Life Cycle Employment and Fertility Across Institutional Environments[*†]

Daniela Del Boca
University of Turin and IZA

Robert M. Sauer
University of Southampton and IZA

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Abstract

In this paper, we formulate a dynamic utility maximization model of female labor force participation and fertility choices and estimate approximate decision rules using data on married women in Italy, Spain and France. The pattern of estimated state dependence effects across countries is consistent with aggregate patterns in part-time employment and child care availability, suggesting that labor market rigidities and lack of child care options are important sources of state dependence. Simulations of the model reveal that Italian and Spanish women would substantially increase their participation rates were they to face the French institutional environment.

Keywords: Female Employment, Fertility, Child Care, Institutions, Decision Rules

J.E.L Subject Codes: J2, J6,C3, D1

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1 Introduction

The growth in women's participation in the labor market, especially among women with children, has been one of the most important economic and social phenomena of the last half century. The large scale movement of women into the labor market after World War II has occurred in many countries, but the level of female employment across countries has not been equalized, and the differential female employment patterns across countries is not well understood. This is true even within Western Europe. Cross-country differences in female labor force participation and attachment within Europe have recently raised serious concerns, particularly in the context of the European Union's attempt to harmonize social policies.[1]

In order to try and better understand cross country differences in female employment patterns, we formulate a dynamic utility maximization model of labor market participation and fertility choices, and estimate approximate decision rules using data on married women in Italy, Spain and France. Limiting the set of countries to only those with "similar" cultural characteristics helps control for unobservable differences such as religion and attitudes towards gender roles. Estimated differences in the relative importance of state dependence and permanent unobserved heterogeneity in life cycle work and fertility choices across these three countries are then correlated with differences in underlying institutions governing employment and social policies.

The reason for focusing on the relative importance of state dependence and unobserved heterogeneity in work and fertility choices in each country is that past research on female labor force participation rates has repeatedly revealed that persistence is an important aspect of the labor supply decisions of married women (see, e.g., Heckman and Willis (1977), Nakamura and Nakamura (1985) and Eckstein and Wolpin (1989)). Serial persistence in participation may be due to state dependence deriving from human capital accumulation or the costs of searching for a new job. For example, a woman leaving the labor market

[1] At the Lisbon summit in March 2000, the European Council stated that Member States should set quantitative targets for higher employment rates in line with EU targets. These were set at 70% for total employment and 60% for women's employment, to be reached by the year 2010. In 2001, intermediate targets of 67% (total) and 57% (for women) were set to be reached by 2005.

to care for a new born may be likely to remain out of the labor market the following year because her human capital (work experience) has "depreciated". It is also possible that job search costs increase with age and differ across participation states.

Serial persistence can also be due to permanent unobserved heterogeneity which reflects differences in mostly immutable preferences for work and/or productivity in the labor market. For example, a woman may not leave the labor market because she has strong preferences for a career. In this case, the unobserved individual component determines current participation irrespective of past participation. Unless properly accounted for, unobserved heterogeneity leads to the possibility of spurious state dependence, in which it appears that working in the past increases the probability of working today, when in fact causality flows from the unobservable to all period-specific choices.

Accurately distinguishing between state dependence and unobserved heterogeneity is not only theoretically interesting, it can also be important for policy evaluation. If there is substantial permanent unobserved heterogeneity then time spent out the labor market around the time of childbirth will have little effect on subsequent employment probabilities. If there is substantial state dependence then having a child, which lowers participation in the short run, will also lower future employment levels because women are not continuing to build human capital or are missing training opportunities. In this latter case, policies aimed at reducing fertility-related absences may reduce human capital depreciation and increase long-run labor market attachment.

Several recent studies of female labor supply have focused on the role of state dependence and unobserved heterogeneity (e.g., Hyslop (1999) and Carrasco (2001)) but, to the best of our knowledge, there is no work that analyzes the differential relative importance of these two factors across countries. In this paper, we hypothesize that in addition to human capital accumulation and search costs, institutional factors (which make it costly to adjust employment levels from one period to the next for agents on both sides of the market) are important underlying sources of cross-country differences in the degree of state dependence. We believe that the estimated variation in the relative importance of state dependence in female labor supply across countries can, in large part, be attributed to differences in the social policy environment, especially regarding labor market flexibility and child care availability.

The rest of this paper is organized as follows. In the next section, we provide a brief background on the relationship between female labor market participation and fertility choices that motivates our model of joint decision-making. In Section 3, we describe the data. Section 4 outlines our model of labor market participation and fertility decisions. Section 5 discusses the estimation strategy. Section 6 presents estimation results. Section 7 relates the estimation results to the social policy environment in each country and performs simulations which quantify the effect of the institutional environment on participation and fertility outcomes. The simulations indicate that Italian and Spanish women would substantially increase their participation rates were they to face the relatively more flexible French employment and child care environment. The last section of the paper summarizes and concludes.

2 Background

In research on female labor supply behavior, the vast majority of empirical studies find a negative effect of fertility on labor supply. However, the effect may not be causal. The negative correlation may be the result of selection effects where women with stronger preferences for motherhood are also those with lower unobservable skills and motivation in the labor market. Using cross sectional data, Mroz (1987) tested the sensitivity of the parameters of the labor supply equation of married women with respect to a number of assumptions, including the exogeneity of fertility. He concludes that conditional on participation, fertility is exogenous to women's labor supply. However, using panel data, Jakubson (1988) arrives at the opposite conclusion. His results reject the exogeneity of fertility hypothesis.

The potential endogeneity of fertility has also been addressed by adopting an instrumental variables methodology. In searching for instruments, researchers have looked at sources of unplanned births (e.g., the presence of twins (Rosenzweig and Wolpin (1980)), and the availability and cost of contraceptives (Rosenzweig and Schultz (1985)). Angrist and Evans (1998) suggest the use of the sibling-sex composition as an instrumental variable, given the plausible exogeneity of sibling-sex composition and the observed correlation between having two children of the same sex and further childbearing. However, this latter approach is particularly difficult to implement using European data since the number of women in Europe with at least two children is typically very small. The main challenge confronting the IV empirical strategy has, not surprisingly, been one of finding suitable instruments.

On a somewhat different track, and more in line with the suggestions of Browning (1992), Hyslop (1999) studies the relationship between participation and fertility by estimating dynamic discrete choice models of female labor force participation. His results indicate that when dynamic factors in female labor supply are excluded, fertility is not exogenous. However, in dynamic specifications with serially correlated errors and/or lagged participation outcomes, he finds no evidence against the exogeneity of fertility hypothesis. One drawback of Hyslop's approach is that he excludes the possibility of interactions between the participation history and fertility as well as a specific (linear) correlation structure between the explanatory variables and the unobservables.

It thus seems fair to say that economists' ability to explain the link between participation and fertility has been decidedly limited. In particular, the difficulty of finding suitable instruments and the very mixed results when testing the exogeneity of fertility hypothesis strongly suggests that fertility decisions should be examined in a more realistic manner, in which the jointness of fertility and labor market participation decisions is directly taken into account (as in Moffitt (1984), Hotz and Miller (1988), Francesconi (2002), Del Boca (2002), and Laroque and Salanie (2005)).

In this paper, we follow this latter approach by considering labor supply and fertility decisions as being jointly planned over the life-cycle. Labor market participation and fertility decision rules are simultaneously determined in our model, in the sense that they are generated by a common constrained lifetime utility maximization problem. We estimate the (approximate) decision rules of the utility maximization model by linking it with a dynamic bivariate probit model with a rich error structure. We then use the estimated approximate decision rules to infer the effect of institutional factors related to employment and social polices on the joint labor market participation and fertility choices of married women.

3 Data

The data used in this study are drawn from the European Community Household Panel (ECHP). The ECHP is a standardized multi-purpose longitudinal survey designed and coordinated by the Statistical Office of the European Communities (Eurostat). The survey is conducted annually on a representative panel of households in each member state of the European Union (EU). The survey covers a wide range of topics on living conditions such as income, employment, poverty and social exclusion, housing, health and migration. The unit of analysis in the ECHP is the family, and information is gathered on all individuals within the household that are sixteen years of age or older. Nonetheless, it is also possible to recover information on family members that are younger than sixteen.

