Careers or Stop Gap Work?

Panel Data Analysis of

Wives' Labour Supply Choices in Spain

Paula Adam

IGIER-Bocconi (Milan, Italy)

European University Institute (Florence, Italy)

September 1996

Acknowledgments

I thank my Ph.D. supervisor Professor John Micklewright, Professor Robert Waldmann for useful and interesting comments, and Goetz Rowher for technical advise and help using his statistical package TDA. I thank IGIER at Milan and the European University Institute at Florence for providing me with the best working conditions for the development of this research. All errors are mine.

Abstract

I include the variables wives' age and cohort and children in a participation equation to explore how the following two economic issues affect participation. First, a structural change in terms of participation over the life-cycle. Because a structural change does not affect all women of the young cohorts, I distinguish between long-run participating women (i.e. those whose participation behaviour resembles that found after the structural change) and a priori inactive women (i.e. those with a traditional behaviour). Second, it explores the impact of current social policies on mothers' participation. Despite that a negative correlation between children and mothers' participation (especially pre-scholars) is considered a stylized fact in the literature, long-run participating women may not withdraw from the labour market after maternity to avoid the likely experience loss (i.e. real wage decline) due to long absences. This analysis is carryed out by exploiting a longitudinal Spanish survey (the ECPF). Despite some lacking variables, the use of panel data methods yields to satisfactory results.

JEL Classification: C21,C23,C25; J13; J22,J24

Address for correspondence

Paula Adam
IGIER
Via Salasco 5,
20136 Milano, Italy.

Phone: +39-2-58 36 3301 (secretariat)
+39-2-58 36 3323 (direct)
Fax: +39-2-58 36 33 02

Email: adam@uni-bocconi.it or adam@datacomm.iue.it

1. Introduction

Female labour force participation has grown throughout the advanced economies, including Spain. This has created a *new* profile of female life-cycle participation that is more convergent with males'. The main change lies in the decline of permanent female withdrawal from the labour market after marriage and childbirth. This 'structural change' coincides with rising female education, real earnings, labour demand in the services' and in some countries, also with the promotion of active labour market policies that favour female labour market participation. Spain differs from the rest of the OECD countries because the increase in participation came later, because participation levels are remarkably low, and because of the scarcity of active labour market policies. This poses the question of whether Spain is really converging with the other OECD countries.

The Spanish economic literature has paid little attention to female participation. Since most studies on this topic are by historians, sociologists and political scientists, existing research findings tend to be only partially related to the economy. The issue is central to economists because changes in female participation have irrevocable effects on the employment structure, on the equilibrium of the welfare state, on consumption demand, and on the overall functioning of the economy.

Women's Participation over the Life-cycle: Is there a Structural Change?

Traditionally, female labour force participation in Spain has been among the lowest of the OECD. Participation has risen since the 1970s by an annual average of 0.4, which is lower than in other OECD countries. But, this has changed since the mid 1980s. Between 1985 and 1992, the participation rate rose from 34.8% to 43.6% (i.e an annual average increase of 1.3 points). The increase is more striking among young women (excluding those in education, aged <25). For the group 25-29, participation rates increased 6.3 points on average from 1984 to 1992.

Table 1
Changes in Married Women's Participation Rates by Cohorts in Spain, 1975-1995

	Participation Rates in					Changes between periods			
Cohorts	1975	1980	1985	1990	1995	75 -80	80-85	85-90	90-95
1976-80					40.9	-	-	-	-
1971-75				31.2	61.4	-	-	31	30
1966-70			32.0	61.4	57.0	-	32	29	-4
1961-65		30.6	54.8	65.2	56.7	31	24	10	-8
1956-60	48.1	34.1	53.3	56.3	54.9	-14	19	3	-1
1951-55	54.8	29.9	40.4	49.0	49.5	-25	11	9	0
1946-50	35.9	23.9	32.8	41.2	39.3	-12	9	8	-2
1941-45	27.1	25.4	31.2	34.6	29.9	-2	6	3	-5
1936-40	26.8	25.0	26.5	29.2	20.8	-2	2	3	-8
1931-35	27.9	24.5	24.5	23.2	12.9	-3	0	-1	-10
1926-30	28.1	22.7	23.7	15.6	3.0	-5	1	-8	-13
1921-25	27.4	20.7	15.9	3.8	0.9	-7	-5	-12	-3
1916-20	24.5	14.2	4.7	0.7		-10	-10	-4	-1
1911-15	21.0	6.7	1.0			-14	-6	-1	-
1910....		1.6					-2	-	-

Notes:
(1) For the years 1975,1980 and 1985, Participation Rates include all not-single women . For the years 1990 and 1995, participation Rates include married women only.
(2) Participation Rates are calculated as the average of the quarterly participation rates given by the National Bureau of Statistics (INE)
(3) Changes between periods are calculated as the difference of one rate minus the other.

Spain's low participation levels are typically attributed to the heritage of the Franco's era. But the causes of change are not so clear. Some authors give a cyclical effect explanation (encouraged worker effect), given the substantial employment growth during the same period (Novales 1989, Albarracin and Artola 1989, Novales and Mateos 1990). Others suggest that it is also due to a 'structural change' (Adam 1996a, 1996c, Arellano and Bover, 1995 and Martinez-Granados 1994). Here the argument is that long term secular trends may be even more important than cyclical fluctuations.

The increase in female participation of the second half in the Eighties was accompanied by:

(1) an increase in female education and in female real earnings due to a shift in labour demand which favoured non-physical, skilled and thus female employment;

(2) a change in women's life-cycle behaviour, reflected in: (a) delayed entry into the labour market due to human capital investment, (b) higher participation rates after marriage and childbirth, and (c) decreasing fertility;

(3) the entry of new cohorts who grew up in a different political regime;

The key piece of evidence is Arellano and Bover's (1995) time-series estimation. Although they find a significant business cycle effect, they conclude that the main effect is due to structural shifts in female earnings potential. Given this, the predictions of Arellano and Bover are that "*(...) the levels of prime age female participation that have been reached and that were never experienced before are here to stay*" (1995:188-189). Table 1 shows evidence of this. Following cohorts, one can see that in the 1980s the participation levels of the same cohorts increased or remained unchanged over time. Changes in participation rates between 1975 and 1980 are negative for any cohort, even for the youngest ones -except the 1961-1965 cohort, which was less than 20 years old in 1980. However, between 1980 and 1985 and between 1985 and 1990 changes in participation are positive for all cohorts (except for the cohorts born before 1935). Take the period 1985-1990. The positive changes are particularly large among cohorts born after 1960 -which reflects the usual entry in the labour market at the beginning of the life-cycle. But changes are also large among women born in the 1950s and -to a lesser extent- those born in the 1940s. Thus, the growth in participation levels is due to the increasing participation among women in fertile and post-fertile, pre-retirement age (aged 25-54).

Despite the *new* life-cycle participation profile and the increase in participation among younger cohorts, female participation rates are still the lowest among OECD countries. Clearly, the 'structural change' (if any) has not affected all women. This suggests that there is one group of women who *a priori* intend *not* to work; I shall call these *a priori non-participating women* in the case that they do participate. Another group of women intends to remain permanently employed. This group I will call *long-run participants.*

Children and Mothers' Paid Work

Policy has not favoured female participation in Spain. Social policies towards mothers discourage female re-entry after childbirth[1]. Maternity leave depends on participation in the social security system, and on payment of taxes during the previous 6 months. Maternity benefits provide 75% of previous wages for 14 weeks. After the first three months there is no national policy and public daycare is very limited. Hence, the incentives for women with pre-school children to enter the labour force are reduced. Nevertheless, previously employed mothers do make use of maternity leave[2]. Once the children arrive at school age (6 years), the incentives to return to work are not very strong. On the one hand, although the Spanish school day is usually long, women find it difficult to return to work because part-time contracts are rare (see OECD, 1995). On the other hand, the loss of experience during maternity absence is quite significant.

The strong negative correlation between the presence of young children in the household and female labour supply is a general finding in the literature (see Browning (1992), Nakamura and Nakamura (1992), and Lehrer and Nerlove (1986)

---

[1] Regardless of (optional) separate income taxation in the household and some public provision for mothers with pre-school children, Spain lies close to the Male Breadwinner Model (Gustafsson and Stafford, 1994).

[2] Seventeen percent of mothers with a child less than 3 months are at work compared to 23.3% of mothers with one child aged 4-12 months (ECPF, pooled data 1985-90).

for reviews of the US case). This correlation weakens as children age and the cost of alternative supervision and care falls (see Gustafsson and Stafford (1994) for a comparative review of the US, Sweden and the Netherlands, and Browing (1992) for the US). However, because of a negative real wage effect, this correlation may still be negative after children reach school age[3].

Table 2

Participation Rates by Children in the ECPF Pooled Subsample (1985-90)

Age of Youngest Child	Participation Rate	Distribution of Mothers' Cohorts 1920s	1930s	1940s	1950s	1960s
<1	27.1	0.0	0.5	10.4	48.1	41.1
1-3	36.4	0.0	0.8	6.6	57.0	35.6
3-6	26.7	0.0	2.2	48.9	26.2	2.4
6-14	20.7	4.3	14.5	68.4	12.8	0.0
>6	9.9	21.4	57.0	21.6	0.2	0.0

Notes:

(1) Participation rates are calculated as the percentage of active over the total working age population.

(2) The distribution of mothers' cohort by number of children and by age of youngest child is presented using row percentages. For example, 17.1% of wives with one child belong to the 1920s cohort.

(3) Children whose age is more than 50 years different from the household married women have not been considered as they are assumed to belong to a third generation.

