On the estimation of the effect of labour participation on fertility

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Abstract In this paper we consider the estimation of the causal effect of female labour market status (participation and employment) on fertility. We focus on the sensitivity of the estimated effect to (i) the assumptions about the exogeneity of labour market status; and (ii) the time interval between the measurement of fertility and employment status. Using Spanish quarterly data, we estimate a switching probit model that accounts for the joint determination of both variables. In order to obtain a behavioural effect of the former on the latter, we look at the timing of conception instead of the timing of birth, and present alternative sets of estimates depending on the accuracy with which conception is measured (yearly or quarterly). Our results show a positive although non-significan effect of participation and employment on the probability of having the firs child, once the sample of women who conceive in the same quarter (or one quarter later) in which labour market status is measured and the endogeneity between both variables is accounted for. We fin that annual data tend to over-estimate the negative effect of employment or participation on the probability of having a child, but the main biases appear when looking at the effect of participation.

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1 Introduction

Increasing female labour supply and decreasing fertility rates are trends observed in many developed countries during the last decades. Spain, for instance, moved from 2.37 children per woman in 1979 to 1.26 children per woman in 2002, while the labour force participation rate of women went from 32 to 42 per cent. These trends suggest a possible relationship between female labour market status and fertility decisions at a household level which has originated a growing interest in the economic models of fertility.

This paper addresses the issue of the empirical relationship between both variables. In particular, we focus on the sensitivity of the estimated effect of labour market status (participation and employment) on fertility to (i) the assumptions about the exogeneity of the former, and (ii) the time interval between the measurement of fertility and employment status. Actually what we measure is the effect of labour market status (participation and employment) on the probability of having a child, that is, on successful fertility choices.

The relationship between fertility and female labour supply has received a great deal of attention in the literature, both from a theoretical and an empirical point of view. Given the opportunity cost of having and raising children, one can expect a negative correlation between labour force participation and fertility. However, it is hard to unveil any causal relationship between labour and family size decisions because both are simultaneously determined by the same economic variables (Mincer 1963). If this is the case at least part of the observed relationship between them is spurious. This is the so called self-selection problem, which implies that participating women would behave differently from those women out of the labour force, independently of any true causal effect of participation on fertility. If endogenous participation is not accounted for, the estimates of the effect of women's labour market activity on fertility will be incorrect and useless to the policy makers concerned with stimulating female employment and/or fertility.

One strand of the literature has treated the endogeneity problem estimating the determinants of fertility and labour supply within a simultaneous equation framework (see Moffi 1984; Hotz and Miller 1988). Since in this paper we are concerned just with a particular part of the system, and not with the system as a whole, we follow an alternative approach. We use an econometric framework which permits consistent estimation of the effect of employment status on fertility accounting for the endogeneity between these two variables. Specificall , we propose a switching probit model with endogenous switching, similar to the one used by Manski et al. (1992). By applying this model, we are able to answer the following question: if a women is working or looking for work and stops doing so for an exogenous reason, then what happens to her decision to have a child? In other words, we try to measure how a woman would change her fertility behaviour if her labour market situation exogenously changed from participation (or employment) to non-participation (or non-employment).

In order to obtain a behavioural effect of labour market status on fertility, we look at the timing of conception rather than the timing of births. As emphasized by Kalwij (1999), this timing issue is especially important. Since births are a consequence of decisions made approximately nine months earlier, the relationship between the outcome of a pregnancy (a birth) and current work decisions has little or no behavioural interpretation. Therefore, what has economic sense is to study the effect of current (or past) work choices on current fertility choices, instead of the effect on current fertility outcomes.

Nevertheless, a problem could arise since in many of the available data sets the information on fertility and employment status is not measured exactly in the same time span. Typically one observes for each household the employment status of the woman at the time of the interview and the number of children present. Thus, regarding childbearing decisions, the only available information is whether or not a new birth takes place between two consecutive interviews, but the precise moment in which the birth takes place is not known and it varies among women in the sample. Consequently, if the data are collected on a yearly basis, for those women in the sample for which the time interval between the actual birth and the observed labour force status is closer (those women already pregnant when labour market status is measured) the fertility decision has already been made. Therefore, the outcome of the pregnancy will not be responsive to current prices and incentives so there is no room for labour supply behaviour to impact fertility behaviour. Notice that this mis-matching problem would be less severe the shorter the timing of the survey. Many available data sets, like the Panel Study of Income Dynamics (PSID) for the U.S., offer annual information.

In this paper we overcome this potential problem and address the importance of accounting for this timing issue. For that purpose, we use longitudinal data from the Spanish Labour Force Survey (*Encuesta de Población Activa*, EPA), which offers information up to six consecutive quarters for the households in the survey. We exploit this feature of the data to compare the estimates from models in which fertility is define on a yearly basis with those in which fertility is measured more accurately using the quarterly information.

As far as the empirical estimation is concerned, using a switching formulation we obtain alternative sets of estimates depending on the accuracy with which the fertility variable is defined both under the assumption of strict exogeneity of employment status and accounting for the endogeneity problem. Two main conclusions emerged from our analysis. First, using annual data we fin a negative effect of participation and employment on fertility, although the effect of participation is stronger than the effect of employment. The negative effect of participation becomes stronger when endogeneity is accounted for, while the negative effect of employment becomes non-significant Second, the estimated effect of labour market status on fertility varies considerably depending on whether we include in the sample women whose pregnancy is underway when labour market status is measured, and therefore lacking behavioural content. Once we select the sample of women who conceive during the same quarter in which participation or employment are measured (or conceive one quarter later), the negative estimated effect disappears becoming positive, although non-significant when the endogeneity is accounted for.

The organization of the paper is as follows. Section 2 reviews the main approaches followed in the literature to analyze the relationship between fertility and participation; Sect. 3 describes the data set used; Sect. 4 presents the econometric model; Sect. 5 contains the estimation results; and, Sect. 6 concludes.

2 Empirical studies

As pointed out by Browning (1992), an important issue when analyzing the empirical relationship between fertility and female labour market status is how to formulate children and labour supply variables. This depends very much on the type of information on children and on labour market offered by household surveys. The type of data available might also determine the type of approach followed to analyze fertility decisions. In this regard, there are two main approaches to estimate fertility equations taking into account labour supply: (i) the static approach, and (ii) the life-cycle approach (see Hotz et al. 1997 for a detailed description of both approaches).