The ECHP began in 1994 (wave 1), following a two-wave pilot survey. Wave 1 covered about 60,000 households and 130,000 individuals in all twelve EU member states (Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and the UK). Austria joined the survey in 1995 (wave 2), Finland joined in 1996 (wave 3) and Sweden joined in 1997 (wave 4). The last year the ECHP was administered was 2002 (wave 9). Eurostat terminated the project in 2003 and replaced it with a new instrument, the EU-SILC (Statistics on Income and Living Conditions), in order to focus more attention on the determinants of poverty and social exclusion.

We analyze ECHP data from Italy, Spain and France, between the years 1994 and 2001 (waves 1 through 8). Italy, Spain and France constitute a natural subgroup of countries within the EU because of common cultural environments (e.g., majority religion and attitudes towards gender roles). Importantly, for our purposes, these countries have similar cultural characteristics but differ substantially in social policies related to labor market flexibility and child care availability.

The sample from each country that we analyze contains women who are between the ages of 21 and 45, who are continuously married or cohabitant with partners that are continuously employed throughout the sample period, and who have complete employment and fertility histories. These restrictions are quite common in the female labor supply literature. They exclude women who might still be enrolled in school or retired and who have a low probability of being fecund. The restriction that all women have complete employment and fertility histories excludes women in the ECHP who could not be contacted or refused to cooperate subsequent to being interviewed in wave 1, as well as women who entered the survey after wave 1.[2] The sample contains 830 women from Italy, 713 women from Spain and 993 women from France.

Table 1 presents descriptive statistics on employment patterns by country. The means in the table are calculated by first computing average values over the eight-year panel for each woman, and then calculating averages over the number of women in the sample.[3] The statistics show large differences in female education levels between countries. For example, in Italy only 8% of the women have tertiary education levels, while in Spain and France the proportions are much higher, 20% and 28%, respectively. The proportion of women whose youngest child in the household is 3 years old or younger is similar in Italy and Spain but relatively higher in France. France also has the highest mean annual partner's earnings (in thousands of Euros), female labor market participation rate, and annual birth rate. The raw data display a positive correlation across countries in work and fertility outcomes.

Table 1 also compares the means of women who do not work all eight years and those who do work all eight years. In all three countries, women who always work are more highly educated and are less likely to have a child in the house than those who never work. Thus, there is the expected negative correlation between fertility and labor supply within each country. Note that the majority of the sample in each country consists of women who either work all eight years or never work. In each country, mean annual partner's earnings are higher amongst women who always work suggesting a complicated non-labor income effect.

In order to get a better picture of changes over time, Figures 1 and 2 display patterns in annual labor market participation rates and annual birth rates over the sample period in each country. Figure 1 illustrates that participation rates over the sample period are always highest in France, second highest in Italy, and lowest in Spain. However, participation rates in Spain converge to those in Italy, while Italian participation rates remain mostly

[2]Nicoletti and Peracchi (2003) analyze the determinants of non-response in the ECHP. They find that attrition after wave 1 is mostly due to migration. Individuals that entered the ECHP after wave 1 were likely to be out of the scope of the survey at that time.

[3]Birth outcomes in the eigth year (wave 8) of the survey are not observed due to a censoring problem.

constant. French participation rates display more fluctuation than do those of Italy and Spain, suggesting the importance of controlling for year effects.

Figure 2 graphically illustrates that birth rates are consistently highest in France over the sample period. Spanish birth rates start out quite high, actually exceeding those in France as well as Italy in 1995, but fall relatively rapidly over time (as participation rates increase). Towards the end of the sample period Spanish birth rates roughly equalize with those in Italy, and both are nearly half the birth rates in France. The birth rates in each country fall over time as the women in the sample age.

The persistence in female labor supply is illustrated in Table 2, which displays the distribution of years worked over the sample period, separately by country. In Italy, the proportion of women who always work and who never work are quite similar, 36% and 39%, respectively. These two modal points account for three-quarters of the distribution. In Spain, relatively less women always work than in Italy, 21%, but more women never work, 46%. The percentages in France are quite different: a larger proportion of women always work, 45%, and a smaller proportion never work ,17%. In all three countries, the two modal points in the distribution are at the "corners".[4]

Strong persistence in labor supply is also displayed in Table 3, which presents, by country, average rates of transition between employment states from year t-1 to year t. The transition rates illustrate that, in France, it is more common for a women to move from nonparticipation to participation than from participation to nonparticipation. In Spain, the opposite is true. In Italy, these two types of transitions occur with equal probability. The diagonals of the transition matrices also suggest that there is an important relationship between persistence and participation: more persistence is associated with lower participation rates.[5]

[4]The descriptive statistics in Tables 1 and 2 can be readily compared to similar statistics for the US reported in Hyslop (1999), and for Germany reported in Croda and Kyriazidou (2004). For example, in both the US and Germany, women who always work are more educated and also have fewer young children than those who never work, but they have lower mean nonlabor income. In the PSID, 48% of married women in the sample always work (11% never work) while in the GSEOP the proportion is 38.5% (15% never work).

[5]Analyzing gender gaps in unemployment, Azmat, Guell, and Manning (2004), have shown that in Italy and Spain, where more women are unemployed relative to men, females are more likely to move from

4 Model

In this section we develop a dynamic utility maximization model of female labor supply and birth decisions that guides the empirical work that follows. The model is similar to the decision framework in Eckstein and Wolpin (1989) and Francesconi (2002), however, since we estimate approximate decision rules rather than exact decision rules, our approach more closely resembles that in Keane and Wolpin (2001*a*).

Consider a married women i who maximizes remaining discounted lifetime utility by choosing, in each year t, whether or not to participate in the labor market, h_{it}, and whether or not to give birth, b_{it}. We abstract from the part-time, full-time (hours) margin and fertility complications/timing issues by assuming that planned live births can occur with certainty within the same year t.

Remaining lifetime utility at time t for woman i is given by

$$V_{it}\left(S_{it}\right) = \max_{\{h_{it},b_{it}\}} E\left[\sum_{t=\tau}^{T} \delta^{\tau-t} U_{it}\left(h_{it}, b_{it}\right) | S_{it}\right] \tag{1}$$

where τ is the theoretical start of the decision process, T is the end of the decision horizon, δ is the subjective discount factor, and S_{it} is the state space at time t. $V_{it}\left(S_{it}\right)$ is the value function and $U_{it}\left(h_{it}, b_{it}\right)$ is the utility flow.

The maximization problem in (1) can be cast in terms of alternative specific value functions, $V_{it}^{bh}\left(S_{it}\right)$, that follow Bellman's equation, i.e.,

$$\begin{aligned} V_{it}(S_{it}) &= \max\left[V_{it}^{00}\left(S_{it}\right), V_{it}^{10}\left(S_{it}\right), V_{it}^{01}\left(S_{it}\right), V_{it}^{11}\left(S_{it}\right)\right] \\ V_{it}^{hb}\left(S_{it}\right) &= U_{it}\left(h_{it}, b_{it}\right) + \delta E\left(V_{i,t+1}(S_{i,t+1}) | h_{it}, b_{it}, S_{it}\right), \; t < T \\ &= U_{iT}\left(h_{iT}, b_{iT}\right), \qquad t = T. \end{aligned} \tag{2}$$

where the utility flow is assumed to be

$$U_{it}\left(h_{it}, b_{it}\right) = C_{it} + \left(\gamma_{0h} + \gamma_{1h} C_{it} + \gamma_{2h} h_{i,t-1} + \gamma_{3h} N_{it} + \varepsilon_{it}^{h}\right) h_{it} + \left(\gamma_{0b} + \varepsilon_{it}^{b}\right) b_{it}. \tag{3}$$

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employment to unemployment and less likely to enter from unemployment to employment, compared to males.

