Labour Force Participation and Child Care Take-up: Simultaneous Decisions?

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1 Introduction

In this paper, the Male-Oriented[1] approach is adopted in order to model the patterns and determinants of the labour force participation decisions for mothers of preschool children and, specially, to model the impact that child care-related policies have in those decisions.

When modelling the patterns and determinants of the labour force participation decision for mothers of preschool children, one must pay special attention to the in‡uence of child care price and take-up. Although there are clearly continuous decisions to be made on the level of provision of child care and the level of supply of labour, it is instinctive to abstract to a degree from this level of detail to focus on discrete decisions[2].

An approach in which both parents' decisions (and not only the mother's) are modelled seems to represent a more appropriate description of a family's decision process in the "developed" societies of the Member States. Nevertheless, the techniques used here to estimate the mother's discrete decisions of child care take-up and labour force participation can bring new light into the later modelling of both parents decision process.

[1] In the literature, this approach is called "The Male Chauvinist Approach". We prefer to refer to it, from now onwards, with the "softer" term of "The Male-Oriented Approach"

[2] Some authors (such as Jenkins and Symons (1994)) argue that one of the main reasons for focusing on the discrete choice between employment and non-employment rather than modelling work hours is simply that most of the action may be in participation rather than hours worked.

In this paper the joint nature of child care take-up and labour force participation decisions is captured using four different binomial models. Each of these models characterizes a particular relationship between the observed and unobserved components of the two binary decisions under consideration. The special feature of this paper is the use of simultaneous models in this specific field[3]. Using this specification it is possible to estimate not only the direct but also the indirect effects of the independent variables on the discrete decisions considered.

The paper is organized as follows: in section 1 the theoretical framework underlying the family's decision process is presented (the analysis of the theoretical framework is specially useful in clarifying the expected relationships between the relevant variables and, therefore, in pointing out the explanatory variables that should integrate the structural equations to be estimated); in section 2 the econometric specification used to obtain the structural parameters' estimates is presented; Section 3 provides the results obtained for the UK; Section 4 concludes.

2 The theoretical Framework

The discrete empirical model of labour force participation and child care take-up presented in this paper is founded on a static one-period model in which a family maximizes a utility function subject to several constraints. This utility function is assumed to increase with family's consumption of market goods (C), mother's leisure (L_M) and child care[4] quality per child (Q). The father's labour supply is taken as given and the mother's decisions are conditioned on the father's hours of work. This is a characteristic of the so-called "Male Chauvinist" approach[5] to modelling household labour supply[6]. The family's utility maximization problem can be formalized as:

$$\underset{(C;Q;L)}{Max}\; U(C;Q;L_M) \tag{1}$$

[3] This specification was first used in this literature by Duncan and Giles (1994).

[4] Some authors refer to "children quality" and not to "child care quality".

[5] We prefer to use the term "Male Oriented" approach.

[6] See Ribar (1992) and Ribar (1995), for a extended explanation of the relationships between the variables of the family's maximization problem in the Male Oriented framework.

s.t.

$$T = L_M + H_M + K_M \qquad \text{(4.1. Mother's Time Constraint.)}$$

$$Q = Q(K_M; F; I; Z) \qquad \text{(4.2. Child Care Quality (per child).)}$$

$$C = w_M H_M + v - P_F(F)F - P_I(I)I \qquad \text{(4.3. Family's Budget Constraint.)}$$

$$H_M \quad F \qquad \text{(4.4. Minimum Child Care Requeriment.)}$$

$$T = K_M + F + I \qquad \text{(4.5. Child's Time Constraint.)}$$

where T is mother's total time; H_M is mother's market time; L_M is mother's non-market, non-child care time; K_M is the mother's time dedicated to look after the children; w_M is the mother's hourly wage; v is the family's non-labour income; P_F is the price of formal child care; F is the number of hours of formal child care used by the family; P_I is the price of informal child care; I is the number of hours of informal child care used by the family; and Z is a set of family's characteristics.

Expression (4.1) is the mother's time constraint. Notice how this formulation allows for the mother to enjoy child-free leisure time. Thus, L_M represents mother's non-market, non-child care time. Most of the existing studies in the area do not contemplate this possibility. Instead, they consider the mother's time expended looking after children as leisure time and, thus, they do not allow for the possibility of having a non-working mother using non-parental child care. The Duncan and Giles (1994) paper was the first to allow for this possibility, and included a child care time constraint similar to the one introduced here.

Expression (4.2) shows that quality of child care is a combination of care provided by the mother (K_M); care provided in the market (F); care provided for free by friends or relatives (I); and a set of family characteristics (Z) thought to influence child care quality or the family's child care quality perceptions: This would be the ideal specification of child care quality. However, at this stage the impact on the other choice variables of using informal child care is not directly taken into account. This is because it would require the estimation of the implicit non-monetary cost of this care and to be able to account directly for its availability. This is an issue many authors make reference to but which has not yet been explicitly addressed in the literature. Instead, in most of the studies, the existence and impact of free care on the family choice is taken into account only by, when estimating the price of formal child care, introducing among the explanatory variables some variables capturing the availability of free child care. This is the approach taken in this paper. Thus, it is assumed that if informal care is available the family will use it (another implicit assumption is made here: that is that the quality of informal child care is above a minimum acceptable level).

No presumption is made about whether the quality of care purchased in the market is less than, equal to, or greater than the quality of child care provided by the mother.

The price of informal child care explicitly appears in the budget constraint (expression 4.3). This constraint states that the family's consumption (C) must not exceed the family's disposable income after paying for child care. The family's total income is given by the sum of the mother's earned income ($w_m H_M$) and the family's unearned income (v). As in all male-oriented models, the father's labour income is taken as given and is included in the maximization problem as a component of v: As explained above, the main difficulty imposed by this budget constraint's specification is the calculation of the price of the informal child care, P_I: In this model this price is assumed to depend on the number of hours of informal care used (I) (which at the same time depends on its contribution to the overall quality of the care received by the child). This specification is considered as the ideal one but, for the reasons just exposed, when proceeding to estimate the family's decision process, explicit reference to the price of informal child care is avoided[7]. Instead, in the econometric specifications, variables intending to capture the

[7] At least until an estimation of this implicit price is available.

influence of the availability of informal child care on both, the price of formal child care and its take-up, are included.

Expression (4.4) rules out the possibility of the family leaving their children on their own and states that the 24 hours per day the child needs to be looked after are shared between the mother's care time (K_M); the time spent in market care (F) and the time spent in informal care (I).

Solving mathematically this maximization problem, one gets a clear idea of how each variable relates with the others in order to maximize the family's utility. From this maximization programme, the relationships between the relevant variables are made explicit and information is obtained about which variables to be included in the equations to be estimated in the econometric analysis.

3 Binomial Models

Four binomial models specifications are used in this paper to capture the joint nature of employment and child care decisions:

1) A Univariate Binomial Model.

2) A Bivariate Binomial Model.

3) A Simultaneous Univariate Binomial Model.

4) A Simultaneous Bivariate Binomial Model.

In order to understand how the binomial models specify the decision process under study, the latent variable approach is exposed here. According to this approach, it is assumed that there is some underlying (and unobserved) latent propensity variable y^* where $y^* \in (-\infty; +\infty)$: While we do not observe y^* directly, we do observe a binary outcome y such that:

$$y = 1(y^* > 0) \tag{2}$$

where $1(y^* > 0)$ is termed the indicator function taking the value 1 if the condition within parentheses is satisfied, and 0 otherwise. Defining the latent variable equation in linear form,

$$y^* = X\beta + u \tag{3}$$

where X is a set of variables thought to influence y^*; β is a set of parameters "quantifying" this influence; and u represents an (unobserved) stochastic component with symmetric density $f(.)$ and corresponding cumulative distribution function $F(.)$. The expected value of the binary variable y conditional on X is given by the expression:

$$
\begin{aligned}
E(y/X) &= \Pr(y = 1/X) \\
&= \Pr(y^* > 0/X) \\
&= \Pr(u > -X\beta) \\
&= 1 - F(-X\beta) \\
&= F(X\beta).
\end{aligned}
\tag{4}
$$

Different models are described depending on the assumptions on the distribution function for u. If it is assumed that u, for example, is distributed standard normally, we have the Probit model, while if the distribution of u is Logistic, we have the Logit model.

3.1 The Univariate Binomial Model

The Univariate Binomial Model is the specification most commonly used in this area. In this specification, the only way in which the labour force participation and the child care take-up decisions might be related is via prices (the price of child care is one of the explanatory variables in the labour force participation equation and the price of leisure, the wage, is an explanatory variable in the paid child care take-up equation.)

This paper estimates a Probit model. The application of the Probit Model to the problem addressed in this study is:

- for the Labour Force Participation Equation, and for i=1,...,n

$$y_{wi} = 1\,(y^*_{wi} > 0) \tag{5}$$

where $y^*_{wi} = X_{wi}\beta_w + u_{wi}$; $u_{wi} \sim N(0;1)$; X_{wi} is a $(1 \times k)$ vector containing the set of k observed variables thought to influence the labour force participation decision; and β_w is a $(k \times 1)$ vector containing the parameters set that relate X_w to y_w.

Therefore, the probability of labour force participation, conditional on X_{wi}; for each mother i, is given by:

$$\begin{aligned} P_{w1i} &= \Pr(y_{wi} = 1 | X_{wi}) \\ &= \Pr(y^{*}_{wi} > 0 | X_{wi}) \\ &= \Pr(u > X_{wi}\beta_{w}) \\ &= \Phi_1(X_{wi}\beta_{w}) \end{aligned} \tag{6}$$

where $\Phi_1()$ is the cumulative distribution function corresponding to a standard normal distribution.

- similarly, for the Formal Child Care Take-up Equation, and for $i=1,...,n$

$$y_{ci} = 1\,(y^{*}_{ci} > 0) \tag{7}$$

where $y^{*}_{ci} = X_{ci}\beta_{c} + u_{ci}$; $u_{ci} \sim N(0;1)$; X_c is the set of observed variables thought to influence formal child care take-up[8]; and β_c is the set of parameters that relate X_c to y_c:

The probability of taking-up formal child care, conditional on X_{ci}; for each family i; is given by:

$$\begin{aligned} P_{c1i} &= \Pr(y_{ci} = 1 | X_{ci}) \\ &= \Pr(y^{*}_{ci} > 0 | X_{ci}) \\ &= \Pr(u > -X_{ci}\beta_{c}) \\ &= \Phi_1(X_{ci}\beta_{c}) \end{aligned} \tag{8}$$

3.2 The Bivariate Binomial Model

The latent variable approach to the Bivariate Binomial model follows the same principle of the univariate model, but in this case the error terms of both the labour force participation and the formal child care take-up equations are assumed to be correlated. Therefore, in this model the simultaneity of the two decisions is captured (in addition to (or instead of) via prices) by allowing a correlation between the unobserved variables influencing each decision.