Studies included in the firs group are in line with the pioneering work of Becker (1960). Within this approach, fertility is define as the total number of children ever born, i.e. completed fertility. With respect to labour market variables, there are two main positions. On the one hand, some authors look at the relationship between wages and completed fertility, usually treating wages as exogenous in the estimation process. This is the case of Wolfe (1980) and Ermisch (1989), among others. On the other hand, other authors have proposed the estimation of structural models in order to take into consideration the mutual determination of fertility and labour force participation behaviour. In these models participation is define as any measure of women's time devoted to work. For example, Willis (1973) uses the lifetime labour supply of wife after marriage, whereas Fleisher and Rhodes (1979) use the proportion of years the mother has worked at least six months since leaving school.

Nevertheless, one of the most important criticism to the static framework is related to its assumption that choices concerning the number of children are made at the beginning of marriage and are not subject to revision. This implies ignoring the inherently sequential nature of fertility decision making. In this regard, the life cycle approach has been considered to provide a more appropriate setting to examine the relationship between women's labour supply and childbearing decisions. In contrast to the static framework, which focuses on completed fertility, life-cycle approach focuses on the timing and spacing of births over the lifetime span. Moffi (1984), Hotz and Miller (1988), Kalwij (1999), Hyslop (1999) and Francesconi (2002) are examples of studies that have analyzed life-cycle female labour force participation and fertility behaviour.

Estimating a life cycle model requires to solve an intertemporal optimization problem, which demands rich data. With the data we use in this paper we perform a more modest work: we estimate a reduced form model which allows us to identify the true exogenous effect of participation and employment on fertility, but we are unable to explain their structural interactions. Guiterrez-Domenech (2007) and Bloemen and Kalwij (2001) also estimate reduced form models. Using duration data, Gutiérrez-Domenech focuses on the timing to marriage and to the birth of a child, while Bloemen and Kalwij estimate a multiple state transition model. Kalwij (2000) estimates a count data model to analyze the effects of female employment status on the number of children.

Moreover, within the life-cycle framework it is important to distinguish between conception and birth. Specificall , what makes economic sense is to study the association between current work choices and current conception choices. Therefore, it should be more appropriated to look at the timing of conception rather than the timing of births. This is because many women could conceive while being employed and leave employment just before childbirth. If we look at the timing of births it would make it appear as if these women schedule childbirth while being non-employed. Some authors approximate this distinction between conception and birth by assuming that a birth in year $t + 1$ is conceived in year t. Thus, the relationship to be estimated is that between employment status in t and conception in t.

However, the accuracy of this adjustment highly depends on the available information in the data set. If the household survey is conducted once a year, typically participation is measured at the time of the interview, but the only available information regarding childbearing is whether or not a new birth takes place between two consecutive interviews. As far as the exact moment in which the birth takes place is not known, it is possible that some women are already pregnant when labour market status is measured. Obviously for these women there is no behavioural effect of employment status on fertility. The mismatching between the timing of both variables is less severe the shorter the time span in which they are measured. Since we use quarterly data, the moment of conception (or birth) is more accurately measured. Therefore, it becomes possible to capture a behavioural relationship free of the alluded bias.

3 Data description

The data set used come from the Spanish Labour Force Survey (*Encuesta de Población Activa*, EPA). The EPA is conducted every quarter by the Spanish National Statistics Offic (INE) on around 60,000 households. It is designed to be representative of the total Spanish population. One sixth of the sample is renewed quarterly; therefore, each household remains in the sample for a maximum of six consecutive quarters. We exploit the longitudinal structure of the survey to obtain rotating panels from the second quarter of 1987 to the fourth quarter of 1997.

3.1 Sample selection and endogenous variables

When studying fertility, it is important to take into account that the decision to have the firs child is quite different from the decision to have other parity. In this analysis we focus on women's decision to have the firs child. Modelling subsequent births is crucial in understanding the low fertility rate in Spain. Nevertheless, this is not the purpose of this paper. Given that our aim is to compare how the estimated effect of employment status varies according to different assumptions, this sample selection should not influenc our conclusions. Moreover, the decision to have the firs child is particularly relevant since around the birth of the firs child the interrelationship between fertility and labour supply is strongest (see Shapiro and Mott 1994), hence it would be desirable to model this. Therefore, our sample includes married women aged 16–45, without children over the six quarters or having the firs child in a certain quarter, depending on the model considered. We focus on married women because in Spain the number of children born out-of-wedlock is very low (according to INE, more than 92% of children born in 1987 are from married women). We determine whether a firs birth has occurred or not using the information on the number of children present in the household in each quarter. So, in order to date with accuracy the moment of birth and, therefore, conception, we need to make the analysis conditional on the number of children to be zero in the firs quarter.

Participation (and the rest of explanatory variables) is define as a dummy variable which equals 1 if the woman is in the labour force (employed or unemployed) in quarter t and 0 if she is out of the labour force. Since the effect of these two labour market situations, employment and unemployment, can be different, we also estimate models in which we measure the effect of employment. In this case, the variable of interest is a dummy which takes the value 1 if the woman is employed in period t and 0 if she is unemployed or out of the labour force.

We defin the dependent variable indicating fertility differently depending on the model considered. First of all, in order to estimate a model on a yearly basis, we disregard the quarterly information on fertility in our data and consider that the only available information for each woman would be that in period t and one year later, that is, in period $t + 4$. In this case, we defin fertility as a dummy variable equals 1 if a child is present in period $t + 4$ and not in period t and 0 if the woman remains childless. Therefore, the variable takes the value 1 regardless the precise quarter in which the birth takes place, being equal to 1 for women having actually the child in $t+1$, $t+2$, $t+3$ or $t+4$. So, it is clear that with annual data we capture a "mixture" of effects, some of them with little economic meaning.

