Life Cycle Employment and Fertility Across Institutional Environments*

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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. We find that first-order state dependence is the most important aspect of female labor supply behavior in all three countries. The ranking of state dependence effects across countries is correlated with aggregate measures of labor market flexibility and child care availability. Simulations of the model suggest that Italian and Spanish women would substantially increase their participation rates were they to face the more flexible 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 amongst the developed economies of Europe. Cross-country differences in female labor force participation rates in Europe have recently raised 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. The focus is on measuring the differential relative importance of state dependence and unobserved heterogeneity in country-specific decision rules, and examining the correlation between state dependence effects and social policies. Limiting the set of countries in the analysis to only those with "similar" cultural characteristics helps further control for unobservable preferences, such as religion and attitudes towards gender roles, that may confound the influence of state dependence.

The reason for focusing on the relative importance of state dependence and unobserved heterogeneity in female work and fertility choices is that past research on female labor force participation has repeatedly shown 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)). Persistence in participation status may be due to state dependence which arises from human capital accumulation or the costs of searching for a new job. The costs of searching for a new job may in turn be influenced by social policies such as employment regulations and the availability of child care. Persistence

[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.

can also be accounted for by permanent unobserved heterogeneity which reflects differences in mostly immutable preferences for work and/or productivity in the labor market. Unless properly accounted for, unobserved heterogeneity can lead to spurious state dependence effects.

Although several recent studies of female labor supply have also concentrated on disentangling state dependence from permanent unobserved heterogeneity (see e.g., Hyslop (1999) and Carrasco (2001)), to the best of our knowledge, there is no previous work that analyzes the differential relative importance of these factors across countries. Thus, no previous studies have examined the hypothesis that institutions governing social policies may be important underlying sources of cross-country differences in the relative importance decomposition. In particular, institutions which make it more costly to adjust employment levels from one period to the next for agents on both sides of the market, should be associated with greater degrees of country-specific state dependence.

Estimation of approximate decision rules clearly indicates that state dependence is the most important factor determining persistence in labor market participation in all three countries. Moreover, we find that the order of state dependence effects across countries is similar to the order in aggregate measures of labor market flexibility and child care availability. Thus, we provide evidence that employment and child care policies which affect participation adjustment costs are important underlying sources of state dependence and persistence.

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 life-cycle model of labor market participation and fertility decisions. Section 5 discusses estimation of approximate decision rules. Section 6 presents the estimation results and assesses model fit. Section 7 correlates the estimated state dependence effects with aggregate measure of social policies and performs a simulation exercise which helps quantify the effect of the institutional environment on participation and fertility choices. The simulations indicate that Italian and Spanish women would substantially increase their labor force participation rates were they to face the relatively more flexible

French institutional environment. The last section of the paper summarizes and concludes.

2 Background

In research on female labor supply behavior, many empirical studies focus on the effects of fertility on labor market participation. A negative effect of fertility on labor supply is often found. However, the effect may not be causal. The negative correlation could be the result of selection, whereby women with stronger preferences for motherhood are also those with lower unobservable skills and motivation in the labor market.

The endogeneity of fertility has been addressed in the past by adopting an instrumental variables approach. 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 using the sibling-sex composition as an instrument, 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 with European data since the number of women with at least two children is typically very small. Not surprisingly, the main challenge confronting the IV strategy in general has been one of finding suitable instruments.

Other studies that do not adopt the IV approach tend to focus on directly testing for the exogeneity of fertility. For example, using cross sectional data, Mroz (1987) tests 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. Conditional on participation, he finds that fertility is exogenous to women's labor supply. However, using panel data, Jakubson (1988) arrives at the opposite conclusion. Hyslop (1999), following suggestions in Browning (1992), tests for the exogeneity of fertility by estimating dynamic discrete choice models of female labor force participation with correlated random effects. His results indicate that when dynamic factors such as state dependence or serial correlation are excluded, fertility is endogenous. However, in dynamic specifications he finds no evidence against the exogeneity of fertility hypothesis.

The difficulty of finding suitable instruments, and the mixed results from previous research that tests for the exogeneity of fertility, suggests that it might be more fruitful to directly model joint participation and fertility decisions (as in, e.g., 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 formulating a dynamic programming model of joint labor market participation and fertility decisions. Following the approach of Keane and Wolpin (2002), we do not structurally estimate exact decision rules but rather show how approximate decision rules can be estimated using more "traditional" discrete choice models. However, we also build on the work of Keane and Wolpin (2002) by developing the connection between estimation of approximate decision rules and more complex discrete choice models. In particular, we derive a connection between approximate decision rules and a dynamic bivariate probit model with nonparametric correlated random effects and $AR(1)$ transitory errors. We also employ a relatively new simulated maximum likelihood algorithm that is easy to implement and that corrects for possible biases due to classification errors in reported participation and birth outcomes (see Keane and Wolpin (2001) and Keane and Sauer (2005)).

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. 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. 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 2000 (waves 1 through 7). Birth outcomes in 2001 (wave 8) of the survey are not observed due to a censoring problem. Hence 2001 is excluded from the estimation sample. We limit the set of countries to Italy, Spain and France because they constitute a natural subgroup of countries within the EU. These three countries have "similar" cultural environments (e.g., majority religion and attitudes towards gender roles). Importantly, they also differ substantially in social policies. This will be demonstrated in Section 7 below.

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 widespread in the female labor supply literature and we adhere to them. 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 (see Nicoletti and Peracchi (2003)). The final estimation sample contains 830 women from Italy, 713 women from Spain and 993 women from France observed over seven years (1994 through 2000). The extent of sample selection generated by these restrictions is similar in each country.

Table 1 presents descriptive statistics by country. The means in the table are calculated by first computing average values over the seven-year panel for each woman, and then calculating averages over all women in the country-sample. 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 2001 Euros), female labor market participation rate, and annual birth rate. The raw data display a positive correlation across countries in work and fertility outcomes.

In order to see how work and fertility choices change over time, Figures 1 and 2 display the annual labor market participation and 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. In the latter part of the 1990s, participation rates in Spain begin to converge to those in Italy, while Italian participation rates remain mostly constant. French participation rates fluctuate a bit more than those in Italy and Spain.

Figure 2 graphically illustrates that birth rates are consistently highest in France over the sample period. Spanish birth rates start out quite high, 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.

An aspect of 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, 37% and 39%, respectively. These two modal points account for more than three-quarters of the distribution. In Spain, relatively less women always work than in Italy, 22%, but many more women never work, 49%. The percentages in France are quite different: a larger proportion of women always work, 46%, and a smaller proportion never work ,18%. In all three countries, the two modal points in the distribution are at the "corners".[2]

Strong persistence in female labor supply can also be discerned from Table 3, which

[2] The descriptive statistics displayed in this section for France, Italy and Spain can be easily compared to similar statistics for the US reported in Hyslop (1999), and for Germany reported in Croda and Kyriazidou (2004).

presents average rates of transition between employment state in year t-1 and employment state in year t. The diagonals of the matrices in each country show that both persistence in participation, and persistence in nonparticipation, is relatively highest in Italy. In France, it is much more common for women to move from nonparticipation to participation, while in Spain there is more movement from participation to nonparticipation. The patterns in the transition matrices are broadly consistent with a negative association between overall participation rates and persistence.[3]

4 Model

In this section we specify a dynamic utility maximization model of female labor supply and birth decisions, and derive the model's approximate decision rules. In the next section, we discuss the details of the approximation as well as the estimation technique and identification.

4.1 Basic Structure

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 possible fertility complications 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

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

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 $U_{it}\left(\cdot\right)$ is the utility flow.

[3] Similarly, 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 employment to unemployment and less likely to enter from unemployment to employment, compared to males.

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

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

In $t < T$, the value of each choice combination is the current period utility flow plus discounted expected lifetime utility in time $t+1$. The state space in time $t+1$, $S_{i,t+1}$, is updated according to the laws of motion in the endogenous state variables to be described below. In $t = T$, there is no future component to the alternative specific value functions.

