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Imputing Individual Effects in Dynamic Microsimulation Models
An application of the Rank Method

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Imputing Individual Effects in Dynamic Microsimulation Models.

An application of the Rank Method.

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Abstract

Dynamic microsimulation modeling involves two stages: estimation and forecasting. Unobserved heterogeneity is often considered in estimation, but not in forecasting, beyond trivial cases. Non-trivial cases involve individuals that enter the simulation with a history of previous outcomes. We show that the simple solutions of attributing to these individuals a null effect or a random draw from the estimated unconditional distributions lead to biased forecasts, which are often worse than those obtained neglecting unobserved heterogeneity altogether. We then present a first implementation of the Rank method, a new algorithm for attributing the individual effects to the simulation sample which greatly simplifies those already known in the literature. Out-of-sample validation of our model shows that correctly imputing unobserved heterogeneity significantly improves the quality of the forecasts.

Keywords: Dynamic microsimulation, Unobserved heterogeneity, Validation, Rank method, Assignment algorithms, Female labor force participation, Italy

JEL Classification: C53, C18, C23, C25, J11, J12, J21

Introduction

Dynamic microsimulation models are used for policy analysis and evaluation, and to project into the future trends of economically relevant variables, taking into account the likely evolution of their determinants. The dynamics of each process are generally governed by coefficients that have been estimated on historical data. The choice of the econometric specification is therefore crucial for the quality of the predictions. This is particularly true when unobserved heterogeneity (UH) is an issue, given that microsimulations have been explicitly developed to allow distributional analysis and hence a thorough consideration of individual differences. However, netting out the estimated coefficients from the effects of individual-specific components does not guarantee better quality forecasts, as long as these individual-specific components are not appropriately simulated. This is an easy task if the simulation sample is the same as the estimation sample (statistical packages generally provide an estimation of the individual effect for each estimation unit), or if "new" simulated individuals enter the simulation without a history of previous outcomes. If this is not the case, drawing from the unconditional estimated distribution of individual effects is wrong, and conditional estimated distributions should be used instead. Given that deriving conditional (posterior) distributions is often very difficult analytically and very burdensome computationally, a different approach has emerged, which consists in drawing all individual effects from their unconditional distributions, and then assigning each random draw to a simulated individual with the aim to minimize an overall distance between realized and simulated outcomes (Panis, 2003). Unfortunately, the available optimal assignment algorithms developed in the operations research literature work in polynomial time (Carpaneto *et al.*, 1988; Burkard *et al.*, 2008), thus increasing a lot the computational burden of the simulation. Simpler solutions, which appear to be common practice in the microsimulation literature, suggest assigning a null individual effect to all simulated individuals, or at best a random draw from the unconditional estimated distributions of the individual effects. In this paper we show that these solutions are inadequate, when discrete-choice processes are involved. We also provide a first empirical test of the Rank method proposed in Richiardi (2012), which works in logarithmic rather than polynomial time. While the method has been shown to provide optimal solutions to the assignment problem, the empirical relevance of correctly imputing the unobserved individual effects to the simulated population was still to be assessed.

This is what we do in the present paper. We develop a discrete-time dynamic microsimulation of labor supply and household formation in Italy, and compare the outcomes in terms of participation rates of different subgroups of the population of four versions of the model: a benchmark in which all processes are modeled by means of simple pooled probit specifications with lagged endogenous variables, and three alternatives in which we specify random effect dynamic probit models, where initial conditions are estimated following Heckman (1981a, 1981b). These three variations differ in how the individual UH is imputed in the simulated population: in the first one we assign a null value for UH to all individuals, in the second one we assign each individual a random draw from the estimated unconditional distribution of UH, while in the third one we use the Rank method to assign each individual the random draw that best matches his observed past history. We show that the differences in projected outcomes are large and significant. We base our estimations on the complete series of the European Community Household Panel (ECHP), which runs from 1994 to 2001, in order to be able to perform out-of-sample validation in the subsequent years. With the limitations arising from the fact that the ECHP was discontinued in 2001, and replaced only in 2004 by a different survey (EU-SILC), and the fact that the most recent years cannot be used for validation due to the impact of the Great Recession, we find evidence that the forecasts obtained with imputation of UH remain sensibly more on track with historical data.

For the purpose of our study, Italy is a particularly apt case, as the female participation rates are still very low as compared to other EU countries, despite having markedly increased over the past decades (Del Boca et al., 2006). This leaves space for a further increase (Leombruni and Richiardi, 2006), and makes the outcome of the microsimulation highly sensitive to the estimated coefficients.

The paper is structured as follows. Section 2 discusses the methodological problem that motivates our analysis; section 3 describes the evolution and the main determinants, according to the literature, of female labor force participation in Italy and elaborates on why this is an interesting testbed for our exercise; section 4 discusses the econometric specifications and estimates; section 5 describes the microsimulation model; section 6 presents our out-of-sample validation of the different imputation methods; section 7 discusses the main results of our preferred specification, where individual effects are imputed with the Rank method; conclusions follow.

2. Unobserved heterogeneity and dynamic microsimulations

Microsimulation models often consider dichotomous processes, e.g. labor market participation, household formation, fertility. They are generally modeled by comparing the value of a latent outcome variable *y^**, assumed to be a function of observable characteristics of the individual, with a threshold.[1] In the case of a probit,

(1)
$$
\begin{aligned}
y^*_{i,t} &= x_{it}'\beta + \varepsilon_{i,t} \\
y_{i,t} &= 1 \quad \text{if} \quad y^*_{i,t} > 0 \\
y_{i,t} &= 0 \quad \text{otherwise} \\
\varepsilon_{\mathrm{i,t}} &\approx \mathrm{N}(0,1)
\end{aligned}
$$

which gives raise to the standard expression

[1] The same argument applies, *mutatis mutandis,*to a multinomial setting with more than two states.

(2) $$\Pr[y_{i,t}=1\,|\,x_{i,t}]=\Phi(x_{i,t}'\beta)$$

where Φ is the cumulative distribution function of a standard normal distribution, x is a vector of strictly exogenous observed explanatory variables for individual *i* at time *t*, and the vector *β* contains the parameters to be estimated.

Often, these processes are characterized by a high degree of persistence, *i.e.* the explanatory power of lagged dependent variables is very high. Including the lagged dependent variable in this settings leads to

(3) $$\Pr[y_{i,t}=1\,|\,x_{i,t},y_{i,t-1}]=\Phi(x_{i,t}'\beta+\gamma y_{i,t-1})$$

with γ being an additional parameter to be estimated.[2]

This poses no problems if observed persistence is only due to true state dependence. In this case, being in a certain state (e.g. participate to the labor market) in a specific time period, in itself, increases the probability of being in the same state in subsequent periods. However, observed persistence may also be due to permanent UH:[3]

(4) $$\varepsilon_{i,t}=\alpha_i+\eta_{i,t}$$

where α_i indicates the individual-specific effect.

According to equation (4), individuals are heterogeneous with respect to characteristics that are relevant for the chance of being (and remaining) in a certain state. For example, an individual might participate to the labor market despite unfavorable observable characteristics, due to favorable unobservable characteristics like a special taste for work, work ethics, need for money *etc*. These characteristics are likely to be at least to some extent persistent over time; therefore, they increase the likelihood that the individual will also participate in the future. These unobserved individual effects work in every respect as omitted variables. As Wooldridge (2005a, p. 27) puts it, "[i]n nonlinear models, much has

[2] An alternative approach is to use Markovian transitions models, where the processes are split up according to the initial state. This amounts to estimate

(5) $$\begin{aligned}\Pr[y_{i,t}=1\,|\,x_{i,t},y_{i,t-1}=0]&=\Phi(x_{i,t}'\beta_0)\\ \Pr[y_{i,t}=1\,|\,x_{i,t},y_{i,t-1}=1]&=\Phi(x_{i,t}'\beta_1)\end{aligned}$$

or, equivalently,

(6) $$\Pr[y_{i,t}=1\,|\,x_{i,t},y_{i,t-1}]=\Phi(x_{i,t}'\beta_0+x_{i,t}'\delta\, y_{i,t-1})$$

The main advantage is the possibility to allow estimated persistence to vary according with the initial state and the observed individual characteristics, at the cost of a higher number of parameters.