Notwithstanding, since we have quarterly information, we can redefin the fertility variable in order to pick up a relationship with behavioural interpretation. Therefore, if we defin fertility as a dummy variable taking the value 1 if a child is present in period $t+3$ and not in $t+2$, $t+1$ and t we are actually measuring the effect of current work choices (measured in period t) on current conception decisions. Specificall , to study this contemporary effect we include women that give birth in the sixth, fifth or fourth quarter they are observed. Labour market status and the rest of explanatory variables are dated on the third, second, or firs quarter they are observed, respectively. Another effect of interest is that of employment status in t on the probability of conceiving in $t + 1$. In order to capture this effect, we defin fertility as taking the value 1 if a child is present in $t + 4$ and not in $t + 3$, $t + 2$, $t + 1$ and t. To study this effect we use those women who give birth in the sixth or fift quarter they are observed, dating the explanatory variables in the second or firs quarter, respectively. Obviously, what has no economic sense is the effect of employment status in t for those women having actually the child in $t+1$ or $t+2$, being this a pure statistical association. Notice that the only difference between what we call models on a quarterly or yearly basis is how the fertility variable is defined In the former case, the exact quarter of birth is known and, therefore, we are able to look at the timing of conception. However, in the latter case we only know if a new birth occurs during the year, i.e. in any of the four quarters of the year. Therefore, this effect is not an aggregation of the quarterly effects. It is just the result of a more imprecise measure of the fertility variable.

After filterin the initial sample we obtain 4,672 women of which 1,022 have the firs child in the sixth, fifth fourth, or third quarter they are observed. Table 1 disaggregates the previous information and shows the number of women having actually the child in each of the periods considered in the sample.

In order to show how the labour market distribution changes along the pregnancy, Table 2 reports the evolution of the labour market status of those women who have had a child in the sixth quarter they are observed. Our data show that the decrease in the labour force participation rates as the birth becomes closer is mainly caused by unemployed women, since employed women show a higher attachment to the labour market. These figure show the importance of looking at the timing of conception rather than the timing of births. Many women conceived while being in the labour force and leave activity just before childbirth. Considering fertility outcomes instead of fertility decisions might lead to the conclusion that these women decide to have a child while being non-employed. Moreover, these changes in the sample composition could bias the estimated effect of employment status on fertility using annual data.

3.2 Explanatory variables

The explanatory variables used in the estimation can be classifie into three groups: demographic variables relating to the woman, demographic variables relating to the husband, and variables relating to household and business cycle conditions.

In the firs group we include age and education. Both are grouped into categories and treated as dummies in the estimation. Traditionally these variables have been considered fundamental in explaining fertility behavior of women. The importance of age is obvious, given the biological constraints faced by women. The relevance of education is also clear, since children have high time costs and higher education

Table 1 Number of women having the firs child per quarter

Sixth quarter	Fifth quarter	Fourth quarter	Third quarter	Any quarter
221	237	272	292	1,022

Table 2 Distribution of new mothers in t by labour market situation (%)

	$t-4$	$t-3$	$t-2$	$t-1$	t
In the labour force	79.64	79.64	74.66	67.42	59.73
Employed	58.82	60.18	57.92	57.47	53.85
Unemployed	20.81	19.46	16.74	9.95	5.88
Out of the labour force	20.36	20.36	25.34	32.58	40.27

t refers to the sixth quarter in which the woman is observed generally increases the opportunity costs of time spent in child care (see Wolfe 1980 and Bloemen and Kalwij 2001 for possible effects of a woman's education on her family size).

Other variables included in the regressions are husband's characteristics (age, education, labour market status and employment sector); and household characteristics (the presence of grandparents and region of residence). Many models consider that husband's time is not productive in the household, so we have considered husband's work decision as exogenous. In order to take into account changes in aggregate conditions, the regional unemployment rate has also been included in the labour market status equation. Finally, we have included time dummies in the fertility equation for each year of the sample period. Appendix A provides sample frequencies of the variables used in the estimation of the different models.

4 The empirical framework

As it has been already emphasized, the purpose of this paper is to estimate the causal effect of participation and employment on fertility and see how the estimated effect changes depending on the sample composition and nature of the data. Nevertheless, given that employment status is not exogenous to fertility decisions, we face an identificatio problem when estimating this relationship. In order to deal with this problem and see how the probability of having a child would vary with employment status if it were exogenously determined, we use a switching regression framework in our empirical specification

To this end it is useful to defin two hypothetical fertility outcomes, y_0 and y_1. Each woman, i, is characterized by values of the variables $(y_{i1}, y_{i0}, z_i, x_i)$. Variable y_{i1} indicates the outcome if the woman were to participate (or to be employed); $y_{i1} = 0$ if the woman would not have a child and $y_{i1} = 1$ otherwise. Similarly, y_{i0} indicates the outcome if the woman were not to participate (or to be out of employment). Here x is a vector of observed variables describing personal characteristics and the business cycle. The binary variable z indicates labour market status and it is define as $z_i = 1$ if the woman participates (or if she is employed) and $z_i = 0$ otherwise.

The effect of participation or employment on fertility for a particular woman will be given by the difference $\Pr(y_{i1} = 1 \mid x_i) - \Pr(y_{i0} = 1 \mid x_i)$. It measures how a particular woman would change fertility behaviour if her employment status switched from $z_i = 0$ to $z_i = 1$. However, for each woman we only observe the value of y_{i1} or y_{i0}, and the other value is censored. As pointed out by Manski et al. (1992), the sampling process generating the data only identifie the conditional probabilities $\Pr(y_{i1} = 1 \mid x_i, z_i = 1)$ and $\Pr(y_{i0} = 1 \mid x_i, z_i = 0)$. Therefore, in the absence of prior information, the data cannot identify the parameters of interest, $\Pr(y_{i1} = 1 \mid x_i)$ and $\Pr(y_{i0} = 1 \mid x_i)$.

One solution to this identificatio problem is to use the standard two-stage or instrumental variables method. Nevertheless, the presence of a dummy endogenous regressor in a binary choice model makes the analysis differ substantially from that in continuous variable models. More precisely, the standard two-stage method leads to an inconsistency with the statistical assumptions of the non-linear discrete models.

Moreover, the alternative linear probability model is incompatible with the observed data when dummy endogenous regressors are present in a binary choice model (see Carrasco 2001 for a detailed discussion on this issue within the context of the effect of fertility on participation).