The utility flow $U_{it}(\cdot)$ in (1) and (2) is assumed to take the general form,

$$U_{it}(\cdot) = U_{it}\left(h_{it}, b_{it}, C_{it}, h_{i,t-1}, N_{it}, L, K, \varepsilon_{it}^{h}, \varepsilon_{it}^{b}\right) \tag{3}$$

where C_{it} is current period consumption, $h_{i,t-1}$ is last period's employment status, N_{it} is the current stock of children, L is an aggregate measure of labor market flexibility, K is an aggregate measure of child care services, and ε_{it}^{h} and ε_{it}^{b} are time t preference shocks to working and giving birth, respectively.

To justify the set of arguments in (3), consider the following linear utility function as an example,

$$U_{it}(\cdot) = C_{it} + \left(\gamma_{0h} + \gamma_{1h}C_{it} + \gamma_{2h}h_{i,t-1} + \gamma_{3h}N_{it} + \varepsilon_{it}^{h}\right) h_{it} + \left(\gamma_{0b} + \varepsilon_{it}^{b}\right) b_{it}. \tag{4}$$

where γ_{2h} is a linear function of the aggregate measures L and K,

$$\gamma_{2h} = \gamma_{2h0} + \gamma_{2h1}L + \gamma_{2h2}K. \tag{5}$$

The parameters in (4) and (5) have straightforward interpretations. γ_{0h} is the marginal utility of working in year t, reflecting the utility cost of work effort. γ_{1h} measures the extent to which the marginal utility of consumption varies with participation status. γ_{2h} captures the utility cost saved from not having to adjust last period's participation status. γ_{3h} is the marginal utility of an additional child when participating in the labor market relative to not participating. γ_{0b} is the marginal utility (or disutility) of giving birth in year t.[4]

Note that γ_{2h} is a key state dependence parameter. As in random coefficient models, γ_{2h} is also further modelled. In equation (5), γ_{2h} is specified to be a (deterministic) function of the institutional environment. This specification explicitly recognizes that the cost of adjusting last period's participation status is influenced by job search costs, which are in turn influenced by the extent of labor market flexibility L (e.g., the supply of part-time jobs and temporary employment contracts). The cost of adjusting last period's employment status is influenced by child care costs, which are in turn influenced by the supply of child care services K.

It is maintained throughout the analysis that L and K are taken as given by the individual decision-maker This can be justified by considering that the supply of part-time jobs, and other flexible employment contracts, as well as the supply of child care services in the countries that we examine, are mostly determined by governments. Lags and inefficiencies in public sector responses to changes in demand, as well as slowly changing institutions in general, serve to reduce the endogeneity problem. Although we will not use proxies for L and K directly in estimation, due to a lack of sufficient individual and time-series variation, equation (5) is important for clarifying the logic of our indirect approach to inferring the effect of social policies. In short, social policies influence the cost of adjusting participation status, and hence the degree of state dependence in female labor supply.

The per-period budget constraint in the lifetime utility maximization model is simply specified as

$$y_{it}^{f} h_{it} + y_{it}^{m} = C_{it} + C_n N_{it} \tag{6}$$

where y_{it}^{f} is the woman's labor market earnings in year t, y_{it}^{m} is the partner's labor market earnings in year t (a proxy for "transitory" nonlabor income), and C_n represents the goods-cost per child. y_{it}^{m} will not be further modeled but will rather appear directly in estimation (in logs). The average of y_{it}^{m} over the sample period (a proxy for "permanent" nonlabor income) will partially determine the distribution of individual preference effects (see below).

[4] Linear utility functions similar to the one specified in (4) have been used before in the literature (see, e.g., Eckstein and Wolpin (1989), Francesconi (2002), and Keane and Wolpin (2002)). Utility functions of this form are generally identifiable in structural estimation.

This helps account for the endogeneity of nonlabor income.

Let the wife's labor market earnings y_{it}^{f} be further determined by

$$y_{it}^{f} = g\left(x_i', H_{it}, r_{it}, t, \varepsilon_{it}^{f}\right) \tag{7}$$

where $g(\cdot)$ is a general function of the covariate vector x_i', accumulated actual work experience during the sample period H_{it}, region of residence in the current period r_{it}, a time effect t, and a productivity shock ε_{it}^{f}.

The vector of covariates x_i' in (7) contains proxies for accumulated human capital prior to the start of the sample period. The start of the sample period for each individual i is denoted as $t = \tau_i$. More specifically, the vector x_i' is $x_i' = \left\{E_{i\tau_i}, a_{i\tau_i}, a_{i\tau_i}^2\right\}$ where $E_{i\tau_i}$ is the education level by the start of the sample period, and a_{τ_i} is the woman's age upon entry to the sample (a proxy for potential experience). As with nonlabor income, the endogeneity of education level is accounted for in estimation by allowing education to partially determine the distribution of individual preference effects. Note that the first period of observed data for each woman $t = \tau_i$, which is the age of entry into the sample, will generally not be the start of the theoretical decision process $t = \tau$. We deal with this initial conditions problem using Heckman's approximate solution, which we will describe in more detail in the next section.

The laws of motion for the endogenous state variables in the dynamic program are,

$$\begin{aligned} N_{i,t+1} &= N_{it} + b_{it} \\ H_{i,t+1} &= H_{it} + h_{it} \end{aligned} \tag{8}$$

where the initial conditions are $N_{it} = N_{i\tau_i}$ and $H_{i\tau_i} = 0$. The initial (reported) stock of children at the start of the sample period is augmented by one for each birth during the sample period. Similarly, accumulated actual work experience during the sample period is augmented by one for each period a woman chooses to work. Note that both N_{it} and H_{it} are potential sources of state dependence in addition to participation adjustment costs working through $h_{i,t-1}$.

4.2 Additional Error Structure

The work and birth preference shocks ε_{it}^{h} and ε_{it}^{b} in the general utility function in (3) are given additional structure as follows,

$$\begin{aligned} \varepsilon_{it}^{h} &= \alpha_i^h + \xi_{it}^h \\ \varepsilon_{it}^{b} &= \alpha_i^b + \xi_{it}^b \end{aligned} \tag{9}$$

where α_i^j, $j = h, b$ are time-invariant individual preference effects, and ξ_{it}^j, $j = h, b$ are transitory preference shocks. The time invariant effects capture permanent unobserved heterogeneity related to immutable (or slowly changing) preferences for a career and for family. The α_i^j's induce serial correlation in the error terms.

Rather than imposing a parametric distribution on the α_i^j's, we assume that they are random with a discrete distribution that has three mass points. That is,

$$\begin{aligned} \alpha_i^h &= \theta_1^h A_{1i} + \theta_2^h A_{2i} \\ \alpha_i^b &= \theta_1^b A_{1i} + \theta_2^b A_{2i} \end{aligned} \tag{10}$$

where A_{1i} is a dummy variable for unobserved "type" 1, A_{2i} is a dummy variable for unobserved "type" 2, and A_{0i} is a dummy for unobserved "type" 0, which is the base type. The structure in (10) allows for distinct career and family preference effects through the coefficients θ_1^j and θ_2^j, $j = h, b$. The exact form of the discrete mixing distribution will be given below.[5]

In order to capture possible persistence in unobserved wage offers, the productivity shock ε_{it}^{f} is also assumed to be serially correlated. However, it is given an $AR(1)$ structure,

$$\varepsilon_{it}^{f} = \rho \varepsilon_{i,t-1}^{f} + v_{it} \tag{11}$$

where v_{it} is a serially uncorrelated transitory error component.

As will become more apparent below, because we estimate approximate decision rules, and do not use data on female wages, the empirical estimates will be robust to several

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

variations on the error structure described above. The important point is that the error structure above provides a more explicit theoretical grounding for introducing random effects and $AR(1)$ serially correlated errors into the estimation of approximate decision rules.

4.3 Approximate Decision Rules

Instead of adopting specific functional forms for $U_{it}(\cdot)$ and $g(\cdot)$, and numerically solving the dynamic programming model for the exact decision rules, we characterize the approximate decision rules of the more general model. An important reason for adopting the approximate solution technique in this context is that the computational burden of calculating an exact solution for each country would be severe.[6]

The first step in the characterization of approximate decision rules involves substituting the female wage into the budget constraint and then substituting the budget constraint into the choice specific $U_{it}(\cdot)$'s.[7] This yields a distinct state space S_{it}^{hb} for each work and birth choice combination.