[8] Notice that it is perfectly plausible that the sets X_w and X_c share several of the variables. In fact, one could even argue that labour force participation and child care take-up are influenced by the same variables, in which case $X_w = X_c$: However, it is more logical to think that X_w and X_c contain both variables common to the two sets and variables exclusive to each one.

Since it is assumed here that this bivariate distribution is a standard normal, the model estimated is a Bivariate Probit model.

This specification has been used in the child care economics literature far less often than have more standard binary choice models.

The Bivariate Probit Model estimated in this paper is, therefore:

- for the Labour Force Participation Equation and for i=1,...,n

$$y_{wi} = 1\,(y^*_{wi} > 0) \tag{9}$$

  where $y^*_{wi} = X_{wi}\beta_w + u_{wi}$; $\begin{pmatrix} u_{wi} \\ u_{ci} \end{pmatrix} \sim BVN(0, \Sigma)$; and X_{wi} and β_w are defined as above

- similarly, for the Formal Child Care Take-up Equation, and for i=1,...,n

$$y_{ci} = 1\,(y^*_{ci} > 0) \tag{10}$$

  where $y^*_{ci} = X_{ci}\beta_c + u_{ci}$; $\begin{pmatrix} u_{wi} \\ u_{ci} \end{pmatrix} \sim BVN(0, \Sigma)$; and X_{ci} and β_c are defined as above.

Due to the correlation of the error terms of the two equations, the probability of labour force participation and the probability of formal child care take-up are directly interrelated. Thus, instead of one expression for each individual probability, only expressions for the combination of both decisions can be obtained. For each family i, conditional on X_{wi} and X_{ci}, these probabilities are given by:

-

$$\begin{aligned} P_{w0c0i} &= \Pr(y_{wi} = 0, y_{ci} = 0 / X_{wi}, X_{ci}) \\ &= \Pr(y^*_{wi} \le 0, y^*_{ci} \le 0 / X_{wi}, X_{ci}) \\ &= \Pr(u_{wi} \le -X_{wi}\beta_{wi}, u_{ci} \le -X_{ci}\beta_{ci}) \\ &= \Phi_2(-X_{wi}\beta_{wi}, -X_{ci}\beta_{ci}, \rho_i) \end{aligned} \tag{11}$$

  where $\Phi_2()$ is the cumulative distribution function corresponding to a standard bivariate normal ($BVN(0, \Sigma)$)distribution and ρ_i is the coefficient of correlation between u_{wi} and u_{ci}.

$$
\begin{aligned}
P_{w1c1i} &= \Pr(y_{wi} = 1, y_{ci} = 1 / X_{wi}, X_{ci}) \\
&= \Phi_2(X_{wi}\beta_{wi}, X_{ci}\beta_{ci}, \rho_i)
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
P_{w0c1i} &= \Pr(y_{wi} = 0, y_{ci} = 1 / X_{wi}, X_{ci}) \\
&= \Phi_1(X_{ci}\beta_{ci}) - P_{w1c1i}
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
P_{w1c0i} &= \Pr(y_{wi} = 1, y_{ci} = 0 / X_{wi}, X_{ci}) \\
&= \Phi_1(X_{wi}\beta_{wi}) - P_{w1c1i}
\end{aligned} \tag{14}
$$

3.3 The Simultaneous Models

Both the Simultaneous Univariate Binomial Model and the Simultaneous Bivariate Binomial Model have been applied to the labour force participation-child care take-up decision by Duncan and Giles (1994). As commented earlier, the use of simultaneous models in this literature can be seen as the result of the search for a specification which fully captures the joint nature of employment and child care decisions. The general version of this kind of model was first developed by Mallar (1977) who proposed a simultaneous equations model with binomial dependent variables in which the endogenous probabilities were assumed to have direct systematic effects on each other. In the structural model of this specification, the probability of each decision appeared as (endogenous) explanatory variable in the probability of the other decision[9]:

$$P_{wi} = F(X_{wi}, P_{ci}, \beta_w, \delta_w) \tag{15}$$

$$P_{ci} = F(X_{ci}, P_{wi}, \gamma_c, \delta_c) \tag{16}$$

[9] One can see that this allows for a higher degree of simultaneity in the decisions, compared with the previous specifications, in which only direct price effects were considered.

for $i = 1, \ldots, n$ where P_{wi} is the probability of labour force participation and it is assumed to depend on both the set of exogenous characteristics X_{wi} specific to each individual i and on the probability of paid child care take-up P_{ci}. Similarly, the probability of formal child care take-up depends on characteristics X_{ci} and the labour force participation probability P_{wi}.

The latent variable approach underlying this specification differs from the non-simultaneous only in the specification of the latent variables:

- for the Labour Force Participation Equation and for i=1,...,n

$$y_w = 1(I_w^* > 0) \tag{17}$$

where $I_w^* = X_w \beta_w + I_c^* \delta_w + u_w$; X_{wi} and β_w are defined as above; I_c^* is the latent variable underlying the formal child care take-up binary outcome; and δ_w is a parameter which captures the relationship between this latent variable and labour force participation.

- similarly, for the Formal Child Care Take-up Equation, and for i=1,...,n

$$y_c = 1(I_c^* > 0) \tag{18}$$

where $I_c^* = X_c \gamma_c + I_w^* \delta_c + u_c$; X_{ci} and γ_c are defined as above; I_w^* is the latent variable underlying the labour force participation binary outcome; and δ_c is a parameter which captures the relationship between this latent variable and formal child care take-up.

Therefore, as in the non-simultaneous models, it is assumed that there exist two latent variables (called indexes from now onwards in order to use the same nomenclature as in Mallar (1977)), I_{wi}^* and I_{ci}^*, linear in parameters, such that:

$$\begin{aligned} P_{w1i} &= \Pr(y_w = 1) \\ &= F(X_w \beta_w + I_c^* \delta_w) \end{aligned} \tag{19}$$

and

$$\begin{aligned} P_{c1i} &= \Pr(y_c = 1) \\ &= F(X_c \gamma_c + I_w^* \delta_c) \end{aligned} \tag{20}$$

In the Univariate Probit specification, F is the cumulative density function of a Univariate standard normal distribution and it is the cumulative density function of a Bivariate standard normal distribution for the Bivariate Probit specification. Thus, the structural form of these indexes is such that:

$$F^{-1}(P_{w1i}) = X_{wi}\beta_w + I^*_{ci}\delta_w \tag{21}$$

$$F^{-1}(P_{c1i}) = X_{ci}\gamma_c + I^*_{wi}\delta_c \tag{22}$$

Traditional estimation of I^*_{wi} and I^*_{ci} involves derivation of the reduced form equations for (21) and (22), which leads to a specification of the form:

$$I^*_{wi} = X_i\pi_w + v_{wi} \tag{23}$$

$$I^*_{ci} = X_i\pi_c + v_{ci} \tag{24}$$

where $\binom{v_{wi}}{v_{ci}} \sim BVN(0;\Sigma)$ in the case of a Bivariate Probit and $v_{wi} \sim N(0;1)$ and $v_{ci} \sim N(0;1)$ in the case of a Univariate Probit.

Given the observability rules $y_{wi} = 1$ if $I^*_{wi} > 0$ ($y_{wi} = 0$ if $I^*_{wi} \leq 0$) and $y_{ci} = 1$ if $I^*_c > 0$ ($y_{ci} = 0$ if $I^*_{ci} \leq 0$), the (reduced form) probabilities of labour force participation and paid child care take-up are:

$$P_{w1i} = \Phi(X_i\pi_w) \tag{25}$$

$$P_{c1i} = \Phi(X_i\pi_c) \tag{26}$$

With the "traditional" (reduced form) method we cannot identify the parameters in the structural indexes and, in particular, we cannot estimate the direct effect of one index on the other. Here is where Mallar's (1977) method has proved to be a clear advance for it allows us to estimate the structural parameters on the Simultaneous Probability Models (Univariate and Bivariate). It consists of a two-stage procedure. In the first stage the reduced form indexes in (23) and (24) are estimated by Probit Maximum Likelihood, obtaining $\hat{I}^*_w$ and $\hat{I}^*_c$. In the second stage the structural model (equations (21) and (22)) is estimated again (by Probit Maximum Likelihood in the case of the Simultaneous Univariate Probit and by Bivariate Probit Maximum Likelihood in the case of the Simultaneous Bivariate Probit) using predictions $\hat{I}^*_w$ and $\hat{I}^*_c$ from the first stage in place of the endogenous variables.

The main attraction of this specification is that it allows for the estimation of the effect of one decision on the other. The structural probabilities are given by:

$$P_{w1i} = F(I^*_{wi} > 0) = \Phi(I^*_{wi} > 0) = \Phi(X_{wi}\beta_w + I^*_{ci}\delta_w) \tag{27}$$

$$P_{c1i} = F(I^*_{ci} > 0) = \Phi(I^*_{ci} > 0) = \Phi(X_{ci}\gamma_c + I^*_{wi}\delta_c) \tag{28}$$

The effect of the paid child care take-up index on the probability of labour force participation is given, therefore, by:

$$\frac{\partial P_{w1i}}{\partial I^*_{ci}} = \delta_w \phi(X_{wi}\beta_w + I^*_{ci}\delta_w) \tag{29}$$

Similarly, the effect of the labour force participation index on the probability of formal child care use is:

$$\frac{\partial P_{c1i}}{\partial I^*_{wi}} = \delta_c \phi(X_{ci}\gamma_c + I^*_{wi}\delta_c) \tag{30}$$

Duncan and Giles (1994) present an interesting interpretation of Mallar's procedure which allows us to separate the effect of each exogenous variable on the probabilities into direct and indirect effects. In order to do so, they divide the exogenous variables into three sets: $X_{\bar{w}}$ is formed by the exogenous variables exclusive to the structural labour force participation index (27); $X_{\bar{c}}$, is formed by the exogenous variables exclusive to the structural formal child care take-up index (28); and X_{wc} is formed by the exogenous variables which appear in both (27) and (28).