Given this problem, the identificatio of the effect of employment status on fertility depends crucially on the available prior information to the econometrician. Thus, we rely on different assumptions about the actual process generating fertility and participation or employment outcomes. As in Carrasco (2001), that prior information about the joint probability distribution of (y_{i1}, y_{i0}, z_i) is expressed through the formulation of a trivariate probit model. Therefore, assuming that the disturbances are distributed tri-variate normal is enough to identify the model and it is not strictly necessary the presence of a regressor in the labour market status equation that does not affect directly the fertility decision. Nevertheless, identificatio based solely on arbitrary functional form assumptions is fragile. In this sense, the presence of a regressor in the participation or employment equation that does not affect the fertility equation could improve the identificatio of the parameters of the model. We have, therefore, relied on a distributional assumption element using in addition an exclusion restriction to identify the parameters of the model. In our application, we have used the regional unemployment rate as an exclusion restriction.

Let us then consider the following switching probit model for N individuals:

$$y_i = \begin{cases} y_{i1} = \mathbf{1}\left(\alpha_1 x_i + u_{i1} \geq 0\right), & \text{if } z_i = 1; \\ y_{i0} = \mathbf{1}\left(\alpha_0 x_i + u_{i0} \geq 0\right), & \text{if } z_i = 0, \end{cases} \tag{4.1}$$

and

$$z_i = \mathbf{1}\left(\beta q_i + \varepsilon_i \geq 0\right), \quad (i = 1, \ldots, N), \tag{4.2}$$

where $\mathbf{1}$ is the indicator function, α_1, α_0 and β are vectors of coefficient which include a constant term, and y_i is the observed fertility outcome for individual i. To simplify notation we drop out the individual subscripts. We assume that u_1, u_0 and ε are normal variables, such that

$$\begin{aligned} \Pr\left(y_1 \mid x\right) &= \Phi\left(\alpha_1 x\right), \\ \Pr\left(y_0 \mid x\right) &= \Phi\left(\alpha_0 x\right), \end{aligned} \tag{4.3}$$

and

$$\Pr\left(z = 1 \mid q\right) = \Phi\left(\beta q\right),$$

where $\Phi\left(.\right)$ denotes the standard normal distribution function and (u_1, u_0, ε) are assumed to be jointly normally distributed with zero mean vector and covariance matrix

$$\sum = \begin{pmatrix} 1 & \rho_{10} & \rho_{1\varepsilon} \\ & 1 & \rho_{0\varepsilon} \\ & & 1 \end{pmatrix}. \tag{4.4}$$

We allow the parameters in the equation for y_1 to differ from those in the equation for y_0 ($\alpha_1 \neq \alpha_0$) . The contribution of unobserved variables is given by the error terms (u_1, u_0, ε). Notice that, although each woman is observed over six consecutive quarters, we do not account explicitly either for time invariant unobserved heterogeneity nor feedback effects from dependent to explanatory variables (Carrasco 2001 presents a switching binary panel data model which accounts for time invariant unobserved heterogeneity and predetermined variables).This could bias our results if time invariant unobserved variables which affect the probability of having a child are correlated with labour market status. Nonetheless, it is not easy to incorporate unobservable heterogeneity in a binary choice model in which in addition there is a dummy endogenous regressor. One can think that the endogeneity between fertility and labour market status may emerge from sample-selection or unobserved heterogeneity. The econometric framework used in this paper accounts for the interaction between these two variables taking into account the self-selection bias, but we do not explicitly account for other forms of time invariant unobserved heterogeneity. Although at least part of the effect of correlated unobserved variables is controlled for, still part of the heterogeneity may remain.

The estimated models differ in their assumptions about the covariance matrix of the disturbances. The most general one does not impose any restrictions on the covariance matrix of (u_1, u_0, ε). This is a switching probit model with endogenous switching similar to the one estimated by Manski et al. (1992) in the context of the effect of family structure during adolescence on high school graduation. This is our preferred model since employment status and fertility outcomes may be jointly determined by processes that cannot be directly observed. In the context of the latent-variable model previously presented, this means that the disturbances (u_1, u_0, ε) are statistically dependent. The standard bivariate probit arises as a special case of this with $\rho_{1\varepsilon} = \rho_{0\varepsilon}$ (or $u_1 = u_0$). Notice that allowing for two different errors is just a generalization that permits the outcome $(y_{i0}, y_{i1}) = (0, 1)$.

Another interesting model results from assuming that ε is statistically independent of (u_1, u_0), which implies that employment status is exogenous to fertility (that is to say, $\rho_{1\varepsilon} = 0$ and $\rho_{0\varepsilon} = 0$). This assumption means that the unobserved factors that affect both variables are uncorrelated. From a probabilistic point of view, this assumption implies that

$$\Pr(y_1 = 1 \mid x) = \Pr(y_1 = 1 \mid x, z), \tag{4.5}$$

and

$$\Pr(y_0 = 1 \mid x) = \Pr(y_0 = 1 \mid x, z). \tag{4.6}$$

Therefore, the sampling process is able to identify these probabilities and the parameters can be estimated by maximizing the binary probit likelihood given in (4.5) and (4.6). Equally, we estimate by maximum likelihood the system (4.3) with no restrictions on the covariance matrix of (u_1, u_0, ε).

The log-likelihood function of the model, from which maximum likelihood estimates can be obtained, is as follows:

$$L\left(\alpha_0, \alpha_1, \beta, \rho_{0\varepsilon}, \rho_{1\varepsilon}\right) = \sum_{y=0,z=0} \log P_{00} + \sum_{y=0,z=1} \log P_{01} + \sum_{y=1,z=0} \log P_{10} + \sum_{y=1,z=1} \log P_{11}, \tag{4.7}$$

where

$$\begin{aligned} P_{00} &= \Pr(y=0, z=0) = \Phi(-\alpha_0 x, -\beta q; \rho_{0\varepsilon}), \\ P_{01} &= \Pr(y=0, z=1) = \Phi(-\alpha_1 x) - \Phi(-\alpha_1 x, -\beta q; \rho_{1\varepsilon}), \\ P_{10} &= \Pr(y=1, z=0) = \Phi(-\beta q) - P_{00}, \\ P_{11} &= \Pr(y=1, z=1) = \Phi(\beta q) - P_{01} = 1 - P_{00} - P_{01} - P_{10}. \end{aligned}$$

Notice that imposing the restriction $\rho_{1\varepsilon} = \rho_{0\varepsilon}$ is equivalent to saying that $\rho_{01} = 1$. However, ρ_{01} is not identifie in the likelihood function. The likelihood is a function of $\rho_{1\varepsilon}$ and $\rho_{0\varepsilon}$, and these are the estimated coefficient of correlation.