[3] In facts, we can get significant estimates of state dependence coefficients even when there is no true state dependence and persistence is only due to permanent UH (Carro, 2007).

been made about the deleterious effects that ignoring heterogeneity can have on the estimation of parameters, even when the heterogeneity is assumed to be independent of the observed covariates. A leading case is the probit model with an omitted variable. Yatchew and Griliches (1985) show that when the omitted variable is independent of the explanatory variables and normally distributed, the probit estimators suffer from (asymptotic) attenuation bias. This result is sometimes cited to illustrate how a misspecification that is innocuous in linear models leads to problems in nonlinear models".[4] Moreover, the individual effect is not independent of the lagged dependent variable, if included among the covariates, as the latter is correlated by construction with the lagged residual, which includes the unobserved permanent individual effect. As a result, estimates of state dependence that fail to account for permanent UH are in general upward biased: the model attributes to true state dependence any individual effect that makes a transition to a different state less likely.[5]

Most microsimulation models now take into account UH, at least in the core processes under study. However, when simulation is involved an additional problem arises, concerning the imputation of the individual effects to the simulated individuals. This is less of an issue in static microsimulations, as the simulation sample generally coincides with the estimation sample, where individual effects can be estimated. On the other hand, dynamic microsimulations generally include many processes (like schooling, household formation, labor market transitions, retirement, etc.): it is quite unlikely that a single dataset exists with all the relevant variables so that it can be used both for estimation of all processes and as a basis for simulation; this being all the more so as models with UH require panel data for estimation. A more common situation is to estimate different processes on different datasets, and then apply the estimated coefficients to some initial population to be simulated forward in time. Moreover, the initial population generally needs to be expanded as the simulation proceeds, possibly including offspring, spouses and immigrants. If the simulated individuals enter the simulation without a history of previous outcomes, the solution is straightforward: sampling random individual effects from the estimated (unconditional) distribution. However, to the extent to which not every individual is simulated from birth (a very unlikely scenario even in cohort models), the simulated individuals in the initial population enter the simulation with a history of previous outcomes. This is also the case whenever the simulated population expands over time with the inclusion of spouses and immigrants. Even newborns can enter the simulation with some pre-set variables. For instance, the ECHP / EU-SILC surveys only record information for individuals aged 16+: if such data are used for estimation of the processes included in the microsimulation (which is common, at least for EU models, given their wide coverage), the simplest solution is to let newborns enter the simulation when they are already grown up, with many education and labor market related events having already been occurred.

[4] See also Cramer (2005).

[5] For applications to models of labor supply, see for instance Haan (2006) and Pacifico (2009).

There are two ways of dealing with the problem of imputing the individual effects to individuals with a history of previous outcomes (Panis, 2003): (i) a Bayesian approach –assigning each individual a random draw from the posterior distribution of heterogeneity given her observed past outcome, and (ii) an optimal assignment approach –sampling all individual effects at once from the unconditional distribution and then assigning to each individual the value for UH that best matches her observed past outcome. Both are generally quite computationally intensive. In particular, existing algorithms developed in the operations research literature work in polynomial time, which is often too slow for practical applications involving several thousand simulated individuals (Richiardi, 2012).

The problem seems to be completely ignored by the microsimulation literature, with the notable exception of Panis (2003). For instance, standard references as Creedy and Kalb (1995), Wolf (2001) and Li and O'Donoghue (2012) do not mention it. Even works focusing on the treatment of UH as Galler (1995) fail to recognize the issue.[6] We have not been able to find a single dynamic microsimulation model where the problem of the imputation of the individual effects is considered. In the absence of specific information, it is reasonable to assume that new individuals are simply given the average individual effect (which is normalized to 0) or, at best, a random draw from the unconditional distributions.

However, as Richiardi (2012) shows, estimating a random intercept discrete choice model (either fixed or random effects) and imputing a null effect to the population to be projected forward in time leads to possibly big biases in forecasting. This is due to the nonlinearity of the latent variable model. To see why, suppose two individuals have the same observables, but they differ because of UH: for the sake of illustration, suppose they have two symmetric individual effects around the mean value of 0. The outcome variable is binary. The average probability of the event of the two heterogeneous individuals is different from the probability of the average individual, with the size of the bias depending on the standard deviation of the individual effect and the direction of the bias depending on the local concavity of the probit or logit transformation: imputing a null individual effect leads to overestimate the probability of the event if the average probability is higher than .5, and to underestimate it if it is lower. Moreover, a break is introduced at an individual level between the past (for which outcomes depend on the true individual effect) and the future (for which outcomes depend only on observables), thus making simulated life trajectories less likely. This can have important consequences, for instance with respect to eligibility to social benefits, seniority accrual, *etc*.

[6] A proper survey of the treatment of UH in dynamic microsimulation models is hampered by the fact that the relevant papers generally devote little space to the presentation of the econometric estimates – sometimes even the list of covariates is missing. This is a well-known problem with the microsimulation approach: being in general large models, developed over the course of many years and often building on pre-existing work, microsimulation models end up being close to black boxes. Sometimes detailed explanations can be found in technical papers that however remain unpublished or have a limited circulation, while published articles often restrict their attention, given the page constraint, on some specific result / addition to the basic model.

While the first problem (the forecasting bias) is solved by attributing each simulated individual a random draw from the unconditional distribution of individual effects, the latter problem (the break in individual trajectories) is even aggravated, given that the distance between the true and the imputed individual effects gets larger –the variance roughly doubles.

On the other hand, the standard algorithm for solving the optimal assignment problem –the so called Hungarian method– involves writing many lines of code (about 500 lines in a standard Matlab implementation) and works in polynomial time –which is feasible, but slow. Richiardi (2012) has developed an algorithm for optimally assigning the individual effects which works in logarithmic time, rather than polynomial time. His Rank algorithm works as follows:

1. Estimate the individual effect model (on the estimation sample).
2. Compute the predicted probability of the observed outcome, by imposing a null individual effect to all individuals, $\Phi(x'\hat{\beta})$.
3. Compute the difference between the observed outcome and the predicted outcome, $y-\Phi(x'\hat{\beta})$.
4. Order this difference from low to high.
5. Extract *N* values from the estimated unconditional distribution of the individual effects, $\tilde{\alpha}$.
6. Extract *N* values from the estimated unconditional distribution of the idiosyncratic disturbances, $\tilde{\eta}$.
7. Construct the error terms $\tilde{\varepsilon} = \tilde{\alpha} + \tilde{\eta}$ and order them from low to high.
8. Assign the individual effects $\tilde{\alpha}$ to the *N* artificial individuals by matching the two rankings above.

In our microsimulation we use this algorithm, thus providing a first example of its implementation.

3. Female labor supply in Italy

Over the last decades, we observed an increasing long-term trend in female participation rate in most OECD countries. Nevertheless, we also observe persistent differences in levels suggesting that different countries are constrained by country-specific institutional and social factors. Ahn and Mira (2002) and Engelhardt *et al.* (2001) have divided the 21 OECD countries into three groups. The high participation group, in which the participation rate was, at the time of the study, above 60%, includes the U.S., Canada, the U.K., Sweden, Norway, Denmark, Finland and Switzerland. The medium participation group includes countries where the participation rate was in the 50-60% range. Finally, the low participation group includes Italy, Spain and Greece, where the female participation rate was lower than 50%. The latter group was also the target of the the Lisbon 2000 Agenda, which set a goal of (at least) 60% for the female employment rate, to be achieved by 2010. By that year, the female employment rate in Italy was still close to 50%, followed only by Malta in the EU27 ranking.

Low female participation has always been a feature of the Italian labor market (Rondinelli and Zizza, 2011). Education level matters in explaining the gender gap in participation rates: lower education levels are associated with larger gaps (Table 1). Even if participation rates of married women increased over the last several decades (Del Boca et al., 2006), employment rates of mothers with children under six in Italy are still very low (Del Boca, 2003): in facts, more than one fourth of women leave the labor market after a birth (Bratti et al. 2005; Casadio et al. 2008).