If Spanish social policy really has an effect on mothers' participation, then participation rates by age of youngest child should be lower for preschool children than for school children. The left part of Table 2 shows an opposite pattern. Mothers whose youngest child is an infant or pre-schooler generally have higher participation

[3] There is a large literature on the effect of children on women's real wages. One line of research focuses on the effect of human capital and experience loss due to long absences from the labour market (Mincer and Ofek (1982), Polachek (1981), Waldfogel (1993), Corcoran *et al* (1983) and Becker (1991) for documentation and Polachek and Siebert (1994) for a survey). Another line focuses on the idea that heterogeneity explains the proportion of wage gap between mothers and childless women (Waldfogel (1993), Hakim (1991) and Korenman and Neumark (1992) for the UK). A third line focuses on the existence of a conflict between family and work (Waldfogel (1993) for the UK). This might be due to effort (Becker 1985), discrimination (Gregg and Machin (1993) for the UK) or opportunities (Jacobsen and Levin (1992) for the UK)).

rates than mothers with school age children, although they seem to make use of maternity leave. The right side of Table 2 adds information on mother cohorts in order to interpret the participation rates. It shows that 99.5% of the youngest children aged less than 3, 77.5% of the youngest children aged 3-6 and 21.8% of the youngest school children have mothers born after 1940. In other words, the higher participation rates of mothers with youngest child of preschool age coincide with a larger concentration of mothers born after 1940. Long-run participating women may avoid long absences from the labour market to maintain their real wages and job position.

The Working Hypothesis

I shall proceed with the following ‘structural change hypothesis’:

> Female participation growth is partly due to a structural change which does not affect all younger women equally. As a consequence, Spanish females can be divided in two groups: *long-run participating women* and *a priori non-participating women.*

As a result of this hypothesis (corollarium):

> Although Spanish social policy does not encourage mothers to return to work after childbirth until the youngest child reaches school age, some mothers behave differently because of their long-run participation intentions.

Following Adam (1996a) and Arellano and Bover (1995), there are three main tools that can allow the parametric analysis of this article to capture hypothetical structural change. Firstly, the use of cohort controls. Secondly, the use of women's education variables. Thirdly, the use of controls for real wage effects. Given the still low participation rates of young married women, cohort effects are expected to explain only a part of structural change. Education is expected to have greater explanatory power, assuming that women study because they intend to participate in the long-run. Real wages are also expected to have strong explanatory power, if increasing real wages are due to growing labour demand in sectors typically occupied by women. Unfortunately, the effect of education cannot be investigated because information on wives' education is not available in the ECPF (see Adam 1996b). This is also a problem for capturing the effect of real wages, because real wages are typically proxied with education variables in a female participation equation. Consequently, in this article I use the available information to control for structural change, but I do not perform a direct test for structural change due to the limited information available. As a remark, although not explained in this article, the model also includes the effects of husbands' employment and income, and wives' non-labour income on wives' participation (see Adam 1996d for a complete description of the model).

This article is organized as follows. Section 2 describes the model and discusses the advantages and limitations of panel data versus cross-section methods. Section 3 describes the subsample and its organization both as a panel of data and as a pooled cross-section. Sections 4 and 5 describe the results. Section 4 describes the life-cycle and cohort effects, Section 5 the effects of children. Section 6 concludes. Appendix 1 gives details on Chamberlain's Conditional Fixed Effects model and Appendix 2 gives some descriptive statistics of the main variables used for the analysis.

2 Estimation of Unconditional Participation Probability Model

2.1 An Estimable Version of the Static Participation Model in Reduced Form

The dependent variable is "wives' labour force participation", observed every three months. It includes unemployment and employment, and its reference period is the week. 'Employment' includes any paid work. 'Unemployment' includes anyone who is not employed but is actively searching. This is modeled as a probabilistic binary choice model, with a distribution function that includes a set of assumed exogenous variables.

Given a set of observations for a number of wives *i=1,...N* and a number of time periods *t=1,...T*, I define a binary state variable Y_{it} for wife *i* at wave *t*, which takes the value 1 if wife *i* participates and 0 otherwise. I also define a vector X_{it} of observable time-variant characteristics and a vector Z_i of observable time-invariant characteristics. Now define a latent variable Y^*_{it} as a function of vectors X_{it} and Z_i in reduced form, where all the elements of X_{it} and Z_i are assumed exogenous. Assuming linearity of $Y^*_{it}(X_{it}, Z_i)$:

$$Y_{it}^* = X_{i't}\alpha + Z_{i'}\beta + u_{it} \qquad (1)$$

where u_{it} is the error term (assumed to be IID) and the constant term is included in vector X_{it}. Then, the participation model can be formally expressed as:

$$\begin{array}{ll} Y_{it} = 1 & \text{if } Y_{it}^* > 0 \\ Y_{it} = 0 & \text{otherwise} \end{array} \qquad (2)$$

Interpreting Y_{it} as a stochastic variable and assuming that all the observations across individuals are independent, the probabilistic model can be expressed as follows:

$$P(Y_{it} = 1) = P(X_{i't}\alpha + Z_{i'}\beta + u_{it} > 0) = 1 - P(X_{i't}\alpha + Z_{i'}\beta > u_{it}) \qquad (3)$$

This type of model can be estimated using limited dependent variable methods by assuming a distribution function for u_{it}. Here I assume a logistic distribution.

2.2 The Problem of Unobserved Heterogeneity

One classical problem in estimating female labour supply and participation is the presence of *unobserved heterogeneity* among individuals[4]. Because the ECPF is not very rich on individual information, unobserved heterogeneity is likely to be important in the estimations. Thus, panel data methods are needed. In addition, the

[4] There is unobserved heterogeneity when individuals with exactly the same observed individual characteristics differ in some unobserved characteristics so that their propensity to experience some event differs. If the unobserved factors have an impact on the probability of the state variable (i.e participation), then panel data are better than cross-section methods.

choice of the econometric model has to fulfill another requirement. The model should be suitable for large N (number of individuals) and small T (number of time periods) as the ECPF data requires.

Define a variable c_i of unobserved individual characteristics. If c_i is ignored, estimation procedures include them in the disturbance term u_{it}, as in equation (1). This yields to inconsistent estimates if unobserved heterogeneity is correlated with observed factors. Decomposing u_{it} with a separate term for unobserved heterogeneity and ε_{it} as the remaining error term, which is randomly distributed, the probabilistic model in equation (3) can be expressed as follows:

$$P(Y_{it} = 1) = P(X_{i't}\alpha + Z_{i'}\beta + c_i > -e_{it}) = 1 - P(X_{i't}\alpha + Z_{i'}\beta + c_i > e_{it}) \qquad (4)$$

The Fixed-Effects Approach

The fixed effects approach treats unobserved heterogeneity as a fixed or constant term. A characteristic of this approach is that Maximum likelihood estimation is only possible with individuals whose realizations of the dependent variable change over the panel length (Chamberlain 1980, 1984). The fixed-effects model is likely to present some extremely difficult estimation problems[5]. However, Chamberlain (1980, 1984) proposes a conditional likelihood estimator as an easier alternative. This is only possible for the logit (but not the probit) model and is applicable to models with unobserved heterogeneity in panel data sets with large N and small T. The idea is that if unobserved heterogeneity does not vary across waves

[5] Maximum likelihood estimation with fixed-effects logit models often presents extremely difficult estimation problems. On the one hand, if there is a large number of individuals, then the number of unknown parameters to estimate becomes intractable. On the other hand, even if we could estimate the parameters, this model leads to inconsistent parameter estimates if the length of the panel is short. This is because the desirable properties of this method are all based on asymptotic results (Chamberlain 1980, 1984). Greene (1991) affirms that for panels with T<10 this method is very problematic. Thus, estimation using the ECPF (with relatively large N and T<10) is definately not applicable.

(c_{is}=c_{it}=c_i for all $s \neq t$, $s=1,...T$, $t=1,...T$), then a logit model can be estimated using conditional likelihood approaches. Chamberlain proposes a likelihood function conditioned on sufficient statistics for the parameters representing the unobserved terms. This gives consistent estimates for the observed covariates and leads to a conditional likelihood which no longer depends on the unobserved heterogeneity (see Appendix 1 for the proof).

Because c_i drops out of the likelihood function, no assumptions on the correlation between the exogenous observables and unobservables need to be imposed[6]. This is an important advantage of the Chamberlain approach, particularly for female labour supply models where unobservables are often correlated with observed covariates. The three main disadvantages of this method are:

(1) No estimates of the unobserved heterogeneity terms (c_i) are obtained because these are eliminated from the likelihood.

(2) The observed time-invariant terms (Z_i) are also eliminated from the likelihood. Thus, no estimates are obtained.

(3) The information used is based solely on individuals who change state at least once during the observed sequence of waves[7]. Note that changes in state are rarely observed in the case of female participation. In the ECPF subsample, 8,699 wives out of 11,802 do not change state during the sequence of waves, i.e, 73.7% individuals in the sample do not contribute to the estimation procedure!

---

[6] What makes the random-effects approach less interesting in the context of limited dependent variables' modelling is the imposed assumption of no correlation between observables and unobservables. That is: $Cov(X_{it}, c_i) = 0$ and $Cov(Z_i, c_i) = 0$. In the particular case of female labour supply, this is very likely to be an unrealistic assumption. Therefore, the random-effects approach is not interesting for the analysis of this article.

[7] That is, the estimation procedure authomatically drops out from the sample the observations whose realizations of the dependent variable remain unchanged.