Thus, the structural probabilities can be expressed as:

$$\begin{aligned} P_{w1i} &= F(X_{\bar{w}i}\beta_{\bar{w}} + X_{wci}(\beta_{wc} + \delta_w \gamma_{wc}) + X_{\bar{c}i}\delta_w \gamma_{\bar{c}}) \\ &= F(X_i \Pi_w) = \Phi(X_i \Pi_w) \end{aligned} \tag{31}$$

$$\begin{aligned} P_{c1i} &= F(X_{\bar{c}i}\gamma_{\bar{c}} + X_{wci}(\gamma_{wc} + \delta_c \beta_{wc}) + X_{\bar{w}i}\delta_c \beta_{\bar{w}}) \\ &= F(X_i \Pi_c) = \Phi(X_i \Pi_c) \end{aligned} \tag{32}$$

Differentiating (33) and (34) with respect to each set of variables we have that:

$$\frac{\partial P_{w1i}}{\partial X_{\bar{w}i}} = \beta_{\bar{w}} \phi(X_i \Pi_w) \tag{33}$$

$$\frac{\partial P_{w1i}}{\partial X_{wci}} = (\beta_{wc} + \delta_w \gamma_{wc}) \phi(X_i \Pi_w) \tag{34}$$

$$\frac{\partial P_{w1i}}{\partial X_{\bar{c}i}} = \delta_w \gamma_{\bar{c}} \phi(X_i \Pi_w) \tag{35}$$

Similarly, the marginal effects on the probability of paid child care take-up are given by:

$$\frac{\partial P_{c1i}}{\partial X_{\bar{w}i}} = \delta_c \beta_{\bar{w}} \phi(X_i \Pi_c) \tag{36}$$

$$\frac{\partial P_{c1i}}{\partial X_{wci}} = (\gamma_{wc} + \delta_c \beta_{wc}) \phi(X_i \Pi_c) \tag{37}$$

$$\frac{\partial P_{c1i}}{\partial X_{\bar{c}i}} = \gamma_{\bar{c}} \phi(X_i \Pi_c) \tag{38}$$

Thus, the direct effect of variable $x_{wc}^{(k)}$ in the "common" set on P_w is given by $\beta_{wc_{(k)}} \phi(X_i \Pi_w)$ and the indirect effect is given by $(\delta_w \gamma_{wc_{(k)}}) \phi(X_i \Pi_w)$.

The direct effect of a variable $x_{\bar{w}}^{(k)}$ belonging to $X_{\bar{w}}$ on P_w is given by $\beta_{\bar{w}_{(k)}} \phi(X_i \Pi_w)$ whereas the indirect effect is null.

The direct effect of a variable $x_{\bar{c}}^{(k)}$ in $X_{\bar{c}}$ on P_w is null and its indirect effect is given by $\delta_w \gamma_{\bar{c}_{(k)}} \phi(X_i \Pi_w)$.

The direct effect of variable $x_{wc}^{(k)}$ in the "common" set on P_c is given by $\gamma_{wc_{(k)}} \phi(X_i \Pi_c)$ and the indirect effect is given by $(\delta_c \beta_{wc_{(k)}}) \phi(X_i \Pi_c)$.

The direct effect of a variable $x_{\bar{w}}^{(k)}$ belonging to $X_{\bar{w}}$ on P_c is null whereas its indirect effect is given by $\delta_c \beta_{\bar{w}_{(k)}} \phi(X_i \Pi_c)$.

The direct effect of a variable $x_{\bar{c}}^{(k)}$ in $X_{\bar{c}}$ on P_c is given by $\gamma_{\bar{c}} \phi(X_i \Pi_c)$ whereas its indirect effect is null.

Notice that without Mallar's procedure it would not have been possible to estimate δ_w or δ_c and, therefore, it would not have been possible to distinguish between direct and indirect effects.

4 Empirical Results

The data used to obtain the estimates comes from the 1991/92 General Household Survey. The sample selected to carry out the estimations are families without absent parents (married or cohabiting) and with at least one child under 5. The reason for using this specific sample is that in the UK compulsory schooling starts when children are 5 years old. Therefore, once the child is five the use of formal child care is not anymore a parental decision. The number of families with married of cohabiting parents with at least one child under 5 in the GHS 91/92 is 904.

Table 4.2 presents a statistical description of the variables used in the econometric analysis.

The variables university; non-white; receives maintenance payments; presence of children aged under 3; presence of children aged 5-11; presence of children aged 12-18; mother is working; family uses formal child care; family uses informal child care; and grandparent lives in the household, are binary dummies taking values 1 or 0. Univ takes the value 1 if the mother has a university degree and 0 otherwise. Non-white is 1 if the mother is not white. Receives maintenance payments is 1 if the mother gets maintenance payments for the children. Presence of children aged under 3 is 1 if there are children in the age range 0-2 in the family. Presence of children aged 5-11 is 1 if there are children in the range 5-11. Presence of children aged 12-18 is 1 if there are children in this age range in the family. Mother is working is 1 if the mother is working in the labour market. Family uses formal child care is 1 if the family is paying for some kind of child care. Family uses informal child care is 1 if the family uses any kind of informal child care for their children.

The variable father's working pattern takes the value 0 if the father does not work, 1 if the father works part-time and 2 if the father works full-time.

Age of the youngest child in the family unit is the age of the youngest child in the family unit.

Mother's age; mother's age squared; family's unearned income; and length of residence are all variables which have been scaled in order to obtain parameter estimates of similar magnitude and also to avoid the estimation's package's over‡ow. Thus, mother's age is de…ned as: (age-30)/10. mother's age squared represents the age squared and is de…ned as (mother's age)¢(mother's age)/10. Length of residence is the number of years the family has been living in the same house, divided by 10. Family's unearned income is the family's weekly unearned income (as explained earlier, in the Male Oriented approach it contains in addition to the real non-wage income in the family, the father's earned income) in pounds, divided by 1000.

Predicted natural logarithm of the child care hourly cost, and Predicted natural logarithm of hourly wage, …nally, are the predicted hourly cost of formal child care (in logarithms) and the predicted net hourly wage (in logarithms) for the mother respectively. In order to obtain estimates of these variables for all the sample, one must use an econometric technique which corrects for the potential sample selectivity bias induced by the fact that data on the hourly wage (hourly cost of child care) is only available for working individuals (families using formal child care). The technique used here is the commonly used in this literature. This is Heckman's two-stage procedure. See Appendix 4.1 for an in depth explanation of the estimations of Predicted natural logarithm of the child care hourly cost, and Predicted natural logarithm of hourly wage.

The explanatory variables considered to influence both the decision of labour force participation and child care take-up, are the level of education of the mother (captured by the dummy university), the mother's ethnic origin (non-white), the age of the youngest child in the family unit (age youngest child in the family unit), the number of children under 5 in the family unit (number of children aged under 5), the presence of children under 3 (presence of children aged under 3), the presence of children in the age range 12-18 (presence children aged 12-18), the length of residence in the same house (length of residence) and economic variables such as the family's non labour income (family's unearned income), if the mother receives maintenance payments (mother receives maintenance payments) and if the family uses any kind of informal care for the under 5s (family uses informal child care), and the father's working pattern (father's working pattern).

Some variables are considered (mainly for parameter identification requirements) to influence directly only the labour force participation equation. These are the mother's age (mother's age) and the mother's age squared (mother's age squared). These could be seen as proxies for work experience.

Other variables only appear in the paid child care take-up equation. These are: the dummy variable indicating if the family has a grandparent living with them (grandparent living in the same household), which mainly picks up differences in the possibilities of non-maternal child care in one's own home; and the variable indicating the number of children in the age range 5-11 existing in the family (presence of children aged 5-11).

These same models are estimated again, this time including as explanatory variables the predicted (ln) hourly wage (predicted ln hourly wage) and the predicted (ln) child care price per hour (predicted ln hourly child care cost).

As with all qualitative dependent variable models of this type, the parameters of the latent relationships presented in section 2 are estimated by Maximum Likelihood.

Since one of key assumptions in a Probit model is that the error terms follow a normal distribution, the Likelihood Ratio (LR) test for Non-Normality in Probit Models has been undertaken for the univariate specifications. Following the advice in the recent article by Simon Peter, "On the use of the RESET test in microeconometric models" (Applied Economics Letters, 2000, 7, 361-365), we also apply a LR test for Non-Normality to the other three speci…cations estimated in this paper. The results of these tests are provided in Appendix 4.4. and show how the Non-Normality hypothesy can be rejected in all the four speci…cations considered.

Table 4.3 shows the estimates for the four speci…cations without price terms, and Table 4.4 shows the estimates obtained when prices were included among the explanatory variables. Notice how, for the labour force participation equation, the only signi…cative estimates which change sign when introducing the hourly wage and the hourly child care cost as regressors are those accompanying the variable university. When controls for these prices are not included, a university degree increases the probability of labour force participation. When controlling for prices, instead, to have a university degree is estimated to have a negative impact on the likelihood of participation. Therefore, the main reason inducing mothers with a university degree to participate at a higher rate than other less educated women are their salaries. Once isolated the e¤ect of these higher salaries, we see how their participation is less likely than less educated women's. For the Child care take-up equation, only those parameters accompanying the constant term in the simultaneous models change sign when introducing the price terms.

Appendix 4.2 shows how hypotheses tests are applied in order to decide which of the two sets of models, those including the price terms or those which do not, are more consistent with the data. The results of these tests strongly support the use of the price terms as regressors in …ve of the six models estimated[10]. Therefore, from this point onwards comments are based on the estimates provided in Table 4.4[11].

The results in Table 4.4 indicate a clear positive relationship between the two decisions under study: both the child care index and the work participation index in the simultaneous models are estimated to be positive and highly signi…cant. Thus, the higher the probability of labour force participation, the higher the probability of the family using formal child care and vice versa. This positive relationship is reinforced by the positive correlation between the non-observed variables in‡uencing each decision[12].

[10] Only for the SUVPM for the Formal Child care take-up equation the hipothesis of the non-signi…cativiy of the two price terms could not be rejected.