For example, consider the basic structure of the model, the linear utility function in (4), and the state dependence equation in (5). Substitution yields the following S_{it}^{hb}'s,

$$\begin{aligned}
S_{it}^{00} &= \{N_{it}, y_{it}^m\} \\
S_{it}^{10} &= \left\{N_{it}, h_{i,t-1}, h_{i,t-1}L, h_{i,t-1}K, x_{it}', H_{it}, r_{it}, t, y_{it}^m, \varepsilon_{it}^h, \varepsilon_{it}^b, \varepsilon_{it}^f\right\} \\
S_{it}^{01} &= \left\{N_{it}, y_{it}^m, \varepsilon_{it}^h, \varepsilon_{it}^b\right\} \\
S_{it}^{11} &= \left\{N_{it}, h_{i,t-1}, h_{i,t-1}L, h_{i,t-1}K, x_{it}', H_{it}, r_{it}, t, y_{it}^m, \varepsilon_{it}^h, \varepsilon_{it}^b, \varepsilon_{it}^f\right\}.
\end{aligned} \tag{12}$$

Note that even though the S_{it}^{hb}'s in (12) differ by choice combination, each choice probability will *not* have a distinct set of covariates. The decision rules of the optimization problem depend on the entire state space, S_{it}, as indicated in (1) and (2). This is because

[6] See the discussion in Keane and Wolpin (1997) on different approaches to structural estimation and especially Keane and Wolpin (2002). See Buchinsky and Gotlibovski (2006) for a different type of approximation.

[7] The overwhelming majority of related studies on labor market participation 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.

the value of a particular choice combination is computed by comparing the values of all choice combinations. Utility maximization implies that S_{it} is the union of S_{it}^{00}, S_{it}^{10}, S_{it}^{01}, and S_{it}^{11}, and each choice probability is a function of all the variables appearing in the state space S_{it}. In the above example, the union of the S_{it}^{hb}'s is,

$$S_{it} = \left\{ N_{it}, h_{i,t-1}, h_{i,t-1}L, h_{i,t-1}K, x_{it}', H_{it}, r_{it}, t, y_{it}^{m}, \varepsilon_{it}^{h}, \varepsilon_{it}^{b}, \varepsilon_{it}^{f} \right\}. \tag{13}$$

To see this more clearly, and without loss of generality, consider the myopic version of the model. In the myopic version there is no future component to the alternative specific value functions even in $t < T$, i.e., $\delta = 0$.[8] Denote $d_{it}^{hb} = 1$ if alternative (h_{it}, b_{it}) is chosen and $d_{it}^{hb} = 0$, otherwise. Utility maximization implies the following comparison of all utility flows in each period t,

$$\begin{aligned}
d_{it}^{00} &= 1 \text{ when } U_{it}(0,0) - U_{it}(j,k) > 0, \ (j,k) \neq (0,0) \text{ or } F_{it}^{00}(S_{it}) > 0 \\
d_{it}^{10} &= 1 \text{ when } U_{it}(1,0) - U_{it}(j,k) > 0, \ (j,k) \neq (1,0) \text{ or } F_{it}^{10}(S_{it}) > 0 \\
d_{it}^{01} &= 1 \text{ when } U_{it}(0,1) - U_{it}(j,k) > 0, \ (j,k) \neq (0,1) \text{ or } F_{it}^{01}(S_{it}) > 0 \\
d_{it}^{11} &= 1 \text{ when } U_{it}(1,1) - U_{it}(j,k) > 0, \ (j,k) \neq (1,1) \text{ or } F_{it}^{11}(S_{it}) > 0
\end{aligned} \tag{14}$$

Estimating approximate decision rules is accomplished by choosing a functional form for $\Pr\left(d_{it}^{hb} = 1\right) = \Pr\left(F_{it}^{hb}(S_{it}) > 0\right)$. The contribution of the optimization model is to provide a firm theoretical grounding for the common set of covariates, S_{it}, that appear in each choice probability. For example, the model implies that both $h_{i,t-1}$ and H_{it} should be included in estimation. This is in contrast to previous research that imposes more arbitrary restrictions such as only a first-order Markov process in lagged choices (see, e.g., Hyslop (1999)).

It also follows from the approximate decision rule approach that estimation will be robust to alternative model structures as long as these alternative structures produce the same S_{it}. For example, incorporating job offer probabilities and/or permanent layoff probabilities in the model, say to indirectly capture the effects of labor market regulations, will not yield

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

different estimates, unless it implies that additional observable covariates should be included in the state space, or there should be an alternative error structure.

5 Estimation

In this section, we develop the connection between estimation of the approximate decision rules and a dynamic bivariate probit model with nonparametric correlated random effects and $AR(1)$ errors. In the second subsection, we describe the simulated maximum likelihood (SML) algorithm used to estimate the approximate decision rules. In the third subsection, we briefly discuss identification issues.

5.1 Estimating Approximate Decision Rules

Estimation of the approximate decision rules of the optimization model proceeds by specifying $Pr\left(F_{it}^{hb}\left(S_{it}\right)>0\right)$ in the following way,

$$\begin{aligned}
\Pr\left(d_{it}^{00}=1\right) &= \Pr\left(F_{it}^{00}\left(S_{it}\right)>0\right)=\int_{-\infty}^{0}\int_{-\infty}^{0} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \\
\Pr\left(d_{it}^{10}=1\right) &= \Pr\left(F_{it}^{10}\left(S_{it}\right)>0\right)=\int_{0}^{\infty}\int_{-\infty}^{0} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \qquad (15)\\
\Pr\left(d_{t}^{01}=1\right) &= \Pr\left(F_{it}^{01}\left(S_{it}\right)>0\right)=\int_{-\infty}^{0}\int_{0}^{\infty} f\left(H_{it}^{*}\left(S_{it}\right),B_{it}^{*}\left(S_{it}\right)\right)dH_{it}^{*}dB_{it}^{*} \\
\Pr\left(d_{t}^{11}=1\right) &= \Pr\left(F_{it}^{11}\left(S_{it}\right)>0\right)=1-\sum\nolimits_{hb\in\{(00),(10),(01)\}}\Pr\left(F_{it}^{hb}\left(S_{it}\right)>0\right)
\end{aligned}$$

where $f\left(\cdot\right)$ is the bivariate normal density. The choice probabilities in (15) are those of a bivariate probit model.[9]

To be consistent with bivariate probit choice probabilities, $H_{it}^{*}\left(S_{it}\right)$ and $B_{it}^{*}\left(S_{it}\right)$ in (15) must be distributed bivariate normal. This accomplished by specifying $H_{it}^{*}\left(S_{it}\right)$ and

[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 (2002)). Bivariate probits are generally more parsimonious.

$B^*_{it}(S_{it})$, for $t > \tau_i$, as linear functions of S_{it},

$$\begin{aligned} H^*_{it}(S_{it}) &= \alpha_{0h} + \alpha_{1h} y^m_{it} + \alpha_{2h} N_{it} + \alpha_{3h} h_{i,t-1} + \alpha_{4h} H_{it} + \alpha_{5h} x'_i + \alpha_{6h} r_{it} + \alpha_{7h} t \\ &\quad + \alpha_{8h} A_{1i} + \alpha_{9h} A_{2i} + \alpha_{10h} \varepsilon^f_{i,t-1} + v_{it} + \eta^h_{it} \\ B^*_{it}(S_{it}) &= \alpha_{0b} + \alpha_{1b} y^m_{it} + \alpha_{2b} N_{it} + \alpha_{3b} h_{i,t-1} + \alpha_{4b} H_{it} + \alpha_{5b} x'_i + \alpha_{6b} r_{it} + \alpha_{7b} t \\ &\quad + \alpha_{8b} A_{1i} + \alpha_{9b} A_{2i} + \alpha_{10b} \varepsilon^f_{i,t-1} + v_{it} + \eta^b_{it} \end{aligned} \tag{16}$$

where the η^j_{it}'s, $j = h, b$ are assumed to be independent of v_{it}, and distributed bivariate normal with zero means and unit variances. The η^j_{it}'s are error components that capture deviations of the approximate decision rules from the exact ones. The exact participation and fertility decision rules would likely have distinct non-linear functional forms. Note that the η^j_{it}'s also including the omitted variables L and K, which are common to $H^*_{it}(S_{it})$ and $B^*_{it}(S_{it})$. The η^j_{it}'s absorb L and K because, as mentioned earlier, their direct effects are not identifiable, due to a lack of sufficient individual and time-series variation in aggregate proxies for labor market flexibility and child care services.