Another difficulty arises when estimation results have to be interpreted. Without information about the unobserved heterogeneity term it is impossible to calculate estimates of the participation probability given a specific vector of covariates. The conditional probabilities can be calculated, but these are difficult to interpret in a practical sense. Rowher (1995) proposes to use the relation of *odds* for different covariate constellations (Ω). That is:

$$\Omega = \frac{P(Y_{it} = 1 | X_{it}, c_i)}{P(Y_{it} = 0 | X_{it}, c_i)} \cdot \frac{P(Y_{it} = 0 | X_{i't}, c_i)}{P(Y_{it} = 1 | X_{i't}, c_i)} = \exp([X_{it} - X_{i't}]\alpha) \qquad (5)$$

for the two covariate vectors X_{it}, and X'_{it}. This is easy to calculate using the right hand side of expression (5). Using Ω one can say that a specific covariate constellation is associated with a higher participation probability than another constellation of covariates[8]. In addition, using Ω one can compare the results obtained with other methods. Both cross-section and panel data methods are used to obtain the results of this article. The first allows us to obtain estimates of time-invariant variables. The second allows us to relax the assumption of uncorrelated unobservables and observables, but the time-invariant effects cannot be obtained.

3. The Data

The ECPF (Spanish household income and expenditures survey) is a rotating panel with a quarterly (theoretical) sample size of 3,200 households. Despite the existence of a Spanish labour force survey, I decided to use the ECPF because of its longitudinal structure, although information on individual characteristics is not very rich, particularly for the spouse of the household head (who are females in 98% of the cases). The two main drawbacks of the ECPF are: (1) there is no information on

[8] The possible values of Ω range from 0 to $+\infty$. If $\Omega < 1$, then X is associated with a lower participation probability than X'. If $\Omega > 1$ then X is associated with a higher participation probability than X'. Finally, if $\Omega = 1$ then X and X' are associated with the same participation probability.

spouses' education; (2) there is no information at a regional level. Only the district size is provided, which allows us to know whether households live in rural or urban areas. After sample selection, the ECPF subsample used for the empirical analysis contains every household headed by (married) couples where the wife is of working age i.e. younger than 65. See Appendix 2 for descriptive statistics, and Adam 1996b for details about the ECPF and its uses for labour market research.

The cross-section analysis is performed by pooling the ECPF subsample. The sample size is 51,551 observations related to 11,802 households. Wives' labour force participation rate in this pooled cross-section is 24.0% (i.e, 12,381 participation observations, against 39,170 non-participation observations). The panel data analysis exploits the longitudinal structure of the ECPF. This is an unbalanced panel of 11,802 households that enter in at least one panel wave and at most in eight panel waves[9]. The number of waves that each household is observed in is given in Table 3. The total number of households with no contribution to the maximum likelihood estimation of Chamberlain's model corresponds to the total number of wives who do not change participation status over the panel waves, i.e. is 8,699 (73.7% of the total number of households). Unfortunately, this is a large number and it indicates that wives in the ECPF are not very mobile. The remaining 26.3% contribute with at least one participation change. In total, 3,103 participation changes are used for the estimation of Chamberlain's model. Therefore, the pooled cross-section and the panel data samples differ in size by a ratio of 1:4. Thus, with pure random sampling and assuming no correlated fixed effects, standard errors change by a ratio of 1:2.

[9] Note that the unbalanced structure of the ECPF panel is not an inconvenience, given that the econometric package used for the calculations (TDA) allows for unbalanced panels (Rohwer, 1995).

Table 3
Maximum Number of Waves in which the ECPF Households are Observed

		Last number of Waves							
	Total	1	2	3	4	5	6	7	8
Number of Households	11,802	1,846	1,523	1,206	1,603	1,570	1,291	1,108	1,655

Note: This table reports the number of households by the last number of waves they participate in the ECPF subsample panel. Recall the maximum number of waves is 8.

Among the group that do not change status (over the panel waves), 78.9% are permanently out of the labour force. The participation rate tends to increase across the panel - from 23.0% in the first wave to 26.3% in the eighth.

4. The Structural Change Hypothesis: Life-cycle and Cohort Effects

In Table 4 I present a simple model where I include wives' age, wives' cohort, plus some control variables, namely, husbands' education, district size and one demand side variable[10]. The base is a husband with no education, a wife born in the 1920s and a district size less than 5,000. Given the time-invariant nature of all variables, a pooled cross-section model has been chosen for the estimation[11]. This gives parameter estimates of the Z_i's for all *I.* The model of column (1) shows that quadratic measures for wives' age are improper. The age effect shows a very flat u-curve, with a maximum at the age of 44. This result differs from the traditional left-

[10] The included characteristics are conventional for a reduced form participation equation. The exception is 'husbands' education' which in this case is used to proxy 'wives' education', given that these are highly correlated. Using other data sets (Encuesta de Estructura y Biografia de Clase, 1991) the correlation coefficient is 0.6 in agerage.

[11] 'Husbands' experience' is not in the specification. Due to the large proportion of "illiterates" and "without education", the standard calculation of 'years of experience' (age minus years of education minus 6) does not apply as these are unlikely to have been working since the age of 6.

hand-peak profile. Quadratic specifications are typically used to approximate non-linear effects, under the assumption that the turning point lies outside the data. However, because in this particular case the turning point lies inside the data, alternative specifications are needed.

Column (2) shows the result of using piecewise specifications (in the form of linear spline functions) for wives' age.[12] The obtained estimates should be interpreted as the slope of the linear function in the corresponding segment. The size of the coefficient is determined by the knots and the slope. For example, the first knot takes the value 3.5 (i.e 17x0.208), assuming the youngest wives are 17 years old.[13] A one year increment raises this effect by 0.208 (i.e the effect increases to 3.71). The second knot takes the value 4.16 (i.e 0.208x20), for wives aged 20. At this point, the marginal effect of an additional year is 0.023. Thus, the effect of being 21 years old is 4.6 (i.e. 4.16+(0.023x21)). Until the age of 30, the marginal increase of every additional year on the participation probability is 0.023. The spline function is at a maximum at the knot of age 30. Thereafter until the age of 39, every additional year decreases the effect by 0.031, and so forth. Of course, these results are sensitive to the arbitrary selection of knots. In this case, I impose that segments be of equal length. A first look at the results shows that the age effect fits with the traditional life-cycle profile (i.e left-hand peak profile), with a peak at the age of 30. This result differs significantly

---

[12] Piecewise specifications (in the form of linear spline functions) are a flexible and useful alternative to quadratic specifications. Linear spline functions are composed of linear segments where each linear segment represents the function for values within a given range. These differ from linear functions in that they allow for knots and peaks, and differ from simple dummies in that each segment is approximated with sloped (rather than flat) linear functions (see Greene (1992) and Johnston (1984) for good descriptions). Their advantage relative to quadratic functions is that linear splines allow the researcher to impose the knots. This avoids a classic problem with quadratic specifications, namely that the direction of the effect sometimes reverses.

[13] In the text, I report the effect αX, but not the final marginal impact on the participation probability (i.e the derivative of the participation probability P with respect to an explanatory variable X with coefficient α). With logit functional forms, the final marginal impact is: $dP/dX = P(1-P)\alpha$. For different values of P one obtains different marginal impacts. If P=0.5, then division of each coefficient by 4 (e.g $\alpha X/4$) shows the maximum marginal impact.

from that obtained with a quadratic specification. The effect of age is very large.[14] At the beginning of the life-cycle, the age effect increases rapidly, especially for the group <20. The effect begins to decrease smoothly for the ages of 30-40 and 40-50, and the decrease accelerates for the ages of 50-60 and 60-65, reaching similar levels to those of wives younger than 20 by the age of 55.

In order to separate pure life-cycle effects from cohort effects, the latter are included in the model. In model (2), these are measured with simple dummies as these turned out to be better than simple continuous variable of the birth year[15]. The results show a small negative effect for the 1930s cohort, and unclear effects for the subsequent cohorts. Although this result does not exclude the *structural change hypothesis*, neither does not support it as it does not show when the structural change occurs (if at all). Therefore, better measures to explore the cohort effects are needed.

I introduce in model (3) cohorts measured with linear spline functions. Consequently, the constant term increases a lot. This compensates for the multiplicative effect of using years of birth rather than dichotomous values. There is an improvement in the fit of the model: the precision of the coefficients is greater (i.e, the t-values), and the log likelihood ratio improves slightly. Moreover, the cohort effects are now all significant and increase with birth year, which was not evident in model (2). The first knot (cohort born in 1920) takes a value of -30.7. Its impact on the participation probability is balanced through the constant term, but still lies in a largely negative range. Despite the low significance of the parameter estimate for the 1920 cohort, its effect on the participation probability is definitely lower than that of any subsequent cohort. The whole set of birth year effects falls within a negative range (because the first knot takes a negative value) with an increasing effect (because all but the first coefficient estimates take a positive value). Although the cohort effects increase very rapidly, this is not reflected in the marginal impact on the participation probability because these

[14] As noted further on, the age effect is the largest found in the model estimation of this table.

[15] Each dummy spans a decade, with the exception of the dummy for 1960-73.

lie in the left-hand-side tail of the logistic distribution. The largest effect is for the 1960s cohort, but the marginal impact relative to the 1920s cohort is insignificant. The results of model (3) show that cohort effects significantly reduce the participation probability, and they suggest that the so called "structural change" has been gradual rather than instant: the rapid increase is steady across birth years.

As a result of using linear spline function specifications for cohorts in model (3) the coefficient estimates of wives' age (also measured with linear spline functions) change dramatically. Wives' age effects no longer show a left-hand peak profile. Rather, the effects now increase with age until the age of 50 age (at a higher rate than the decrease rate found in model (2)), and the size of the effects is twice as large. This must be interpreted with caution. The final impact on the participation probability is the result of combining both cohort and age effects. For example, women aged 50 belong to the cohort born between 1935 and 1940[16]. Figure 1 compares the simulated probabilities plotted against age obtained when one uses cohort dummies in model (2), and when one uses linear spline functions for cohorts in model (3). The simulated probabilities are calculated for women observed in 1988, married to a husband with primary school, living in districts 20,000-50,000 with an unemployment rate average (for male household heads) of 5%. This simulation reveals important findings. The probability profile obtained without proper cohort controls (dummies) looks rather similar to the traditional left-hand peak profile, while that obtained with linear spline functions reveals a profile that resembles that observed in other OECD countries, except that probability levels are lower. In the latter case, women aged 30-50 have the highest probabilities (with the maximum around age 40 with 0.5 participation probability), and women younger than 40 and older than 50 have similar probabilities.