[11] The …nding that the speci…cations with price terms …t best the data is very reassuring given our interest in simulating the e¤ects on labour force participation and child care take-up of policies in‡uencing those price terms.

[12] The correlation coe¢ cient estimated for both the bivariate probit model and the simultaneous bivariate probit is positive and highly signi…cative.

We turn now to comment on the most relevant effects on the decision taking process of the explanatory variables. For a more intuitive interpretation of the structural model estimates, Table 4.6 separates the total marginal effects into direct and indirect effects.

We start by commenting on the estimates for the economic variables:

For the four models estimated, the family's unearned income has a positive impact on the probability of the mother taking up a paid job and a negative impact on the likelihood of the family's using formal child care. As expected, the direct effect of the family's unearned income on the likelihood of labour force participation is estimated to be positive, whereas the indirect effect is negative and of a much lower magnitude. The direct effects of the family's unearned income on the likelihood of child care take-up are positive and much higher in absolute value than its negative indirect effects.

The fact that the mother receives maintenance payments increases the likelihood of the mother's labour force participation, and the likelihood of formal child care take-up. It seems, therefore, that whereas the receipt of maintenance payments enhances the affordability of paid child care and, therefore, the likelihood of formal child care take-up, its amount is not enough to allow their recipients not to take up a paid job. The positive direct effect of maintenance payments on the likelihood of labour force participation shows us that the reason for their positive relationship is not only due to these families' higher likelihood of formal child care take-up. This positive direct effect might seem a bit counterintuitive, but we shouldn't give much importance to it since the parameter is not found to be significative different from zero for any of the two decisions and in any of the four models estimated.

As expected, the effect of the predicted hourly wage on the likelihood of both the mother's labour force participation and formal child care take-up is found to be highly significant and positive for the four models estimated. Therefore, its direct and indirect effects on both decisions are positive.

The effect of predicted hourly costs of formal child care on the likelihood of the mother's labour force participation is negative. Though this parameter is not significative in any of the four specifications, its sign shows how the price of formal child care decreases the net hourly wage perceived by the mother when deciding if taking up a paid job. The effect of the price of child care on the likelihood of formal child care take up is found to be positive, though not significative either. This sign could seem counterintuitive from an economic point of view, but it is not if taking into account that variables capturing the quality of the formal child care are not included in the estimations. Therefore, if we agree in that the higher the quality the higher the price, the positive relationship between price of child care and the probability of take-up shows that British parents put child care quality before child care price when taking the decision on formal child care take-up. Looking at table 4.6 we see, as expected, how the direct impact of the price of formal child care on the likelihood of the mother's labour force participation is negative whereas its indirect e¤ect is positive (and smaller, in absolute value). The direct e¤ect of child care price on the likelihood of formal child care take-up is positive and the also smaller indirect e¤ect is negative.

We see also that the more children under …ve there are in the family unit, the lower is the likelihood of the mother's taking up a paid job. This is what we expected, since the higher the number of children, the more expensive it is to replace the mother's work as child carer. In other words, the lower is the mother's perceived net salary. Also, the higher is the mother's time value at home. However, the e¤ect of the number of children under …ve on the likelihood of formal child care take-up is estimated to be positive. This tells us that when the number of children under …ve grows not only the mothers are more likely to stay at home looking after them but also the family needs extra help which they get in the formal child care market. Table 4.6 corroborates that the direct e¤ect of the number of children under …ve on the likelihood of the mother's labour force participation is negative and its indirect e¤ect is positive (and smaller in magnitude than the direct). Contrarily, the indirect e¤ect of the number of children under …ve on the likelihood of formal child care take-up is negative and the direct e¤ect is positive (and higher in magnitude).

The e¤ect of the number of children in the age range 5-11 on the likelihood of formal child care take up is, however, found to be negative: the bigger the number of children aged 5-11, the lower the likelihood of formal child care take-up. This shows that extra help in looking after the children is needed the most the younger are the children. Therefore, the indirect[13] e¤ect of the number of children in the age range 5-11 on the likelihood of the mother's labour force participation is negative.

The e¤ect of the children's age on the likelihood of both labour force participation and formal child care take-up is, according to the non-simultaneous

[13] We can not estimate the direct e¤ect since we chose not to include number of children under 12 among the explanatory variables for the labour force participation equation.

models estimates, positive, and according to the simultaneous models estimates, negative. The reason for this divergence in signs is found in Table 4.6: we can see how the (negative) indirect effect of this variable is bigger, in absolute value, than the (positive) direct effects. Whereas the sign of the parameters' estimates in the simultaneous models is always equal to the direct effect's sign[14], the sign of the parameters' estimates in the non-simultaneous models is equal to the overall effect. Therefore, if the indirect negative effect is bigger, in absolute value, than the positive direct effect, we would expect a negative overall effect, which is the sign estimated by the non-simultaneous models. We are not going to go further into this explanation, mainly because none of the parameters is found to be statistically significant. However, we can see how a negative sign is clearly much more intuitive: the younger the children, the more difficult it is to find reliable formal child care, and at the same time the mother's care is seen as more necessary. Therefore, the younger the children, the higher the mother's value as child carer and the lower her perceived net wage (once compensated by child care costs). Also, the lower the availability of suitable child care. The signs for the parameter accompanying the dummy presence of children under 3 corroborate this intuition. Again this result is quite common in the relevant literature. According to the child development experts, it is when children are 0-2 that they need the most attention from the child care giver. A negative sign could reflect that families know about the kind of care favours children's quality, and that families do search for the "best" child care for their children. Of course, it could also be simply the direct consequence of the existence of maternity leave arrangements (which, if that was the case, could be seen as a good tool to induce the use of child care of high quality).

The presence of children in the age range 12-18 decreases the likelihood of the mother's labour force participation and also the likelihood of the family taking up formal child care. Therefore, for the two decisions, the direct and indirect effects of this variable are negative. The negative effect on the likelihood of formal child care take-up shows how children in this age range can be seen as a potential source of informal child care, therefore, reducing the need for buying child care in the market. However, this parameter is not statistically significant for any of the two equations and for any of the four

[14] Looking at the section in which the simultaneous models are presented, we can see how the parameters' estimates are equal to $\frac{de}{\left(\frac{\sum_{i=1}^{n}\phi(x_i\beta_i)}{n}\right)}$ where de stands for direct effect.

models estimated. The same applies to the variable presence of children aged 5-11: its impact on the likelihood of formal child care take-up is estimated to be negative, but the parameter is not statistically signi…cant.

The fact that at least a grandparent lives in the same household decreases the likelihood of formal child care take-up. This shows how a grandparent might be a source of informal child care. Therefore, the presence of a grandparent in the household has also a negative (indirect[15]) e¤ect on the likelihood of labour force participation.

The longer has the family lived in the same neighbourhood the lower is the likelihood that the mother is participating in the labour force. This could be pointing towards a higher attachment to the place of residence and, therefore, to a lower disposition to move somewhere else in order to …nd a job. The e¤ect of the length of residence on the likelihood of formal child care take-up is estimated to be positive. This could be showing a higher knowledge of the reliability and a¤ordability of high-quality child care in the area. Table 4.6 shows how, once again, the opposite sign of the direct and the indirect e¤ects on both decisions.

As expected, the use of some form of informal (free) child care provided by people not living in the same household, increases the likelihood of the mother's labour force participation at the same time that decreases the likelihood of formal child care take-up.

The longer hours the father is at work, the more likely it is that the mother takes up a paid job. This is in line with the positive correlation between partners' working patterns found in most developed countries. The sign of the impact of the father's working pattern on the likelihood of formal child care take-up is di¤erent depending on the model estimated: in the non-simultaneous models this sign is estimated to be positive, whereas in the simultaneous models the sign is estimated to be negative. Di¤erently to the case of the variable age of the youngest child in the family unit commented above, in this case the magnitude of the indirect e¤ect is not bigger than the direct e¤ect's and, therefore, we can not argue that the reason for the divergence in signs is that the overall e¤ect (sum of the direct and indirect e¤ect) is positive and the sign of the parameter's estimate in the simultaneous model is the one estimated by the simultaneous models. In this case the sum of the direct and the indirect e¤ect is positive, and not negative as the sign of

[15] We can not estimate the direct e¤ect since we chose not to include grandparent living in the household among the explanatory variables for the labour force participation equation.

the parameter's estimate obtained with the non-simultaneous models. Once again, however, we are not going to go into much trouble trying to explain the meaning of this sign divergence, because the only parameter found to be signi…cant (and only at a 10% signi…cance level) is the one estimated in the bivariate model. According to this estimate, the longer the father's working hours the higher the probability of the family's taking up paid child care.

To have a university degree reduces the likelihood of the mother's labour force participation at the same time that increases the chances of formal child care take-up. The negative e¤ect of a university degree on the likelihood of labour force participation might seem rather counterintuitive …nding[16]. However it is not if we accept that a university degree may be a signal of both worker quality and ability to learn qualities that propitiate that this group of women have it relatively easier to …nd an attractive job after leaving the job market for several years in order to look after their children. At the same time, there is the common believe that highly educated women's housework time has a relatively higher marginal value than less educated women's. Since child care is part of the housework, the negative e¤ect of a university degree on the likelihood of labour force participation might re‡ect the family's concern for child care quality. However, we have also found that those women with a university degree are also more likely to take-up formal child care. This does not necessarily go against the previous argument, since children development's psychologists strongly recommend that children over 2 interact with other children through for example nursery care. It could well be that women with a university degree are relatively more aware of this and, in addition to provide child care themselves, make relatively more use of formal child care.

Table 4.4 also reveals that non-white mothers tend to have a lower probability to take up formal child care. This is probably due to the higher availability of child care providers that no doubt can be found in certain race groups in which extended families are still a fact. The impact of race on the likelihood of labour force participation is di¤erent depending on the model estimated: whereas the non-simultaneous models estimate a negative relationship between being non-white and the mother's labour force participation, the simultaneous model estimate a positive relationship. However, this parameter is not statistically signi…cant in any of the four models estimated.

[16] This is a …nding obtained in other similar studies (WHICH??).