Because the choice probabilities in (15) are conditional on unobserved type, they must be weighted by type probabilities in order to obtain unconditional likelihood contributions for each individual. The three mass point probabilities, which constitute the mixing distribution of the individual effects, are specified as

$$\begin{aligned} \Pr(A_{1i}) &= L^A_1(y^m_{ip}, E_{i\tau_i}) \\ \Pr(A_{2i}) &= L^A_2(y^m_{ip}, E_{i\tau_i}) \\ \Pr(A_{0i}) &= 1 - \Pr(A_{1i}) - \Pr(A_{2i}) \end{aligned} \tag{17}$$

where $L^A_k(\cdot)$, $k = 1, 2$ are logistic in form with different coefficients for each k. The logistic function ensures that each mass point probability remains between zero and one during iterations. As mentioned earlier, the type probabilities are functions of nonlabor income and education. More specifically, "permanent" nonlabor income y^m_{ip} enters the type probabilities, rather than transitory nonlabor income y^m_{it}, where y^m_{ip} is the average of y^m_{it} over the sample period. Entering the endogenous variables y^m_{ip} and $E_{i\tau_i}$ into the type probabilities is motivated by the correlated random effects model (see Chamberlain (1984))[10]

[10] Preliminary estimations indicated that separate permanent and transitory nonlabor income effects were

In order to explicitly address the initial conditions problem in the dynamic bivariate probit, we make use of the Heckman approximate solution (Heckman (1981)). The Heckman approximate solution to the initial conditions problem entails specifying $H_{it}^{*}(S_{it})$ and $B_{it}^{*}(S_{it})$ functions in the initial sample period $t = \tau_i$ without lagged endogenous state variables, and with errors that are correlated with the error terms in $t > \tau_i$.

The $H_{i\tau_i}^{*}(S_{i\tau_i})$ and $B_{i\tau_i}^{*}(S_{i\tau_i})$ functions take the form,

$$\begin{aligned} H_{i\tau_i}^{*}(S_{i\tau_i}) &= \lambda_{0h} + \lambda_{1h} y_{i\tau_i}^{m} + \lambda_{2h} x_i' + \lambda_{3h} r_{i\tau_i} + \lambda_{4h} A_{1i} + \lambda_{5h} A_{2i} + v_{i\tau_i} + \eta_{i\tau_i}^{h} \\ B_{i\tau_i}^{*}(S_{i\tau_i}) &= \lambda_{0b} + \lambda_{1b} y_{i\tau_i}^{m} + \lambda_{2b} x_i' + \lambda_{3b} r_{i\tau_i} + \lambda_{4b} A_{1i} + \lambda_{5b} A_{2i} + v_{i\tau_i} + \eta_{i\tau_i}^{b} \end{aligned} \quad (18)$$

where the correlation between the initial period errors and the errors during the sample period arises through the time-invariant individual effects and the $AR(1)$ serial correlation in $\varepsilon_{i,t-1}^{f}$ (see equation (11)).[11]

Equations (15)-(18) establish the link between the approximate decision rules of the model and a dynamic bivariate probit with nonparametric correlated random effects, $AR(1)$ errors, and Heckman's approximate solution to the initial conditions problem. Estimation of the approximate decision rules of this form would be difficult using classical maximum likelihood techniques. In particular, calculation of choice probabilities with $AR(1)$ serially correlated errors requires multiple integration. Thus, it is more computationally practical to use SML. The SML algorithm that we employ is described in the next subsection.

5.2 The SML Algorithm

The SML algorithm that we use to estimate the approximate decision rules was originally developed in Keane and Wolpin (2001) for estimating the exact decision rules of dynamic programming problems and overcoming missing data problems. In Keane and Sauer (2005), the algorithm was tested and shown to also be useful for estimating more general dynamic discrete choice models. The algorithm is easier to implement than other SML algorithms

hard to empirically identify when entered together into either (16) or (17). There was no other set of covariates that could be empirically identified in the type probabilities.

[11] The variance of v_{it_i} is adjusted so that the productivity shock is stationary. In addition, α_{10b} in (16) is set to zero for purposes of identification. Thus, $AR(1)$ serial correlation affects only $H_{it}^{*}(S_{it})$.

(e.g., GHK) since it relies on unconditional simulations of the model. The algorithm also corrects for biases that arise in non-linear discrete choice models due to classification error in reported choices.

The SML algorithm proceeds as follows. For each individual, and for each unobserved type, two independent standard normal deviates are drawn in the initial sample period. The standard normal deviates are transformed into bivariate normal deviates using the lower diagonal Choleski factor of the bivariate normal distribution. The standard normal deviates are also used for generating the $AR(1)$ serial correlation in subsequent periods as in equation (11).

Given a trial vector of parameters, draws for the error terms, and the covariates reported in the data, $H^*_{i\tau_i}(S_{i\tau_i})$ and $B^*_{i\tau_i}(S_{i\tau_i})$ are calculated according to (18). The simulated participation and birth choices in the initial sample period are then determined by $h^m_{i\tau_i} = I\left(H^*_{i\tau_i}(S_{i\tau_i}) > 0\right)$ and $b^m_{i\tau_i} = I\left(B^*_{i\tau_i}(S_{i\tau_i}) > 0\right)$, where m represents the replication number. Given initial period simulated choices, the state space is updated according to (8).

Simulated choices for the subsequent six decision periods are then constructed by drawing additional bivariate normal deviates in each period, computing the values of $H^*_{it}(S_{it})$ and $B^*_{it}(S_{it})$ in (16), and then determining $h^m_{it} = I(H^*_{it}(S_{it}) > 0)$ and $b^m_{it} = I(B^*_{it}(S_{it}) > 0)$. The state space is updated accordingly. This procedure is repeated a total of M times ($M = 750$) for each unobserved type, and each individual, to form the type-specific simulated choice sequences $\left\{\left\{\{h^m_{it}\}^T_{t=\tau_i}\right\}^N_{i=1}\right\}^M_{m=1}$ and $\left\{\left\{\{b^m_{it}\}^T_{t=\tau_i}\right\}^N_{i=1}\right\}^M_{m=1}$ for each woman in the sample.

Formation of the type-specific likelihood contribution for each woman i entails specifying classification error rates that relate simulated choices in period t (h^m_{it} and b^m_{it}) to the reported choices in the data for that period (h^*_{it} and b^*_{it}). The classification error rate model is,

$$\begin{aligned}
\pi^h_{01tm} &= \Pr(h^*_{it} = 1 \mid h^m_{it} = 0) = L^h_1(h^m_{it}) \\
\pi^h_{10tm} &= \Pr(h^*_{it} = 0 \mid h^m_{it} = 1) = L^h_2(h^m_{it}) \\
\pi^b_{01tm} &= \Pr(b^*_{it} = 1 \mid b^m_{it} = 0) = L^b_1(b^m_{it}) \\
\pi^b_{10tm} &= \Pr(b^*_{it} = 0 \mid b^m_{it} = 1) = L^b_1(b^m_{it})
\end{aligned} \tag{19}$$

where $\pi^j_{00tm} = 1 - \pi^j_{01tm}$ and $\pi^j_{11tm} = 1 - \pi^j_{10tm}$ for $j = h, b$. $L^j_k(\cdot)$, $k = 1, 2$, $j = h, b$

are logistic functions. The classification error rates are given a logistic form to ensure that estimated probabilities remain between zero and one during iterations. As is common in the classification error literature, the probability of reporting a particular choice is a function of the current true (simulated) choice but is not directly affected by covariates (see Hausman, Abrevaya and Scott-Morton (1998)).

Note that because there are M simulated participation and birth choices in every period t, for each unobserved type of individual, two sequences of classification error rates will be generated for each unobserved type. The two classification error rate sequences are $\left\{\left\{\pi^h_{jktm}\right\}_{t=\tau_i}^T\right\}_{m=1}^M$ and $\left\{\left\{\pi^b_{jktm}\right\}_{t=\tau_i}^T\right\}_{m=1}^M$ where j denotes the simulated choice h^m_{it} (b^m_{it}) and k denotes the reported choice h^*_{it} (b^*_{it}).