	Italy		EU15	
	Men	Women	Men	Women
	%			
Low education	64.5	32.6	67.3	46.4
Medium education	80.7	63.1	82.2	71.2
High education	86.5	77.5	90.4	84.0
Total	73.6	51.2	78.8	65.6

Table 1. Participation rates by level of education, 2010. Source: our elaboration on Eurostat data.

The following factors further help explaining the gender participation gap. First, in spite of the recent institutional changes, the Italian labor market still remains highly regulated: strict rules apply to hiring and firing and specify the types of available employment arrangements; these labor market regulations have been largely responsible for the high female and youth unemployment rates (Bertola *et al.*, 2001). Thus, women have hard time times to enter and re-enter (after breaks during childbearing years) the labor market. This situation affects also participation rates since discouraged women may decide to drop out of the labor force.

Second, part-time employment is still not common in Italy: it accounts for less than 30% of female employment, while it is above 75% in the Netherlands (Eurostat data for 2010): this is detrimental to the participation of married women, particularly those with children (Del Boca, 2002).

Third, women get a disproportionate share of the burden with respect to housework and child bearing within the family. In facts, the reconciliation of roles within and outside the family is more difficult for a working mother than for a working father, and often the strategies adopted are completely different: as the budget constraint becomes more binding men typically increase the time devoted to paid work and women decrease their working time or even exit the labor market (Anxo et al., 2007; Mencarini and Tanturri, 2004; Lo Conte and Prati, 2003).

Fourth, the public childcare system is inadequate and does not help enough in reducing the direct costs of participation; in particular, the number of available slots is limited with respect to Oecd standards (especially in some regions in the South) and the hours of childcare offered are typically non compatible with full-time jobs. As for what concerns children in school age, things do not improve much as school days often end in the mid-afternoon, much earlier than the end of full-time work days (Del Boca, 2002; Del Boca and Vuri, 2007).

Finally, a general cultural attitude against female participation in the labor market, which also partly explains the factors reviewed above, is only slowly fading away, as older generations are replaced by younger cohorts.

Of all these determinants, in our model we take explicitly into account the demographic evolution of the population and the changes in its composition by level of education, while we keep the institutional factors (labor market regulations and the public childcare system) as fixed. By considering a cohort effect, we proxy changes in the general cultural attitude, in the division of labor within the family and in the availability of part-time employment.

4. Data, econometric specifications and estimation results

4.1 The data

Input estimations are run using Italian micro-data from all eight waves 1994 to 2001 of the European Community Household Panel (ECHP). The ECHP was a survey conducted annually and provided detailed information on income, work and employment, poverty and social exclusion, housing, health, and many other diverse social indicators concerning living conditions of private households and individuals (aged 16+). Cross section and longitudinal weights were provided in order to achieve representativeness of the total population. The main advantage of ECHP is that it allows analyzing participation in the labor market, schooling and household formation from a dynamic point of view.

The initial population is a random extraction (with replacement) from the 2001 Italian subsample of the ECHP. A large part of the initial population is therefore included in the estimation sample, a case which would make it possible to use the estimated individual effects, rather than imputing them. As we will explain in the validation section, we exploit this continuity between the estimation sample and the simulation sample to assess the advantages of the Rank method (or of any other optimal assignment algorithm for what matters here) over the simpler solutions of imputing a null individual effect or sampling from the unconditional distribution of the individual effects. Moreover, the ECHP was discontinued in 2001 and replaced only three years later by the European Union Statistics on Income and Living conditions (EU-

SILC), a data source that provides micro data with a focus on objective living and employment conditions. At least for the first years after the survey was launched, with too short a longitudinal dimension, using the old estimates on the new population would have been the only choice.

Notwithstanding some disruptions in the time series of indicators between the ECHP and the EU-SILC data due to changes in the sampling strategy, in the structure of the questionnaire and in some of the definitions (European Communities, 2005), we use the 2005-2008 Italian data of the EU-SILC to perform validation analysis of the different simulation approaches.[7]

4.2 Modelling approach

In the econometric literature, there are two ways of treating UH: random effects or fixed effects models. Interested readers can refer to Honoré (2002) for a full discussion on the choice between these two approaches. This paper follows the random effects approach in order to have a fully specified model in which one can estimate all the quantities of interest, including the coefficients of time invariant characteristics (e.g. gender). This allows not only to interpret the coefficients correctly –as in standard microeconometric papers– but, of most importance here, to simulate forward the evolution of the initial population. The random effects approach usually lead to more efficient estimators of the parameters of the model if the distributional assumptions are satisfied. Moreover, traditional maximum likelihood estimator of non-linear panel data models with fixed effects generally exhibits considerable bias in finite sample when the number of periods is not large.[8]

In order for the model's results to be fully parameterized the initial conditions also have to be specified. An initial condition problem arises when the start of the observation period does not coincide with the start of the stochastic process generating individual experiences (iHeckman, 1981a; Arulampalam *et el.*, 2000).[9] Our way to deal with this issue is to use the estimator suggested by Heckman (1981a,

[7] The Italian component of the EU-SILC panel data is available only from 2005 onwards.

[8] Fixed effects estimators of nonlinear panel model can be severely biased due to the incidental parameters problem. This problem arises because unobserved individual characteristics are replaced by sample estimates, biasing estimates of model parameters. As far as we know, the solution proposed are not sqrt(N)-consistent (Honoré and Kyriazidou, 2000; Hahn, 2001; Honoré and Tamer, 2004). Some authors propose modified maximum likelihood estimators that reduces the order of the bias (i.e. Cox and Reid, 1987; Arellano, 2003; Carro, 2007; Arellano and Hahn, 2007; Val, 2009). The latter estimators work only "moderately" well when T is larger than 8, but this is not our case. Recently, Hoderlein *et al.* (2011) has proposed a nonparametric procedure that generalizes the conditional logit approach leading to an estimator based on nonlinear stochastic integral equations that seems to works moderately well in finite sample Monte Carlo simulations.

[9] In dynamic panel data models with unobserved effects, the initial condition problem is an important issue. Many authors studied dynamic linear models with an additive unobserved effect with a special focus on the treatment of the initial condition problem (see, for example, Ahn and Schmidt, 1995; Anderson and Hsiao, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; Hahn, 1999]). The initial condition problem is much more difficult to resolve within non-linear models. Honoré (1993) and Honoré and Kyriazidou (2000) offer examples of the treatment of the initial condition problem in a semi-parametric context. The interested reader can also refer to

1981b)[10]. His approach involves the specification of an approximation to the reduced form equation for the initial condition and allows for cross-correlation between the dynamic equation and the initial condition:

(7) $$\Pr[y_{i,0} = 1 \mid \alpha_i] = \Phi(z_{i,0}'\lambda + \theta\alpha_i)$$

where z_i is a vector of exogenous covariates (including x_{i0} and, eventually, additional variables that can be viewed as "instruments" such as pre-sample variables).[11] Exogeneity corresponds to $\theta = 0$ and can be tested accordingly. Equations (3), (4) and (7) together specify a complete model for the process that can be estimated by maximum likelihood (for details about the estimation see Arulampalam and Steward, 2007).

We use the random effects dynamic probit model for estimating male and female labor force participation, unemployment and living in consensual union. For these processes, we also estimate simple probit models. The other processes (education and fertility) are also modeled by means of probit models.

4.3 Initial status

ECHP and EU-SILC data cover individuals aged 16+. Since we need information on lagged status, individuals enter the simulation at age 17. Assignment to the initial status (in education, activity, employment) is random, based on observed probabilities (Table 2).

	In education	**Active**	**Unemployed**
		Males	
North	79.8%	17.2%	8.6%
Centre	86.0%	10.4%	15.0%
South	82.3%	12.2%	46.9%
		Females	
North	86.7%	12.1%	19.0%
Centre	86.8%	10.2%	35.0%
South	83.7%	9.9%	55.8%

Table 2. Status at age 17. Source: our elaboration on Italian LFS data (2001).

