the observations with $D=2$, L is replaced by L_a (and similarly for those with $D=0$). The resulting estimator is known as Simulated Maximum Likelihood (SML).⁷ For fixed R , the estimator is inconsistent. If R tends to infinity with the number of observations, the estimator is consistent. Moreover, provided that draws for different individuals are independent, ML and SML will be asymptotically equivalent as $R / \sqrt{N} \rightarrow \infty$, where N is the number of observations (cf. Gourieroux and Monfort, 1990).

(4) Using Complementary Data

A problem with the estimation procedures described above is the lack of data on wage rates. In the data set to be used, containing farmers' wives only, no more than 44 women have a formal job. Instead of estimating α and σ from these 44 observations only, it is possible to use the full data set of married women to estimate a wage equation. The implicit assumption, that the wages of farmers' wives are determined in the same way as wages of other married women, seems a reasonable one. Estimates for α and σ_v based on the whole data set are given in Callan (1991). The sample used there contains 1,712 married women, 324 of whom are employed with observed wage rate. We use results corrected for selectivity bias (column 3 of Table 1, Callan, 1991). Thus,

7. See Lerman and Manski (1981) or Gourieroux and Monfort (1990).

instead of estimating all the parameters simultaneously, an alternative approach is to assume that α and σ_v are equal to the Callan (1991) estimates and estimate the other parameters. In principle, the standard errors have to be corrected for the fact that α and σ_v are replaced by their estimates. We present the uncorrected standard error estimates, which thus may be biased downwards. This problem does not seem to be too serious, because of the relatively large number of observations used to estimate α and σ_v . Estimation results based on a wage equation which includes only the farmers' wives in the present sample provide a check on this procedure, as outlined below.

Some idea of the reliability of this procedure can also be gained by testing the structural stability of the wage equation over the full sample as against two sub-samples: the 44 farm wives and 282 non-farm wives. As expected, least squares estimates show that structural stability of the wage equation as between the full sample and sub-samples of farm and non-farm wives is not rejected at the 5 per cent confidence level.

IV RESULTS

Parameter Estimates: Basic Model

Parameter estimates of the basic model are set out in Table 1. The first two columns show maximum likelihood estimates, where the parameters α and σ_v in the wage equation are not estimated, but set equal to the estimates based on a larger data set (cf. Callan, 1991, Table 1, column 3). Simultaneous estimation of the wage equation (using observed wage rates for the 44 farm wives with a formal job) with the rest of the model was undertaken:⁸ according to a likelihood ratio test, relaxing the restrictions that α and σ_v are equal to the Callan (1991) values does not yield significant improvement.⁹ Moreover, the standard errors of these alternative estimates were close enough to those reported here to suggest that the problem of underestimating standard errors in the "complementary data" procedure is not a serious one. Thus, we confine our attention to estimates which use the wage equation from Callan (1991). The results in the first column are based on the assumption that Σ is a diagonal matrix, and thus imposes exogeneity of W . The second set of estimates shows the consequences of relaxing the conditions on Σ .

The estimates of the correlation coefficients are very imprecise. An upper-bound on $\rho(1,2)$ had to be imposed to ensure that Σ is positive definite. Thus no standard error for the estimate of $\rho(1,2)$ could be computed. The standard errors for the other correlation coefficients are huge and suggest that, from a practical point of view, there is no point in estimating Σ with the data at

8. Detailed results are available in Callan and Van Soest (1993).

9. The test statistic is 15.24, which is well below the 5 per cent critical value $X_{14}^2 = 23.7$.

hand, even though the model is identified in theory. However, a likelihood ratio test based on the restricted and unrestricted likelihoods clearly rejects diagonality of Σ .