The effects of age and agesquared on the likelihood of labour force participation are rather intuitive, mainly if considering age as a proxy for working experience: the higher the working experience, the higher the likelihood of labour force participation. The negative effect of age squared shows how the (positive) contribution of experience on the likelihood of participation decreases with experience. Or, equivalently, that the marginal contribution of experience on the likelihood of participation is decreasing (though positive). Since these two variables are appearing only in the labour force participation equation, we can only estimate an indirect effect on the formal child care take-up decision. This effect is positive for the variable age and negative for the variable age squared. This means that the more working experience the mother has, the more likely is that the family takes up formal child care (probably to avoid her to leave the job). Again, the marginal contribution of age on this likelihood is decreasing.

4.1 Hypotheses Testing

Hypotheses tests have been carried out in order to consider which of the four specifications estimated above is most consistent with data[17].

The four models constitute a nested set. Thus, the Simultaneous Bivariate Probit represents the most general specification and can be used as a benchmark or unrestricted specification. The Simultaneous Univariate Probit would be the same model but estimated imposing the restriction that the correlation among the error terms of the two equations (ρ) is equal to zero. The Bivariate Probit Model is the Simultaneous Bivariate Model with two restrictions: the parameters accompanying the indexes in each equation (δ_w and δ_c) are restricted to be zero. Finally, the most restricted specification is the Univariate Probit Model, since in it all three restrictions are imposed.

TABLE 4.1: Model Nested Structure

SBVPM	
SUVPM	$\rho = 0$
BVPM	$\delta_w = \delta_c = 0$

[17] Before testing across these four specifications, tests have been applied in order to see if the inclusion of the predicted hourly wage and the predicted hourly child care price terms in each specification provide a model more consistent with the data.

UVPM ½ = $\pm_w$ = $\pm_c$ = 0

Appendix 4.3 presents the relevant values of the statistic and the critical values used to carry out all the hypotheses tests. Since, as seen above, the results of the tests in Appendix 4.2 show that the speci…cations which include the price terms as regressors …t the data better, the rest of tests are applied to those models only.

The most unrestricted model is found to be the most consistent with the data: when testing the UVPM versus the BVPM we …nd that the BVPM …ts the data better; when testing the UVPM versus the SUVPM we …nd that the best …t is obtained with the SUVPM; that the SBVPM is more consistent with data than the UVPM; that the SBVPM provides a better …t than the BVPM; and that the SBVPM has a superior performance than the SUVPM. Therefore, it seems that the SBVPM is the speci…cation most consistent with our data. Table 4.2 summarizes the results of the hypothesis tests.

5 Conclusions

In general the results obtained with the four di¤erent speci…cations are rather intuitive and there are no important contradictions for the estimates obtained from the di¤erent models. In most of the cases in which contradictory results between the speci…cations do exist, an explanation can be found by observing the direct and indirect e¤ects provided by the simultaneous models.

The estimates of the correlation coe¢cient (½) are positive and highly signi…cant in both the BVPM and the SBVPM. Therefore, there is statistical evidence to state that the unobserved variables in‡uencing the labour supply decision do in‡uence also child care take-up.

The main attractive of this empirical work is the use of simultaneous techniques which allows for the separation of direct and indirect e¤ects of each variable on the decisions of interest. Moreover, hypotheses testing of the nested structure of the four models estimated seems to show that simultaneous models are more consistent with data. Up to now only Duncan and Giles (1994) have applied this speci…cation to the modelling of the joint decisions of labour force participation and paid child care use. The estimates of the parameters for both the child care and the work index obtained by Duncan and Giles coincide in sign with the ones found here. They are positive and highly signi…cant, showing that the higher the mother's likelihood to work, the higher the family's likelihood to take-up paid child care and vice versa. The estimated correlation coefficients of the unobserved variables influencing each decision are also positive, highly significant and relatively large (0.4198 for the SBVPM and 0.4239 for the BVPM in this study and 0.242 for both specifications in Duncan and Gile's).

In my opinion, the estimation of a simultaneous specification is of much use for the future development of this research since it provides a clearer sight on the way in which the families take the decisions on labour supply and formal child care take-up. This information is mainly useful in our case since we are interested in obtaining structural estimates of the intensity of the relationships between the exogenous and endogenous variables thought to intervene in the decision process. In order to estimate these structural parameters, a choice must be made of the functional form of the utility function the family is maximizing and the knowledge of the existence of simultaneity between both decisions rules out a big number of functional forms. As we saw in section 4, the latent variable approach applied to Simultaneous models shows that these models are consistent with a non-separable utility function. Since the models that best fit our data are the simultaneous ones (in particular, the simultaneous bivariate probit), the specific functional form we ought to use to obtain structural estimates of the family's decision process under study will have to be one which presents this non-separability in its arguments.

6 Appendix 4.1

6.1 Wages Estimation.

Available wages are unobserved for mothers who are not employed. Therefore, in order to estimate the relevant model, these unobserved wages must be estimated …rst.

Wages for all the mothers in the sample are estimated using reduced-form equations in which demand-side regional demographic variables are used, together with standard human capital ones, as instruments. The human capital variables include age (as proxy for experience) and education. Labour demand e¤ects are measured by variables such as the unemployment rate in the respondents' region of residence.

In order to correct for the potential selectivity bias which results from the fact that wages for all the sample are estimated using data only on working women's wages, Heckman's two-stage procedure is used. This procedure, used by all the authors in this literature, has proved successful at correcting for that selectivity bias. In the …rst stage of this procedure, the discrete choice of labour force participation is modelled by a Probit Model and estimated on the entire sample. In the second stage these estimates are used to construct the Hazard rate[18] for the sample of working women. This estimated Hazard rate is then included as explanatory variable (the selectivity correction term) in the Ordinary Least Square (OLS) estimation of the regression of the working women's hourly wage on a set of instrumental variables thought to in‡uence that hourly wage.

The results of this speci…c wages' estimation are presented in Table A1.

The coe¢cient accompanying the hazard rate (λ) is negative and signi…cant. This means that if the possibility of selectivity bias, had not been taken into account,the estimated wages would be higher, on average. In other words, the hourly wage available to those women participating in the labour market is on average higher than the hourly wage available to non-working women.

The estimated in‡uence of the instrumental variables on the log of the

[18] The Hazard rate (λ_i) is de…ned as: $\lambda_i(z_i' \cdot \hat{\gamma}) = \frac{\phi(z_i' \cdot \hat{\gamma})}{\Phi(z_i' \cdot \hat{\gamma})}$; where $\hat{\gamma}$ is the set of the parameters' estimates obtained in the …rst stage; z_i' is the set of values of the instrumental variables for individual i; ϕ is the density function corresponding to a Normal distribution; and Φ is the Normal Cumulative density function.

hourly wage is rather intuitive: the log of the hourly wage rate increases with the woman's human capital. That is, with the woman's age and with her qualifications (those women who left school at 16 are estimated to have a lower hourly wage than those women who stayed in education for longer). The results for those variables capturing the demand-side effects are also on line with intuition: wages are estimated to be higher in metropolitan areas, where labour demand tends to be greater than in non-metropolitan areas; the length of time the family has lived in the same address could be seen as an indicator of the knowledge of the area's labour market (with its offered wages and working conditions) and, thus, the higher this knowledge, the higher the estimated hourly wage. Those women living in the North West, the Eastmidlands, the Westmidlands, the South East, London or Wales are expected to have on average a higher hourly wage than those living in Eastanglia (the reference region). Instead, those living in Scotland, Yorkshire and Humberside, the South West or in the North West, have on average lower hourly wages. The increase of the hourly wage with the unemployment rate is rather counterintuitive but in any case, this variable is not statistically significant.

The hourly wage rate decreases with age squared (it meaning that the increase in the wage due to age is marginally decreasing with age).

The variables used in estimating the participation probit are those used for the estimation of the hourly wage plus other regressors capturing family composition effects (number of children aged under 12 in the family unit; presence of children aged 5-11; number of children aged under 5); cultural conditionants (race); the family's financial stability (if the mother receives child maintenance benefit and the family's unearned income); and the availability of informal child care (presence of children aged 12 to 18 in the household and the husband's working hours).

6.2 Formal Child Care Prices Estimation

Estimating the hourly price of formal child care for those families not using this child care mode raises similar selectivity concerns to the ones faced when estimating the hourly wage rate. Therefore, the estimation of the hourly child care price must take into account the possibility that selectivity bias affects the estimates. The technique used to correct for this potential bias is, as in the hourly wage's estimation, Heckman's two stage procedure.[19]

The results of the estimation of the hourly price of formal child care for our sample, are presented in Table 2.

The regressors used for the estimation of the hourly child care cost equations aim to capture variations in demand and supply. On the demand side, the number and ages of children is clearly important. To capture supply-side differences, variables summarizing the type of area the respondent lives in (metropolitan or non-metropolitan), and the density of day-nursery provision in the region in which the family lives, are used. Regional data on the average weekly earnings for nurseries and day care centres is used as a direct measure of child care provider wages (one of the components making up for most of the expenditure of running a child care centre).

The negative parameter accompanying the hazard rate tells us that those families using formal child care face a higher price than the one available to families who do not use formal care. This result might seem rather counter-intuitive, since one would expect that families with lower child care prices available will use more child care than those faced with higher prices (the usual income effect). However, if accepted that the price of child care reflects its quality (that is, the higher the quality the higher the price), then a logical explanation for that result is that what stops families with low price care available to use this care is its relatively low quality.

The variables used to estimate the child care take-up equation, capture differences in the mother's human capital (age and education); differences in family's composition (number of children aged under 12 in the family unit, presence of children aged 5 to 11, and number of children aged under 3); financial stability (if the family lives in rented accommodation (and if rented from the private sector or from the local authority), the family's unearned income, and if the family receives child maintenance benefits); cultural differences (race); availability of informal child care (number of families living in the same household, presence of children aged 12 to 18, family's length of residence in the same address, and the father's work pattern); differences in use of informal child care; and supply-side effects (availability of day care places in the region).

Formal child care price increases with the supply-side variables: that is, with the region's average weekly earnings of the staff working in the child

[19] See Appendix 2 for an explanation of this procedure.

care sector and with the number of daycare places available in the region (one would expect the opposite sign for this availability variable. However, this parameter is not statistically significant). Those families living in a metropolitan area face higher prices compared with those families living in non-metropolitan areas.

Table 1 shows that the more children under 5 in the family unit, the lower the hourly child care price available to the family. This might reflect the possible existence of discounts available to families with more than one child and/or the family's use of cheaper modes of child care the more children needed to be looked after.