γ_{0h} in (3) is the marginal utility of working in year t, which could be negative if there is a utility cost to work effort. C_{it} is current period consumption and γ_{1h} measures the extent to which the marginal utility of consumption varies with participation status. Lagged participation, $h_{i,t-1}$, affects current period utility and γ_{2h} captures the cost of adjusting participation status. N_{it} is the number of children in the household and γ_{3h} is the marginal utility of an additional child when participating in the labor market relative to not participating. N_{it} follows the law of motion

$$N_{i,t+1} = N_{it} + b_{it}. \tag{4}$$

γ_{0b} is the marginal utility (or disutility) of giving birth in year t, and ε_{it}^{h} and ε_{it}^{b} are shocks to the utility of working and giving birth, respectively.

The per-period budget constraint in the maximization problem is assumed to be

$$y_{it}^{f} h_{it} + y_{it}^{m} = C_{it} + C_n N_{it} \tag{5}$$

where y_{it}^{f} is the woman's labor market earnings in year t and y_{it}^{m} is the partner's labor market earnings (non-labor income). C_n represents the goods-cost per child.

After substituting (5) and (4) into (3), the four utility flows relevant for the corresponding alternative specific value functions $V_{it}^{bh}\left(S_{it}\right)$ become

$$\begin{aligned}
U_{it}(0,0) &= y_{it}^{m} - C_n N_{it} \\
U_{it}(1,0) &= \gamma_{0h} + (1+\gamma_{1h})\, y_{it}^{f} + (1+\gamma_{1h})\, y_{it}^{m} + (\gamma_{3h} - (1+\gamma_{1h})\, C_n)\, N_{it} \\
&\quad + \gamma_{2h} h_{i,t-1} + \varepsilon_{it}^{h} \\
U_{it}(0,1) &= \gamma_{0b} + y_{it}^{m} - C_n\,(N_{it}+1) + \varepsilon_{it}^{b} \\
U_{it}(1,1) &= (\gamma_{0h} + \gamma_{0b}) + (1+\gamma_{1h})\, y_{it}^{f} + (1+\gamma_{1h})\, y_{it}^{m} \\
&\quad + (\gamma_{3h} - (1+\gamma_{1h})\, C_n)\,(N_{it}+1) + \gamma_{2h} h_{i,t-1} + \varepsilon_{it}^{h} + \varepsilon_{it}^{b}.
\end{aligned} \tag{6}$$

Further, let the female earnings functions be

$$y_{it}^{f} = g\left(x_{it}', H_{it}, \varepsilon_{it}^{f}\right) \tag{7}$$

where $g(\cdot)$ is an unspecified function of the covariate vector, x_{it}', accumulated actual work experience during the sample period, H_{it}, and a productivity shock, ε_{it}^{f}. The vector of covariates x'_{it} contains proxies for accumulated human capital prior to the start of the sample period. That is, $x'_{it} = \left\{E_{i\tau_i}, a_{i\tau_i}, a^2_{i\tau_i}\right\}$ where $E_{i\tau_i}$ is the education level at the start of the sample period for individual i, $t = \tau_i$, and a_{τ_i} is the woman's age at $t = \tau_i$.[6] $a_{i\tau_i}$ and $a^2_{i\tau_i}$ control for accumulated (potential) work experience prior to $t = \tau_i$. Accumulated (actual) work experience during the sample period follows the follows the law of motion

$$H_{i,t+1} = H_{it} + h_{it}. \tag{8}$$

The initial condition is $H_{i\tau_i} = 0$.[7]

Assuming no serial correlation in the error terms ε^f_{it}, ε^h_{it} and ε^b_{it}, (6) and (7) imply that the set of state variables, S^{hb}_{it}, corresponding to each choice combination is distinct. Specifically,

$$\begin{aligned}
S^{00}_{it} &= \{N_{it}, y^m_{it}\} \\
S^{10}_{it} &= \left\{N_{it}, h_{i,t-1}, x'_{it}, H_{it}, y^m_{it}, \varepsilon^f_{it}, \varepsilon^h_{it}\right\} \\
S^{01}_{it} &= \left\{N_{it}, y^m_{it}, \varepsilon^b_{it}\right\} \\
S^{11}_{it} &= \left\{N_{it}, h_{i,t-1}, x'_{it}, H_{it}, y^m_{it}, \varepsilon^f_{it}, \varepsilon^h_{it}, \varepsilon^b_{it}\right\}.
\end{aligned} \tag{7}$$

In the case of serial correlation, which we consider in estimation, the S^{hb}_{it}'s are simply augmented with the past values of the error terms.

Note that even though S^{hb}_{it}'s in (7) differ by choice combination, the decision rules of the optimization problem depend on the entire state space, S_{it}, as indicated in (1) and (2). This is because the value of a particular choice combination is computed by comparing the values of all choice combinations. S_{it} is the union of S^{00}_{it}, S^{10}_{it}, S^{01}_{it}, and S^{11}_{it}, and each choice probability is a function of S_{it} rather than the corresponding subset S^{hb}_{it} in (7).

To see this more clearly, consider, without loss of generality, the myopic version of the model. In the myopic version of the model there is no future component to the alternative

[6] The first period of observed data ($t = \tau_i$) for each woman will generally not be the start of the theoretical decision process for all individuals, $t = \tau$. How we deal with this initial conditions problem will be described in more detail below.

[7] For identification purposes, y^m_{it} is not further specified and will appear directly in the estimating equations as a measure of nonlabor income (in logs).

specific value functions, i.e., $\delta = 0$.[8] Denote $d_{it}^{hb} = 1$ if alternative (h_{it}, b_{it}) is chosen and $d_{it}^{hb} = 0$, otherwise. Per-period utility maximization implies the following comparison of utility flows in period t,

$$\begin{aligned}
d_{it}^{00} &= 1 \text{ if and only if } U_{it}(0,0) - \max\left[U_{it}(1,0), U_{it}(0,1), U_{it}(1,1)\right] = F_{it}^{00}(S_{it}) > 0 \\
&= 0 \text{ otherwise} \\
d_{it}^{10} &= 1 \text{ if and only if } U_{it}(1,0) - \max\left[U_{it}(0,0), U_{it}(0,1), U_{it}(1,1)\right] = F_{it}^{10}(S_{it}) > 0 \\
&= 0 \text{ otherwise} \qquad (8) \\
d_{it}^{01} &= 1 \text{ if and only if } U_{it}(0,1) - \max\left[U_{it}(0,0), U_{it}(1,0), U_{it}(1,1)\right] = F_{it}^{01}(S_{it}) > 0 \\
&= 0 \text{ otherwise} \\
d_{it}^{11} &= 1 \text{ if and only if } U_{it}(1,1) - \max\left[U_{it}(0,0), U_{it}(1,0), U_{it}(0,1)\right] = F_{it}^{11}(S_{it}) > 0 \\
&= 0 \text{ otherwise}
\end{aligned}$$

Estimation of approximate decision rules, in either myopic or dynamic versions of the model, simply involves choosing a particular specification for $Pr\left(F_{it}^{hb}(S_{it}) > 0\right)$. The contribution of the optimization model is to provide a theoretical grounding for the common set of covariates, S_{it}, that appears in estimating equations. For the dynamic utility maximization model specified above, S_{it}, is

$$S_{it} = \left\{N_{it}, h_{i,t-1}, x'_{it}, H_{it}, y_{it}^{m}, \varepsilon_{it}^{f}, \varepsilon_{it}^{h}, \varepsilon_{it}^{b}\right\}. \qquad (9)$$

5 Estimation

In this section, we detail our empirical strategy for estimating the approximate decision rules of the dynamic optimization problem described above. In the first subsection, we develop the connection between the approximate decision rules and a dynamic bivariate probit model with nonparametric correlated random effects and AR(1) serially correlated transitory errors. In the second subsection, we outline the simulated maximum likelihood (SML) algorithm used to estimate the empirical model.

[8] In the dynamic version of the model, each alternative specific value function at time t has S_{it} as an argument by virtue of the fact that the expected maximum future returns component compares the values of all choice combinations in the future.