As a scenario, we assume that the share of students will (linearly) converge to 100% by the end of the simulation period (2050).

Heckman (1981a, 1981b), Hsiao (1986), Orme (1997) and Wooldridge (2005b) for a discussion of alternative ways of handling initial conditions in a dynamic non-linear model with UH.

[10] Other possible estimators are the ones proposed by Orme (1997) and Wooldridge (2005). However, the three estimators provide similar results (Arulampalam and Stewart, 2007).

[11] If the vector z_i does not include instruments, the model is identified by the functional form.

4.4 Education

In Italy school attendance is compulsory until age 16, while it is generally illegal to work under 15.[12] Primary school has 8 grades, and students should normally complete it at 13-14. Then, they compulsorily enrol in secondary school, which should last for 5 years. According to Sistan (2006, 2007), secondary school attendance from age 16 to age 18 is above 80% (2005 data), while the probability of achieving a diploma is slightly above 70% (67% for males and 78% for females). Early school leavers (individuals aged 18-24 that achieved at least an education level equal to ISCED 2) are about 22%, higher than the EU-25 average (15%).

Among those who achieved a diploma, three in four enrol at university (79% females; 66% males), while less than one in two of those enrolled actually graduate (51% females; 37% males). Among those who make it, 52% graduates before age 25 and 80% before age 29. Overall, university enrolment rate is about 56%, about the OCSE average (54%). Enrolment rates have increased from 1998 to 2005 (+16%). Dropouts after the first year of university are about 20%, and they remain significant even later. Graduation rates have remained fairly stable over the years. Very few people come back to formal education, once left.

Coherently with this picture, we estimate two separate equations, one for secondary school attendance and one for university attendance. In both cases the probability of being a student at time *t* is modeled as a function of sex, age, age-squared, year of birth and area of residence. Moreover, the model estimation is conditioned on not having entered the labor market. Estimates are reported in Table 3. The probability of being enrolled in secondary school decreases with age, as individuals are supposed take a diploma at about 18-19 years old.

	Secondary school (Probit)			**University (Probit)**		
	Coef.		SE	Coef.		SE
Female	-0.008		0.069	0.113	*	0.055
Age	-11.285	**	2.665	0.691	**	0.214
Age-squared	0.287	**	0.070	-0.016	**	0.004
Centre	0.090		0.098	0.010		0.070
South	0.087		0.081	0.110	**	0.033
Year of birth	0.073	**	0.021	0.036	**	0.014
Constant	-33.024		50.76	-77.856	**	27.901

Table 3. Enrolment. Source: our elaboration on ECHP 1994-2001 data.

[12] Illegal dropouts are approximately zero in primary school and about 1.5% in secondary school (Sistan, 2006).

Unfortunately, the exact moment of graduation is often only poorly observed in ECHP. For this reason, in the microsimulation we use the same coefficients for graduation as in Leombruni and Richiardi (2006), estimated on the 1993-2003 Italian Labor Force Surveys (RTFL) data. Graduation is modeled by means of a constant probability in the relevant age brackets for secondary school, and with a linear term in age for university (Figure 1).

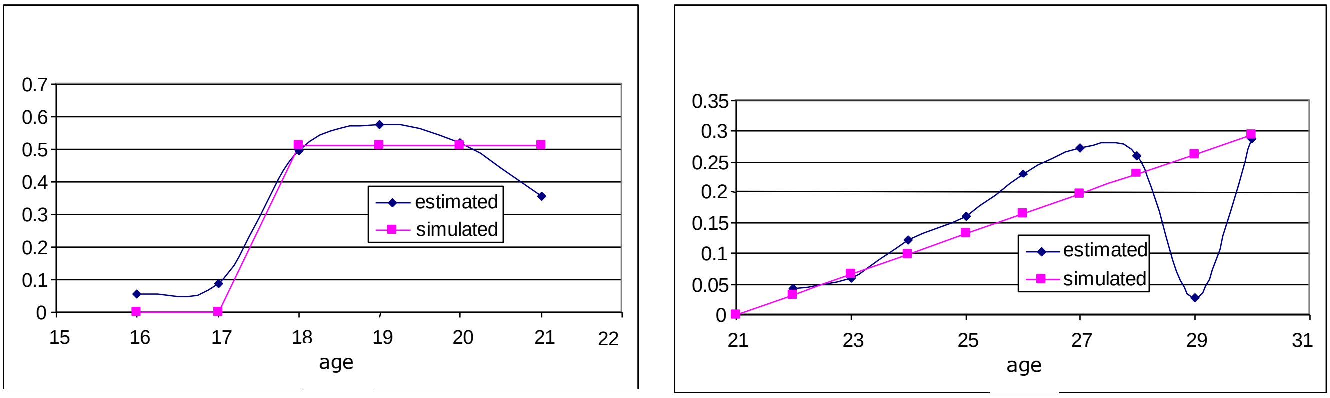

Figure 1. Probability of graduating, high school (left panel) and university (right panel). Source: Leombruni and Richiardi (2006).

4.5 Unemployment and male participation

The unemployment status at time *t* is modeled as function of lagged unemployment status, age, education level, area of residence, the status of student at time *t*-1 and the overall unemployment rate.

Male participation at time *t* is modeled as a function of lagged participation, age, year of birth, education level, area of residence and the status of student at time *t*-1. In both cases, the model estimation is conditioned on not being retired or student. We first estimate standard probit models. To account for UH and solve the initial conditions problem, we then estimate dynamic random effects models. The estimated coefficients and standard errors are shown in Table 4. To compare the probit coefficients with those from the random effects estimators, the latter need to be multiplied by an estimate of $1/\sqrt{(1+\sigma_a^2)}$, where σ_a represents the size of UH (see Arulampalam, 1999). Allowing for the different normalizations, the scaled estimate for lagged participation (unemployment) is 0.5 (0.7), significantly less than the pooled probit estimate. Participation (unemployment) yesterday increases the probability of participating (being unemployed) today. The relationship between male participation and age follows the usual inverse U-shape. Higher education increases male participation and decreases the probability of being unemployed. Living in the south of Italy decreases male participation and increases the probability of being unemployed.

	Unemployment						Male Participation					
	Probit			Dynamic RE model			Probit			Dynamic RE model		
	Coef.		Robust SE	Coef.		SE	Coef.		Robust SE	Coef.		SE
Lag(participation)	---		---	---		---	1.766	**	0.052	0.799	**	0.077
Lag(unemployment)	1.785	**	0.026	1.123	**	0.039	---		---	---		---
Female	0.356	**	0.022	0.592	**	0.049	---		---	---		---
Age	-0.148	**	0.009	-0.256	**	0.020	0.130	**	0.011	0.326	**	0.026
Age^2	0.002	**	0.0001	0.002	**	0.000	-0.002	**	0.000	-0.004	**	0.000
High education	-0.246	**	0.038	-0.582	**	0.083	0.287	**	0.066	0.341	**	0.115
Medium education	-0.237	**	0.022	-0.368	**	0.045	0.110	**	0.032	0.170	**	0.058
Centre	0.283	**	0.035	0.463	**	0.078	-0.054		0.046	-0.104		0.088
South	0.783	**	0.028	1.508	**	0.065	-0.155	**	0.035	-0.313	**	0.069
Year of birth	---		---	---		---	-0.006		0.007	0.010		0.014
Lag(student)	1.147	**	0.043	0.504	**	0.116	0.205	**	0.061	-0.026		0.135
Unempl. rate	11.354	**	1.585	10.076	**	2.828	---		---	---		---
_cons	-0.167		0.229	1.403	**	0.476	9.376		13.075	-24.420		27.245
σ_a	---		---	1.256			---		---	1.071		

Table 4. Unemployment and male participation estimates. Source: our elaboration on ECHP 1994-2001 data.