[16] The ECPF includes pooled cross-sections of five different years. Thus, women at the age of, say, 50 belong to five different cohorts. For example, if observed in 1985, then their birth year is 1935.

Table 4

Pooled Cross-Section Logit Model

The Effects of Wives' Age and Cohort, and Some Control Variables

	(1)		(2)		(3)	
constant	-1.696	(5.1)	-4.680	(1.6)	21.784	(0.5)
Wives' Age	0.087	(5.8)				
(Wives' Age)^2	-0.001	(8.1)				
Wives' Age						
$\leq$ 20			0.208	(1.4)	0.258	(1.7)
21-30			0.023	(2.0)	0.085	(5.2)
31-40			-0.031	(4.6)	0.072	(6.3)
41-50			-0.014	(1.9)	0.070	(5.7)
51-60			-0.078	(9.2)	-0.020	(1.4)
> 60			-0.158	(5.9)	-0.165	(4.5)
Wives' Cohort						
1920-29					-0.016	(0.8)
1930-39	-0.078	(1.1)	-0.185	(2.5)	0.063	(4.9)
1940-49	-0.166	(1.6)	-0.123	(1.2)	0.102	(8.6)
1950-59	0.004	(0.0)	0.023	(0.2)	0.119	(10.2)
1960-73	0.216	(1.6)	0.210	(1.5)	0.060	(3.0)
Husbands' Education						
Illiterate	-0.222	(2.4)	-0.230	(2.5)	-0.221	(2.4)
Primary	-0.187	(6.1)	-0.189	(6.2)	-0.199	(6.5)
Lower Secondary	0.088	(2.1)	0.086	(5.1)	0.070	(1.7)
Upper Secondary	0.013	(0.3)	0.008	(0.2)	-0.017	(0.4)
Lower University	0.589	(10.8)	0.590	(10.8)	0.576	(10.5)
Upper University	0.816	(14.6)	0.812	(14.5)	0.803	(14.3)
District Size						
5,000-10,000	0.156	(3.6)	0.150	(3.5)	0.172	(3.9)
10,000-20,000	0.032	(0.7)	0.027	(0.6)	-0.005	(0.1)
20,000-50,000	0.238	(2.6)	0.239	(5.6)	0.160	(3.7)
50,000-100,000	-0.245	(5.8)	-0.247	(5.8)	-0.213	(5.1)
100,000-500.000	0.038	(1.1)	0.040	(1.1)	0.095	(2.6)
more than 500,000	0.089	(2.2)	0.089	(2.2)	0.131	(3.3)
Unemployment Rate	-0.062	(9.8)	-0.062	(9.8)	-0.013	(1.6)
Number of Observations	51,551		51,551		51,551	
Number of Households	11,802		11,802		11,802	
Degrees of Freedom	19		23		24	
Log-L Ratio ($logL_0/logL$)	0.948		0.947		0.923	

Notes: (1) Wives' age in models (2) and (3) is specified as a linear spline function. Wives' cohort in model (3) is specified as a linear spline function. (2) t-values in brackets. Base: Husband with no studies - which is considered different than illiterate-, district <5,000 and (only in specification (1)) wife's cohort 1920s. (3) Unemployment rate refers to male household heads in districts of same size.

It has been argued that part of the structural change is correlated with education. In other words, a long-term participation behaviour is expected from highly educated women. Unfortunately, this effect is difficult to estimate because the ECPF does not have information on the education of the spouses of household heads. Given the fairly high correlation between the education of husbands and wives in Spain (see footnote 10), I include 'husbands' education' in the model, while recognizing that this variable may well capture other aspects such as 'husbands' labour market status' or 'husbands' earnings'. The base is 'husband with no studies'.[17] The estimates of husbands' education do not vary significantly across the models of Table 4. Hence, I focus the discussion on model (3). The most notable finding is that wives' participation probability increases with husbands' education. In particular, the estimates for university educated husbands are much larger than those of non-university educated husbands. Wives married to upper university educated husbands are up to 20% more likely to participate than women married to men with no studies. Similarly, women married to lower university educated men are 14% more likely to participate, while the penalty of being married to primary school educated or illiterate men is 5%. Finally, the effect of husbands' education is smaller than wives' age, and bigger than cohorts.

The reduced form model used allows for demand side controls. I use a variable that captures the (average) unemployment rate of male household heads by district size and quarter in the ECPF subsample.[18] From models (1) and (2), this control variable

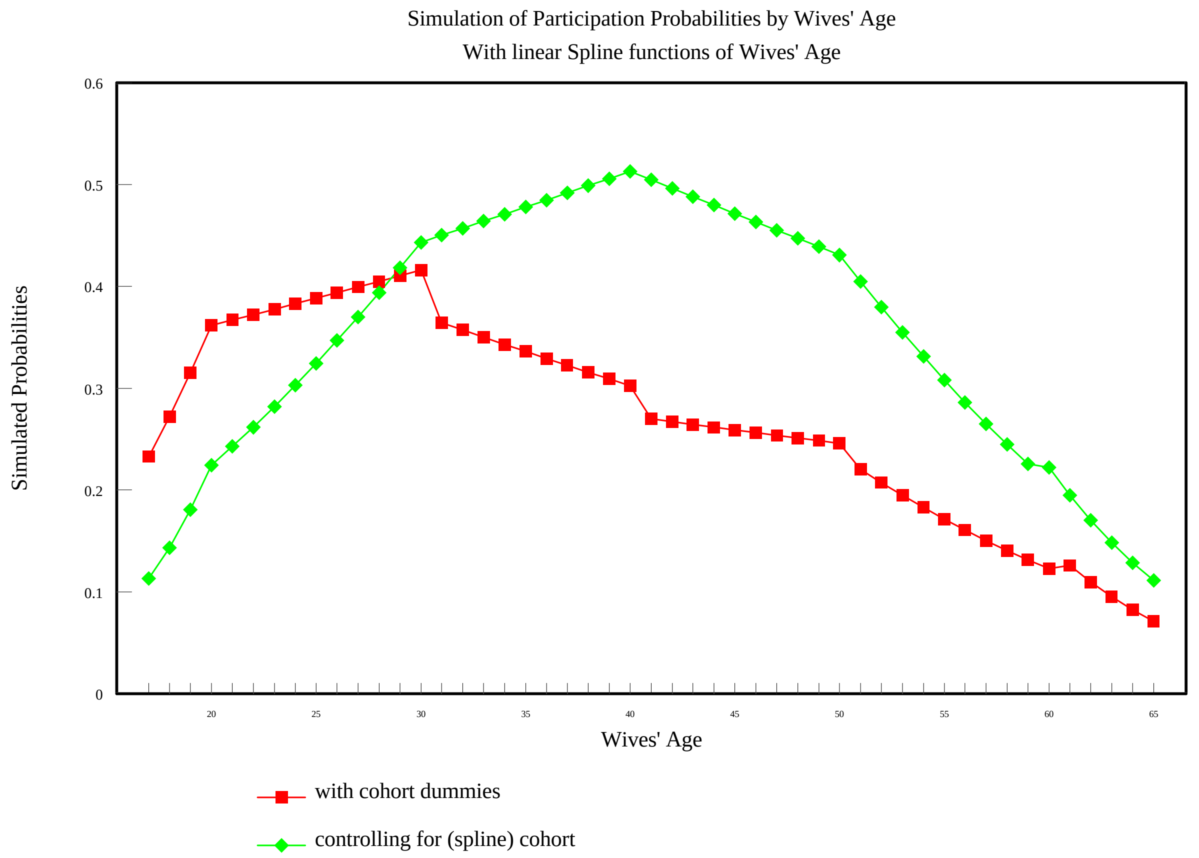
---

[17] Note that 20% of husbands declar to have "no education" , while 1.9% declare to be "illiterate" in the ECPF. Note also that 63.3% of "no educated" husbands and 77% of illiterate husbands are more than 50 years old in the ECPF. Given the large number of "no educated" husbands and given that most of them grew up before, during and right after the civil war, the category "no educations" does not necessarely have to be associated with uneducated and unskilled individuals, but with absence of "titles", a very common situation among these cohorts. Just to put an example, it is not uncommon to see in Spain managers of small firms aged over 50 who declare not to have any studies at all. Thus, it is reasonable to consider separately "illiterates" and "no educated" as two categories with absolutely different meanings.

[18] To capture regional demand side aspects the "unemployment rate of household heads" is a better measure than the "unemployment rate of the whole population". Spain had high unemployment

clearly has a negative effect on participation. However, the coefficient estimate obtained in model (3) shows a rather different result. Demand side control has now a smaller (and insignificant) effect, probably due to unobservables simultaneously correlated with demand side factors.

Figure 1



Finally, control dummies accounting for the size of the residence district are introduced in the models of Table 4. The base is a "district with less than 5,000 inhabitants". The results show that women living in mid size districts of 50,000-100,000 inhabitants (probably small urban areas) are clearly less likely to participate

---

rates in all regions in the 1980s. What really distinguishes depressed regions from prosperous regions is the extent of unemployment among household heads.

This variable has 168 values (24 quarters for 7 district size groups) relative to the average household head's unemployment rate (in the ECPF) in every combination of quarters and district size.

than otherwise (relative to women living in the smallest districts). The higher effect comes from the small districts. The hypothesis that the effects of "districts 5,000-10,000", "districts 20,000-50,000" and “districts >500,000" are equal is not rejected at a 0.05 significance.