5 Estimation results

In this section we report the estimates from the different models described in Sect. 4. First of all, we compare the results from the model that treats participation as strictly exogenous with those from the model that treats participation as endogenous. Secondly, we examine the consequences of definin fertility with more or less accuracy. We stress that with annual information at least part of the estimated relationship lacks economic interpretation. Finally, we present a similar set of estimates for the effect of employment, instead of participation, on the probability of having the firs child.

5.1 The estimated effect of participation and employment on fertility

To evaluate the effect of participation (or employment) on the conception probability, we calculate the average effect for all women. For each woman we compute

$$\widehat{y}_{0i} = \widehat{E}(y_{i0} \mid x_i) = \Phi(\widehat{\alpha}_0 x_i), \quad i = 1, \ldots, N, \tag{5.1}$$

and

$$\widehat{y}_{1i} = \widehat{E}(y_{i1} \mid x_i) = \Phi(\widehat{\alpha}_1 x_i), \quad i = 1, \ldots, N, \tag{5.2}$$

Table 3 Average estimated effect of participation on the probability of having a child

	Annual data	Quarterly data	
		Conception in $t+1$	Conception in t
(a) Participation treated as exogenous ($\rho = 0$)			
$\widehat{\pi}$	−0.105 (0.02)	−0.006 (0.01)	−0.012 (0.01)
(b) Participation treated as endogenous($\rho \neq 0$)			
$\widehat{\pi}$	−0.553 (0.13)	0.134 (0.11)	0.137 (0.13)
Correlation coefficien			
ρ	0.796 (0.22)	−0.581 (0.49)	−0.512 (0.41)

where N is the total number of individuals. Then, the average effect of interest is given by

$$\widehat{\pi} = \frac{1}{N} \sum_{i=1}^{N} (\widehat{y}_{1i} - \widehat{y}_{0i}). \tag{5.3}$$

Table 3 presents the average estimated effects of participation. Estimates in panel (a) do not take into account the endogeneity between fertility and participation. Estimates in panel (b) account for this problem. In both cases we present different estimates depending on the definitio of fertility. Tables 6, 7 and 8 in Appendix B reports the maximum likelihood estimates for the different models considered. For models in which endogeneity is accounted for, we cannot reject the null hypothesis $\rho_{1\varepsilon} = \rho_{0\varepsilon}$, therefore we only report estimates imposing this restriction. Notice that this result is not surprising since the difference between the two models is that the model for which $\rho_{1\varepsilon} = \rho_{0\varepsilon}$ does not allow for the possibility that a woman would have a child in the case of participating but not have a child while not participating. Although this is a possible situation, this result suggests that women in our sample do not behave in that way.

Before discussing the results, it is worth mentioning that we exclude from the fertility equation a variable, the regional unemployment rate, that will help us to identify the parameters of the model. It is well-known that it is extremely hard to come up with an instrument to identify the effect of employment status on fertility. Although our main identificatio source comes from the assumptions about the covariance matrix of the disturbances, the inclusion of a regressor in the employment status equation that does not directly affect the fertility equation could improve the identificatio of the parameters of the model. We have checked the sensitivity of the results to the identificatio restriction imposed by performing estimates including the unemployment rate as an additional explanatory variable in the fertility equation. We found that there is no direct impact of unemployment rate on fertility.[1]

[1] The results are available upon request.

The effects in the firs column of Table 3 have been obtained definin fertility on a yearly basis. In this case, as we explained in Sect. 3, fertility takes the value 1 if a child is present in period t but not one year before. Estimates in panel (a) suggest that participation reduces the probability of conception by approximately 10 percentage points. These "direct" participation effect on fertility is consistent with the casual observation typically found in the literature that any measure of female labour supply is negatively correlated with any measure of the presence of young children. However, once endogeneity is accounted for, estimates in panel (b) show that the average effect of participation increases considerably. Therefore, the negative effect of participation is underestimated under the assumption that participation does not reflec differences in preferences.

However, as we have already discussed, annual data does not allow us to identify the precise moment of birth. Therefore, the previous sample can include women who are already pregnant when participation is measured. For these women there is no room for the labour supply decision to impact on the fertility decision, since the latter has already been made. Consequently, the estimates in the firs column of Table 3 can lead to mistaken conclusions about the behavioural effect of participation on fertility.

In order to deal with this issue, we take advantage of the quarterly structure of our data to redefin the fertility variable with more precision. Table 3 shows different estimated effects of participation on fertility depending on the quarter in which the birth takes place. Notice that these estimates make sense from a behavioural point of view and are the relationships of interest. Interestingly, these estimates are markedly different from the ones obtained under the annual design. Specificall , when participation is treated as exogenous, we do not fin a significan effect of current participation on current conception or on conception in next period. Moreover, when we relax the exogeneity assumption (panel b) estimates of the behavioural effect of participation on fertility indicate that the average effect of participation is positive, although not significan at standard levels. Angrist and Evans (1998) and Angrist (2001) obtain similar qualitative results: the lack of control of the endogeneity exaggerates the negative correlation between children and labour supply.

Since the impact of being employed or unemployed can be different, Table 4 presents a similar set of estimates for the effect of employment on the probability of having the firs child (Tables 9, 10, 11 report the maximum likelihood estimates). Our results indicate that when measuring conception using quarterly instead of yearly data, the negative effect of employment on fertility vanished, becoming positive although non-significan when endogeneity is accounted for. Therefore, it seems that the results on the impact of employment go in the same direction than the effect of participation, except that in general the effects are of a smaller magnitude and less significan (specially the annual effect which accounts for the endogeneity of employment).