5.1 A Dynamic Bivariate Probit with Nonparametric Correlated Random Effects and AR(1) Errors

We estimate the approximate decision rules of the optimization problem developed in the previous section by specifying $Pr\left(F_{it}^{hb}\left(S_{it}\right)>0\right)$ in the following way,

$$\begin{aligned}
\Pr\left(d_{it}^{00}=1\right) &= \Pr\left(F_{it}^{00}\left(S_{it}\right)>0\right)=\int_{-\infty}^{0}\int_{-\infty}^{0} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \\
\Pr\left(d_{it}^{10}=1\right) &= \Pr\left(F_{it}^{10}\left(S_{it}\right)>0\right)=\int_{0}^{\infty}\int_{-\infty}^{0} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \qquad (10)\\
\Pr\left(d_{t}^{01}=1\right) &= \Pr\left(F_{it}^{01}\left(S_{it}\right)>0\right)=\int_{-\infty}^{0}\int_{0}^{\infty} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \\
\Pr\left(d_{t}^{11}=1\right) &= \Pr\left(F_{it}^{11}\left(S_{it}\right)>0\right)=1-\sum\nolimits_{hb\in\{(00),(10),(01)\}}\Pr\left(F_{it}^{hb}\left(S_{it}\right)>0\right)
\end{aligned}$$

where $f\left(\cdot\right)$ is the bivariate normal density. The choice probabilities in (10) are those of a bivariate probit model.[9]

H_{it}^{*} and B_{it}^{*} in (10) are assumed to be the following functions of the state space S_{it} from the optimization model,

$$\begin{aligned}
H_{it}^{*} &= \alpha_{0h}+\alpha_{1h}N_{i,t-1}+\alpha_{2h}h_{i,t-1}+\alpha_{3h}H_{i,t-1}+\alpha_{4h}y_{it}^{m}+\alpha_{5h}E_{i\tau_i}+\alpha_{6h}a_{i\tau_i}+\alpha_{7h}a_{i\tau_i}^{2}+u_{it}^{h} \qquad (11)\\
B_{it}^{*} &= \alpha_{0b}+\alpha_{1b}N_{i,t-1}+\alpha_{2b}h_{i,t-1}+\alpha_{3b}H_{i,t-1}+\alpha_{4b}y_{it}^{m}+\alpha_{5b}E_{i\tau_i}+\alpha_{6b}a_{i\tau_i}+\alpha_{7b}a_{i\tau_i}^{2}+u_{it}^{b}
\end{aligned}$$

where $u_{it}^{h}=g_{h}\left(\varepsilon_{it}^{f},\varepsilon_{it}^{h},\varepsilon_{it}^{b}\right)$ and $u_{it}^{b}=g_{b}\left(\varepsilon_{it}^{f},\varepsilon_{it}^{h},\varepsilon_{it}^{b}\right)$ are composites of the original error terms in S_{it}.

In order to produce a nonparametric random effects bivariate probit, assume that the $g_{h}\left(\cdot\right)$ and $g_{b}\left(\cdot\right)$ functions transform the original error terms so that we get the following structure for u_{it}^{h} and u_{it}^{b},

$$\begin{aligned}
u_{it}^{h} &= \alpha_{i}^{h}+\xi_{it}^{h} \qquad (12)\\
u_{it}^{b} &= \alpha_{i}^{b}+\xi_{it}^{b}
\end{aligned}$$

[9] One could also adopt a specification for $Pr\left(F_{it}^{hb}\left(S_{it}\right)>0\right)$ such that a four choice multinomial probit or logit is generated (as in Keane and Wolpin (2001a). Bivariate probits are generally more parsimonious.

where α_i^j, $j = h, b$ are time-invariant individual effects and ξ_{it}^j, $j = h, b$ are transitory shocks. Further assume that the individual effects are random with a discrete distribution that has three mass points. That is, let u_{it}^h and u_{it}^b be

$$\begin{aligned} u_{it}^h &= \theta_1^h A_1 + \theta_2^h A_2 + \xi_{it}^h \\ u_{it}^b &= \theta_1^b A_1 + \theta_2^b A_2 + \xi_{it}^b \end{aligned} \tag{13}$$

where A_1 is a dummy variable for unobserved "type" 1, A_2 is a dummy variable for unobserved "type" 2, and A_0 is a dummy for unobserved "type" 0, which is the base type.[10]

The three type probabilities, which define the discrete nonparametric distribution of the individual effects, are given the following structure,

$$\begin{aligned} \Pr(A_1) &= L_1(y_{ip}^m, E_{i\tau_i}) \\ \Pr(A_2) &= L_2(y_{ip}^m, E_{i\tau_i}) \\ \Pr(A_0) &= 1 - \Pr(A_1) - \Pr(A_2) \end{aligned} \tag{14}$$

where $L_i(\cdot)$, $i = 1, 2$ is the logistic function with different coefficients for each i. The logistic function ensures that the mass point probabilities remain between zero and one. The structure in (13) and (14) allows the individual effects in (12) to have distinct distributions (be heteroskedastic) as well as correlated.

The type probabilities in (14) are functions of permanent nonlabor income y_{ip}^m and education $E_{i\tau_i}$. Permanent nonlabor income is calculated as the log of the sample average of partner's annual earnings over the sample period. Because both nonlabor income and the education are potentially endogenous, specifying the type probabilities as a function of these variables produces a nonparametric correlated random effects version of the dynamic bivariate probit model.[11]

[10] In preliminary estimations, three types were found to fit the data better than two. Four types did not produce a significant increase in the value of the log-likelihood function.

[11] Preliminary estimations indicated that separate permanent and transitory nonlabor income effects were hard to empirically identify when entered into both (11) and (14). The log of annual earnings was, however, easily identified when it appeared as the only nonlabor income variable in (11), and the log of permanent nonlabor income was easily identified when it appeared as the only nonlabor income variable in (14).

In addition to nonparametric correlated random effects, we allow the transitory shock ξ_{it}^h in (12) to be $AR(1)$ serially correlated. Serial correlation in ξ_{it}^h may arise, for example, from unobserved female wage offer shocks that persist over time.[12] The transitory shocks take the form,

$$\begin{aligned} \xi_{it}^h &= \rho \xi_{i,t-1}^h + v_{it}^h \\ \xi_{it}^b &= \xi_{it}^b \end{aligned} \tag{15}$$

where v_{it}^j, $j = h, b$ are assumed to be independent and distributed standard normal.[13]

In order to address the initial conditions problem that arises in dynamic discrete choice models in general, we employ the Heckman approximate solution (Heckman (1981)). The Heckman approximation involves specifying H_{it}^* and B_{it}^* functions in the initial sample period, $t = \tau_i$, with no lagged endogenous state variables, distinct coefficients from those in (11), and error terms that are correlated with the error terms during the sample period. Accordingly, we specify $H_{i\tau_i}^*$ and $B_{i\tau_i}^*$ as,

$$\begin{aligned} H_{i\tau_i}^* &= \lambda_{0h} + \lambda_{1h} y_{i\tau_i}^m + \lambda_{2h} E_{i\tau_i} + \lambda_{3h} a_{i\tau_i} + \lambda_{4h} a_{i\tau_i}^2 + u_{i\tau_i}^h \\ B_{i\tau_i}^* &= \lambda_{0b} + \lambda_{1b} y_{i\tau_i}^m + \lambda_{2b} E_{i\tau_i} + \lambda_{3b} a_{i\tau_i} + \lambda_{4b} a_{i\tau_i}^2 + u_{i\tau_i}^b \end{aligned} \tag{16}$$

where $u_{i\tau_i}^j$, $j = h, b$ has the same structure as in (13) but different coefficients. The errors $u_{i\tau_i}^j$ and u_{it}^j $j = h, b$ are correlated because they are functions of the same unobserved type dummies. The variances of the transitory errors in the initial sample period are also adjusted so that they are equal to the variances of the transitory errors during the sample period.