4.6 Female labor market participation and household formation

We estimate two separate equations, one for labor market participation and one for the choice of living in consensual union.[13] Reflecting our interest in uncovering the presence of dynamic spillover effects from participation to marriage, and from marriage to participation, the equations for female labor market participation and household formation also include cross-effect lagged variables, which are assumed weakly exogenous. Therefore, both participation and living in consensual union at time *t* are modeled as a function of lagged participation, lagged consensual union status, the existence of children under three (at time *t*-1), age, year of birth, level of education, area of residence and being a student (at time *t*-1). Moreover, model estimation is conditioned on not being retired or a student at time *t*. Dummies for the area of residence also capture regional differences in the availability of childcare and other (local)

[13] Female labor force participation and the choice of living in consensual union may of course be correlated. A joint determination of female participation and marital status can be treated extending the dynamic random effects model allowing for correlation in the error terms (see Alessie et al., 2004; Devicienti and Poggi, 2011). Since this is not the focus of the present paper, we do not consider this issue further.

institutional factors. In order to simplify the model and keep a dichotomous participation outcome variable we do not explicitly model work hours. This implies that we do not consider the availability of part-time. Since the share of female part-time employment in the total employment has increased almost linearly since 1990, from about 10% to about 30% with few regional differences[14], this increase is caught by the cohort effect.

As a benchmark, the estimates of the standard pooled probit models are reported in Table 5, columns 1 and 2. Then, column 3 and 4 report the coefficients and standard errors of the dynamic probit model with random effects. As explained above, the random effects probit and pooled probit models involve different normalizations. The scaled estimate of the coefficient on lagged participation (living in consensual union) is 0.9 (2.2), significantly less than the pooled probit estimate: this indicates that omitting permanent UH leads to overestimation of state dependence. There is a lot of heterogeneity that cannot be accounted for by the explanatory variables: the estimated σ_a is equal to 1.2 (0.89). Instead, the estimated coefficients on the other covariate are similar (sometime larger) than the pooled estimates.

Estimated coefficients generally have the expected sign: participation at time *t*-1 increases the probability of participating at time *t*, while living in consensual union and having small children reduce it; having a better education is associated with higher activity rates, while living in the Center and especially in the South of Italy is associated with lower activity rates.

Quite obviously, we find that living in consensual union in any one year strongly increases the probability of living in consensual union in the next year. The probability also increases if the woman has young children. The relationship with age is again inverse U-shaped. The level of education and the area of residence are not significant; instead, being a student at time *t*-1 reduces the probability of living in consensual union at time *t*.

[14] In 2010 the share of female part-time employment was 30.5% in the North, 29.0% in the Centre and 25.4% in the South (Italian LFS data).

Female participation (females)	**Probit** Coef.		Robust SE	**Dynamic RE model** Coef.		SE
Lag(participation)	2.387	**	0.027	1.417	**	0.038
Lag(union)	-0.417	**	0.027	-0.595	**	0.049
Lag(children under 3)	-0.159	**	0.032	-0.197	**	0.050
Age	0.038	**	0.007	0.087	**	0.015
Age2	-0.001	**	0.000	-0.001	**	0.000
High education	0.808	**	0.047	1.665	**	0.093
Medium education	0.371	**	0.021	0.775	**	0.044
Centre	-0.116	**	0.027	-0.355	**	0.064
South	-0.270	**	0.021	-0.738	**	0.052
Year of birth	0.000		0.004	0.009		0.008
Lag(student)	0.549		0.056	0.272	*	0.121
Constant	-1.326		7.845	-19.025		16.684
σ_a				1.218		
Union (females)	**Probit** Coef.		Robust SE	**RE model** Coef.		SE
Lag(participation)	-0.049		0.033	-0.093		0.052
Lag(union)	3.795	**	0.043	3.010	**	0.075
Lag(children under 3)	0.347	**	0.098	0.516	**	0.122
Age	0.074	**	0.010	0.263	**	0.036
age2	-0.001	**	0.000	-0.003	**	0.000
High education	-0.001		0.060	-0.170		0.093
Medium education	-0.029		0.032	-0.135	*	0.057
Centre	0.052		0.042	0.145	*	0.073
South	0.015		0.031	0.003		0.053
Year of birth	0.002		0.007	-0.026		0.014
Lag(student)	-0.530	**	0.066	-0.706	**	0.090
Constant	-7.667		13.146	44.404		28.285
σ_a				0.890		

Table 5. Female participation and household formation estimates. Source: our elaboration on ECHP 1994-2001 data.

Finally, we estimate the probability of having a child at time *t*, as a function of the presence of children aged under three at time *t*-1, the number of children at time *t*-1, dummies about the labor market status at time *t*-1 (in education, in the labor force, in employment), age, level of education, area of residence and the overall fertility rate. Moreover, model estimation is conditioned on living in consensual union and being in the age bracket 17-45. Estimates are reported in Table 6. Again, the coefficients go in the expected direction: the probability of having a child latter initially increases and then decreases with age, decreases if in the household there are already children under three, decreases with the number of children in the household. Having high education increases the probability of having a child, for a given age. No significant geographical differences are found.

Motherhood	**Probit**		
	Coef.		Robust SE
Lag (children under 3)	-0.571	**	0.050
Lag (no. children)	-0.371	**	0.084
Lag (participation)	-0.037		0.046
Lag (unemployment)	-0.087		0.072
Lag (student)	-0.216		0.153
Age	0.287	**	0.043
Age2	-0.006	**	0.001
High education	0.227	**	0.072
Medium education	0.039		0.043
Centre	0.062		0.060
South	0.092		0.073
Fertility rate	11.716	*	5.106
Constant	-4.628	**	0.722

Note: the sample includes only women aged 17-45.

Table 6. Birth probability estimates. Source: our elaboration on ECHP 1994-2001 data.

5. The microsimulation model

Our model is a discrete-time dynamic microsimulation of labor supply, with an open population: flags are switched on and off for partners and children for the female population, but no simulated individuals are actually matched. The microsimulation is comprised of four modules: Demography, Education, Household formation and Employment. Individuals are simulated in the age bracket 17-54, from 2002 to 2050. The overall structure of the microsimulation is depicted in Figure 2. Standard simulation runs involve a base year population of about 40,000 individuals, representative of 60 millions Italians.