5. The Effects of Children: Are Social Policies Effective?

5.1 The costs of child care and alternative supervision

Before discussing the direct effects of children, I describe the problems of measuring the costs of child care. Most surveys lack information on the costs of all the types of child care potentially available to a given family. One solution is to employ proxies. Heckman (1974) uses "residence in an urban area" to proxy for the "availability of low-cost care from relatives and friends living nearby". This proxy is not the best for Spain, where rural families stay close to relatives. Other authors use "residence in the same area" under the assumption that all families living in a given area face the same child care cost and availability environment. This is probably a better measure for Spain.

My model cannot control for "area of residence" because the ECPF does not give regional information. A less satisfactory solution is to use information on "size of the residential district" in the specifications of Table 4. This variable has the inconvenience that the distinction between rural or urban areas cannot be made (except for the "district with >500,000 inhabitants", which refers to Madrid and Barcelona), and the geographic region is unknown. As in other countries, female participation varies notably among different Spanish regions (see Van der Laan, 1995). Hence, including "size of residential district" in a female labour supply model is ambiguous, as it may well capture other effects related to the demand side. Browning says that "*consistency requires that we should cross these proxies with the children variables and not simply include them as additional right hand side variables* (1992, p 1459)". However, I prefer to retain it as a discrete control variable and leave the interpretation open, because the ambiguity may become multiplicative in an interactive specification. The results have been commented on the previous section.

In the literature, "availability of relatives" is sometimes used as a proxy for the "availability of low-cost care" or "alternative child care arrangements"[19]. In Spain, where families tend to remain close, the presence of other family members in the household (e.g. older members) may well provide an alternative source of child care. In the models of Table 5 I include information on the "availability of relatives", using the variable "number of relatives >65 living in the household”, excluding the husband. The obtained effects are discussed in the next sub-section (to show how they change with different specifications of children). Note that interpretation should be made with caution because this variable may well capture other aspects correlated with female participation, like a "rural family effect” -rural families tend to remain together to a larger extent than urban families. It may also capture a "traditional family effect” -”traditional families” are more likely to accommodate older relatives in the same dwelling than “new families” do. These household types are more likely to present low "declared" female participation rates.

5.2 The direct effect of children

[19] Weller (1977) uses the 1960 and 1970 US Census to examine how the correlation between children ever born and employment status is affected by the presence of relatives in the household. He uses several subsets. For some subsets the correlation is weaker in families with available relatives, and for other subsets no clear pattern is found. Clifford and Tobin (1977) suggest that the presence of young children constrains the participation of black mothers to a lesser extent than that of white mothers because of the more extended family arrangements among black households in the US.

As explained, Spanish policy should induce mothers of pre-school children to non-participation, although previously working mothers are expected to make use of maternity leave. For mothers with school age children, the opportunity cost of working should be lower, but the decline in real wages after long absences is likely to lower the re-entry probability. Measures such as "age of youngest child" together with "total number of children" are universally accepted as good specifications in female labour supply estimation (Browning, 1992). Cumulative measures of children (e.g. "number of children by age") are also often used.

Table 5

Logit Model of Participation

The Effects of Children

	Pooled Cross-Section				Conditional Fixed-Effects			
	(1)		(2)		(3)		(4)	
Number of Children by Age								
< 1	-0.460	(7.8)			-0.981	(4.7)		
1-3	-0.219	(7.5)			-0.809	(4.1)		
3-6	-0.293	(11.8)			-0.590	(3.2)		
6-14	-0.221	(14.5)			-0.461	(3.2)		
Total			-0.163	(17.2)			-0.075	(0.7)
Age of Youngest Child								
< 1			0.037	(0.4)			-0.591	(2.4)
1-3			0.341	(3.8)			-0.170	(0.9)
3-6			0.161	(2.0)			0.360	(2.2)
6-14			-0.037	(0.4)			-0.467	(1.6)
Number of Older Members	0.179	(6.0)	0.169	(5.6)	-0.195	(0.7)	-0.254	(1.0)
Number Observations	51,551		51,551		3,103		3,103	
Number Households	11,802		11,802		3,103		3,103	
Degrees Freedom	29		30		4		5	
Log-L Ratio	0.916		0.916		0.253		0.254	

Notes: (1) The specification in models (1) and (2) includes the variables of model (3) in Table 4
(2) In the fixed effects' specification in models (3) and (4) none of the time-invariant variables nor variables with trivial variation such as wife's age (i.e the variables of Table 4) are included.
(3) t-values in brackets. Base: no children in addition to the base of every specific model.
(4) Household head's unemployment rate by district size has not been included in the specifications of this table as it was not significant.

Assuming uncorrelated unobservables

Using cross-section methods, model (1) in Table 5 shows that the “number of children” variables are not very good at capturing the effect of children. The base is childless women and mothers with children aged over 14 (i.e over upper secondary school age). The effects of children are largely negative (although not as large as the cohort effects). Mothers with one child less than age one are 12% less likely to participate than childless women or mothers with children over 14.[20] Mothers with one child aged 1-3 are 6% less likely to participate. In other words, the penalty of having an infant is equal to the penalty of having two preschool children aged 1-3. Mothers with one child aged 3-6 are 7% less likely to participate. The penalty of school age children is similar to the penalty of older preschoolers. This result is unexpected and ambiguous. One would expect the lower supervision cost to lower the penalty on participation. Also, the behaviour of mothers with children aged 6-14 may well be driven by the presence of younger children in the household. In fact, 92.3% of households with children 6-14 have also at least another child of age 3-6, and 72.3% have at least another child aged 1-3. Similarly, 57.3% of households with children aged 3-6 have at least another children aged 1-3.

Model (2) in Table 5 shows the results after estimating a cross-section model with variables accounting for “age of the youngest child” plus “total number of children. Although these are universally accepted as good measures to capture the effects of children, the overall results are totally unexpected -except for the effect of "total number of children", which is consistent with the results of model (1) Table 5. The first surprise is that the effect of having an infant is not significant. In addition, the

[20] The variable "number of children aged < 1" takes value 0 or positive integers. However, for obvious reasons only the possibility of taking values 0 or 1 are discussed in the text.

One could argue that the variable "number of children aged <1" is endogenous in the model. To ensure that the inclusion of this variable does not "contaminate" the results I estimated the same regressions excluding this variable. The results do not change substantially. For this reason, I decided to include this variable in the model specifications.

effect of the youngest child being aged 1-3 is the largest child effect found (in the participation probability). Women with a youngest child aged 1-3 are 9% more likely to participate than childless women or women with a youngest child over 14! Also unexpected is the positive effect of the youngest child being of age 3-6. Finally, and again unexpectedly, the effect of having the youngest child of school age is insignificant. Hence, the whole set of coefficient estimates totally disagrees with the predictions of any theory of mothers' labour supply, given the Spanish policy, but are totally consistent with the bivariate results of Table 2.

The coefficient estimate of the variable "presence of older household members" shows, in models (1) and (2) in Table 5, a relatively large positive effect of similar size to that of youngest child aged 3-6. A third specification was estimated (although not shown in the table) with interactions between the age of youngest child and the presence of older relatives in the household. This aimed to capture a different behaviour between mothers with relatives at home and mothers without them. The results showed a large positive effect of children without relatives at home, particularly among preschoolers aged 1-3. This suggests that "older members" do not capture well alternative child care arrangements and that the effect of children aged 1-3 may instead be driven by a long-run participation effect.[21] But there are also other interpretations of what this variable really measures. For instance, it may capture a 'traditional way of living', which may be correlated with lower female participation.

Controlling for Unobserved Heterogeneity

The omission of important variables (e.g. wives' education) is a drawback of models (1) and (2) in Table 5, because it irrevocably leads to biased results. In addition, these results are obtained under the assumption that the unobserved c_i is uncorrelated with the included explanatory variables. Models (3) and (4) show how

[21] Recall from Table 2 that 97% of mothers with youngest child aged 1-3 are born after the 1950s.

the results change when one relaxes this assumption using the Conditional Likelihood approach. These models present similar specifications to those of models (1) and (2), the difference being that the time-invariant variables are not included.

Table 6

Relation of Odd Ratios (Ω)

for different combinations of Number of Children by Age

Age of Children		<1	1-3	3-6	6-14	<1	1-3	3-6	6-14
Number of Children		1	1	1	1	2	2	2	2
Age of Children	Number of Children	*In the Pooled Cross-Section Logit Model*							
<1	1	1	0.8	0.9	0.8	1.6	0.9	1.1	1.0
1-3	1	1.3	1	1.1	1.0	2.0	1.2	1.4	1.3
3-6	1	1.2	0.9	1	0.9	1.9	1.2	1.3	1.2
6-14	1	1.3	1.0	1.1	1	2.0	1.3	1.4	1.3
<1	2	0.6	0.5	0.5	0.5	1	0.6	0.7	0.6
1-3	2	1.0	0.8	0.9	0.8	1.6	1	1.2	1.0
3-6	2	0.9	0.7	0.8	0.7	1.4	0.9	1	0.9
6-14	2	1.0	0.8	0.9	0.8	1.6	1.0	1.2	1
		In the Conditional Fixed Effects Logit Model							
<1	1	1	0.8	0.7	0.6	2.7	1.9	1.2	0.9
1-3	1	1.2	1	0.8	0.7	3.2	2.3	1.5	1.1
3-6	1	1.5	1.2	1	0.9	3.9	2.8	1.8	1.4
6-14	1	1.7	1.4	1.1	1	4.5	3.2	2.1	1.6
<1	2	0.4	0.3	0.3	0.2	1	0.7	0.5	0.4
1-3	2	0.5	0.5	0.4	0.3	1.4	1	0.7	0.5
3-6	2	0.8	0.7	0.6	0.5	2.2	1.6	1	0.8
6-14	2	1.1	0.9	0.7	0.6	2.8	2.0	1.3	1

Notes:

(1) The odd ratios (Ω) of the pooled cross-section logit model are calculated from model (1) of Table 3. The Ω of the fixed effects model are calculated from model (3) of Table 4.
(2) See Section 2.2 for definition and calculation of the odd ratios.
(3) The vertical combinations correspond to the X vector, and the horizontal to the X' vector in Ω as defined in equation (5). Therefore, an odd ratio of, say 1.4 is interpreted as "the combination X has a higher probability than the combination X'". Both parts can be divided in four sub-matrices. The top-left gives the odds ratios of one child relative to one child by age. The bottom-right part gives the odds ratios of two children relative to two children by age. The top-right gives the odds ratios of one child relative to two children by age and the bottom-right the ratios of two children relative to one child by age.