Estimation of the dynamic bivariate probit model described above is difficult using classical maximum likelihood techniques. Calculation of the choice probabilities with $AR(1)$ serially correlated errors requires multiple integration, which generally causes standard

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[12] Following the overwhelming majority of the related literature on labor market participation, we substitute out for the wage and do not incorporate observed wage data in estimation (see, e.g., Magnac (2000)). Eckstein and Wolpin (1989) is an exception.

[13] At an earlier stage, we considered serial correlation in ε_{it}^b, which may arise from unobserved and persistent changes in habits related to fecundity, however, identification problems arose.

quadrature techniques to breakdown. Estimating by SML is a more computationally practical approach. The particular SML algorithm that we use to estimate the model, described briefly below, was originally developed in Keane and Wolpin (2001*b*) for estimating the exact decision rules of dynamic programming problems. The algorithm was shown in Keane and Sauer (2005) to be also useful for estimating more general dynamic discrete choice models of the type formulated above.

5.2 The SML Algorithm

The SML algorithm that we employ can be outlined, for simplicity, as follows. Denote the observed data by $\{h_i^*, b_i^*, X_i\}_{i=1}^N$, where $h_i^* = \{h_{it}^*\}_{t=\tau_i}^T$ is woman i's reported participation history, $b_i^* = \{b_{it}^*\}_{t=\tau_i}^T$ is woman i's reported birth history, and $X_i = \{X_{it}\}_{t=\tau_i}^T$ is the history of covariates. Unconditional simulation of the likelihood function proceeds in the following way,

1. Draw M times from the joint distribution $\left(u_{i\tau_i}^h, ..., u_{iT}^h, u_{i\tau_i}^b, ..., u_{iT}^b\right)$, for each woman i, to form the correlated error sequences $\left\{\left\{\{u_{itm}^h\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$ and $\left\{\left\{\{u_{itm}^b\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$. This involves drawing uniform and standard normal variates according to (13), (14), and (15).

2. Given $\left\{\{X_{it}\}_{t=\tau_i}^T\right\}_{i=1}^N$, $\left\{\left\{\{u_{it}^m\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$, and $\left\{\left\{\{u_{itm}^b\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$, construct M simulated participation histories, $\left\{\left\{\{h_{it}^m\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$, and M simulated birth histories, $\left\{\left\{\{b_{it}^m\}_{t=\tau_i}^T\right\}_{i=1}^N\right\}_{m=1}^M$ for each woman i, according to (11) and (16) where $h_{it}^m = I\left(H_{it}^{*m} > 0\right)$ and $b_{it}^m = I\left(B_{it}^{*m} > 0\right)$.

3. Construct the classification error rates $\left\{\left\{\pi_{jktm}^h\right\}_{t=\tau_i}^T\right\}_{m=1}^M$ and $\left\{\left\{\pi_{jktm}^b\right\}_{t=\tau_i}^T\right\}_{m=1}^M$ for each woman i (see below), where j denotes the simulated choice h_{it}^m (b_{it}^m) and k denotes the reported choice h_{it}^* (b_{it}^*).

4. Form an unbiased simulator of the likelihood contribution for each woman i as:

$$\widehat{P}\left(h_i^*, b_i^* \mid \theta, X_i\right) =$$

$$\frac{1}{M}\sum_{m=1}^{M}\prod_{t=\tau_i}^{T}\left(\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi_{jktm}^{h} I\left[h_{it}^{m}=j, h_{it}^{*}=k\right]\right\}\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi_{jktm}^{b} I\left[b_{it}^{m}=j, b_{it}^{*}=k\right]\right\}\right) \tag{17}$$

where θ is the vector of model parameters.

The two classification error rates (out of the four that appear in (17)) that are estimated along with the other parameters of the model are

$$\begin{aligned} \pi_{01tm} &= \pi_{01tm}^{h} = \pi_{01tm}^{b} = \Pr\left(h_{it}^{*}=1 \mid h_{it}^{m}=0\right) = \Pr\left(b_{it}^{*}=1 \mid b_{it}^{m}=0\right) \\ \pi_{10tm} &= \pi_{10tm}^{h} = \pi_{10tm}^{b} = \Pr\left(h_{it}^{*}=0 \mid h_{it}^{m}=1\right) = \Pr\left(b_{it}^{*}=0 \mid b_{it}^{m}=1\right) \end{aligned} \tag{18}$$

where $\pi_{00tm} = 1 - \pi_{01tm}$ and $\pi_{11tm} = 1 - \pi_{10tm}$. Note that the probability of reporting a particular choice is allowed to be a function of the true (simulated) choice but is not directly affected by covariates. Classification error in reported participation status is also assumed to be independent of classification error in reported birth outcomes, and both are constrained to occur at the same rate.[14] The classification error rates in (17) are given a logistic form to ensure that the probabilities remain between zero and one. For more details on the algorithm, a discussion of identification, and an illustration of the biases that arise if classification error is not accounted for in non-linear discrete choice models, see Keane and Sauer (2006).

6 Estimation Results

6.1 Point Estimates and Standard Errors

Table 4 reports selected SML estimates of the dynamic bivariate probit model specified in the previous section.[15] Additional parameterizations in the model, not mentioned earlier,

[14] Distinct classification error rates for participation and birth outcomes were hard to empirically identify.

[15] The data for 2001 (wave 8) are not included in estimation due to incomplete fertility information in that year.

are the splitting of the education variable $E_{i\tau_i}$into two dummies, $E^s_{i\tau_i}$ and $E^t_{i\tau_i}$ representing achievement of secondary and tertiary levels of education, respectively (as in Table 1). The stock of children at the beginning of period t, N_{it}, is also split into two dummy variables. One dummy is for the youngest child being three years of age or less and the other is for the youngest child being older than three. The base category is no children at all (also as in Table 1). In addition, the H^*_{it} and B^*_{it} functions in (11) and (16) are augmented to include year and region effects within each country.

The first two columns of Table 4 present the estimation results for France. Column (1) reveals a negative effect of nonlabor income and a negative effect of the youngest child being three years of age or less on labor market participation. Both effects are precisely estimated. Secondary and tertiary levels of education have significant positive effects on labor market participation. Participation in the previous period has a strong positive impact on participation in the current period, even controlling for accumulated potential experience before the start of the sample period and accumulated actual experience during the sample period, indicating an important role for state dependence.

The importance of permanent unobserved heterogeneity is revealed by the strong and precisely estimated coefficients on the unobserved type dummies, A_1 and A_2. Type 1 women are more likely to participate in the labor market relative to type 0 women, and type 2 women are less likely to participate in the labor market relative to type 0 women. The estimated $AR(1)$ serial correlation coefficient also suggests nonnegligible dynamics in transitory unobservables.

The estimates in Column (2) show that the presence of very young children as well as older children significantly decrease the propensity to give birth. Having achieved a tertiary level of education significantly increases the propensity to give birth. There are also important unobserved heterogeneity effects. Type 1 women are more likely to give birth (and work) than type 0 women. Type 2 women are more likely to give birth (but less likely to work) than type 0 women.

The estimated type probabilities for France, shown at the bottom of Columns (1) and (2), indicate that, on average, type 1 and 2 women account for three-quarters of the population, with type 1 individuals being the majority, 53%. Nonlabor income and education have significant effects on a woman's unobserved type (not shown in the table). The significance of these variables implies that nonlabor income and education are endogenous, and that it was important to account for this in estimation (albeit indirectly).

The estimated classification error rates for France, shown below the estimated type probabilities, reveal that the probability of reporting to be participating in the labor market, when the true state is nonparticipation, is .065. The probability of reporting to be not participating, when the true state is participation, is .021.[16] Although small in magnitude, both classification error rates are significantly different from zero. Note that ignoring even a small amount of classification error can lead to large biases in the importance of unobserved heterogeneity and state dependence.[17]

Columns (3) – (6) display the corresponding results for Italy and Spain, respectively. The point estimates are, qualitatively, similar to those reported in Columns (1) and (2) for France. Interestingly, the same pattern of coefficients on the type dummies are obtained in both the work and birth equations. Previous participation status is also very important, as is serial correlation in the transitory errors. In contrast to France, in both Italy and Spain, accumulated actual work experience significantly decreases the propensity to give birth. There are also differences in the type proportions in the population, indicating significantly different distributions of permanent unobserved heterogeneity across the three countries. Nonlabor income and education also significantly affect the type probabilities in Italy and Spain. The classification error rates for Italy and Spain are similarly small in magnitude but significantly different from zero, as for France.