Table 1: *Estimates of the Basic Model*

Method	I		II		III	
	ML		ML		SML	
Σ	Diagonal		Free		Diagonal	
No. of draws	—		—		50	
	parameter	std.error	parameter	std.error	parameter	std.error
<i>Correlations</i>						
rho(u ₁ ,u ₂)	0	—	0.8418*	—	0	—
rho(u ₁ ,v)	0	—	-0.1400	0.5160	0	—
rho(u ₂ ,v)	0	—	0.2154	0.5960	0	—
<i>Employment versus Non-participation</i>						
constant	-1.5520	28.5576	-5.1307	21.5148	-2.1830	28.6542
log age	2.8984	15.8265	3.8290	11.8012	3.2118	15.8843
log 2 age	-0.7368	2.1759	-0.6944	1.5992	-0.7800	2.1850
young 0-4	-0.4424	0.3857	-0.2324	0.2715	-0.4440	0.3875
log fam size	-0.1965	0.3343	0.0421	0.2400	-0.2015	0.3376
reg unemp _{rt}	-3.6089	5.3385	-5.4829	3.4848	-3.5223	5.3634
log inc. hus	-0.0494	0.0676	-0.0060	0.0466	-0.0505	0.0681
log farm size	-0.1707	0.1561	-0.0299	0.1130	-0.1692	0.1569
dum cattle	0.2980	0.2688	0.2981	0.1803	0.3104	0.2712
dum soil 1	0.1969	0.2636	0.2816	0.1822	0.1998	0.2650
dum soil 3	-0.0938	0.5170	0.1374	0.3051	-0.1061	0.5197
dum debt os	-0.5881	1.4633	-1.2659	1.0453	-0.6012	1.4574
log debt os	0.1229	0.1633	0.1862	0.1181	0.1235	0.1625
log wage rt	1.0072	0.2651	0.7561	0.2831	1.0498	0.2676
<i>Relative Assisting versus Non-Participation</i>						
constant	-38.4688	25.4719	-19.5815	20.5113	-35.1564	24.8541
log age	20.9443	13.7976	11.4184	11.1279	19.0147	13.4452
log 2 age	-2.8089	1.8460	-1.6224	1.4900	-2.5439	1.7975
young 0-4	0.0123	0.2597	-0.1665	0.2367	0.0052	0.2547
log fam size	0.4252	0.2486	0.3016	0.2227	0.4099	0.2419
reg unemp _{rt}	-9.3229	3.2719	-8.0377	2.7582	-8.5976	3.1010
log inc. hus	0.0708	0.0417	0.0452	0.0381	0.0651	0.0403
log farm size	0.2227	0.1175	0.1435	0.1008	0.2016	0.1126
dum cattle	0.1368	0.1536	0.1667	0.1392	0.1407	0.1498
dum soil 1	0.3217	0.1704	0.3094	0.1499	0.3033	0.1647
dum soil 3	0.4928	0.2210	0.4452	0.2140	0.4916	0.2166
dum debt os	-1.7462	0.7641	-1.7663	0.7138	-1.7279	0.7490
log debt os	0.2217	0.0865	0.2316	0.0809	0.2189	0.0849
log wage rt	-0.7501	0.4190	-0.2078	0.3192	-0.5906	0.3828
log likelihood		-307.57		-297.83		-308.06

Notes: *upper bound imposed because Σ must be positive definite.

Wage equation estimates from Callan (1991) in all cases.

The sets of estimates for the parameters β_1 , γ_1 , β_2 and γ_2 are not too different. In the equation determining the choice between non-participation and employment, only the log wage rate is significant (at the 5 per cent level), with the expected positive sign. In the equation determining the choice between non-participation and relative assisting, some significance levels tend to vary. Significance levels for the first estimator, which imposes most constraints, are not systematically larger than for the second estimator. The general conclusions are comparable. The main difference concerns the estimated impact of the wage rate. In both cases the effect is negative, but its magnitude and significance level vary.

Since the likelihood ratio test suggests that some of the error correlations are non-zero, we concentrate on the second panel in discussing the equation dealing with relatives assisting as against non-participation. Two variables dealing with farm debt are significant: a negative coefficient on a dummy for whether or not there is any debt, offset by a positive coefficient on the log of the amount outstanding. The effect of having a debt on the probability of participation as a relative assisting is negative if the debt is below £2,050, and positive otherwise. Since the amounts of debt outstanding are in practice quite large, most wives in families with outstanding debt have a higher probability of participation as a relative assisting than wives in similar families without debt. While there is a potential endogeneity in this area, debt overhang can also be the result of exogenous shocks such as those which pushed farm incomes to low levels in the mid-1980s. It seems from these estimates that one response to such debt overhang could have been to increase labour input by becoming a relative assisting.