In model (3), the sign and significance of the parameter estimates are similar to those of the analogous model (1).[22] However, the size of the effects differ: in model (3) they fall monotonically as the age of children increases. In addition, when controls for unobserved heterogeneity are used, the effect of "number of older members in the household" is not significant. There are two possible explanations for this. One, the impact is difficult to estimate because variation on this variable over time (at the individual level) is very small. Two, the effect found with cross-section methods may capture other correlated unobservable factors such as, say, "rural household" or "traditional family".

To interpret the results obtained with conditional fixed-effects methods, and compare them with those obtained with cross-section methods, Table 6 shows the relation of odds ratios (Ω) for different combinations of number of children by age obtained in the pooled cross-section logit model (top part) and in the fixed effects logit model (bottom part). The first remarkable result is that the odds ratios are neither very high nor very low, meaning that the probabilities associated with every combination are not very different. Comparing the odds ratios of the cross-section model, note that the participation probability associated with children aged 1-3 relative to any other combination is always equal to that associated with children aged 6-14 relative to the same combination. Moreover, having children aged 3-6 relative to any other combination is always associated with a lower probability than that associated with children aged 1-3 (or 6-14) relative to the same combination. In the fixed effects logit model, the off-diagonal odds ratios in the top-left and bottom-right sub-matrices take values greater than 1 if these are below the diagonal, and lower than 0 if these are above the diagonal. Consequently, the older the children, the higher the participation probabilities for a given family size. The odds ratios in the bottom-left (top-right) sub-matrix all take values below (above) 1, except for that of two children aged 6-14

[22] Model (3) may not seem interesting given that its analogous model (1) does not capture the response of mothers to the price of child care. However, a comparison of the results using different methods is worthwhile.

relative to one child less than 1 (and vice versa). Thus, the participation probability of women with two children of any age is lower than that of women with only one child of any age, except for women with two children 6-14 relative to women with one infant. Comparing the odd ratios obtained with cross-section methods and with panel data methods, note that the fixed-effects' odds ratios with values greater than 1 (below 1) are in general larger (smaller) than the analogous ratios obtained in the cross-section model. This implies that the maximum impact obtained with the panel data method is greater than that obtained with the cross-section method.

While model (3) represents an improvement with respect to previous cross-section estimations, the results of model (4) are preferable because better measures for children are used. Many interesting results arise from model (4). Firstly, the effect of older relatives is again insignificant, which supports the hypothesis that this variable captures other aspects which are correlated with female participation (e.g. "rural family", "traditional family"). Secondly, the effect of "total number of children" is negligible and insignificant, which contrasts with the results of model (3). As with the variable "number of older members", this may well be due to the presence of correlated unobservables. For example, unobservables such as "traditional living" are usually associated with low female participation rates and with large families (comprising a number of children above the average and the presence other relatives living in the household, usually grandparents). Note that this is just an example; there are other possible interpretations. Thirdly, the effects of the age of the youngest child now appear quite different from those obtained with pooled cross-section methods. The most important difference is the estimated effect of infants and younger preschoolers (aged 1-3). The penalty on participation for women with an infant relative to childless women or mothers with the youngest child >14 is 14.8%. Moreover, the effect of the youngest child being 1-3 is now insignificant. Equally important are the estimated effects of older preschoolers. Mothers with the youngest child aged 3-6 are 9% more likely to participate than childless mothers or those with the youngest child >14.

Table 7

Relation of Odd Ratios (Ω)

for different combinations of Age of Youngest Child

Age of Youngest Child	<1	1-3	3-6	6-14
		In the Pooled Cross-Section Logit Model		
<1	1	0.7	0.9	1.1
1-3	1.4	1	1.2	1.5
3-6	1.1	0.8	1	1.2
6-14	0.9	0.7	0.8	1
		In the Conditional Fixed Effects Logit Model		
<1	1	0.7	0.4	0.9
1-3	1.5	1	0.6	1.4
3-6	2.6	1.7	1	2.3
6-14	1.1	0.7	0.4	1

Notes:

(1) The odd ratios (Ω) of the pooled cross-section logit model are calculated from model (2) of Table 4, and the odds ratios of the fixed effects logit model are calculated from model (4) of Table 4. See Section 2.2 for definition and calculation of the odd ratios.

(2) The vertical combinations correspond to the X vector and the horizontal to the X' vector (see Section 2.2, equation (5)).

To compare the cross-section and the panel data results i.e. model (2) versus model (4), Table 7 shows the odd ratios of the pooled cross-section model (top part) and the fixed effects model (bottom part). In both models, the participation probability of mothers with an infant is lower than that of all other mothers (with the exception of mothers with a youngest school child in the cross-section model). Mothers whose youngest is preschool age have higher participation probabilities than mothers with an infant and with a youngest school child in both models, but lower than mothers with older preschoolers in the panel data model. Mothers with an older preschool child have higher participation probabilities than all other mothers, with the exception of mothers with a youngest preschoolers in the cross-section model. The odds ratio of older preschoolers relative to infants more than doubles using panel data rather than cross-section methods, meaning that panel data methods capture a much larger effect for older preschoolers relative to infants than cross-section methods do. In both models, mothers whose youngest child is aged 6-14 have lower participation probabilities than mothers whose youngest child is younger (with the exception of mothers with an infant in the panel data model). The odds ratio of youngest child aged 6-14 relative to youngest child aged 3-6 halves in the fixed effects model, as compared with the cross-section model, meaning that panel data methods capture a much smaller effect of school age children relative to older preschoolers than cross-section methods.

In sum, the presence of unobservables that are correlated with observed explanatory factors has been detected in the female participation equations. This is why, having controlled for unobserved heterogeneity, I obtain significantly different results from those found using pooled cross-section methods. In particular, it has been found that the total number of children and the number of older relatives have insignificant effects if one controls for unobserved heterogeneity, while these are highly significant without such controls. Moreover, a penalty on participation of having an infant has been found, as it decreases the participation probability by 15% relative to childless women or mothers with a youngest child in upper secondary school. The presence of a youngest child aged 3-6 significantly raises the participation probability (the maximum impact is 9%). This indicates that mothers do not respond to the negative incentives of the Spanish policy. The likely return to work of mothers after the youngest child reaches the age of 3 is consistent with the *structural change hypothesis*. This is interpreted as a long-run participation effect of women who do not want to lose their human capital investment by prolonged absence the labour force, despite the cost of alternative child-care. Given that a large number of women with preschool children actually belong to cohorts born after 1940 (see Table 2), this is a plausible interpretation. But this does not exclude the possible presence of a priori non-participating women who withdraw from the labour force after childbirth.

5.3 Contrasting the results with other authors' findings

Comparing my results with other empirical studies of female labour supply that take children as explanatory variables is not easy because Spanish studies of the issue are scarce. None use "age of youngest children" variables, but rather "number of children" variables; also none use panel data methods.

García *et al* (1989) find a large negative effect of the "number of children" on hours worked, which is not different from the effect of "number of children less than 6".[23] They conclude that the age of children has no differential effect on the labour supply of mothers, and what counts is the number of children. Using simulations, they note that the participation probability decreases with wives' age for a given number of children and with the number of children for a given age of wives. However, the effect of children is more important. The participation probability of average wives with three children is 40% lower than that of childless average wives, for a given age of 25. This difference increases with wives' age. Interestingly, the authors find that the marginal effect of an additional child is similar to that of being ten years older.

San Segundo's (1993) study is similar to mine, both in terms of using the same data set, and in terms of cross-section results.[24] She shows that the number of preschool

---

[23] García *et al* (1989) estimate a married women's labour supply equation (the endogenous variable is "number of hours worked per day") using a subsample of the 1985 cross-section survey *Encuesta sobre la Situación Laboral de la Mujer*, carried out by the *Instituto de la Mujer* and the *Centro de Investigaciones Sociológicas*. The sample size after sample selection is 2,050 married women younger than 65. The children variables they use are "total number of children" and "number of children less than 6" to allow for the effect of preschool children.

[24] San Segundo (1993) estimates a participation logit model for spouses of household heads where the head is younger than 65. She uses the EPF (1980 and 1990) and ECPF (1985 and 1987) data sets and exploits them by applying one cross-section regression for each year. Her model is similar to mine in that she uses the same data (different years) and we specify similar endogenous variable. The main differences between her participation equation and mine are: (1) her endogenous variable is defined as "participation of female and male spouses of household heads", while I use "participation of female heads and female spouses of heads"; (2) she applies cross-section methods to estimate four models for the 1980, 1985, 1987 and 1990 samples; (3) she does not allow for cohort effects, while I apply pooled cross section methods and panel data methods using years 1985 to 1990; (4) age is

children (age less than 5) has a negative effect (but smaller than the effect of household heads' education and wives age) in the four years considered (1980, 1985, 1987 and 1990); the number of school children aged 5-14 has also a negative effect (but smaller) only in 1980, 1985 and 1987; and the number of children older than 14 have a negative effect only in 1980 and 1985. The author concludes that participation decisions of spouses of heads tend to depend less and less on household size. Instead, they are only conditioned by the presence of preschool children. The loss of significance across time for school children found by San Segundo coincides with the unusual increase in participation of married women since 1986 (see Adam 1996a). This suggests that my results in Table 5 may well be driven by behavioural change over the second half of the 1980s. Unfortunately, the models in Table 5 cannot control for the time trend because age and cohort effects are already included.[25]

Martínez-Granado's paper (1994) stands out because it allows for *structural change* controls in the estimations.[26] She finds a negative effect in a female (reduced form) participation equation which is stronger for preschool than for school children. However, in a structural labour supply equation she finds that *"... having children has a negative effect on hours offered, although the effect is surprisingly stronger if children are in school age*" (pp 27). She finds this result "surprising", but I think it has to do with the use of *structural change* controls. It is consistent with the result in model (4) of Table 5, where youngest preschool children (3-6) raise participation by 36%, while younger school children reduce it by 47%, relative to upper secondary school children and childless situations.