7 Appendix 4.2

To test which specifications, those including price terms or those which not include prices, fit best the data, the standard test of "overall significance" is used. This test tests the joint significance of the slope parameters in the Maximum Likelihood models of binary choice and exploits the result that, for any two models where one model is a restricted version of the other, the statistic:

$$-2 \cdot \ln(L_R / L_{UR}) = 2 \cdot (\ln L_{UR} - \ln L_R) \sim \chi^2_r$$

where r represents the number of restrictions imposed; L_R is the log Likelihood of the restricted model; and L_{UR} is the log Likelihood of the unrestricted model.

In this case, the restricted model is that in which the parameters accompanying the price terms are assumed to be equal to 0. Therefore, since there are two price terms in each model, the restricted model imposes two restrictions:

$$\beta_{ccp} = \beta_w = 0$$

where β_{ccp} is the estimate of the parameter accompanying the predicted hourly price of child care, and β_w is the estimate of the parameter accompanying the predicted hourly wage.

Thus, the null hypothesis (H_0) is:

$$H_0 : \beta_{ccp} = \beta_w = 0$$

whereas the alternative hypothesis (H_A) is:

$$H_A : \beta_{ccp} \text{ or } \beta_w \text{ (or both) } \neq 0$$

The relevant statistic is:

$$2 \cdot (\ln L_{UR} - \ln L_R)$$

This statistic follows a χ^2 distribution if H_0 is true.

As we know, the critical value corresponding to a χ^2 distribution with two degrees of freedom depends on the level of significance (α) chosen:

-for α = 10% the critical value is 4.605

-for α = 5% the critical value is 5.991

-for α = 1% the critical value is 9.210

The log Likelihood values for each estimated model are the following:

- UVPM for the Labour Force Participation Equation without prices (restricted model): $LogL = -530.5529$
- UVPM for the Labour Force Participation Equation with prices (unrestricted model): $LogL = -520.6338$
- UVPM for the Child care Take-up Equation without prices (restricted model): $LogL = -520.3501$
- UVPM for the Child care Take-up Equation with prices (unrestricted model): $LogL = -516.0564$
- BVPM without prices (restricted model): $LogL = -1024.8919$
- BVPM with prices (unrestricted model): $LogL = -1011.0607$
- SUVPM for the Labour Force Participation Equation without prices (restricted model): $LogL = -528.4599$
- SUVPM for the Labour Force Participation Equation with prices (unrestricted model): $LogL = -519.2044$
- SUVPM for the Child care Take-up Equation without prices (restricted model): $LogL = -514.5960$
- SUVPM for the Child care Take-up Equation with prices (unrestricted model): $LogL = -513.2834$
- SBVPM without prices (restricted model): $LogL = -1018.0124$
- SBVPM with prices (unrestricted model): $LogL = -1007.5532$

Therefore, the results for the tests of hypotheses are the following:

7.0.1 UVPM for the Labour Force Participation equation

Statistic's value: 19.8382=) it falls in the critical region for ® = 1% =) H_A is consistent with our data=) the model with price terms …ts the data better than the model without price terms.

7.0.2 UVPM for the Formal Child Care Take-up equation

Statistic's value: 8.5874=) it falls in the critical region for ® = 5% =) H_A is consistent with our data=) the model with price terms …ts the data better than the model without price terms.

7.0.3 BVPM

Statistic's value: 27.7166=) it falls in the critical region for ® = 1% =) H_A is consistent with the data=) the model with price terms …ts our data better than the model without price terms.

7.0.4 SUVPM for the Labour Force Participation equation

Statistic's value: 18.511=) it falls in the critical region for ® = 1% =) H_A is consistent with the data=) the model with price terms …ts the data better than the model without price terms.

7.0.5 SUVPM for the Formal Child Care Take-up equation

Statistic's value: 2.6252=) it falls outside the critical regions for any of the three levels of signi…cance considered. Therefore, we cannot reject the null hypothesis $H_0 : \bar{}_{ccp} = \bar{}_{w} = 0$ =) the model without price terms …ts the data better than the model with price terms.

7.0.6 SBVPM

Statistic's value: 20.9184=) it falls in the critical region for ® = 1% =) H_A is consistent with our data=) the model with price terms …ts our data better than the model without price terms.[20]

[20] Not so "clearly" as the other two models did, since for a signi…cance level of 1%, we cannot reject H_0 and, thus, it would be the model without prices which …ts best with the data.

8 Appendix 4.3

As seen in section 5; the models estimated integrate a nested structure which allows to test every model against the others and, therefore, to test which of the four specifications considered fits best with the data.

As in Appendix 3, the statistic used to test these hypotheses is the one used to test the overall significance of the regression[21]. According to this test, if the null hypothesis is true, then the statistic $-2 \cdot \ln(L_R/L_{UR})$ follows a χ^2_r distribution[22].

The Log Likelihood values relevant to these tests are, in this specific case:

- for the UVPM[23] : $\text{Log}L = -1036.6902$
- for the BVPM : $\text{Log}L = -1011.0607$
- for the SUVPM : $\text{Log}L = -1032.4878$
- for the SBVPM : $\text{Log}L = -1007.5532$

The results of each hypothesis test are shown below:

8.0.7 UVPM versus BVPM

Restricted model: UVPM

Null Hypothesis (H_0) : $\rho = 0$

Alternative Hypothesis (H_A) : $\rho \neq 0$

Critical Values ($r = 1$) :

-for $\alpha = 10\%$ the critical value is 2.706

-for $\alpha = 5\%$ the critical value is 3.841

-for $\alpha = 1\%$ the critical value is 6.635

Statistic's value: 51.259 $\Rightarrow$ it falls in the critical region for $\alpha = 1\%$ $\Rightarrow$ H_A is consistent with the data $\Rightarrow$ the BVPM fits the data better than the UVPM.

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[21] See Appendix 2 for an explanation on how this hypothesis test is implemented.

[22] Where r represents the number of restrictions imposed; L_R is the log Likelihood of the restricted model; and L_{UR} is the log Likelihood of the unrestricted model.

[23] The "total" Log Likelihood for the Univariate models has been calculated as the sum of the Log Likelihoods of each equation.

8.0.8 UVPM versus SUVPM

Restricted model: UVPM

$H_0 : ±_W = ±_C = 0$

$H_A : ±_W; ±_C$ (or both) 6= 0

Critical Values (r = 2) :

-for ® = 10% the critical value is 4.605

-for ® = 5% the critical value is 5.991

-for ® = 1% the critical value is 4.605

Statistic's value: 8.4048=) it falls in the critical region for ® = 1% =) H_A is consistent with the data=) the SUVPM …ts the data better than the UVPM.

8.0.9 UVPM versus SBVPM

Restricted model: UVPM

$H_0 : ½ = ±_W = ±_C = 0$

$H_A : ½; ±_W; ±_C$ (or any combination) 6= 0

Critical Values (r = 3) :

-for ® = 10% the critical value is 6.251

-for ® = 5% the critical value is 7.815

-for ® = 1% the critical value is 11.34

Statistic's value: 58.274=) it falls in the critical region for ® = 1% =) H_A is consistent with the data=) the SBVPM …ts the data better.

8.0.10 BVPM versus SBVPM

Restricted model: BVPM

$H_0 : ±_W = ±_C = 0$

$H_A : ±_W; ±_C$ (or one of the two) 6= 0

Critical Values (r = 2) :

-for ® = 10% the critical value is 4.605

-for ® = 5% the critical value is 5.991

-for ® = 1% the critical value is 4.605

Statistic's value: 7.015=) it falls in the critical region for ® = 1% =) H_A is consistent with the data=) the SBVPM …ts the data better than the SUVPM.

8.0.11 SUVPM versus SBVPM

Restricted model: UVPM

$H_0 : \rho = 0$

$H_A : \rho \neq 0$

Critical Values (r = 1) :

-for $\alpha = 10\%$ the critical value is 2.706

-for $\alpha = 5\%$ the critical value is 3.841

-for $\alpha = 1\%$ the critical value is 6.635

Statistic's value: 49.8692 $\Rightarrow$ it falls in the critical region for $\alpha = 1\%$ $\Rightarrow$ H_A is consistent with the data $\Rightarrow$ the SBVPM fits the data better than the SUVPM.

8.1 Appendix 4.4

In order to test for the Normality of the error terms in a Univariate Probit Model, a Likelihood Ratio Test is performed. This text consists basically in calculating the value of the statistic $2(\text{Log } L_N - \text{Log } L_0)$, which under the null hypothesi of normality is distributed as a χ^2_2.

In this expression, Log L_0 is the maximised log-likelihood from the estimation of a probit model with a latent equation such as $y^*_{wi} = X_{wi}\beta_w + u_{wi}$. This equation estimates $\tilde{\beta}$; are then to be used to create the test variables $\left(X_{wi}\tilde{\beta}_w\right)^2$ and $\left(X_{wi}\tilde{\beta}_w\right)^3$. These test variables are then added to an auxiliary regression

$$y^*_{wi} = X_{wi}\beta_w + \delta_1\left(X_{wi}\tilde{\beta}_w\right)^2 + \delta_2\left(X_{wi}\tilde{\beta}_w\right)^3 + u_{wi}$$

The maximised log-likelihood from this auxiliary regression is Log L_N in the test statistic's expression.

The values of Log L_N for the univariate models estimated in this paper are:

- UVPM for the Labour Force Participation Equation without prices : $\text{Log} L_N = -529.8641$
- UVPM for the Labour Force Participation Equation with prices : $\text{Log} L_N = -519.6081$

- UVPM for the Child care Take-up Equation without prices: $LogL_N$ = ¡519:7533

- UVPM for the Child care Take-up Equation with prices: $LogL_N$ = ¡515:7068

The values of $Log\ L_0$ for the univariate models estimated in this paper are:

- UVPM for the Labour Force Participation Equation without prices: $LogL_0$ = ¡530:5529

- UVPM for the Labour Force Participation Equation with prices: $LogL_0$ = ¡520:6338

- UVPM for the Child care Take-up Equation without prices: $LogL_0$ = ¡520:3501

- UVPM for the Child care Take-up Equation with prices: $LogL_0$ = ¡516:0564

Therefore, the statistic 2(Log L_N ¡ Log L_0) are:

- UVPM for the Labour Force Participation Equation without prices: 1:3776

- UVPM for the Labour Force Participation Equation with prices: 2:0514

- UVPM for the Child care Take-up Equation without prices: 1:1936

- UVPM for the Child care Take-up Equation with prices: 0:6992

The critical values for a $Â^2_2$ are:

-for ® = 10% the critical value is 4.605
-for ® = 5% the critical value is 5.991
-for ® = 1% the critical value is 4.605

Therefore, given these three signi…cance levels, the statistic's value is out of the critical region for any of the four models considered. Therefore, the null Hypothesis of the error terms' Normality can't be rejected.