Farm wives are also more likely to participate as relatives assisting on larger farms, though this is significant only at the (one-sided) 10 per cent level. Standard production function considerations would lead to such an effect: one would expect the marginal product of labour to rise with farm size. The other statistically significant coefficients are somewhat more difficult to interpret: there is a positive coefficient on both soil type 1 (the most fertile soils) and soil type 3 (the least fertile), as well as on the regional unemployment rate. The coefficient on the regional unemployment rate, (as measured by the CSO Labour Force Survey) is heavily influenced by observations for one region: Donegal/North-West. A dummy for this region (or its exclusion) seems, from some additional analysis, to lead to the expected negative effect of the regional unemployment rate on farm wives' participation in the paid labour market, with the influence on participation as a relative assisting becoming insignificantly different from zero. The estimated effects of other variables are not much changed by the inclusion of this dummy variable.

In the third column of Table 1, we present simulated maximum likelihood

estimates of the basic model, under the same assumptions as used in column 1. Fifty draws of v per observation (denoted $R=50$) were used to generate the SML estimates, but very similar parameter estimates and standard errors were obtained for $R=5$ and $R=10$. Standard errors for the SML estimates tend to be somewhat underestimated relative to the ML estimates in column 1, but the differences are not large. Somewhat surprisingly, the difference between the results for $R=5$ and those for $R=50$ are smaller than the differences between the exact ML results and those with $R=50$. $R=50$ thus seems to yield reasonable results. Therefore, $R=50$ will also be used in the alternative models, in which comparison with exact ML is computationally intractable.

A two-step estimation procedure, again based on the wage equation estimates for the full sample, leads to somewhat different results. The selection equations are estimated as a multinomial probit model, and, as discussed above, the estimates need to be rescaled to compare them with those in Table 1, so they are not reported here. Without actually carrying out the rescaling procedure in too much detail (and without correcting standard errors), some conclusions can still be drawn. Again, all parameters in the employment versus non-participation equation are insignificant, except for the log wage rate. The sign of γ_1 is again positive, but the magnitude of the coefficient, at 1.88, is somewhat out of line with the other estimates. This cannot be explained by rescaling. The estimates in the middle panel of Table 1 imply that $V\{u_1 + \gamma_1 v\} \approx 1.08$, so the estimate of γ_1 should be rescaled from 1.88 to 1.95. However, the rescaling factor depends on the very inaccurate estimate of $\text{Cov}\{u_1, v\}$.

For the relative assisting versus non-participation parameters, the parameter corresponding to the log of the wage becomes significantly negative. This suggests that women who are able to command a high wage either tend to participate in paid employment, or else to work in the home, but not to participate as relatives assisting. Otherwise, parameter estimates and significance levels largely correspond to those in Table 1. Rescaling has only a limited rôle to play here, because of the small absolute value of γ_2 in the second panel of Table 1.

Parameter Estimates: Multinomial Logit Model

Simulated maximum likelihood was used to estimate for the multinomial logit version of the model, again using the estimates of the wage equation from the full sample.¹⁰ A likelihood ratio test based on estimates of the endogenous and exogenous wage versions of the model rejects the null $\mu_1 = \mu_2 = 0$, implying that W is endogenous. However, the estimates of the μ_j seem

10. The full results for the alternative models are available in Callan and Van Soest (1993); here we simply report the main features.

rather inaccurate, and the separate hypotheses $\mu_j = 0(j=1,2)$ cannot be rejected at the 5 per cent level. This finding corresponds to what was found in the multinomial probit model.

Qualitative conclusions from the estimates of the selection equations remain largely the same as those from the basic model. Choosing between employment and non-participation is only significantly affected by the wage. The wage rate coefficients are of similar magnitude as those in Table 1 if appropriately rescaled.

Parameter Estimates: Non-linear Models

Finally, some non-linear models are estimated, using (3') instead of (3). Some of the insignificant regressors have been removed. For comparison, the basic linear model was re-estimated with a reduced set of regressors. Estimates of the non-linear version of the model suggest that the Box-Cox parameter appears to be quite large (larger than 1), but may also be very imprecise. In the non-linear form of the basic model, the t-value of λ suggests that it is not significantly different from 0 at any reasonable level. On the other hand, a likelihood ratio test, based on comparing the likelihood values of the basic model with the reduced set of regressors, and the corresponding non-linear version, suggests that the Box-Cox transformation does yield significant improvement. In the multinomial logit case, in which we also allowed for correlation between v and the u_j 's, the estimate differs significantly from 0 at the 10 per cent level, but the standard error is quite large. Moreover, the presence of the Box-Cox transformation makes estimating γ_1 and γ_2 much harder. The standard errors increase and significance levels drop strongly. Estimates of the correlation structure (i.e., μ_1 and μ_2) are substantially affected. However, the parameter estimates for the other regressors in the selection equation are not much changed.