---

specified with linear measures in her model; (5) she includes a dummy accounting for the sex of the household head; (6) children are measured with "number of children" variables, accounting for children less than 5, between 5 and 14 and more than 14.

[25] With panel data spanning several years one can only identify two out of three of age, birth year and time trend -but not all three. Hence, I have chosen time trend dummies not to be included.

[26] Martínez-Granado (1994) estimates a reduced form probit model of participation using 28,400 observations in the EPA-1990. Then, she uses the obtained results to estimate a structural equation of female labour supply with different cross-section data sets. The children variables are "number of children less than 6" for preschoolers and "number of children aged 6-11" for school children.

6. Summary and Conclusions

My conclusions relate to substantive issues, given that the framework and methodology used are standard and widely used in the literature. However, this is, as far as I know, the first attempt to apply this model and methodology to the ECPF data set. I use the Fixed-Effects Model of Chamberlain to estimate a standard female participation model in reduced form. Despite the omission of important variables, the obtained results are satisfactory --in part due to the use of panel data methods. Panel data methods help to control for bias due to the existence of unobservables correlated with (assumed) exogenous variables. In addition, the approach supports the hypothesis raised in the introduction.

With respect to life-cycle and cohort effects, there is evidence to support the hypothesis of behavioral change. Using linear piece-wise specifications, wives' age effects correspond to a perfect traditional life-cycle profile (also called left-hand-peak profile), with a maximum peak at ages around 30. However, when adding cohort controls (also using piece-wise specifications) the estimated age effects are quite different, i.e. close to the profile in other OECD countries, with a maximum effect at ages 30 to 50. Interestingly, demand side controls lose significance when cohort controls are used. Thus, the existence of unobserved factors correlated with wives' cohort and demand side factors is not rejected. Finally, a positive effect of education (using the proxy of husbands' education) has been found.

The effects of children are very different than those found by authors who use cross-section methods. Also my results change dramatically when one relaxes the assumption of uncorrelated unobservables. Panel data estimations show that mothers do not fully respond to the negative incentives of Spanish policy. The likely return to work of mothers after the youngest child reaches the age of 3 is consistent with the *structural change hypothesis* and is interpreted as the effect of long-run participating women who avoid prolonged absences from the labour force, despite the cost of alternative child-care. This does not exclude the presence of a priori non-participating women who withdraw permanently from the labour force after childbirth. Of course, this is simply my interpretation of the results; there are certainly others. I could not perform a direct test for the structural change hypothesis due to lack of information. Education is one of the most important pieces of missing information, but even if available it would not totally solve the problem given that "education" and "long run participation intentions" are not likely to be perfectly correlated.

Indirect measures of the costs of child care and alternative supervision such as "presence of older relatives in the households" or "district size" have been included in the model. A possible interpretation for the results of "presence of older relatives in the households" is that this captures "traditional" families where wives tend to participate less (in declared work).

References

Adam, P (1996a) “Some Features of the Spanish Labour Market and Institutions”, in *Labour Force Transitions of Married Women in Spain*, Chapter 1, Doctoral Thesis, European University Institute, Florence, Italy.

Adam, P (1996b) “The ECPF, Its Uses for Labour Market Research and for this Thesis’ Research” in *Labour Force Transitions of Married Women in Spain*, Chapter 2, Doctoral Thesis, European University Institute.

Adam, P (1996c) “Mothers in an Insider-Outsider Economy: The Puzzle of Spain”, *Journal of Population Economics*, August (forthcoming).

Adam, P (1996d) “Labour Force Participation of Married Women: Unconditional Approach”, Chapter 3, Doctoral Thesis, European University Institute.

Albarracín J, Artola C (1989) “Oferta y Demanda de Trabajo en el período 1977-1988” *Boletín Económico*, Banco de España, July 103-114.

Andersen EB (1973) “Conditional Inference and Models for Measuring” Copenhagen: Mentalhygiejnisk Forlag.

Arellano M, Bover O (1994) “Female Labour Force Participation in the 1980s: The Case of Spain”, *Investigaciones Económicas* (segunda época), Vol XIX(2), May.

Becker G (1985) “Human Capital, Effort, and the Sexual Division of Labor”, *Journal of Labor Economics*, 3(1).

Becker G (1991) *A Treatise on the Family*. Harvard University Press: Cambridge Mass.

Browning M (1992) “Children and Household Economic Behaviour” *Journal of Economic Literature*, Vol XXX (september), 1434-1475.

Chamberlain G (1980) “Analysis of Covariance with Qualitative Data” *Review of Economic Studies* 47, 225-238.

Chamberlain G (1984) “Panel Data” In: Griliches Z (Ed) *Handbook of Econometrics*, Intriligator, Vol II, pp 1247-1317, Amsterdam, North-Holland.

Clifford WB, Tobin PL (1977) “Labor Force Participation of Working Mothers and Family Formation: Some Further Evidence”, *Demography*, 14(3):273-84.

Corcoran M, Duncan G, Ponza M (1983) “A Longitudinal Analysis of White Women’s Wages” *Journal of Human Resources*, 28(4):497-520.

Garcia J, González-Paramo JM, Zabalza A (1989) "Una Aproximación al Coste de Eficiencia de la Tributación Familiar en España" *Moneda y Credito*, Segunda Epoca, 1988.

Giannelli G, Micklewright J (1993a) "Estimating Fixed-Effects Binary Choice Models with Long Panels: A practical Approach to the Conditional Logit Model" *Statistica*, ???

Giannelli G, Micklewright J (1993b) "Why do Women Married to Unemployed Men have Lower Participation Rates?", European University Institute mimeo

Greene WH (1993) *Econometric Analysis*, Second Edition, Macmillian, NY.

Gregg P, Machin S (1993) "Is the Class Ceiling Cracking? Gender Pay Differentials and Access to Promotion UK Executives", LSE, CEP.

Gustafsson S, Stafford F (1994) "Three Regimes of Child Care: The United States, the Netherlands and Sweden". In: BLANK RM (Ed) *Social Protection Versus Economic Flexibility: Is there a Trade-off?* University of Chicago Press. Chicago.

Hakim C (1991) "Grateful Slaves and Self-Made Women" *European Sociological Review*, 7(2).

Heckman J (1974) "The effects of Child Care Programs on Women's Work Effort", *Journal of Political Economy*, March-April, 82(2, partII), S136-63.

Jacobsen J, Levin L (1992) "The Effects of Intermittent Labour Force Attachment on Female Earnings". Paper presented at AEA Conference, New Orleans, December 1991.

Johnston J (1984) *Econonometric Methods*, Third Edition, New York:MacGraw-Hill.

Koreman S, Neumak D (1992) "Marriage, Motherhood and Wages" *Journal of Human Resources*, 27(2).

Lehrer E, Nerlove M (1986) "Female Labor Force Behavior and fertility in the United States" *Annual Review of Sociology*, 12, 181-204.

Martinez-Granado M (1994) "An Empirical Model of Female Labour Supply for Spain" *CEMFI working paper* 9412.

Maddala GS (1983) "Limited Dependent Variable Models Using Panel Data" *Journal of Human Resources*, XXII(3), 307-338.

Mincer J, Ofek (1982) “Interrupted Work Careers: Depreciation and Restoration of Human Capital”, *Journal of Human Resources*, 17, 3-24, Winter.

Nakamura A, Nakamura M (1992) “The Econometrics of Female Labour Supply and Children” *Economic Review*, 11(1), 1-71, 93-96.

Novales A (1989) ”La Incorporación de la Mujer en el Mercado de Trabajo en España: Participación y Ocupación”, *Moneda y Crédito* (segunda época), 188.

Novales A, Mateos B (1990) “Actividad Económica y Participación Laboral de las Mujeres y los Jóvenes”. In: *Estudios sobre Participación Activa, empleo y Paro en españa*, Colecciones FEDEA, Madrid.

OECD (1995) *Women and Structural Change: New Perspectives.* Chapter 3, Paris

Polachek S (1981) “Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure” *The Review of Economics and Statistics*, 63,60-69.

Rowher G (1995) *Transition Data Analysis: A Practical Introduction with TDA*, University of Bremen (Germany) and European University Institute (Florence, Italy) mimeo.

San Segundo MJ (1993) “Los Ingresos de los Hogares y la Estructural Familiar”, *I Simposium sobre Igualdad y Distribución de la Renta y la Riqueza*, Fundación Argentaria, Vol II(3), pp 199, Madrid.

Van der Laan (1995) “Gender and Labour Market Participation: an Analysis of Future Developments in the regions in the European Union” Erasmus Centre for Labour Market Analysis, NL. Mimeo.

Waldfogel J (1993) “Women Working for Less: A Longitudinal Analysis of the Family Gap” *STICERD, Welfare State Program discussion paper* wsp/93.

Weller RH (1977) “Wife’s Employment and Cumulative Family Size in the United States, 1970 and 1960”, *Demography*, 14(1):43-65.