An unbiased simulator of the type-specific likelihood contribution for each woman i is then formed by calculating the product of participation classification error rates over time, calculating the product of birth classification error rates over time, multiplying these two products together, and then averaging over the M replications. More formally,

$$\widehat{P}\left(h^*_i, b^*_i \mid A_{1i}, A_{2i}, \theta\right) =$$

$$\frac{1}{M}\sum_{m=1}^{M}\prod_{t=\tau_i}^{T}\left(\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi^h_{jktm} I\left[h^m_{it}=j, h^*_{it}=k\right]\right\}\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi^b_{jktm} I\left[b^m_{it}=j, b^*_{it}=k\right]\right\}\right) \tag{20}$$

where h^*_i and b^*_i are vectors containing woman i's reported participation and birth outcomes over the sample period, and θ is the vector of model parameters. This particular formulation of the type-specific conditional likelihood contribution assumes that classification error in reported participation status is independent of classification error in reported birth outcomes. Construction of the unconditional likelihood contribution for each woman i requires weighting the conditional likelihood contributions in (20) by the mixing distribution in (17).

Because the sample log-likelihood is not everywhere smooth in θ, the objective function is maximized using a non-gradient based optimization routine. However, standard errors are computed off of a sample log-likelihood that is smooth in $\widehat{\theta}$, where the smoothing is accomplished by forming importance sampling weights (see Keane and Wolpin (2001) and Keane and Sauer (2005) for details).

5.3 Identification

The main identification issues that arise in this context are i) separate identification of state dependence, permanent unobserved heterogeneity, and $AR(1)$ serial correlation, and ii) separate identification of classification error rates from all other parameters of the model. We will briefly discuss these two issues in turn.

For purposes of illustration, consider the data on reported participation outcomes only. The strong persistence in participation status, as demonstrated in Tables 2 and 3, could be solely due to serial correlation in the error term (either in the form of random effects or an $AR(1)$ error component). If this were the case, then conditional on the current X, lagged X's would not help to determine current participation status. However, if true state dependence is present, then conditional on the current X, lagged X's will help to determine the current employment outcome, assuming that there is no direct effect of lagged X's. This is the variation in the data which distinguishes state dependence from serial correlation.

Although one can nonparametrically identify separate state dependence and serial correlation effects, it is not possible to distinguish state dependence from different forms of serial correlation (e.g., random effects or an $AR(1)$ error) without parametric assumptions (see Chamberlain (1984)). Moreover, if serial correlation in the errors is incorrectly modelled, one may obtain a spuriously significant state dependence coefficient. Misspecification of the degree of state dependence can also lead to incorrect inferences about serial correlation. For these reasons, it is important to include general forms of state dependence and serial correlation in the model, as we do in equation (16). Note that identification of the non-parametric discrete mixing distribution follows from the analysis in Heckman and Singer (1984).

The conditions required for separate identification of classification error rates from the other parameters of the model were previously analyzed in a static discrete choice context by Hausman, Abrevaya and Scott-Morton (1998). They show that full identification (as opposed to semi-parametric identification up to scale) requires a non-linear true choice probability, as well as a monotonicity condition. The corresponding monotonicity condition in our case is $\pi^h_{01tm}+\pi^h_{10tm} < 1$, which states that the sum of participation classification error rates should not exceed one. This condition ensures that the probability a woman reports participating in the labor market is increasing in the true probability, say $F(X_{it}'\beta)$, which in turn is increasing in $X_{it}'\beta$. A further discussion on the identification of classification error rates can be found in Keane and Sauer (2006). Keane and Sauer (2006) also empirically demonstrate that large biases in the relative importance of state dependence and unobserved heterogeneity can result if even a small amount of classification error in the data is ignored.

6 Estimation Results

6.1 Point Estimates and Standard Errors

Table 4 reports selected SML estimates of the approximate decision rule coefficients in (16), and their standard errors. The first two columns of the table present estimation results for the French $H_{it}^{*}(S_{it})$ and $B_{it}^{*}(S_{it})$ functions. Column (1) reveals negative effects of transitory nonlabor income and very young children on labor market participation. Both effects are precisely estimated. More education has a significant positive effect on labor market participation. The state dependence effect associated with lagged participation status has a very strong positive impact, while the state dependence effect arising from accumulated human capital during the sample period is not strong nor precisely measured. The estimated coefficient on $\varepsilon_{i,t-1}^{f}$ suggests nonnegligible dynamics arising from unobserved productivity shocks.[12]

The coefficients on A_{1i} and A_{2i} indicate a strong and precisely measured influence of permanent unobserved heterogeneity. 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 estimates in Column (2) show that the presence of a child in the house (regardless of the age of the child) significantly decreases the propensity to give birth. The youngest

[12] Because of a lack of regional relocation in the data, r_{it} in (16) appears in estimation as a set of exogenous region dummies. The time effect t appears as unrestricted year dummies. $E_{i\tau_i}$ is discretized into $E_{i\tau_i}^{s}$ and $E_{i\tau_i}^{t}$, representing secondary and tertiary education levels, respectively. N_{it} is discretized into $ychild_{it} \leq 3$ and $ychild_{it} > 3$, representing the youngest child being three years of age or less, and the youngest child being older than three.

child being less than three has a relatively stronger impact. Having achieved a tertiary level of education in France 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). Nonlabor income and secondary education increase the probability of being type 1 and type 2 relative to type 0, while tertiary education decreases the type 1 and 2 probabilities. The significance of these variables implies that nonlabor income and education are indeed endogenous, and that it was important to account for this in estimation (albeit indirectly). It is also important to note that the main influence of nonlabor income on birth outcomes is indirect through the type probabilities.

The estimated classification error rates for France reveal that the probability of reporting participation in the labor market, when the true state is nonparticipation, is .065. The probability of reporting nonparticipation, when the true state is participation, is .021. 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. Although small in magnitude, both estimated classification error rates are significantly different from zero.[13]

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 productivity shocks. Note that the point estimate of the effect of lagged participation is strongest in magnitude in Italy and second strongest in Spain

[13] Keane and Sauer (2006) obtain classification error rates for reported labor market participation that are similar in magnitude.

(marginal effects will be examined below).

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 across countries, indicating substantially different distributions of permanent unobserved heterogeneity. Nonlabor income and education significantly affect the type probabilities in Italy and Spain in the same directions as in France. The classification error rates for Italy and Spain are small in magnitude as in France, but are all significantly different from zero.

6.2 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. Second, participation and birth outcomes are simulated according to the estimated approximate decision rules. The third step is to run separate linear regressions of the simulated participation and birth outcomes on the variables appearing in the approximate decision rules. The coefficients produced by these linear regressions are the simulated marginal effects.

The estimated marginal effects in Table 5 clearly illustrate the overriding importance of state dependence arising from lagged participation status. 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 for permanent unobserved heterogeneity (the type dummies) are much smaller than the marginal effect of lagged participation status, but are generally the second most important determinant of current participation status.

The marginal effects in the birth equations indicate that age (not shown) and the presence of children are the strongest determinants in each country. The effects of nonlabor income and education are weak. Permanent unobserved heterogeneity is much more important than previous participation status or actual work experience during the sample period.

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. In what follows, we will discuss the results for the participation equation only.

The base specification for the adjusted R-squared analysis (referred to as the X's) includes nonlabor income, age of youngest child dummies, age, age-squared and education dummies. The adjusted R-squared, $\overline{R}_1^2$, for this specification is quite low. $\overline{R}_1^2$ is .06 in France, .13 in Italy and .14 in Spain. Adding the region and year dummies to the base specification (referred to as the fe's) yields a $\overline{R}_2^2$ which is only slightly higher. Adding the simulated serially correlated productivity shock ($AR(1)$) has a more substantial effect. $\overline{R}_3^2$ reaches .16 in France, .26 in Italy, and .27 in Spain. However, adding permanent unobserved heterogeneity (the A's) instead of the serially correlated productivity shock yields a much more substantial rise. $\overline{R}_4^2$ increases to .53 in France, .48 in Italy and ..39 in Spain. Adding the A's and the $AR(1)$ shock simultaneously also shows that permanent unobserved heterogeneity is relatively more important than $AR(1)$ serial correlation.