Evaluation of Results

In order to get some insight in the implications of the parameter estimates for the wage rate sensitivity of the choice between non-participation, formal employment, and relative assisting, we computed the estimated probabilities of the three states as a function of the wage rate, for someone whose other (own, husband's, household's and farm characteristics) are equal to the average in the sample. The results for eight sets of parameter estimates are presented in Figure 1.

In general, the probability of formal employment increases with the wage, whereas the probability of relative assisting decreases with the wage. This corresponds to the estimated wage parameter in the employment equation. Note that a positive wage rate coefficient in the employment versus

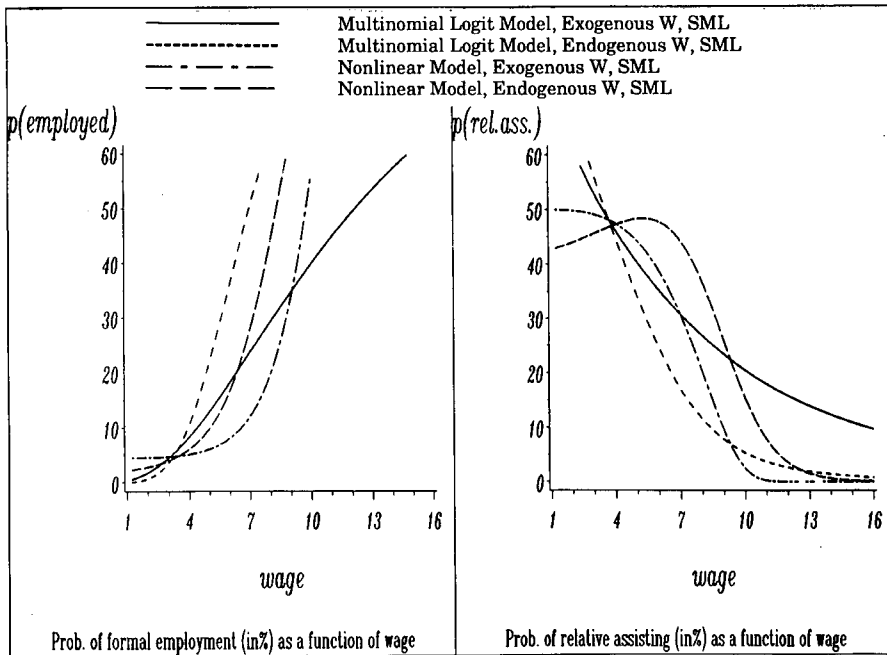
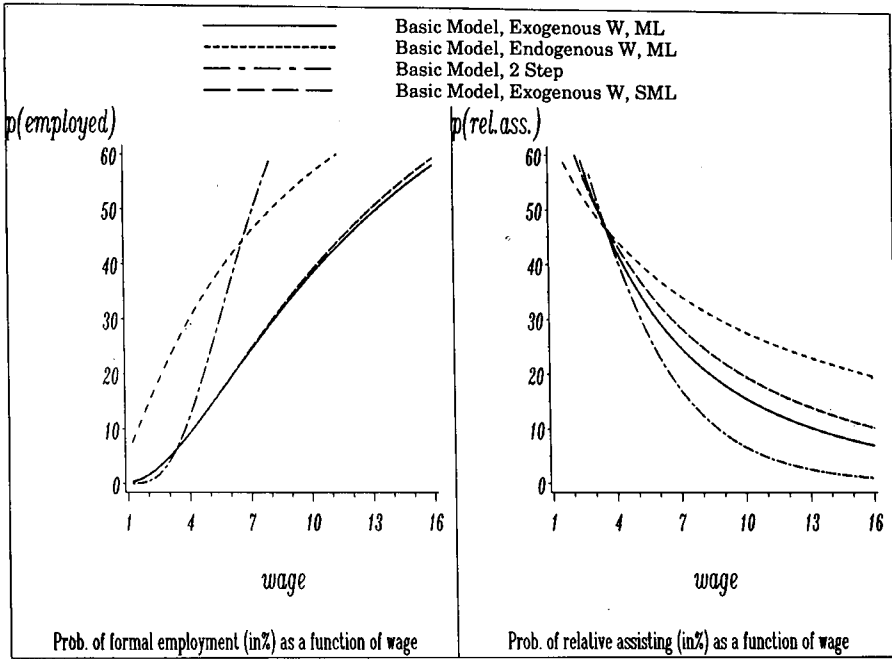