Two types of conclusions can be derived from these results. Firstly, the sensitivity of the estimated relationship to the nature of the data. Many data sets do not allow to identify the pregnancy period. Therefore, once a woman has decided to conceive, it does not make any sense to study the behavioural effect of labour supply on fertility decisions. We have shown that, in these cases, the estimated effect does not have a clear interpretation. Secondly, the contrast between the estimates with and without accounting for the endogeneity of participation and employment emphasizes the point

Table 4 Average estimated effect of employment on the probability of having a child

	Annual data	Quarterly data	
		Conception in $t+1$	Conception in t
(a) Employment treated as exogenous ($\rho = 0$)			
$\widehat{\pi}$	−0.056 (0.01)	−0.016 (0.01)	−0.031 (0.01)
(b) Employment treated as endogenous ($\rho \neq 0$)			
$\widehat{\pi}$	−0.042 (0.13)	0.091 (0.11)	0.108 (0.11)
Correlation coefficien			
ρ	−0.032 (0.30)	−0.379 (0.37)	−0.383 (0.29)

Annual data refers to the case in which the exact quarter of birth is unknown. Quarterly data refers to the case in which conception occurs in quarter $t+1$ or t, where t is the quarter in which participation and employment are measured. Standard errors in brackets calculated using the Delta Method

that different individuals behave differently due to heterogeneous characteristics and that we need to be cautious in assuming exogeneity for labour market status.

6 Conclusions

In this paper we have analyzed the estimated effect of female labour market status (participation and employment) on the probability of having the firs child. In order to obtain a causal effect we need to account for the endogeneity between both variables. Moreover, it is also crucial to account for the problems arising from the nature of the data. The way in which the variables of interest are formulated is highly conditioned by the nature of the available information. The contrast between the sets of estimates presented emphasizes that by using annual information on fertility we are actually capturing a mixture of effects that can lead to incorrect estimates of the behavioural effect of labour market status on fertility.

Our results, using a trivariate probit model, show that the estimated effect of participation and employment on fertility is sensitive not only to exogeneity assumptions but also to the sample composition. We fin that at least part of the estimated relationship obtained using annual data lacks economic meaning. We show that when using annual data there is a negative effect of participation and employment on fertility, regardless of the exogeneity or endogeneity assumptions. However, the previous effects could be contaminated by the inclusion in the sample of women for which there is no behavioural effect of labour market status on fertility. Once we use more accurate information and select the sample of women who conceive during the same quarter in which participation or employment are measured (or one quarter later), we fin a positive although non-significan effect on the fertility decision. This result does not show up when labour market status is treated as a strictly exogenous variable in the fertility equation. Therefore, it seems that annual data tend to over-estimate the negative effect of employment or participation on the probability of having a child, but the main biases appear when looking at the effect of participation.

Appendix A

See Table 5.

Table 5 Variable means

Variable	Annual data	Quarterly data	
		Conception in $t+1$	Conception in t
Fertility	0.219 (0.41)	0.111 (031)	0.167 (0.37)
Participation	0.768 (0.42)	0.787 (0.41)	0.781 (0.41)
Employment	0.577 (0.49)	0.590 (0.49)	0.585 (0.49)
Wife			
Age 16–24	0.157 (0.36)	0.152 (0.36)	0.157 (0.36)
Age 25–29	0.413 (0.49)	0.394 (0.49)	0.402 (0.49)
Age 30–34	0.216 (0.41)	0.219 (0.41)	0.218 (0.41)
Age35–45	0.214 (0.41)	0.235 (0.42)	0.223 (0.42)
Education			
Primary	0.218 (0.41)	0.225 (0.42)	0.222 (0.42)
Secondary	0.583 (0.49)	0.580 (0.49)	0.582 (0.49)
University	0.199 (0.40)	0.195 (0.40)	0.196 (0.40)
Husband			
Labour market status			
Employed	0.901 (0.30)	0.897 (0.30)	0.896 (0.30)
Non-employed	0.099 (0.30)	0.103 (0.30)	0.104 (0.30)
Education			
Primary	0.267 (0.44)	0.276 (0.45)	0.272 (0.45)
Secondary	0.569 (0.49)	0.562 (0.50)	0.566 (0.50)
University	0.165 (0.37)	0.162 (0.37)	0.162 (0.37)
Age	32.8 (0.07)	33.1 (0.07)	32.9 (0.07)
Economic sector			
Farming	0.055 (0.23)	0.056 (0.23)	0.055 (0.23)
Industry and constr.	0.347 (0.48)	0.344 (0.48)	0.347 (0.48)
Service	0.499 (0.50)	0.498 (0.50)	0.494 (0.50)
Other variables			
Grandparent in hhold.	0.043 (0.20)	0.045 (0.21)	0.043 (0.20)
Region			
South	0.231 (0.42)	0.222 (0.42)	0.228 (0.42)
Center	0.201 (0.40)	0.202 (0.40)	0.199 (0.40)
East	0.373 (0.48)	0.373 (0.48)	0.375 (0.48)
North	0.195 (0.39)	0.203 (0.40)	0.198 (0.40)
Reg. unemployment rate	0.189 (0.07)	0.188 (0.07)	0.188 (0.07)
No. observations	4,672	4,125	4,398

Annual data refer to the case in which fertility indicates a birth along the year but the exact quarter is unknown. Quarterly data refers to the case in which conception occurs in quarter $t+1$ or t, where t is the quarter in which participation, employment and the rest of explanatory variables are measured. Standard errors in brackets

Appendix B

See Tables 6, 7, 8, 9, 10, and 11.