6.2 Linearized Marginal Effects and Relative Importance Decomposition

The top panel of Table 5 reports selected marginal effects, corresponding to the point estimates reported in Table 4. The marginal effects are calculated in the following way. First, stochastic elements of the model are drawn from their estimated distributions (as in the

[16] As mentioned earlier, the classification error rates for reported birth outcomes are constrained to be equal to the classification error rates for reported participation outcomes.

[17] This is shown in Keane and Sauer (2006) who obtain classification error rates for labor market participation of similar magnitudes.

SML algorithm described earlier). Second, participation and birth outcomes are simulated according to the estimated approximate decision rules. Third, separate linear regressions of simulated outcomes on all of the variables appearing in the model are estimated. The marginal effects are thus linear approximations.

The estimated marginal effects clearly illustrate the overriding importance of previous participation status (state dependence) for determining current participation status in all three countries. Having participated in the labor market in the previous period increases the probability of participating in the current period by 66 percentage points in France, 82 percentage points in Italy, and 78 percentage points in Spain. The marginal effects of the type dummies (permanent unobserved heterogeneity) are relatively smaller, but show the type dummies to be the next most important determinants of participation. Interestingly, education has a similar marginal effect to the presence of young children, although opposite in sign. For birth outcomes, age (not shown) and the presence of children are the strongest determinants. Unobserved type and education come next in the hierarchy.

An additional way to measure the relative importance of the factors determining labor market participation and birth outcomes is to add different sets of variables to the linear regressions on the simulated data, and examine the changes in the adjusted R-squared. The results of this exercise are reported in the bottom panel of Table 5. The base specification for both the work and birth equations includes only the observed covariates (nonlabor income, fertility outcome dummies, age and education dummies).

The adjusted R-squared when only observed covariates are included in the participation equation, $\overline{R}_1^2$, is quite low. $\overline{R}_1^2$ is .06 in France, .13 in Italy and .14 in Spain. Adding the fixed effects (year and region dummies) to the base specification yields a $\overline{R}_2^2$ which is only slightly higher than $\overline{R}_1^2$. Adding the value of the simulated serially correlated shock only to the base specification has a more substantial effect. $\overline{R}_3^2$ reaches .16 in France, .26 in Italy, and .27 in Spain. Adding only the type dummies (unobserved heterogeneity) yields a relatively more substantial increase in the adjusted R-squared. $\overline{R}_4^2$ increases to .53 in France, .48 in Italy and ..39 in Spain. Adding both accumulated actual labor market experience and previous year's participation status produces the greatest increase in the adjust R-squared. $\overline{R}_5^2$ jumps to .77 in France, .89 in Italy and .85 in Spain.

According to the way we perform a relative importance decomposition, state dependence is clearly the most important factor in explaining the persistence in participation status. State dependence is also relatively more important in Italy and Spain than in France. The corresponding exercise for birth outcomes shows, in contrast, that the observable covariates (including age and fertility) and unobserved heterogeneity are the most important determinants of the propensity to give birth.

7 Discussion

The estimation results presented in the previous section reveal substantial cross-country variation in both the level of female labor market participation and the extent of state dependence. In particular, we find that state dependence is stronger in Italy and Spain (where labor market participation rates are relatively lower) compared to France, while unobserved heterogeneity is relatively more important in France than it is in Italy and Spain. While it is true that some of the cross-country differences in the relative importance of state dependence and unobserved heterogeneity may reflect cultural attitudes regarding gender roles, they may also reflect systematic differences in the institutional constraints faced by individuals. Given the relative homogeneity of the three countries under consideration, we believe the second aspect is likely to be the most important.

In the next subsection, we analyze a set of aggregate statistics on employment protection, part-time work availability and child care in France, Italy and Spain, and note a connection between these statistics and the pattern of state dependence effects estimated in the model. In the second subsection, we use the estimated approximate decision rules to perform additional simulations. Specifically, we quantify the effect of the institutional environment on participation and fertility choices by examining how these choices would change if women in one country were to face the institutional constraints (estimated decision rule parameters) of another country.

7.1 Labor Market Rigidities and Inadequate Child Care Options

The constraints faced by individuals in the three countries under consideration can be readily compared through aggregate statistics on employment protection, part-time work availability and child care. Consider first the employment protection index. The employment protection index ranks countries on the basis of employment protection legislation (EPL), i.e., on the basis of regulations governing individual dismissals and hiring of workers (e.g., severance pay and advance notice). Theoretical models clearly indicate that employment should be more stable and individual employment relationships more durable when EPL is stricter. Given a constant cyclical wage pattern, higher firing costs stabilize employment in downturns but also deter employers from hiring in upturns. To the extent that firing costs prevent termination of existing employment relationships, sharp employment reduction is less likely in countries with stringent job security provisions. Stricter EPL should, therefore, be associated not only with lower labor market participation rates, but also stronger state dependence effects.

Column (1) of Table 6 shows a ranking of Italy, Spain and France in terms of EPL. The ranking does not reveal sharp differences between the three countries, but Italy does have a higher index score as well as the greatest degree of estimated state dependence. Column (2) compares the three countries according to the proportion of workers employed in part-time jobs. The proportion of workers employed in part-time jobs can be considered an indication of labor market flexibility. In more flexible labor markets, one would expect less state dependence, i.e., more movements in and out of unemployment. According to this latter measure, there are much sharper differences between the countries. Italy and Spain are similar, while France is much more flexible. This is highly consistent with the pattern of estimated state dependence effects in the model. Italy and Spain have relatively lower proportions of individuals employed part-time and stronger state dependence coefficients (marginal effects) than France.

Differences between Italy, Spain and France, consistent with the pattern of estimated state dependence effects, also arise when we consider child care outcomes. Column (3) reports the percentage of children less than three years of age in child care. Italy and Spain have very low percentages, while in France the percentage is considerably higher. Column

(4) compares the average opening hours of child care (for children less than three years of age). France has greater availability of child care on this measure as well. Column (5) compares child benefits as a percentage of GDP. The French percentage far exceeds the percentages in Italy and Spain, which are both less than 1% of GDP.[18]

The data in Table 6 clearly indicate that in Italy and Spain, relative to France, both market and nonmarket options for working mothers are more limited. Part-time work is in relatively scarce supply, benefits for families with children are much lower, and child care services are typically inadequate in quantity and characterized by extreme rigidity in the number of weekly hours available (Del Boca (2002)). Women that decide to bear a child either do not withdraw from the labor market or never re-enter after childbirth. Moreover, women that are employed tend to have full-time work commitments, which is not compatible with having many children, so overall fertility is lower (Boeri, Del Boca and Pissarides (2005)). Thus, countries with less labor market flexibility and less family friendly policies have individuals concentrated more often in the always work and never work categories. The costs of changing employment from one period to the next are higher, generating a greater extent of state dependence in female labor market participation.

7.2 Measuring the Effect of the Institutional Environment

In Table 7, we report the results of a simulation exercise which further quantifies the influence of the institutional environment on labor market participation and birth rates. In the simulation, predicted participation and birth outcomes are generated for each women in one country, using the SML estimates of the approximate decision rules for an alternative country. The results of the counterfactual exercise are partial equilibrium only, in the sense that the background characteristics (education, nonlabor income, etc.) are assumed to remain the same after changing the institutional environment. In order to partially address this problem, the effects of permanent unobserved heterogeneity and serial correlation are neutralized in the simulation.