Appendix 1
Controlling for Unobserved Heterogeneity with Fixed-Effects Logit Model

This appendix describes the conditional fixed-effects method of Chamberlain and shows how this method controls for unobserved heterogeneity (Chamberlain 1980, 1984, and Andersen 1973). To simplify, I illustrate this proof for the case of T=2.

Define a probabilistic model that allows for unobserved heterogeneity, where the dependent variable is binary and c_i is fixed, as described in equation (4) in Section 2.2. Assume a logistic distribution for the error term ε_{it}. Then, the model can be written as follows:

$$P(Y_{it} = 1) = 1 - F(X_{i't}\,\alpha + Z_{i'}\,\beta + c_i) = \frac{\exp(X_{i't}\,\alpha + Z_{i'}\,\beta + c_i)}{1 + \exp(X_{i't}\,\alpha + Z_{i'}\,\beta + c_i)} \qquad (6)$$

The problem with maximum likelihood estimation of fixed effects models with limited dependent variable specifications is that they lead to inconsistent parameter estimates if the length of the panel is short. Chamberlain (1980, 1984) proposes a conditional likelihood estimator to solve this problem, which is only possible for the logit model. The idea is that if the c_i terms do not vary across waves (i.e $c_{is}=c_{it}=c_i$ for all *t* different than *s*, *s=1,...T*, *t=1,...T*), then a logit specification of the model can be estimated with conditional likelihood approaches. Chamberlain proposes a likelihood function conditioned on sufficient statistics for the parameters representing the unobserved factors (c_i). Of course, this sufficient statistic should be an expression which has no c_i in it. The sufficient statistics allways used are:

$$\sum_t^T Y_{it} \qquad (7)$$

For the logit model the conditional maximum likelihood estimator of α is consistent, provided that the conditional likelihood function satisfies regularity conditions, which impose mild restrictions on the c_i. I now illustrate the method and show that it leads to a conditional likelihood which no longer depends on the unobserved heterogeneity terms (Maddala, 1983).

Let T=2 and consider the conditional probability $P(Y_{it} \bullet \Sigma Y_{it})$. Because T equals 2, the sufficient statistic ΣY_{it} can only take values 0, 1, or 2, and the conditional log-likelihood function becomes:

$$logL = \sum_i \sum_t \; (Prob[(0,0)|\Sigma Y_{it} = 0] + Prob[(1,1)|\Sigma Y_{it} = 2] + \\ + Prob[(1,0)|\Sigma Y_{it} = 1] + Prob[(0,1)|\Sigma Y_{it} = 1]) \tag{8}$$

The sufficient statistic takes a value 0 if $Y_{i1}=0$ and $Y_{i2}=0$. In this case, the probability of not participating in any period, conditional on the sufficient statistic being equal to 0, equals 1:

$$P[(0,0) \bullet \Sigma Yit=0] = 1 \tag{9}$$

The sufficient statistic takes value 2 if $Y_{i1}=1$ and $Y_{i2}=1$. The probability of participating in all periods, conditional on the sufficient statistic being equal to 2, equals 1:

$$P[(1,1) \bullet \Sigma Yit=2] = 1 \tag{10}$$

The sufficient statistic takes value 1 either if $Y_{i1}=1$ and $Y_{i2}=0$ or if $Y_{i1}=0$ and $Y_{i2}=1$. In this case, the conditional probabilities are not straightforwrad as they do not equal 1.

$$\begin{aligned} &P[(1,0) \bullet (1,0) \text{ or } (0,1)] \\ &P[(0,1) \bullet (1,0) \text{ or } (0,1)] \end{aligned} \tag{11}$$

Using (9) and (10), the first two terms of the conditional log-likelihood function of equation (8) cancel out (since they equal 1). Therefore, observations whose dependent variable (Y_{it}) does not change over the panel waves (i.e when $\Sigma Y_{it}=0$ and $\Sigma Y_{it}=T$) do not contribute to the conditional likelihood function. That is, the conditional log-likelihood function equals:

$$logL \;=\; \sum_i \sum_t \;(Prob[(1,0)\_(1,0)\_or\ (0,1)] \;+\; Prob[(0,1)\_(1,0)\ or\ (0,1)]) \qquad (12)$$

Let us now expand each term of the conditional log-likelihood function separately.

$$P[(1,0)|(1,0)\ or\ (0,1)] \;=\; \frac{P(1,0)}{P(1,0)+P(0,1)} \qquad (13)$$

Using (6), each term of expression (13) can be decomposed as follows.

$$P(1,0) \;=\; \frac{\exp(X_{i'1}\alpha + Z_{i'}\beta + c_i)}{1+\exp(X_{i'1}\alpha + Z_{i'}\beta + c_i)} \cdot \frac{1}{1+\exp(X_{i'2}\alpha + Z_{i'}\beta + c_i)} \qquad (14)$$

$$P(0,1) \;=\; \frac{1}{1+\exp(X_{i'1}\alpha + Z_{i'}\beta + c_1)} \cdot \frac{\exp(X_{i'2}\alpha + Z_{i'}\beta + c_i)}{1+\exp(X_{i'2}\alpha + Z_{i'}\beta + c_i)} \qquad (15)$$

Because the denominators are the same in all terms of expression (13), these are automatically removed and we obtain the following expression for (13):

$$P[(1,0)|(1,0)\ or\ (0,1)] \;=\; \frac{\exp(X_{i'1}\alpha + Z_{i'}\beta + c_i)}{\exp(X_{i'1}\alpha + Z_{i'}\beta + c_i) \;+\; \exp(X_{i'2}\alpha + Z_{i'}\beta + c_i)} \qquad (16)$$

Now, rearranging expression (16),

$$P[(1,0)|(1,0)\ or\ (0,1)] \;=\; \frac{\exp(Z_{i'}\beta)\ \exp(c_i)\ \exp(X_{i'1}\alpha)}{\exp(Z_{i'}\beta)\ \exp(c_i)\ [\exp(X_{i'1}\alpha) \;+\; \exp(X_{i'2}\alpha)]} \;=\; \frac{\exp(X_{i'1}\alpha)}{\exp(X_{i'1}\alpha)+\exp(X_{i'2}\alpha)} \qquad (17)$$

$$P[(1,0)|(1,0)\ or\ (0,1)] \;=\; \frac{\exp[(X_{i1} - X_{i2})'\alpha]}{1 \;+\; \exp[(X_{i1} - X_{i2})'\alpha]} \qquad (18)$$

and dividing by $\exp(X_{i2}'\alpha)$:

we obtain an expression which does not depend on the observed and unobserved time-invariant factors (Z_i and c_i). In addition, if $X_{i1}=X_{i2}$ then the X's are also cancelled out of the specification. By analogy,

$$P[(0,1)|(1,0) \text{ or } (0,1)] = \frac{\exp(X_{i'2}\alpha)}{\exp(X_{i'1}\alpha)\_+ \exp(X_{i'2}\alpha)} = \frac{\exp[(X_{i1} - X_{i2})'\alpha]}{1 + \exp[(X_{i1} - X_{i2})'\alpha]} \qquad (19)$$

which has the same features as (18). So, the conditional log-likelihood function (8) does not depend on observed and unobserved time-invariant factors:

$$\log L = \sum_i \sum_t \frac{\exp[(X_{i1} - X_{i2})'\alpha]}{1 + \exp[(X_{i1} - X_{i2})'\alpha]} + \frac{1}{1 + \exp[(X_{i1} - X_{i2})'\alpha]} \qquad (20)$$

Therefore, for the case of T=2 we have a model which can be estimatd by a standard logit routine. The features of this model are:

(1) estimation is over the cases with $\Sigma Y_{it}=1$,

(2) the explanatory variables enter in differences,

(3) no estimates of parameters relating to unobserved characteristics are obtained, and

(4) no estimates of the characteristics that do not change over the panel length (i.e Z_i and X_{it} if $X_{i1} = X_{i2}$) are obtained.

An advantage of this method is that it allows the observed covariates X_{it} to be correlated with c_i because c_i fall out of the likelihood function. This is particularly important for the estimation of female participation models, given that unobservables are often correlated with observed covariates.

For general *T*, the contribution of individual *i* to the likelihood is:

$$\frac{\exp[(\Sigma_{t=1}^{T} X_{it} Y_{it})'\alpha]}{\Sigma_{d^* \in D_i} \exp[(\Sigma_{t=1}^{T} X_{it} d_t)'\alpha]} \qquad (21)$$

$$\text{where} \quad D_i = \{d^* = (d_1,...,d_T) \text{ with } d_t = 0 \text{ or } d_t = 1 \text{ and } \Sigma_t^T d_t = \Sigma_t^T Y_{it}\}$$

In principle, this technique is not limited to small T. However, the computational burden in the denominator becomes enormous as T gets large. Greene (1991) actually affirms that for T larger than 5 or 6 the computational burden becomes excessive. Giannelli and Micklewright (1993a, 1993b) propose a two-stage method that avoids the excessive computational burden. I do not use this method because in my particular case the number of observations contributing to the likelihood is relatively low, and the panel length is not too long.

Appendix 2

Descriptive Statistics of Some ECPF Variables

Means of Some ECPF Demographic Variables

Variable	Mean	Variable	Mean
Head of the Household (male=1)	0.98	Number of Members aged < 1	0.03
Wife's Age	44.3	Number of Members aged 1-3	0.30
Husband's Age	47.5	Number of Members aged 3-6	0.93
Husband's Experience	35.6	Number of Members aged 6-14	0.70
Husband's Years of Schooling	6.12	Number of Members > 65	0.12
Number of Household Members	4.09	Residence District	
Number of Income Recipients	1.70	<5,000	0.17
		5,000-10,000	0.10
		10,000-20,000	0.10
		20,000-50,000	0.11
		50,000-100,000	0.13
		100,000-500,000	0.25
		>500,000	0.14

Notes: Means are calculated from the overall pooled data set. Thus, the sample size is 51,504 observations.