Table 6 Effect of participation

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.189	0.06	0.169	0.09	0.202	0.07
30–34	0.272	0.08	−0.110	0.19	0.073	0.09
35–45	0.363	0.10	−0.384	0.32	−0.410	0.12
Education						
Secondary	0.444	0.06	0.235	0.14	0.140	0.08
University	0.923	0.09	0.649	0.23	0.337	0.10
Husband						
Employed	−0.246	0.08	−0.108	0.15	0.148	0.09
Education						
Secondary	−0.013	0.06	−0.023	0.09	0.014	0.07
University	−0.107	0.08	0.025	0.15	−0.047	0.09
Age	−2.112	0.49	−0.457	1.09	−2.638	0.71
Economic sector						
Farming	−0.152	0.09	0.044	0.15	−0.182	0.13
Service	0.176	0.05	0.050	0.09	0.022	0.05
Other variables						
Grandparent	−0.160	0.09	−0.049	0.17	0.012	0.16
Region						
South	–		−0.019	0.11	0.033	0.07
East	–		0.035	0.09	−0.060	0.06
North	–		−0.121	0.11	−0.077	0.08
Unemployment rate	−1.602	0.23	–	–	–	–
Annual dummies						
1988	–		−0.100	0.18	0.029	0.14
1989	–		−0.020	0.17	0.171	0.13
1990	–		0.012	0.19	0.185	0.14
1991	–		0.112	0.17	0.174	0.14
1992	–		−0.016	0.17	0.169	0.14
1993	–		−0.055	0.16	0.090	0.13
1994	–		−0.037	0.16	−0.008	0.13
1995	–		−0.012	0.17	0.159	0.13
1996	–		0.095	0.17	0.103	0.14
Constant	1.292	0.18	1.968	0.33	−0.624	0.25
Coeff of participation	−2 592 (SE 0 41)					
Log-likelihood	−4,606 98					
No observations	4,672					

Maximum likelihood estimates with annual data. Given the parametrization used, the coefficien of participation is given by the difference between the intercepts of the two fertility equations

Table 7 Effect of participation

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.172	0.07	0.069	0.19	0.100	0.12
30–34	0.177	0.09	−0.362	0.23	−0.029	0.13
35–45	0.266	0.11	−0.785	0.29	−0.545	0.16
Education						
Secondary	0.425	0.06	−0.202	0.20	−0.049	0.20
University	0.917	0.09	−0.423	0.45	−0.108	0.35
Husband						
Employed	−0.261	0.09	0.401	0.28	0.182	0.12
Education						
Secondary	0.001	0.06	−0.233	0.17	−0.044	0.08
University	−0.074	0.09	−0.016	0.28	−0.132	0.12
Age	−0.025	0.01	−0.015	0.02	−0.017	0.02
Economic sector						
Farming	−0.157	0.10	0.299	0.23	−0.260	0.21
Service	0.169	0.05	−0.141	0.14	−0.072	0.07
Other variables						
Grandparent	−0.103	0.10	0.102	0.31	0.164	0.20
Region						
South	–	–	−0.128	0.18	0.086	0.09
East	–	–	−0.137	0.16	−0.164	0.08
North	–	–	−0.032	0.18	−0.063	0.09
Unemployment rate	−1.265	0.31	–	–	–	–
Annual dummies						
1988	–	–	0.034	0.34	−0.253	0.21
1989	–	–	−0.129	0.33	0.017	0.18
1990	–	–	−0.213	0.38	−0.001	0.19
1991	–	–	0.060	0.35	0.084	0.19
1992	–	–	−0.330	0.35	0.096	0.18
1993	–	–	−0.194	0.35	−0.061	0.19
1994	–	–	−0.066	0.34	−0.011	0.18
1995	–	–	0.107	0.34	0.046	0.18
1996	–	–	−0.054	0.36	−0.072	0.19
Constant	1.500	0.19	−1.077	0.96	−0.336	0.33
Coeff. of participation	0.740 (SE 1.05)					
Log-likelihood	3,319.07					
No. observations	4,125					

Maximum likelihood estimates with quarterly data. Fertility takes the value 1 if conception occurs in $t+1$ and 0 otherwise, being t the quarter in which participation is measured. (See note to Table 6)

Table 8 Effect of participation

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.192	0.07	−0.012	0.15	0.110	0.10
30–34	0.228	0.08	−0.503	0.18	0.015	0.12
35–45	0.321	0.10	−1.063	0.27	−0.554	0.14
Education						
Secondary	0.434	0.06	−0.268	0.17	−0.049	0.16
University	0.905	0.09	−0.324	0.37	−0.079	0.26
Husband						
Employed	−0.213	0.08	−0.008	0.19	0.182	0.10
Education						
Secondary	−0.023	0.06	0.027	0.13	−0.032	0.08
University	−0.091	0.09	0.132	0.21	−0.089	0.10
Age	−0.024	0.00	−0.020	0.02	−0.018	0.01
Economic sector						
Farming	−0.125	0.09	0.137	0.19	−0.083	0.14
Service	0.180	0.05	−0.261	0.12	−0.096	0.06
Other variables						
Grandparent	−0.149	0.10	0.023	0.25	−0.073	0.20
Region						
South	–	–	0.236	0.13	0.125	0.08
East	–	–	0.020	0.13	−0.086	0.07
North	–	–	−0.106	0.17	−0.052	0.08
Unemployment rate	−1.494	0.30	–	–	–	–
Annual dummies						
1988	–	–	−0.488	0.27	−0.281	0.17
1989	–	–	−0.514	0.27	−0.157	0.16
1990	–	–	−0.402	0.28	−0.061	0.15
1991	–	–	−0.151	0.25	−0.156	0.16
1992	–	–	−0.229	0.24	−0.125	0.15
1993	–	–	−0.411	0.27	−0.245	0.16
1994	–	–	−0.273	0.25	−0.374	0.17
1995	–	–	−0.308	0.26	−0.076	0.15
1996	–	–	−0.031	0.24	−0.280	0.16
Constant	1.425	0.19	−0.060	0.90	−0.010	0.28
Coeff. of participation	0.049 (SE 0.98)					
Log-likelihood	3,974.77					
No. observations	4,398					

Maximum likelihood estimates with quarterly data. Fertility takes the value 1 if conception occurs in t and 0 otherwise, being t the quarter in which participation is measured. (See note to Table 6)