In the top panel of Table 7, Italian and Spanish women face the estimated French decision

[18] The extension of Allocation Parentale d' ´Education (APE) to births of parity 2 in 1994 is often cited as a cause of the recent growth in fertility (Laroque and Salanie (2005)).

rule parameters (institutional environment). The results indicate that if Italian women, who have not completed secondary education, were to make work and birth decisions in the relatively more flexible French institutional environment, they would increase their average participation rate over the sample period by 17.5 percentage points. However, their average birth rate would increase by a negligible 0.3 percentage points. Among Italian women who have completed secondary education, the participation rate would increase by relatively less, 3.8 percentage points, and the birth rate would decrease by a negligible amount (0.2 percentage points). The main advantage of the more flexible French environment would be much a higher average employment rate among less educated Italian women.

If Spanish women were to face the more flexible French institutional environment, the participation rate of less educated women would increase by a very large 29.4 percentage points. More educated women would also increase their participation rate by a substantial amount (21.9 percentage points). The increase in the average birth rate among less educated Spanish women would be a negligible 0.1 percentage points, but more educated Spanish women would increase their average birth rate by a nonnegligible 2.1 percentage points. In contrast to Italian women, both less educated and more highly educated Spanish women would increase their average labor market participation rate were they to face the French institutional environment, and more educated women would increase their average birth rate.

The two bottom panels of Table 7 perform the analogous experiments of having French and Spanish women face the Italian parameters, and French and Italian women face the Spanish parameters. The results are mostly symmetric. French women would decrease their average participation rates in the Italian and Spanish institutional environments, and Spanish women would benefit, in terms of employment outcomes, from the Italian institutional environment.

8 Conclusion

In this paper, we formulated a dynamic utility maximization model of female labor force participation and fertility choices and estimated approximate decision rules using data from the ECHP on married women in Italy, Spain and France. Focusing on a small set of culturally similar countries helps isolate the underlying institutional causes of cross-country variation in the relative importance of permanent unobserved heterogeneity and state dependence in female labor market participation decisions. The estimation results indicate that state dependence is the most important factor in determining life cycle female labor supply in each of the three countries. State dependence effects are stronger in Italy and Spain relative to France, and the estimated pattern of state dependence effects is highly consistent with the differential availability of part-time employment opportunities and child care across the three countries.

Our study suggests that more severe labor market rigidities and relatively more inadequate child care options are important underlying sources of state dependence in female labor supply behavior. This is in addition to the "usual suspects" of human capital accumulation and search costs that depend on employment status. We also quantify the effects of the institutional environment by simulating counterfactual female participation and birth outcomes when women in one country face the institutional environment (approximate decision rule parameters) of a different country. The results of the simulation indicate that Italian and Spanish women would substantially increase their average participation rates were they to face the relatively more flexible French employment and child care environment.

Table 1

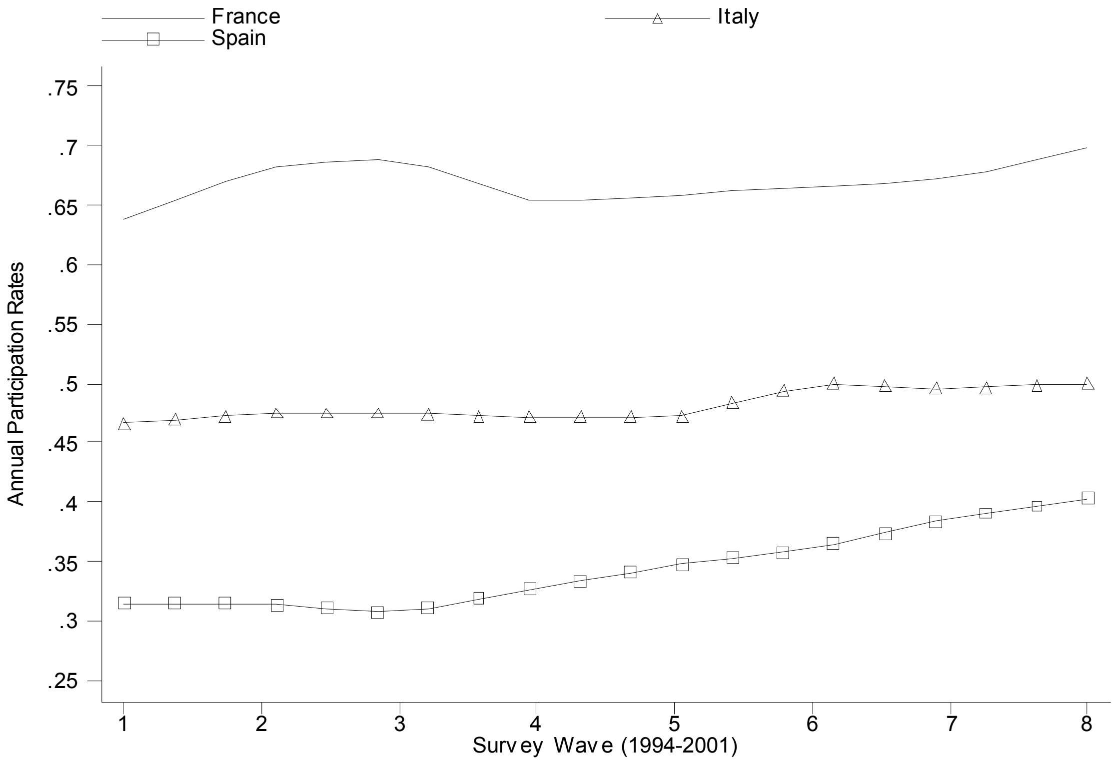
Descriptive Statistics by Employment Pattern and Country

	Italy			Spain			France		
	Work 0 years	Work 8 years	Full sample	Work 0 years	Work 8 years	Full sample	Work 0 years	Work 8 years	Full sample
Age	38.34	38.53	38.31	37.78	38.53	37.77	37.47	38.07	37.13
	(5.33)	(4.85)	(5.19)	(5.53)	(5.29)	(5.51)	(5.60)	(5.48)	(5.78)
Tertiary Education	.02	.16	.08	.09	.46	.20	.16	.36	.28
Secondary Education	.31	.73	.52	.27	.71	.39	.56	.80	.73
Youngest Child 0-3	.11	.10	.10	.12	.11	.11	.15	.11	.14
Youngest Child >3	.88	.78	.82	.84	.80	.82	.78	.77	.74
Male	16.56	17.45	16.91	17.34	21.70	17.74	20.56	21.34	20.51
Earnings	(7.66)	(7.66)	(7.54)	(9.05)	(13.24)	(9.98)	(16.22)	(24.46)	(19.21)
Birth Rate	.041	.040	.042	.052	050	.050	.065	.049	.065
Work Rate	0	1	.48	0	1	.34	0	1	.67
N	324	302	830	327	153	713	166	447	993

Note: Means are calculated over eight years of data for each women and over all women in the sample. Standard deviations of the continuous variables are in parentheses.