In order to assess the relative importance of state dependence, the next specification adds lagged participation status to the X's and the fe's. Notice that $\overline{R}_6^2$ jumps dramatically to .77 in France, .89 in Italy and .85 in Spain. This again illustrates the overriding importance of state dependence relative to permanent unobserved heterogeneity and $AR(1)$ serial correlation. The next experiment adds accumulated experience during the sample period to lagged participation status, the X's and the fe's. There is virtually no change in the adjusted R-squared. In the final row of the panel, all of the variables appearing in the approximate decision rules are joined together. $\overline{R}_8^2$ increases by relatively little over $\overline{R}_6^2$ in all three countries. According to the way in which we devise the relative importance decomposition, state dependence arising from lagged participation status is by far the most important factor in explaining the persistence in female labor supply. There is also a clear ordering. State dependence is relatively more important in Italy and Spain than in France.

6.3 Model Fit

The reliability of our results rests to a certain extent on the ability of the estimated approximate decision rules to fit the raw data. We assess model fit by comparing descriptive statistics produced from simulations of the estimated model to the descriptive statistics displayed earlier. Figure 3 compares the annual participation rates across countries in the raw data (as in Figure 1) to predicted participation rates. As can be seen clearly in the graph, the predicted rates track the actual rates very well. The order in the level of participation rates across countries is reproduced, as are the trends over time within each country.

Figure 4 compares the annual birth rates in the raw data (as in Figure 2) to predicted annual birth rates. Again, the order in the level of birth rates across countries is reproduced as are the time/age trends in each country. However, the fit is relatively less good than in Figure 3. Figure 4 indicates that the model slightly under-predicts birth rates in each country. Very low birth rates in each country is probably an important reason why it is more difficult to fit these rates, as opposed to participation rates.

Table 6 displays the distribution of years worked during the sample period (as in Table 3) and the corresponding predicted distribution. Notice that the predicted distribution reproduces the two modal points at zero and seven years worked. The predicted distribution also reproduces the correct ordering of modal points across countries. The proportion working zero years in France and Italy is captured accurately, but is slightly over estimated in Spain. The proportion working all seven years is captured well in Spain and Italy, but is a bit too high in France.

Continuing in the direction of dimensions in the data which are generally more difficult to fit, Table 7 compares actual and predicted transition matrices. In France, the diagonal rates are a bit too high. However, the ordering of transition frequencies is exactly reproduced. In Italy, the fit is better. The ordering of transition frequencies is again exactly reproduced. In Spain, as opposed to France and Italy, the model predicts too many transitions out of employment and hence the employment to employment transition rate is too high.

Overall, the fit of the model to the data is quite good. The good fit suggests that the estimated approximate decision rules are reasonable proxies for the exact decision rules, and reliable benchmarks for the policy simulations we perform below.

7 Discussion

The estimated approximate decision rules reveal that state dependence, arising from the cost of adjusting participation status from one period to the next, is stronger in Italy and Spain (where labor market participation rates are relatively lower) compared to France. Using equation (5) as motivation, in the next subsection we note the connection between aggregate proxies for labor market flexibility and child care availability and the cross-country pattern of state dependence effects estimated in the model.

In the second subsection, we use the estimated approximate decision rules to perform additional simulations. 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 estimated decision rule parameters of another country. Since we hold constant the country-specific distribution of unobserved heterogeneity, any change in work and fertility choices will be driven almost entirely by differential state dependence effects, and hence differences in employment and social policies.

7.1 Labor Market Flexibility and Child Care Services

As a proxy for labor market flexibility, consider 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 indicate that employment should be more stable 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. Since stricter EPL generally leads to less turnover, and an overall lower supply of jobs, it should be associated with higher job search costs and stronger state dependence. Column (1) of Table 6 ranks France, Italy and Spain in terms of EPL. Consistent with equation (5), Italy has the highest index score as well as the greatest degree of estimated state dependence. On the other hand, there are no differences in the index score between Spain and France.

Column (2) compares the three countries according to the proportion of workers employed in part-time jobs. Assuming that the underlying demand for part-time work is the same in all three countries, then the higher the proportion of workers employed in part-time jobs, the greater is the supply of such jobs and the more flexible is the labor market. According to this measure, there are sharper differences between the countries. Italy and Spain are similar, but France has a much higher proportion of workers employed in part-time work. This second proxy is also consistent with the cross-country pattern of estimated state dependence effects.

If we likewise assume that the underlying demand for child care services is the same in each country, then the percentage of children in child care will proxy for the supply of child care services and the level of child care search costs. Column (3) reports the percentage of children less than three years of age in child care in France, Italy and Spain. Consistent with equation (5), Italy and Spain have much lower percentages relative to France. Column (4) compares the across countries the average opening hours of child care (for children less than three years of age). France has a greater availability of child care services on this measure as well. Column (5) compares public child benefits as a percentage of GDP. The French percentage far exceeds the percentages in Italy and Spain.[14]

Overall, the data in Table 6 indicate that in Italy and Spain, relative to France, part-time work is in relatively scarce supply and child care services are typically inadequate in quantity and characterized by extreme rigidity in the number of weekly hours available (see also Del Boca (2002)). This raises job search costs and child care search costs and leads to stronger state dependence in female labor supply. Because of the substantial adjustment costs, 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 also lower (see also Boeri, Del Boca and Pissarides (2005)).

[14] 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)).

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 (e.g., nonlabor income and education) are assumed to remain the same after changing the institutional environment. Moreover, we hold constant the country-specific distribution of unobserved heterogeneity in the simulations, so that any change in work and fertility choices will be driven almost entirely by differential state dependence effects, and hence differences in employment and social policies.

In the top panel of Table 7, Italian and Spanish women face the estimated French decision rule parameters. 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 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 only 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 small amount (0.2 percentage points). The main advantage of the more flexible French environment would be much a higher participation 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 birth rate among less educated Spanish women would be a negligible 0.1 percentage points, but more educated Spanish women would increase their birth rate by 2.1 percentage points. In contrast to Italian women, both less educated and more highly educated Spanish women would increase their labor market participation rates were they to face the French institutional environment, and more educated Spanish women would increase their 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 participation rates in the Italian and Spanish environments, and Spanish women would benefit, in terms of participation outcomes, from the Italian environment. There is an especially large increase in the participation of more educated Spanish women when facing the Italian parameters. This is because the effect of secondary education on participation decisions is much stronger in Italy than in Spain.

Overall, the simulations suggest that institutions that promoted more flexible labor markets and child care availability in Italy in Spain, as in France, would lead to a considerable convergence to the higher French female labor market participation rates. Note that since we have limited the set of countries to only those with similar cultural characteristics (such as majority religion and attitudes towards gender roles), these simulations provide a better approximation to the influence of employment and social policies than if we had attempted to include a larger set of countries in the study. Nonetheless, the simulations probably provide only an upper bound on the effect of the institutional environment.

8 Conclusion

In this paper, we formulate a dynamic utility maximization model of female labor market participation and fertility choices and estimate approximate decision rules using data from the ECHP on married women in Italy, Spain and France. The main focus of the paper is to estimate the relative importance of state dependence and permanent unobserved heterogeneity in work and family preferences across countries. The estimated approximate decision rules indicate that in each country first-order state dependence is by far the most important factor in explaining the persistence in female labor supply behavior. The first-order state dependence effect reflects the costs of adjusting participation status from one period to the next, and we indirectly examine the relationship between these estimated costs of adjustment and aggregate measures of social policies. We find that the ranking of state dependence effects across countries is correlated with the ranking in the extent of labor market flexibility and the supply of child care services.

We also use the estimated approximate decision rules to quantify the effects of the institutional environment by simulating counterfactual female participation and birth outcomes when women in one country face the approximate decision rule parameters of a different country. Because we hold constant the distribution of unobserved heterogeneity, and because of the overriding importance of the first-order state dependence effect in each country, changes in simulated outcomes will be mostly due to different employment and child care policies. The results of the simulation suggest that Italian and Spanish women would substantially increase their participation rates were they to face the relatively more flexible French environment. The convergence of Italian and Spanish participation rates to the higher French rates is especially pronounced amongst less educated women.

One limitation of our study is that we were only able to provide indirect evidence on the effects of social policies on female labor market participation and persistence. This is the only way to proceed when aggregate proxies for social policies do not vary sufficiently over individuals and over time. If better proxies for social policies were to become available, then direct evidence of policy effects might be obtainable by directly entering the proxies into the individual's approximate decision rules. This remains an area for future data collection and research.