Figure 1: Sensitivity of Probability of Participation to Wage Rate

non-participation equation also implies a negative effect of potential wages on the probability of relative assisting. This effect may dominate the (often small and insignificant) wage effect through the relative assisting versus non-participation equation.

Although the direction of the effect is the same in all models, its magnitude varies a lot. For the basic model with diagonal covariance matrix, simulated ML and ML yield very similar results. This appears to be the case even for smaller values of R than the one (R=50) depicted. The two-step estimates however suggest a much larger sensitivity. The graph for the SML estimates of the multinomial logit model with exogenous wage rates is again quite similar to the ML or SML basic model results.

The model extensions which allow for wage rate endogeneity or non-linearity through a Box-Cox transformation, yield quite different patterns, suggesting a larger wage rate sensitivity estimates. In calculating the probabilities for these simultaneous models, the correlation between the errors has been ignored. This may explain part of the differences.

Similar graphs as a function of age, for a fixed value of the wage rate (£2.95 per hour) show that the probability of formal employment decreases with age, whereas the probability of being a relative assisting is increasing at most ages, and, according to most of the results, decreasing at higher ages. The differences between the various graphs tend to be somewhat smaller than in Figure 1. In particular, the ML and SML results for the basic model are again quite similar.

Figure 1 is based on point estimates of the relevant parameters, and do not reveal the uncertainty due to the fact that parameters are replaced by their estimates. Therefore, we have also computed some asymptotic confidence intervals for wage rate elasticities. These elasticities are intricate non-linear functions of the estimated parameters. Therefore, instead of using the delta method, we have used simulations to obtain the confidence intervals, as in Van Soest (1992). This boils down to drawing from the estimated asymptotic distribution of the parameter estimator, and looking at the distribution of resulting elasticities. This method avoids the need to take derivatives and works well as long as the elasticities are differentiable functions of the parameters.

The results in Table 2 are all based on 100 draws. Of the 100 resulting elasticities, we present the median, the mean, and the first and ninth decile. In some cases, the drawn parameter values are such that the probability of a certain state becomes very small. In that case the (absolute) value of the elasticity can be extremely large. To reduce the impact of this type of outliers, it seems better to look at the median than at the mean. The first and ninth decile values can be interpreted as an approximate 80 per cent two-sided