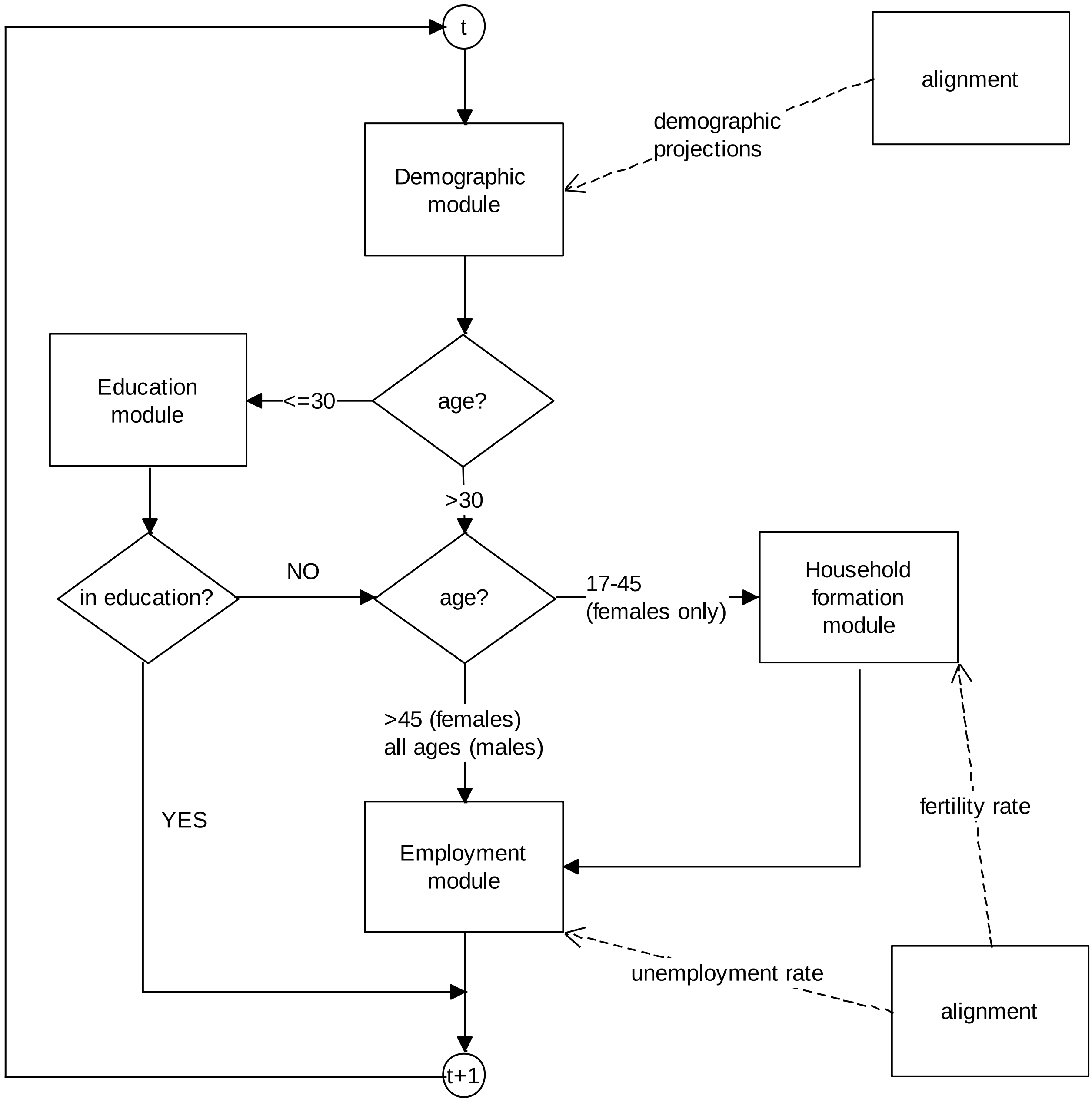

Figure 2. Structure of the microsimulation model.

5.1 Demographic module

Population is aligned to official demographic projections by year, age, gender and macro-area of living (North, Center and South of Italy). Whenever the population is over-represented in a given age, gender and area cell, simulated individuals are killed at random. Whenever the population is under-represented, new individuals are created by cloning at random existing individuals in the same cell (in adjacent cells if the cell is empty). We do not model (internal nor external) migration.

5.2 Education module

We separately model enrolment and graduation, both for secondary school and university. Individuals enter the simulation at 17, after completion of compulsory education. Dropouts at 16 are modelled by aligning the initial status (in education, in the labor force, in employment) to the observed frequencies (see Table 2 above). Dropouts from school exit the education module and enter the labor market module. Students can graduate from secondary school starting at age 18. Those who fail to graduate before age 22 exit the education module and enter the labor market module. Secondary school graduates can enter university. University participation is allowed until age 30, while graduation can take place beginning at age 21. University dropouts leave the education module and enter the labor market module. We make the simplifying assumption that people never go back to education, once they have left. This is justified, as already discussed, by the very small number of students of older ages.

The detected (linear) trends toward higher high school participation are stopped for individuals born in 1990 or later, while those toward higher university participation are stopped for individuals born in 1985 or later (we prudentially assume all trends have already come to an end in the base year).

The flowchart of the Education module is represented in Figure 3.

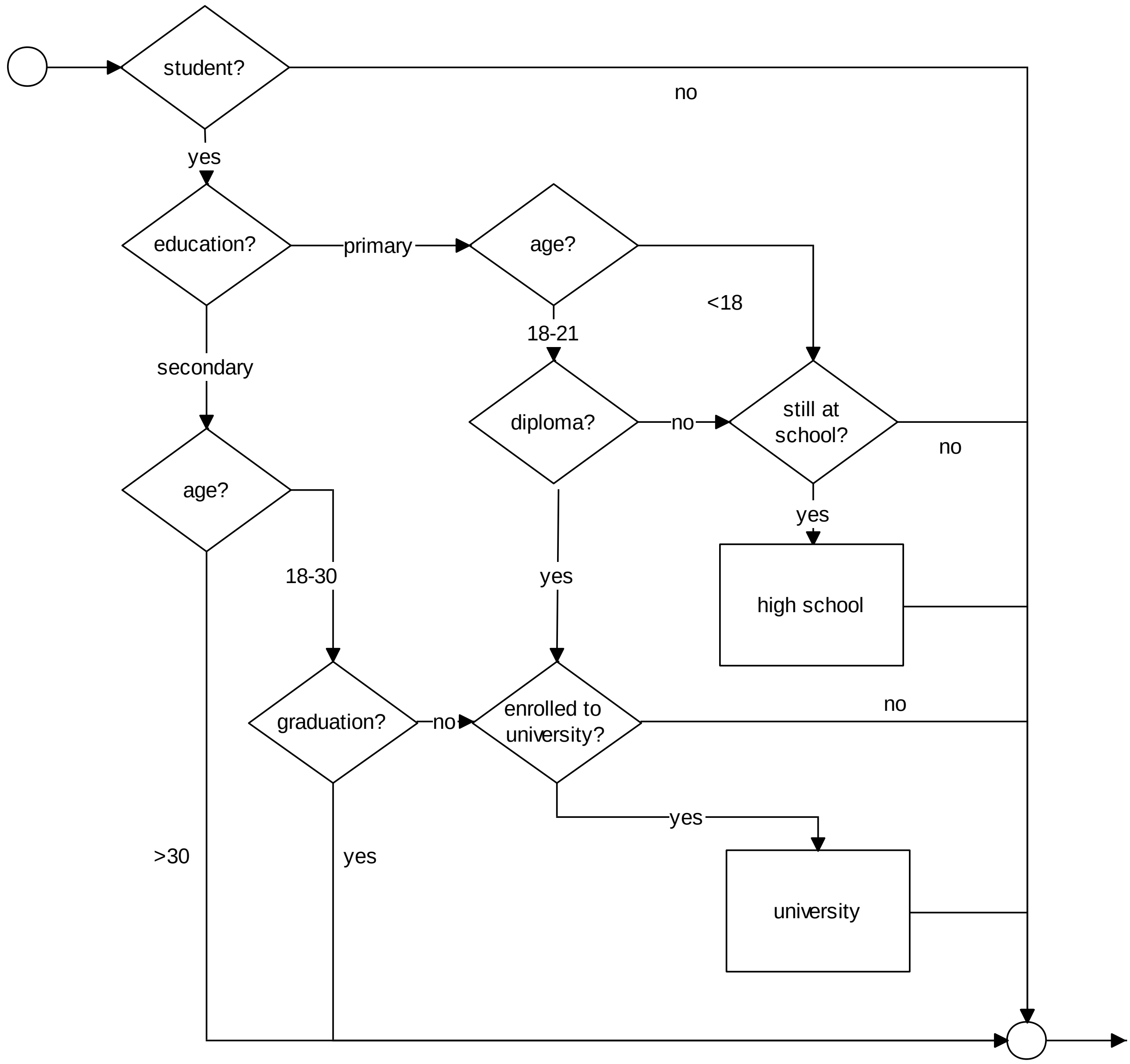

Figure 3. The Education module.

5.3 Household formation module

Given that the presence of a partner is not relevant, at a first order approximation, for male labor market participation, the household formation module is only applied to the female population.[15] It is comprised of two sub-modules: Living in consensual union and Maternity. Women aged 17 or older and who are not student can enter a consensual union. Note that at young ages not living in consensual union is likely to be a choice, while at older ages it might also reflect a partner's death, hence a state of widowhood. The (linear) cohort effect in the equation for living in consensual union is stopped for individuals born in 1990 or

[15] Living in union might well affect the decision about how much to work, and possibly wages; however, we do not model work hours, nor wages.

later. Women aged 17-45 who live in a consensual union can have children. The total amount of births in each year is aligned with demographic data. The flowchart of the Household formation module is represented in Figure 4.