Table 1

Descriptive Statistics by Country

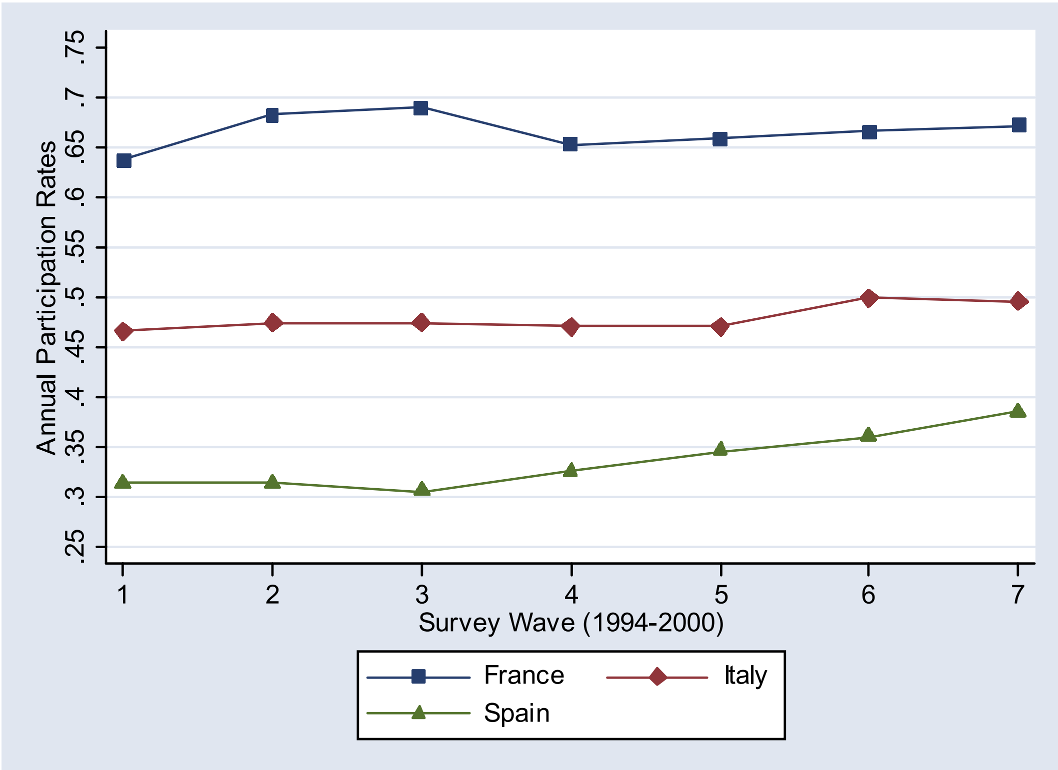
	France	Italy	Spain
Age	36.64	37.81	37.27
	(5.79)	(5.19)	(5.51)
Secondary Education	.73	.52	.49
	-	-	-
Tertiary Education	.28	.08	.20
	-	-	-
Youngest Child 0-3	.15	.11	.12
	-	-	-
Youngest Child >3	.73	.81	.81
	-	-	-
Husband's Earnings	20.10	16.61	17.34
	(20.09)	(7.35)	(9.73)
Birth Rate	.06	.04	.05
	-	-	-
Employment Rate	.66	.48	.34
	-	-	-
N	993	830	713

Note: Individual means for each women over seven years are calculated, and then the means are averaged over all women in the country sample. Husband's earnings are in thousands of 2001 Euros. Standard deviations of continuous variables are in parentheses.

Figure 1

Annual Participation Rates by Country

(1994-2000)

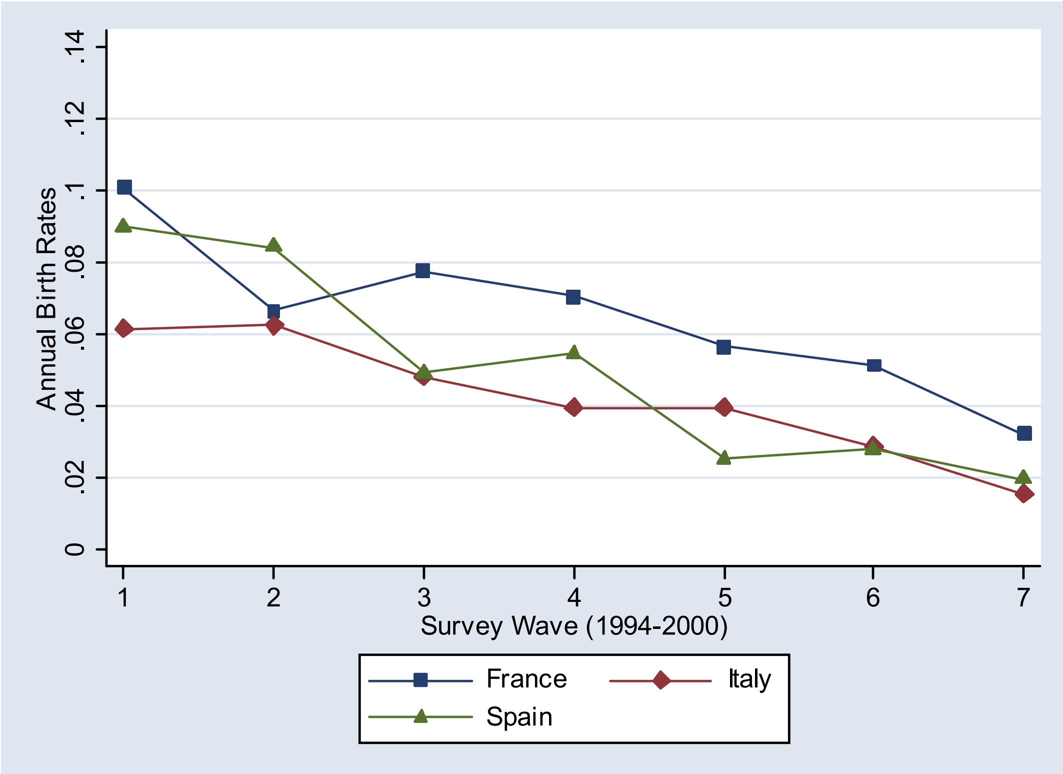


Note: Survey wave 1 corresponds to the year 1994 and survey wave 7 corresponds to the year 2000.

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.

Table 2

Distribution of Panel Years Worked by Country

(Column Percentages)

Years Worked	France	Italy	Spain
0	.180	.395	.492
1	.045	.053	.086
2	.039	.042	.060
3	.050	.037	.048
4	.058	.032	.036
5	.068	.034	.027
6	.099	.037	.032
7	.459	.369	.219
	1.000	1.000	1.000

Table 3

Employment Transitions by Country

(Row Percentages)

France		
	Work in t	
Work in t-1	0	1
0	.839	.161
1	.073	.927
Italy		
	Work in t	
Work in t-1	0	1
0	.932	.068
1	.064	.936
Spain		
	Work in t	
Work in t-1	0	1
0	.928	.072
1	.112	.888

Table 4

Selected SML Point Estimates and Standard Errors

	France		Italy		Spain	
	Work	Birth	Work	Birth	Work	Birth
	(1)	(2)	(3)	(4)	(5)	(6)
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)
$h_{i,t-1}$	1.7499	−.0357	2.1426	.1359	1.8681	.0336
	(.0835)	(.1373)	(.1170)	(.1571)	(.1390)	(.2140)
A_{1i}	1.6432	1.1187	2.0312	1.2444	1.6137	1.0539
	(.0993)	(.1282)	(.1327)	(.2357)	(.1897)	(.3098)
A_{2i}	−1.3122	1.0689	−1.4669	1.0359	−1.3456	1.3129
	(.1172)	(.1409)	(.1383)	(.2354)	(.2062)	(.3158)
$\varepsilon_{i,t-1}^f$	.5933	–	.7778	–	.7361	–
	(.0341)		(.0127)		(.0237)	
$\Pr(A_{1i})$,$\Pr(A_{2i})$	(.5382, .2237)		(.3300, .5444)		(.4753, .3818)	
π_{01},π_{10}	(.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			
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_{1i}	.127	.058	.063	.035	.073	.026
A_{2i}	−.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 Decomposition			
$\overline{R}^2_1$ (X's)	.060	.117	.128	.075	.136	.064
$\overline{R}^2_2$ (X's,fe)	.063	.133	.143	.084	.142	.072
$\overline{R}^2_3$ (X's,fe,$AR(1)$)	.159	.133	.260	.084	.274	.072
$\overline{R}^2_4$ (X's,fe,A's)	.529	.143	.478	.087	.392	.082
$\overline{R}^2_5$ (X's,fe,$AR(1)$,A's)	.623	.143	.596	.087	.523	.082
$\overline{R}^2_6$ (X's,fe,$h_{i,t-1}$)	.773	.133	.887	.084	.850	.077
$\overline{R}^2_7$ (X's,fe,$h_{i,t-1}$,H_{it})	.774	.133	.887	.084	.850	.077
$\overline{R}^2_8$ (X's,fe,$AR(1)$,A's,$h_{i,t-1}$,H_{it})	.821	.144	.900	.088	.870	.085