Figure 1

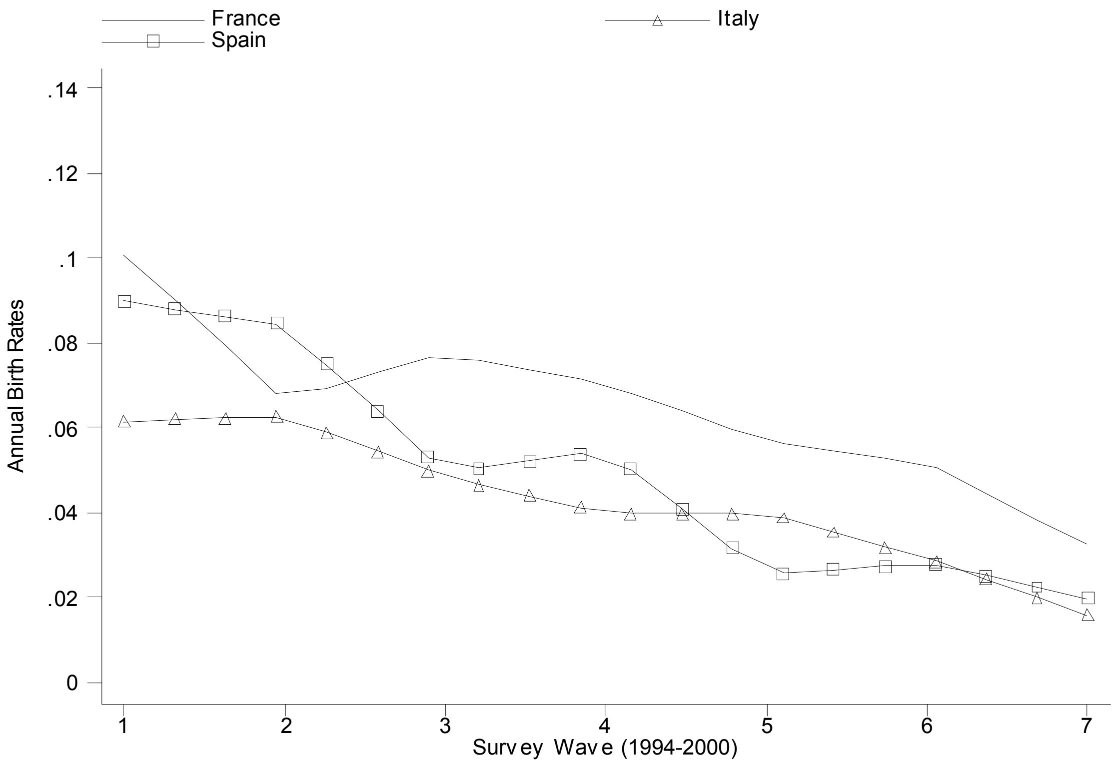
Annual Participation Rates by Country (1994-2001)



Note: Survey wave 1 corresponds to the year 1994 and survey wave 8 corresponds to the year 2001.

Figure 2

Annual Birth Rates by Country (1994-2000)



Note: Survey wave 1 corresponds to the year 1994 and survey wave 7 corresponds to the year 2000. The data on birth outcomes for survey wave 8 (year 2001) are not complete and, therefore, not considered.

Table 2

Distribution of Years Worked by Country

(Column Percentages)

Work Years	Italy	Spain	France
0	.390	.459	.167
1	.043	.094	.044
2	.037	.056	.037
3	.039	.048	.043
4	.034	.042	.041
5	.024	.030	.054
6	.028	.028	.066
7	.041	.030	.097
8	.364	.215	.450
	1.000	1.000	1.000

Table 3

Employment Transitions by Country

(Row Percentages)

Italy

	Work in t	
Work in t-1	0	1
0	.933	.067
1	.063	.937

Spain

	Work in t	
Work in t-1	0	1
0	.925	.075
1	.111	.889

France

	Work in t	
Work in t-1	0	1
0	.838	.162
1	.068	.868

Table 4

Selected SML Point Estimates and Standard Errors

	France		Italy		Spain	
	Work	Birth	Work	Birth	Work	Birth
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(y_{it}^m)$	$-.3623$	.0818	$-.3782$	.0854	$-.4556$	.0637
	(.0515)	(.0792)	(.0590)	(.0493)	(.0667)	(.1032)
$ychild_{it} <= 3$	$-.7366$	-1.2369	$-.3982$	-1.2533	$-.5711$	-1.2188
	(.1176)	(.1525)	(.1994)	(.2090)	(.1754)	(.2433)
$ychild_{it} > 3$	.0007	$-.4963$	$-.4077$	$-.5734$	$-.1195$	$-.5768$
	(.0962)	(.1240)	(.1418)	(.1516)	(.1244)	(.1842)
$E_{i\tau_i}^s$	.7814	.1514	2.0501	.3800	1.1410	.0899
	(.0783)	(.1191)	(.0855)	(.1133)	(.1246)	(.2156)
$E_{i\tau_i}^t$	.9280	.6013	1.3016	.6311	1.2949	.6163
	(.0750)	(.1075)	(.1513)	(.2066)	(.1483)	(.2545)
H_{it}	.0777	$-.0474$	.2377	$-.0872$	.2987	$-.2325$
	(.0424)	(.0466)	(.0444)	(.0492)	(.0520)	(.0713)
h_{it-1}	1.7499	$-.0357$	2.1426	.1359	1.8681	.0336
	(.0835)	(.1373)	(.1170)	(.1571)	(.1390)	(.2140)
A_1	1.6432	1.1187	2.0312	1.2444	1.6137	1.0539
	(.0993)	(.1282)	(.1327)	(.2357)	(.1897)	(.3098)
A_2	-1.3122	1.0689	-1.4669	1.0359	-1.3456	1.3129
	(.1172)	(.1409)	(.1383)	(.2354)	(.2062)	(.3158)
ρ	.5933	–	.7778	–	.7361	–
	(.0341)		(.0127)		(.0237)	
$\Pr(A_1), \Pr(A_2)$	(.5382, .2237)		(.3300, .5444)		(.4753, .3818)	
π_{11}, π_{00}	(.0648, .0210)		(.0472, .0167)		(.0669, .0241)	
Log-Likelihood	-4092.48		-2652.73		-2474.69	
N	993		830		713	

Note: All specifications also include a quadratic in age, year and region dummies.

Table 5

Selected Marginal Effects and Relative Importance Decomposition

	France		Italy		Spain	
	Work	Birth	Work	Birth	Work	Birth
	(1)	(2)	(3)	(4)	(5)	(6)
			Marginal Effects			
$\log(y^m_{it})$	$-.023$	$-.000$	$-.015$	.006	$-.022$	.002
$ychild_{it} <= 3$	$-.056$	$-.154$	$-.014$	$-.103$	$-.027$	$-.100$
$ychild_{it} > 3$	.002	$-.078$	$-.014$	$-.057$	$-.004$	$-.064$
$E^s_{i\tau}$	.049	.004	.059	.016	.043	.007
$E^t_{i\tau}$	.055	.057	.047	.022	.053	.022
A_1	.127	.058	.063	.035	.073	.026
A_2	$-.146$	.055	$-.056$	.024	$-.043$	.043
H_{it}	.001	$-.003$	.002	$-.003$	.009	$-.004$
$h_{i,t-1}$	.656	$-.005$	.816	.004	.779	$-.006$
			Relative Importance			
$\overline{R}^2_1$ (base X's)	.060	.117	.128	.075	.136	.064
$\overline{R}^2_2$ (X's + fixed effects)	.063	.133	.143	.084	.142	.072
$\overline{R}^2_3$ (X's + epsilon)	.159	–	.260	–	.274	–
$\overline{R}^2_4$ (X's + type dummies)	.529	.143	.478	.087	.392	.082
$\overline{R}^2_5$ (X's + state dependence)	.774	.133	.887	.084	.850	.077
N	993		830		713	

Note: Base X's include nonlabor income, fertility, age, and education. The fixed effects are year and region dummies. State dependence includes both accumulated actual work experience and lagged participation status.

Table 6

Employment Protection and Child Care

Country	Employment Protection Index (1)	Part Time Work (2)	% Child Care (<3) (3)	Child Care Opening hours (4)	Child Benefits (% GDP) (5)
Italy	1.5	17.4	7	8	0.9
Spain	1.4	17.2	5	6	0.4
France	1.4	31.0	39	10	2.8

Note: The Employment Protection Index is derived from Blanchard and Wolfers (2000). The data on public child care and child care benefits are drawn from the OECD, Eurostat, and Fondazione Innocenti statistics.

Table 7

Simulated Effect of Institutional Environment on Women's Work and Birth Decisions

	Less than HS Educ. % Point Change in Rate of		More than HS Educ. % Point Change in Rate of	
	Participation	Birth	Participation	Birth
	French Parameters			
Italian Women	17.5	0.3	3.8	-0.2
Spanish Women	29.4	0.1	21.9	2.1
	Italian Parameters			
French Women	-17.8	-0.4	-0.5	-0.4
Spanish Women	12.0	-0.3	21.7	2.3
	Spanish Parameters			
French Women	-30.0	-0.1	-24.0	-2.1
Italian Women	-12.4	0.2	-24.3	-1.3

Note: The numbers in parentheses are the simulated percentage point changes assuming no permanent unobserved heterogeneity or transitory serial correlation.

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