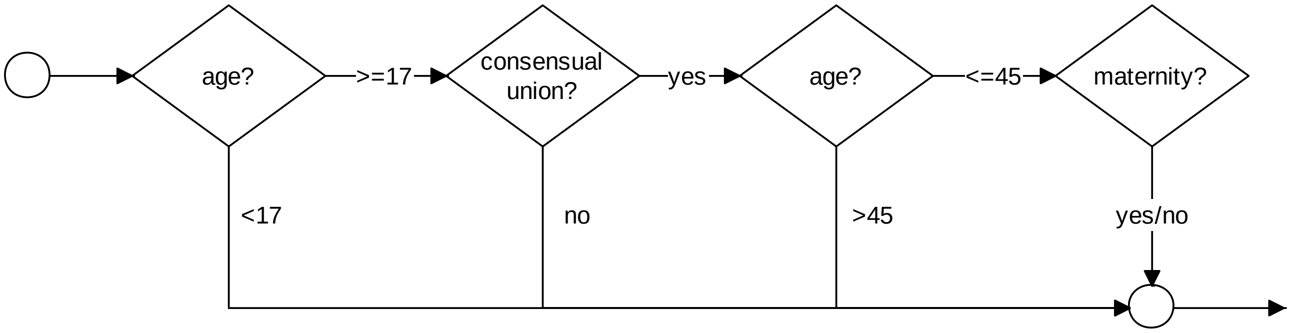

Figure 4. The Household formation module (females only).

5.4 Employment module

The labor market module is applied to all individuals who are not in education or retired (remember individuals enter the simulation above the minimum working age). We consider retirement only for those individuals who are already retired in the initial population, and assume no one can retire before age 55 as the simulation proceeds (this is in line with the recent reforms of the Italian pension system).

The employment module is composed of two sub-modules: Labor market participation and Unemployment. Labor market participation is modeled separately by gender, and the model for females is conditional on household composition. The (linear) cohort effects in the equations for labor market participation are stopped for individuals born in 1990 or later. Alignment with an exogenous trend is performed for the overall unemployment rate for the 17-54 population. Consequently, the Unemployment module is to be regarded as a model of unemployment rate differentials, rather than unemployment rate levels. This is justified by the fact that we do not model the demand side: the overall unemployment rate is therefore considered as an exogenous parameter of the simulation. We assume that the effect of the Great Recession on unemployment will gradually fade away, and that by 2015 we will be back to the pre-crisis level of 10%. To get away with business cycle considerations, the unemployment rate is then kept constant for all subsequent simulation periods. The flowchart of the Employment module is represented in Figure 5.

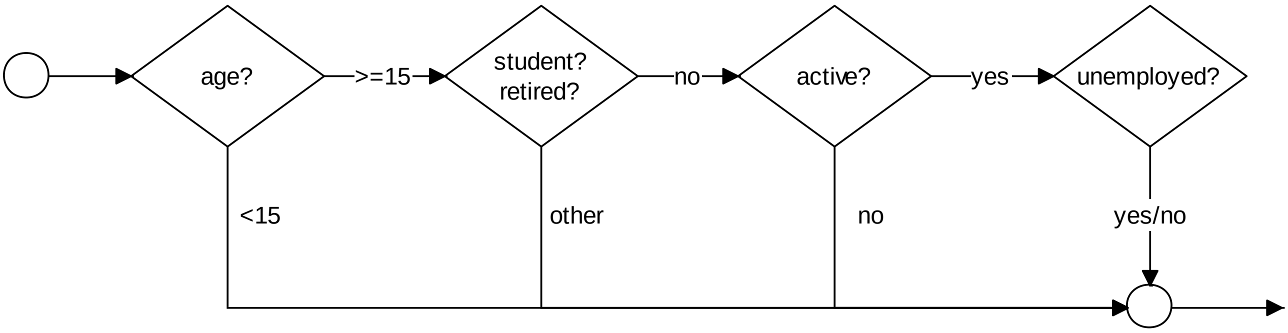

Figure 5. The Employment module.

6. Model comparison and validation

The credibility of a dynamic microsimulation model is based on its capacity to reproduce observed data or known benchmarks such as outside projections. Accordingly, an important aspect of dynamic microsimulation modeling is the validation of results produced by the simulation exercise. However, the applied literature has devoted little attention to validation procedures and the quantification of uncertainty around model predictions (Wolf, 2001), and there is currently no apparent consensus among practitioners on what constitutes a best practice. In this section, we focus on a specific aspect of validation: ex-post validation of model outcome, based on a comparison of simulated female participation rates with the actual participation trends computed using the Italian EU-SILC data over the period 2005-2008. The four versions of the model that we test are labeled *Probit* (pooled probit estimates), *Null* (dynamic random effect probit estimates without imputation of random effects), *Unconditional* (dynamic random effect probit estimates with imputation of random effects from the unconditional distributions), *Rank* (dynamic random effect probit estimates with imputation of random effects by means of the Rank method).

Figure 6 shows the projected activity rates in the age group 17-54. Depending on the estimation method we get significant differences in both males and females participation rates. For females, these differences become larger over time: at the end of the simulation period, the difference between predictions obtained under the Rank and the Null scenario amount to almost 10 percentage points. This corresponds almost exactly to the bias we expect due to nonlinearity of the probit transformation, for the estimated standard deviation of the individual effects: +4% (+8%) for the Null scenario at the beginning (end) of the simulation period, when the average activity rate under the Rank scenario is .57 (.65). Also expected, given the theoretical results (Richiardi, 2012), is the similarity between the Rank and the Unconditional scenario, when cross-sectional figures are considered.

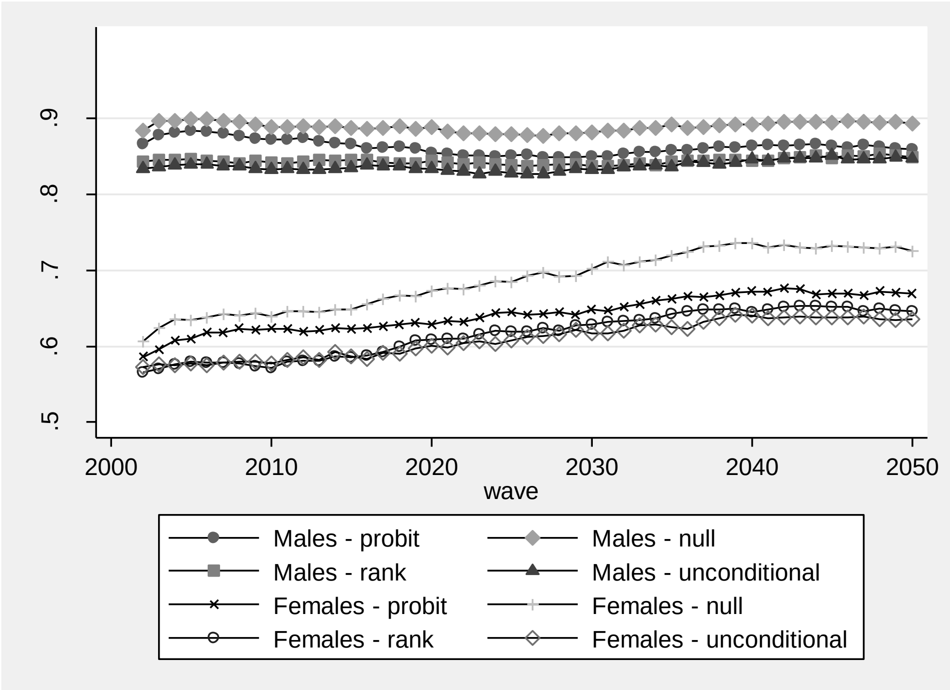

Figure 6. Projected participation rates, individuals aged 17-54.

The simulation projections can be compared with the observed participation rates for the period 2005-2008 as computed using EU-SILC data (Table 7). Predictions obtained using the Rank method and those obtained sampling from the unconditional distributions of the individual effects are slightly lower than the observed activity rates both in term of average and transition probabilities. The true data lie in between the Probit and the Rank/Unconditional forecasts. The Null forecasts do indeed overestimate both female participation rates and transition probabilities in and out the labor market. Hence, improving the estimates of the coefficients by considering UH but failing to impute it to the simulated population results in forecasts that are even worse than forecasts based on simpler (and misspecified) models.