Table 4.10. VARIABLES' CONTRIBUTION TO PROBABILITY. AT MEAN VALUES				
	SUVPM	SUVPMWP	SBVPM	SBVPMWP
	Contribution	Contribution	Contribution	Contribution
Labour Force Participation Equation				
Variables in both equations				
university	0.0486	-0.1663	0.0442	-0.1793
non-white	0.0031	0.0425	0.0002	0.0406
age youngest child	0.0466	0.0449	0.0435	0.0399
receives maintenance	0.1772	0.2484	0.1769	0.2423
family's unearned	-0.2275	-0.3077	-0.2267	-0.2982
number children <5	-0.2609	-0.4530	-0.2707	-0.4680
presence children <3	-0.0593	-0.1029	-0.0610	-0.1031
presence children 12-18	-0.0771	-0.0849	-0.0786	-0.0846
residence length	-0.0630	-0.1043	-0.0656	-0.1092
hourly u5 ccprice		-0.0936		-0.1073
hourly wage		0.5773		0.5814
father's working pattern	0.1764	0.2470	0.1825	0.2464
use informal child care	0.1425	0.1897	0.1512	0.1938
Variables in the Labour Force Participation equation only				
constant 1	-0.4091	-0.8741	-0.4181	-0.8402
age	0.1725	0.1318	0.1760	0.1314
age squared	-0.0916	-0.0831	-0.0935	-0.0810
Variables in the Child Care Take-up equation only				
constant 2	0.0379	-0.1489	0.0306	-0.1532
number children 5-11	-0.0364	-0.0419	-0.0348	-0.0392
grandparents in hh	-0.0733	-0.0824	-0.0862	-0.0974
Child Care Take-up Equation				
Variables in both equations				
university	-0.0462	-0.0397	-0.0413	-0.0454
non-white	-0.0393	-0.0835	-0.0396	-0.0734
age youngest child	0.0131	0.1035	0.0157	0.1218
receives maintenance	0.0285	0.0267	0.0339	0.0266
family's unearned	0.1601	0.1338	0.1527	0.1217
number children <5	0.3344	0.4317	0.3208	0.3960
presence children <3	-0.0943	-0.0179	-0.0908	-0.0942
presence children 12-18	-0.0107	-0.0310	-0.0040	-0.0180
residence length	0.1434	0.1647	0.1409	0.1725
hourly u5 ccprice		0.1548		0.1694
hourly wage		-0.0612		-0.1106
father's working pattern	-0.2128	-0.1622	-0.2043	-0.1709
use informal	-0.4294	-0.3889	-0.4160	-0.3860
Variables in the Labour Force Participation equation only				
constant 1	0.2379	0.3078	0.2389	0.3632
age	-0.1003	-0.0464	-0.1005	-0.0568
age squared	0.0533	0.0293	0.0534	0.0350
Variables in the Child Care Take-up equation only				
constant 2	0.1200	-0.3954	0.0995	-0.4085
number children 5-11	-0.1154	-0.1114	-0.1132	-0.1045
grandparents in hh	-0.2323	-0.2188	-0.2802	-0.2596

TABLE 4.11. PARAMETER ESTIMATES REDUCED FORM INDEXES				
	without prices		with prices	
	Coefficient	t-value	Coefficient	t-value
Labour Force Participation equation				
constant	-1.3700	-3.90	-2.1928	-2.27
age	0.6588	5.55	0.4168	3.16
age squared	-0.3343	-2.82	-0.2343	-1.91
university	0.1978	1.16	-0.3291	-1.56
non-white	-0.2077	-1.18	-0.1239	-0.68
age youngest child	0.0297	1.07	0.0262	0.92
receives maintenance	0.2844	1.14	0.2629	1.04
family's unearned income (ln)	-0.5275	-5.20	-0.5463	-5.31
house owned	-0.2234	-0.82	-0.2503	-0.91
number children <5	-0.3914	-3.92	-0.6232	-2.06
grandparents in the hh	0.2618	0.80	0.2808	0.86
presence children <3	-0.2332	-1.85	-0.2686	-2.11
presence children 5-11	-0.2151	-1.97	-0.1916	-1.66
presence children 12-18	-0.2942	-1.59	-0.2365	-1.26
residence length	-0.2450	-1.89	-0.2853	-1.84
hourly price child care			-0.2534	-0.80
hourly net wage			1.1870	4.29
father's working pattern	0.6553	7.03	0.6356	6.74
use informal child care	0.5317	5.60	0.4964	5.18
Child Care Take-up Equation				
constant	-0.4476	-1.27	-1.8108	-1.79
age	0.3848	3.25	0.3020	2.28
age squared	-0.2060	-1.74	-0.1714	-1.41
university	0.2796	1.64	0.1137	0.54
non-white	-0.3996	-2.21	-0.4228	-2.28
age youngest child	0.1190	4.26	0.1263	4.38
receives maintenance	0.2343	0.97	0.2310	0.96
family's unearned income (ln)	0.1681	1.62	0.1389	1.31
house owned	0.0132	0.05	0.0322	0.12
number children <5	0.9507	8.00	1.2079	4.09
grandparents in the hh	-0.4145	-5.70	-0.3753	-4.80
presence children <3	-0.5526	-1.40	-0.5185	-1.32
presence children 5-11	-0.4573	-3.61	-0.4702	-3.70
presence children 12-18	-0.3032	-1.62	-0.2803	-1.49
residence length	0.1261	0.94	0.2162	1.36
hourly price of u5 cc			0.3221	0.99
hourly net wage			0.3621	1.32
father's working pattern	0.1011	1.16	0.1103	1.25
use informal child care	-0.5721	-5.82	-0.5781	-5.84

Table 4.3. PARAMETER ESTIMATES (NO PRICE TERMS)

	UVPM		BVPM		SUVPM		SBVPM	
Labour Force Participation Equation								
	Coef	t-value	Coeff.	t-value	Coeff	t-value	Coeff	t-value
constant	-1.5013	-	-1.5042	-	-	-	-	-
age	0.6143	5.28***	0.5332	4.58***	0.5185	4.13***	0.5203	4.00***
age squared	-0.3041	-	-0.2677	-	-	-2.36**	-	-
university	0.2139	1.26	0.2160	1.34*	0.1128	0.64	0.0990	0.59
non-white	-0.1863	-1.09	-0.1822	-1.03	-	-0.08*	-	-0.13
age youngest child	0.0107	0.42	0.0148	0.56	-	-0.36	-	-0.31
receives maintenance	0.2601	1.04	0.2700	0.94	0.1819	0.72	0.1968	0.69
family's unearned	-0.5422	-	-0.5212	-	-	-	-	-
number children <5	-0.3748	-	-0.3634	-	-	-	-	-
presence children <3	-0.2301	-1.83*	-0.2388	-1.86**	-	-0.51	-	-0.55
presence children 12-	-0.3071	-1.67*	-0.2871	-1.47*	-	-0.97	-	-0.96
residence length	-0.2394	-1.84*	-0.2141	-1.65**	-	-2.10**	-	-2.09**
father's working	0.6718	7.27***	0.6695	7.19***	0.6184	6.42***	0.6169	6.40***
use informal child	0.5325	5.62***	0.5346	5.54***	0.7060	5.51***	0.7021	5.57***
CHILD CARE INDEX					0.3148	2.03**	0.3017	1.97**
Child Care Take-up Equation								
constant	-	-1.49	-	-1.61*	0.3614	0.84	0.2999	0.69
university		2.30**	0.3874	2.45***	0.1630	0.92	0.1785	1.04
non-white	-0.3557	-1.98**	-0.3639	-1.99**	-	-1.54	-	-1.51*
age youngest child	0.1292	4.68***	0.1237	4.29***	0.1052	3.68***	0.1049	3.48***
receives maintenance	0.2214	0.92	0.2206	0.89	0.0771	0.32	0.0873	0.35
family's unearned	0.2338	2.33**	0.2206	2.29**	0.4762	3.82***	0.4553	3.66***
number children <5	0.9163	7.77***	0.8735	7.28***	1.1130	8.4***	1.0815	8.05***
number children 5-11	-0.3752	-	-0.3379	-	-	-	-	-
granparents in the	-0.5984	-1.57	-0.7033	-1.96**	-	-1.77*	-	-2.19**
presence children <3	-0.4818	-3.85**	-0.4712	-	-	-2.46**	-	-
presence children 12-	-0.1940	-1.10	-0.1820	-1.01	-	-0.79	-	-0.69
residence length	0.2405	1.87*	0.2343	1.62*	0.2717	2.10**	0.2650	1.78**
father's working	0.1112	1.29	0.1142	1.33*	-	-1.93*	-	-1.75**
use informal child	-0.5727	-	-0.5573	-	-	-	-	-
WORK INDEX					0.5825	3.36***	0.5447	3.15***
RHO			0.4226	7.95***			0.4163	7.74***

Table 4.4. PARAMETER ESTIMATES (WITH PRICE TERMS)