Table 2: Wage Rate Elasticities

	Wage Rate = Ir£5				Wage Rate = Ir£10			
	Median	Mean	Decile Cut-offs		Median	Mean	Decile Cut-offs	
			10th	90th			10th	90th
Basic model, wage exogenous, ML (Table 1, Col. 1):								
NP	0.285	0.197	-0.437	0.668	-0.924	-1.067	-2.288	-0.171
E	2.845	2.908	2.051	3.813	2.437	2.513	1.830	3.387
RA	-1.692	-1.688	-2.744	-0.556	-4.035	-4.091	-6.875	-1.382
Basic model, wage endogenous, ML (Table 1, Col. 2):								
NP	-0.608	-0.627	-1.595	0.443	-1.531	-1.700	-3.588	0.080
E	1.239	1.241	0.801	1.589	1.178	1.163	0.830	1.543
RA	-0.739	-0.764	-1.216	-0.339	-1.542	-1.643	-2.570	-0.881
Two-step estimates:								
NP	-0.607	-0.536	-1.777	0.530	-4.537	-5.169	-8.840	-1.545
E	4.420	4.433	2.755	6.156	2.072	2.304	1.058	3.700
RA	-2.276	-2.538	-4.145	-0.957	-7.653	-8.096	-13.404	-3.338
Basic Model, wage exogenous, SML (Table 1, Col. 3):								
NP	0.089	0.063	-0.611	0.672	-0.957	-1.183	-2.763	-0.023
E	2.954	2.982	1.964	4.114	2.554	2.632	1.593	3.717
RA	-1.331	-1.397	-2.552	-0.502	-3.050	-3.337	-6.351	-1.136
Multinomial logit model, wage exogenous, SML:								
NP	0.148	0.021	-0.812	0.666	-1.092	-1.374	-3.236	0.095
E	2.901	2.957	2.029	4.054	2.909	2.833	1.408	4.229
RA	-1.214	-1.318	-2.453	-0.352	-3.247	-3.314	-5.473	-1.321
Multinomial logit model, wage endogenous, SML:								
NP	-0.365	-0.419	-1.540	0.512	-5.229	-5.473	-8.774	-2.775
E	4.784	4.822	3.494	6.177	1.999	2.171	1.041	3.650
RA	-2.211	-2.307	-3.627	-1.328	-8.035	-8.363	-11.611	-5.142
Non-linear model, wage exogenous, SML:								
NP	0.164	0.278	0.003	0.802	0.003	-2.804	-12.717	0.593
E	0.738	0.846	0.025	1.950	4.642	-3.069	0.026	9.682
RA	-0.238	-0.417	-1.170	-0.004	-2.670	-93.736	-96.675	-0.007
Non-linear model, wage endogenous, SML								
NP	-0.725	-1.355	-4.303	0.498	-13.858	-20.249	-56.512	-1.257
E	3.954	3.023	-3.433	6.258	2.460	-2.169	-28.467	6.107
RA	-0.739	-0.880	-2.843	1.066	-12.783	-14.181	-30.490	0.059

Notes: NP: non-participation, E: formal employment, RA: relative assisting.

confidence interval. We computed elasticities at two levels of the wage rate, Ir£5 and Ir£10. Our calculations are based on the same sets of estimates as those used in Figure 1.

Parameter estimates for the non-linear models seem to be quite inaccurate, and elasticities vary wildly. One of the reasons is that estimates of state probabilities are sometimes quite small. The number of observations is probably

too small to let the asymptotics work well. Using bootstrapping might be an alternative.

For the other models, results seem more reliable. Again, SML and ML based results for the basic model are quite similar, and similar to the basic multinomial logit results with exogenous wage rates. The wage rate elasticity of formal employment is significantly positive (at the one sided 10 per cent level), and may take on values between 1.5 and 4. The wage rate elasticity of relative assisting is significantly negative, but the confidence intervals are quite large. The sign of the wage elasticity of non-participating is not unambiguously determined.

V CONCLUSIONS

While Census and Labour Force Survey data suggest that the numbers of relatives assisting on family farms declined to very low levels, more detailed sectoral investigations suggest otherwise. Evidence from the ESRI household survey drawn in 1987 confirms that the status of relative assisting on family farms is indeed a numerically important one, although their number is still much smaller than according to the EC Farm Structures Survey. In our sample of farmers' wives, 40 per cent are relatives assisting in farm work, and only 11 per cent are engaged in off-farm employment. Hardly anyone is engaged in the two activities simultaneously.

We have estimated a number of models which explain the choice between relative assisting, off-farm employment, and neither of these activities (non-participation). We have focused upon the sensitivity of the choice between the three activities with respect to the wage rate. We find that the magnitude of the estimated elasticities vary with the model specification. In particular, allowing for wage rate endogeneity has a large impact. This result corresponds to those of Mroz (1987) for labour supply elasticities of (all) married women in the US. The elasticities vary to a lesser extent with the chosen estimation technique.

In spite of these differences, most models have some important features in common. The own wage elasticity of off-farm employment is significantly positive and often quite high, compared to participation and labour supply elasticities of married women in general (cf. Killingsworth and Heckman, 1986, for example). The wage elasticity of participation as a relative assisting is significantly negative in most models, and smaller in absolute value than that of off-farm employment. Exceptions are the non-linear models, according to which significance levels are quite low. These models however seem over-parameterised, given the limitations of the available data. In the choice between off-farm employment and non-participation, all models lead to

the conclusion that the rôle of wages is central. Other characteristics are generally insignificant. The choice between non-participation and participating as a relative assisting is also affected by physical characteristics such as farm size and soil type, together with economic considerations such as the level of debt outstanding.