Table 9 Effect of employment

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.187	0.06	0.014	0.09	0.245	0.10
30–34	0.312	0.07	−0.346	0.13	0.127	0.13
35–45	0.320	0.09	−0.962	0.17	−0.365	0.17
Education						
Secondary	0.230	0.06	−0.098	0.10	0.006	0.11
University	0.571	0.07	−0.005	0.18	0.096	0.16
Husband						
Employed	0.129	0.07	0.188	0.12	0.271	0.13
Education						
Secondary	0.087	0.05	−0.042	0.09	0.074	0.09
University	0.060	0.07	−0.015	0.13	0.072	0.11
Age	−0.475	0.46	−2.887	0.93	−2.770	0.90
Economic sector						
Farming	−0.052	0.09	0.094	0.15	−0.109	0.16
Service	0.159	0.04	−0.018	0.08	−0.059	0.07
Other variables						
Grandparent	−0.011	0.10	0.131	0.18	0.001	0.19
Region						
South	–	–	0.066	0.11	0.137	0.11
East	–	–	−0.178	0.09	0.032	0.08
North	–	–	−0.262	0.11	0.003	0.10
Unemployment rate	−2.568	0.26	–	–	–	–
Annual dummies						
1988	–	–	0.089	0.23	−0.077	0.21
1989	–	–	0.092	0.22	0.061	0.20
1990	–	–	0.233	0.22	0.097	0.20
1991	–	–	0.137	0.22	0.051	0.20
1992	–	–	0.138	0.21	0.106	0.20
1993	–	–	0.102	0.22	0.071	0.20
1994	–	–	0.139	0.21	−0.108	0.20
1995	–	–	0.291	0.21	0.012	0.20
1996	–	–	0.211	0.21	0.016	0.20
Constant	0.132	0.17	0.248	0.40	−0.427	0.45
Coeff. of employment	−0.675 (SE 0.70)					
Log-likelihood	−5,285.11					
No. observations	4,672					

Maximum likelihood estimates with annual data. Given the parametrization used, the coefficien of employment is given by the difference between the intercepts of the two fertility equations

Table 10 Effect of employment

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.139	0.06	0.130	0.12	0.121	0.12
30–34	0.242	0.08	−0.279	0.17	0.039	0.15
35–45	0.254	0.10	−0.931	0.22	−0.355	0.21
Education						
Secondary	0.236	0.06	−0.089	0.13	0.106	0.16
University	0.566	0.08	−0.025	0.21	0.061	0.24
Husband						
Employed	0.133	0.07	0.091	0.15	0.144	0.17
Education						
Secondary	0.064	0.06	−0.121	0.11	−0.071	0.11
University	0.067	0.08	−0.281	0.16	−0.085	0.14
Age	−0.007	0.00	−0.012	0.01	−0.034	0.01
Economic sector						
Farming	−0.063	0.09	0.197	0.19	−0.375	0.22
Service	0.150	0.05	0.034	0.10	−0.134	0.08
Other variables						
Grandparent	0.041	0.10	0.005	0.24	0.141	0.23
Region						
South	–	–	−0.004	0.13	0.096	0.13
East	–	–	−0.284	0.12	−0.100	0.10
North	–	–	−0.170	0.13	0.007	0.11
Unemployment rate	−2.388	0.29	–	–	–	–
Annual dummies						
1988	–	–	−0.120	0.27	−0.229	0.25
1989	–	–	−0.061	0.25	−0.025	0.23
1990	–	–	−0.080	0.27	−0.072	0.23
1991	–	–	−0.029	0.26	0.117	0.23
1992	–	–	−0.063	0.25	0.047	0.22
1993	–	–	−0.160	0.26	−0.064	0.24
1994	–	–	−0.034	0.25	−0.051	0.23
1995	–	–	0.099	0.25	0.033	0.22
1996	–	–	−0.046	0.26	−0.139	0.23
Constant	0.268	0.18	−0.747	0.51	0.070	0.54
Coeff. of employment	0.816 (SE 0.84)					
Log-likelihood	−4,006.30					
No. observations	4,125					

Maximum likelihood estimates with quarterly data. Fertility takes the value 1 if conception occurs in $t+1$ and 0 otherwise, being t the quarter in which employment is measured. (See note to Table 9)

Table 11 Effect of employment

Variable	β	SE	α_0	SE	α_1	SE
Wife						
Age						
25–29	0.175	0.06	−0.007	0.10	0.193	0.11
30–34	0.300	0.07	−0.439	0.13	0.155	0.15
35–45	0.311	0.10	−1.128	0.19	−0.320	0.18
Education						
Secondary	0.231	0.06	−0.111	0.11	0.015	0.12
University	0.551	0.08	−0.041	0.18	−0.023	0.18
Husband						
Employed	0.135	0.07	0.039	0.12	0.160	0.15
Education						
Secondary	0.057	0.05	−0.041	0.10	−0.018	0.09
University	0.041	0.08	−0.061	0.15	−0.065	0.12
Age	−0.008	0.00	−0.015	0.01	−0.032	0.01
Economic sector						
Farming	−0.016	0.09	0.022	0.16	−0.085	0.16
Service	0.190	0.04	−0.182	0.08	−0.079	0.07
Other variables						
Grandparent	−0.020	0.10	0.093	0.20	−0.273	0.25
Region						
South	–	–	0.165	0.11	0.170	0.11
East	–	–	−0.168	0.10	−0.012	0.08
North	–	–	−0.184	0.11	0.009	0.10
Unemployment rate	−2.494	0.27	–	–	–	–
Annual dummies						
1988	–	–	−0.347	0.22	−0.392	0.20
1989	–	–	−0.240	0.20	−0.284	0.18
1990	–	–	−0.165	0.21	−0.177	0.18
1991	–	–	−0.086	0.21	−0.274	0.18
1992	–	–	−0.176	0.20	−0.191	0.18
1993	–	–	−0.187	0.21	−0.424	0.19
1994	–	–	−0.239	0.20	−0.491	0.19
1995	–	–	0.052	0.20	−0.306	0.18
1996	–	–	−0.052	0.20	−0.394	0.18
Constant	0.240	0.17	−0.163	0.40	0.380	0.43
Coeff. of employment	0.543 (SE 0.67)					
Log-likelihood	−4,665.52					
No. observations	4,398					

Maximum likelihood estimates with quarterly data. Fertility takes the value 1 if conception occurs in t and 0 otherwise, being t the quarter in which employment is measured. (See note to Table 9)

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