	UVPM		BVPM		SUVPM		SBVPM	
Labour Force Participation Equation								
	Coef	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
constant	-	3.05***	-	-	-	-1.87*	-	-1.81**
age	0.3710	2.87***	0.3119	2.48***	0.2910	2.12**	0.2949	2.09**
agesq	-	-1.77*	-	-1.57*	-	-1.52	-	-1.55*
university	-	-1.58	-	-1.87**	-	-1.87*	-	-2.07**
non-white	-	-0.64	-	-0.55	0.0632	0.31	0.0592	0.28
age youngest child	0.0145	0.53	0.0157	0.56	-	-0.34	-	-0.36
maintenance pay	0.2436	0.97	0.2517	0.85	0.1675	0.66	0.1812	0.62
family's unearned	-	-	-	-	-	-	-	-
number children <5	-	-1.62	-	-1.68**	-	-2.31**	-	-
presence children <3	-	-2.09**	-	-	-	-0.81	-	-0.85
presence children 12-	-	-1.31	-	-1.16	-	-0.73	-	-0.73
residence length	-	-1.55	-	-1.52*	-	-2.00**	-	-2.05**
hourly u5 ccprice	-	-0.33	-	-0.48	-	-0.92	-	-1.02
hourly wage	1.2128	4.41***	1.3053	4.72***	1.1703	4.23***	1.2031	4.28***
father's working	0.6536	6.99***	0.6513	7.03***	0.6006	6.09***	0.5998	6015***
use informal child	0.4971	5.20***	0.4979	5.09***	0.6550	4.91***	0.6539	4.98***
CHILD CARE INDEX					0.2868	1.71*	0.2783	1.72**
Child Care Take-up Equation								
constant	-	-2.23**	-	-	-	-1.05	-	-1.08
university	0.0452	0.22	0.0591	0.29	0.0194	0.09*	0.0345	0.17
non-white	-	-2.10**	-	-2.15**	-	-1.76*	-	-1.73**
age youngest child	0.1331	4.65***	0.1299	4.30***	0.1150	3.89***	0.1152	3.66***
receives maintenance	0.2181	0.90	0.2143	0.87	0.1065	0.43	0.1151	0.46
family's unearned	0.1714	1.66*	0.1596	1.60*	0.3828	2.80***	0.3616	2.60***
number children <5	1.1740	4.00***	1.1887	3.98***	1.3284	4.41***	1.3034	4.33***
number children 5-11	-	-	-	-	-	-	-	-
granparents in the hh	-	-1.41	-	-1.81**	-	-1.61	-	-2.03**
presence children <3	-	-	-	-	-	-	-	-
presence children 12-	-	-1.14	-	-1.06	-	-0.88	-	-0.79
residence length	0.2885	1.87*	0.3039	1.76**	0.3274	2.11**	0.3261	1.86**
hourly u5 ccprice	0.3140	0.97	0.3775	1.14	0.3117	0.96	0.3203	0.95
hourly wage	0.6526	2.67***	0.6329	2.48***	0.3635	1.34	0.3663	1.30*
father's working	0.1139	1.30	0.1180	1.35*	-	-1.24	-	-1.05
use informal child	-	-	-	-	-	-	-	-
WORK INDEX					0.4622	2.40**	0.4229	2.17**
RHO			0.4239	7.75***			0.4198	7.61***

TABLE 4.5. EFFECTS ON Pw (NO PRICE TERMS)				
	SUVPM		SBVPM	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
Variables common to both Indexes				
university	0.0398	0.0335	0.0348	0.0341
non-white	-0.0052	-0.0573	-0.0090	-0.0536
age youngest child	-0.0035	0.0216	-0.0030	0.0201
receives maintenance	0.0641	0.0158	0.0691	0.0167
family's unearned income	-0.2025	0.0978	-0.1994	0.0871
number children <5	-0.1988	0.2286	-0.1917	0.2069
presence children <3	-0.0264	-0.0673	-0.0292	-0.0616
presence children 12-18	-0.0660	-0.0290	-0.0684	-0.0240
residence length	-0.0969	0.0558	-0.0962	0.0507
father's working pattern	0.2180	-0.0576	0.2167	-0.0491
use informal child care	0.2489	-0.1810	0.2466	-0.1617
Variables specific to the LFP Index				
constant 1	-0.4335	nil	-0.4343	nil
age	0.1828	nil	0.1828	nil
age squared	-0.0971	nil	-0.0971	nil
Variables specific to the Child care Index				
constant 2	nil	0.0743	nil	0.0574
number children 5-11	nil	-0.0714	nil	-0.0653
grandparents in the hh	nil	-0.1436	nil	-0.1616

TABLE 4.6. EFFECTS ON Pc (NO PRICE TERMS)				
	SUVPM		SBVPM	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
Variables common to both Indexes				
university	0.0551	0.0120	0.0605	0.0101
non-white	-0.0943	-0.0016	-0.0949	-0.0026
age youngest child	0.0356	-0.0011	0.0355	-0.0009
receives maintenance	0.0260	0.0194	0.0296	0.0201
family's unearned income	0.1609	-0.0611	0.1542	-0.0580
number children <5	0.3761	-0.0600	0.3664	-0.0558
presence children <3	-0.1107	-0.0080	-0.1091	-0.0085
presence children 12-18	-0.0477	-0.0199	-0.0425	-0.0199
residence length	0.0918	-0.0293	0.0898	-0.0280
father's working pattern	-0.0947	0.0658	-0.0869	0.0630
use informal child care	-0.2979	0.0751	-0.2862	0.0717
Variables specific to the LFP Index				
constant 1	nil	-0.1308	nil	-0.1263
age	nil	0.0552	nil	0.0532
age squared	nil	-0.0293	nil	-0.0282
Variables specific to the Child care Index				
constant 2	0.1222	nil	0.1016	nil
number children 5-11	-0.1175	nil	-0.1156	nil
grandparents in the hh	-0.2364	nil	-0.2861	nil

TABLE 4.7. EFFECTS ON Pw (WITH PRICE TERMS)				
	SUVPM		SBVPM	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
Variables common to both Indexes				
university	-0.1355	0.0030	-0.1465	0.0049
non-white	0.0214	-0.0512	0.0200	-0.0468
age youngest child	-0.0036	0.0180	-0.0037	0.0164
receives maintenance	0.0567	0.0167	0.0611	0.0164
family's unearned income	-0.1987	0.0599	-0.1961	0.0516
number children <5	-0.2771	0.2080	-0.2805	0.1859
presence children <3	-0.0413	-0.0574	-0.0441	-0.0515
presence children 12-18	-0.0483	-0.0244	-0.0507	-0.0203
residence length	-0.1098	0.0512	-0.1133	0.0465
hourly u5 cc price	-0.1003	0.0488	-0.1113	0.0457
hourly wage	0.3963	0.0569	0.4057	0.0522
father's working pattern	0.2034	-0.0301	0.2023	-0.0239
use informal child care	0.2218	-0.1289	0.2205	-0.1122
Variables specific to the LFP Index				
constant 1	-0.6535	nil	-0.6360	nil
age	0.0985	nil	0.0994	nil
age squared	-0.0621	nil	-0.0613	nil
Variables specific to the Child care Index				
constant 2	nil	-0.1846	nil	-0.1762
number children 5-11	nil	0.0278	nil	-0.0451
grandparents in the hh	nil	-0.0175	nil	-0.1120

TABLE 4.8. EFFECTS ON Pc (WITH PRICE TERMS)				
	SUVPM		SBVPM	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
Variables common to both Indexes				
university	0.0065	-0.0383	0.0115	-0.0404
non-white	-0.1090	0.0060	-0.1096	0.0055
age youngest child	0.0383	-0.0010	0.0385	-0.0010
receives maintenance	0.0355	0.0160	0.0385	0.0168
family's unearned income	0.1277	-0.0561	0.1209	-0.0541
number children <5	0.4431	-0.0783	0.4357	-0.0774
presence children <3	-0.1223	-0.0117	-0.1208	-0.0122
presence children 12-18	-0.0520	-0.0136	-0.0475	-0.0140
residence length	0.1092	-0.0310	0.1090	-0.0313
hourly u5 cc price	0.1040	-0.0283	0.1071	-0.0307
hourly wage	0.1212	0.1119	0.1224	0.1119
father's working pattern	-0.0642	0.0574	-0.0560	0.0558
use informal child care	-0.2748	0.0626	-0.2630	0.0608
Variables specific to the LFP Index				
constant 1	nil	-0.1846	nil	-0.1762
age	nil	0.0278	nil	-0.0451
age squared	nil	-0.0175	nil	-0.1120
Variables specific to the Child care Index				
constant 2	-0.3822	nil	-0.4131	nil
number children 5-11	-0.1077	nil	-0.1056	nil
grandparents in the hh	-0.2115	nil	-0.2626	nil

Table 4.9. VARIABLES' CONTRIBUTION TO PROBABILITY. AT MEAN VALUES

	UVPM	UVPMWP	BVPM	BVPMWP
Labour Force Participation Equation				
	Contribution	Contribution	Contributio	Contributio
constant	-0.5875	-0.0081	-0.5890	-1.0783
age	0.2404	0.0108	0.2088	0.1221
age squared	-0.1190	-0.0062	-0.1048	-0.0706
university	0.0837	-0.0097	0.0846	-0.1501
non-white	-0.0729	-0.0033	-0.0713	-0.0400
age youngest child	0.0042	0.0004	0.0058	0.0061
receives	0.1018	0.0071	0.1057	0.0985
family's unearned	-0.2122	-0.0166	-0.2041	-0.2167
number children <5	-0.1467	-0.0137	-0.1423	-0.1950
presence children <3	-0.0900	-0.0077	-0.0935	-0.1075
presence children	-0.1202	-0.0071	-0.1124	-0.0912
residence length	-0.0937	-0.0070	-0.0838	-0.0927
hourly u5 ccprice		-0.0029		-0.0572
hourly wage		0.0355		0.5109
father's working	0.2629	0.0191	0.2621	0.2549
use informal child	0.2084	0.0145	0.2093	0.1949
Child Care Take-up Equation				
constant	-0.1928	-0.4913	-0.2062	-0.3504
university	0.1440	0.0100	0.1461	0.0087
non-white	-0.1342	-0.0858	-0.1373	-0.0584
age youngest child	0.0488	0.0296	0.0467	0.0191
receives	0.0836	0.0485	0.0832	0.0315
family's unearned	0.0882	0.0381	0.0832	0.0234
number children <5	0.3458	0.2609	0.3295	0.1745
number children 5-	-0.1416	-0.0760	-0.1275	-0.0449
granparents in the	-0.2258	-0.1195	-0.2653	-0.0960
presence children <3	-0.1818	-0.1097	-0.1778	-0.0707
presence children	-0.0732	-0.0446	-0.0687	-0.0279
residence length	0.0908	0.0641	0.0884	0.0446
hourly u5 ccprice		0.0698		0.0554
hourly wage		0.1450		0.0929
father's working	0.0420	0.0253	0.0431	0.0173
use informal	-0.2161	-0.1306	-0.2102	-0.0836