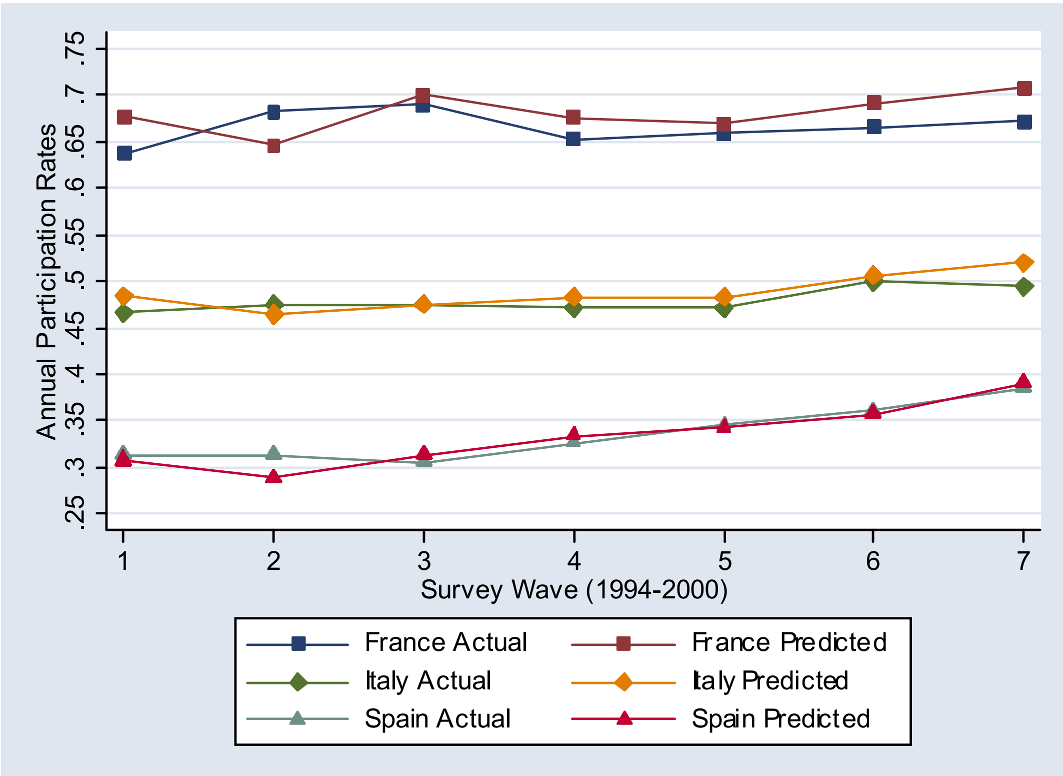
Note: The X's include nonlabor income, children dummies, age, age-squared and education dummies. The fixed effects (fe) are year and region dummies.

Figure 3

Annual Participation Rates by Country

Actual vs. Predicted

(1994-2000)



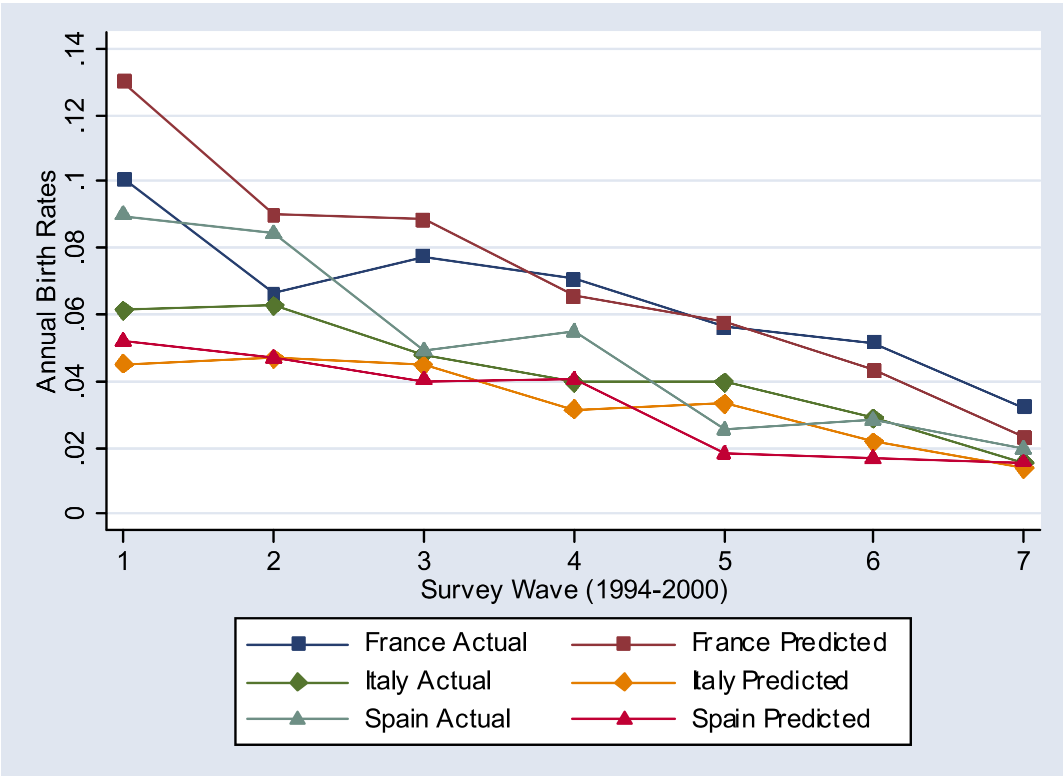
Note: Survey wave 1 corresponds to the year 1994 and survey wave 7 corresponds to the year 2000.

Figure 4

Annual Birth Rates by Country

Actual vs. Predicted

(1994-2000)



Note: Survey wave 1 corresponds to the year 1994 and survey wave 7 corresponds to the year 2000.

Table 6

Distribution of Panel Years Worked by Country

Actual vs. Predicted

(Column Percentages)

Years Worked	France		Italy		Spain	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
0	.180	.195	.395	.423	.492	.562
1	.045	.039	.053	.033	.086	.044
2	.039	.033	.042	.035	.060	.030
3	.050	.041	.037	.024	.048	.028
4	.058	.035	.032	.030	.036	.035
5	.068	.061	.034	.027	.027	.037
6	.099	.034	.037	.010	.032	.013
7	.459	.561	.369	.418	.219	.251

Table 7

Employment Transitions by Country

Actual vs. Predicted

(Row Percentages)

France

Actual			Predicted		
	Work in t			Work in t	
Work in t-1	0	1	Work in t-1	0	1
0	.839	.161	0	.907	.093
1	.073	.927	1	.035	.965

Italy

Actual			Predicted		
	Work in t			Work in t	
Work in t-1	0	1	Work in t-1	0	1
0	.932	.068	0	.966	.034
1	.064	.936	1	.025	.975

Spain

Actual			Predicted		
	Work in t			Work in t	
Work in t-1	0	1	Work in t-1	0	1
0	.928	.072	0	.963	.037
1	.112	.888	1	.033	.967

Table 8

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)
France	1.4	31.0	39	10	2.8
Italy	1.5	17.4	7	8	0.9
Spain	1.4	17.2	5	6	0.4

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 9

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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