The small number of observations (395 in total, with only 44 off-farm employees) is an obvious limitation to our empirical work.¹¹ First, many of the estimates are imprecise. This is reflected by large standard errors and low significance levels. It particularly hampers our attempts to analyse more flexible models in which the log wage enters non-linearly. Second, it is not clear to what extent the properties of the estimators in the small finite sample deviate from the asymptotic properties used in the analysis. This cannot be seen from our results. The similarity between some of the outcomes of different estimators for the same model may be somewhat reassuring in this respect. Moreover, the lack of specific information on farm output and the value added by a woman's work as a relative assisting limits the amount of structure we can use in the models. This limits their direct value for policy analysis.

Nevertheless, some tentative conclusions of relevance to policy can be drawn. First, there appear to be no significant differences between the off-farm wages of farmers' wives and other married women. Second, the relatively large number of farm households and the option of relative assisting for farmers' wives explains a small but significant part of the gap between married women's participation as employees in Ireland and the OECD average. The large wage elasticity of off-farm participation suggests that female off-farm participation may well increase if women's off-farm productivity level increases, for example through education or training. It should be realised however that this will be accompanied by a decrease in activity as relative assisting. This substitution of labour input away from agricultural production towards off-farm work may be desirable under the new CAP structures. Finally, the data show that off-farm employment and relative assisting are hard to combine. This may be a further indication of the lack of part-time jobs in Ireland, due to fixed costs of formal employment or to demand-side constraints. A more thorough analysis of these issues, which though untypical for farm households are of more general relevance to married women's participation, is beyond the scope of the present paper.

11. So too is the fact that the data refer to one year only, given the year-to-year variability of farm incomes.

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APPENDIX A

Variable Descriptions

log AGE	log of (woman's age at last birthday)
log 2 AGE	square of log AGE
YOUNG 0-4	dummy: =1 when woman has a child aged less than 4
FAM SIZE	family size = 2 + number of dependant children, as defined by conditions for receipt of child benefit
REG UNEMPRT	regional unemployment rate
log INC HUS	log of (husband's off-farm employment income (£/week) +1) <i>Note:</i> Income from farming is not included, because it is impossible to separate the return to husbands and wives when both are working on the farm.
FARM SIZE	farm size in acres
dum CATTLE	dummy: =1 when farm system is cattle
dum SOIL 3	dummy: =1 when soil type = 3 (least fertile)
dum SOIL 1	dummy: =1 when soil type = 1 (most fertile)
dum DEBT OS	dummy: =1 when farm debt outstanding is positive
log DEBT OS	log of (amount of debt outstanding +1)
log WAGE RT	log of (gross hourly wage rate)

APPENDIX B

Sample Characteristics

	<i>Non-participants</i>			<i>Employees</i>			<i>Relatives Assisting</i>		
	<i>Mean</i>	<i>Std dev</i>	<i>Coeff var</i>	<i>Mean</i>	<i>Std dev</i>	<i>Coeff var</i>	<i>Mean</i>	<i>Std dev</i>	<i>Coeff var</i>
AGE	48.7	9.8	0.2	39.6	9.8	0.2	46.7	9.3	0.2
YOUNG 0-4	0.20	0.40	2.0	0.34	0.48	1.4	0.25	0.43	1.7
FAM SIZE	1.57	1.66	1.1	2.07	1.89	0.9	2.23	1.91	0.9
REG UE RT	16.6	2.81	0.2	15.7	2.69	0.2	15.8	2.44	0.2
INC HUS	22.9	59.6	2.6	22.6	82.0	3.6	39.8	98.2	2.5
FARM SIZE	61.3	46.1	0.8	71.9	51.6	0.7	65.3	44.2	6.8
dum SOIL 1	0.27	0.44	1.6	0.41	0.50	1.2	0.36	0.48	1.3
dum SOIL 3	0.14	0.35	2.5	0.09	0.29	3.2	0.18	0.39	2.2
dum DEBT OS	0.20	0.40	2.0	0.48	0.51	1.1	0.27	0.45	1.7
OS	8092	12299	1.5	14068	13894	1.0	14392	18369	1.3
DEBT OS*	—	—		6.66	4.24	0.6	—	—	
WAGE RT									

*statistics for those with positive debt