True data			**Simulated data**			
Dataset			**Probit**	**Null**	**Rank**	**Unconditional**
ECHP	1994	52.85				
	1995	53.22				
	1996	53.66				
	1997	53.80				
	1998	55.52				
	1999	55.49				
	2000	54.76				
	2001	56.24				
EUSIC	2005	59.78	61.02	63.41	58.01	57.48

2006	60.28	61.77	63.83	57.91	57.89
2007	59.10	61.77	64.26	57.81	58.01
2008	60.07	62.34	64.06	57.78	57.93
Probability of participate at time t					
if not participate at t-1	17.06	14.22	34.69	20.29	20.68
if participate at t-1	91.05	93.79	85.78	89.09	88.41
Probability of not participate at time t					
if not participate at t-1	82.94	85.78	65.31	79.71	79.32
if participate at t-1	8.5	6.21	14.22	10.91	11.59

Table 7. Validation results: female participation rates (%), individuals aged 17-54.

The practical equivalence between imputing individual effects *via* the Rank method or sampling from the unconditional distributions breaks down dramatically when individual life histories are considered.

To document this, we have estimated the same simple probit models as described in section 4 on couples of adjacent years: the first set of estimates is performed on 2000-2001, entirely on ECHP data; the second set is performed on 2001-2002, by merging the first year of the simulation output with ECHP data; then, other sets follow entirely on simulation data.[16] We are interested in the coefficient of the lagged endogenous variable, as a descriptive measure of state persistence. Table 8 shows the results.[17] The first column refers to the years 2000-2001 and is computed on true data: it is thus invariant to the model considered and constitutes our target. The second column is computed using the true data as base year (2001) and the first period of the simulated data as final year (2002): it thus encompass any discontinuity in life trajectories due to the imputation method. Theory suggests that state persistence (the coefficients of the lagged endogenous variables) should be lower for the Unconditional scenario, intermediate for the Null scenario and higher (though still below the target) for the Rank scenario. The third column reports the averages of the coefficients of the lagged endogenous variables computed over the couples of years 2002-2003 to 2007-2008, estimated on simulated data. Theory suggests that state persistence should pick up again, with the coefficients under the Rank and the Unconditional scenario broadly similar and higher than those under the Null scenario.

[16] This validation strategy exploits the fact that the initial population in the simulation coincides with the last sample used for estimation. This, together with our desire to use all years from 2005 to 2008 for validation, explains why we have used a 2001 sample from ECHP data rather than a 2005 sample from EU-SILC data for our initial population.
[17] We do not report results for unemployment as this process is subject to alignment.

	ECHP 2000-2001	ECHP/sim 2001-2002	sim 2002-2008
Union			
Unconditional	3.810	1.648	2.626
	(0.087)	*(0.019)*	*(0.034)*
Null	3.810	2.285	2.150
	(0.087)	*(0.022)*	*(0.036)*
Rank	3.810	3.111	2.826
	(0.087)	*(0.026)*	*(0.035)*
Participation (males)			
Unconditional	2.550	1.426	1.728
	(0.075)	*(0.024)*	*(0.033)*
Null	2.550	1.901	1.763
	(0.075)	(0.026)	(0.051)
Rank	2.550	2.599	1.858
	(0.075)	*(0.028)*	*(0.308)*
Participation (Females)			
Unconditional	2.542	0.638	1.856
	(0.056)	*(0.015)*	*(0.024)*
Null	2.542	0.974	0.938
	(0.056)	*(0.015)*	*(0.024)*
Rank	2.542	2.057	1.990
	(0.056)	*(0.017)*	*(0.024)*

Table 8. Coefficients of lagged endogenous variables (standard errors in parenthesis), same probit models as for input estimation. Estimation is performed on couple of years (the third column reports averages over results from 2002-2003 to 2007-2008).

This is broadly in line with what we find. State persistence decreases in the first year of the simulation for the Unconditional scenario, as the true individual effects governing past outcomes are replaced by random draws from the unconditional distributions, which are by definition uncorrelated with the true individual effects. From the second year of the simulation onward state persistence picks up again, and individual trajectories keep the memory of the artificial discontinuity of the previous year. Under the Null scenario, on the other hand, state persistence decreases less that under the Unconditional scenario on the first year, but then remains stationary at this level. Only under the Rank scenario state persistence remains reasonably close to the true value, keeping the discontinuity of lifetime trajectories in the first period of the simulation at a minimum.

7. Microsimulation results: females participation rates

In this section we focus exclusively on the results obtained under the Rank scenario (dynamic probit models with random effects imputed using the Rank method), our preferred specification. Even if the female participation rate is expected to increase substantially under this scenario, it will remain below 70% for many decades to come (see again Figure 6). Most dynamics will take place in the two decades to 2025, when the baby boom generation will have moved to retirement age. These results confirm previous findings (Morciano, 2007; RGS, 2004, 2005, 2006), as showed in Table 9.

	Age: 15-64 Morciano (2007)	RGS (2004)	Age: 17-54 Rank Method*
		%	
2005	53.0	52.3	55.7
2010	53.3	54.0	55.6
2015	55.2	55.0	57.1
2020	57.0	55.0	58.9
2025	58.9	55.7	59.7
2030	61.2	57.1	61.7
2035	64.2	59.1	63.1
2040	65.5	61.4	63.4
2045	65.9	62.1	64.6
2050	66.0	62.5	64.5

Table 9. Comparison with *DYNAMO* and RGS projections.

Figure 7 compares the activity rate for young adult men with that for young adult women according to their marital status (in the age group 17-54, having completed education). Activity rates in these groups are higher, even if the female participation rate is still currently below 75%, as compared to more than 90% for young adult men. The gender gap between young adult men and women is actually large. In particular, the gap between young adult men and women living in a consensual union is actually larger than 30 percentage points and it will only partially decrease in the medium run. This is partly the result of our assumption that only women living in consensual union can have children –indeed, the majority of them (about 74.5%) have at least a child under 18. However, the penalization for families is expected to decrease over time: this is reflected by the fact that the activity rate for single women is projected to remain roughly constant at around 75%, while the activity rate for women living in consensual union will grow from 55% to 65% by 2025. The penalization for the number of children is also expected to shrink considerably: the participation gap between women without children and women with three or more children is larger than

20 percentage points at the beginning of the simulation period but is expected to decrease to 1.5 percentage points by 2025 (Figure 8).

Figure 9 shows that the differentials in female participation rate by education level are expected, if anything, to widen further, suggesting that a main driver in the increase in the female participation rate is the increase in the fraction of the female population with higher education.

Finally, Figure 10 shows the differences in the projected participation rates for young adult women by region and household composition. Activity rates for women without children are projected to remain constant, while the already documented increase in the participation rates of women with children will be stronger in the South.

From the factors illustrated above emerges a complex picture which points to some convergence in the activity rates of men and women, and in the activity rates of women with and without children, though the transition will be incomplete and slow, with respect to the one needed to meet the Lisbon 2010 (not to speak of Europe 2020) targets. The changes are mainly due to an increase in the education levels of women with children. This is coherent with a literature suggesting that education is able to break traditional roles and increase female participation. For example, couples with higher education have a more even division of household labor compared to those with lower levels of education (Gershuny and Robinson, 1988; Mencarini and Tanturri, 2004). Moreover, highly educated women have higher opportunity costs or “more to lose” if they do not participate in the labor market and are able to outsource domestic tasks easily.

Is it possible to speed up the convergence process? Institutions and related policies that support women and men to achieve work-life balance can also help in promoting female participation in the labor market. They include tax regulations, employment regulations, in particular with respect to flexible and part-time work, and policies that favor the use of contraceptives. These policies might also contribute to a change in the cultural norms surrounding working women, hence further supporting mothers in combining work and family commitment, and promoting participation. Of greatest importance, an increase in the availability, affordability and use of childcare over all Italian regions, which we keep constant throughout the simulation, will likely end up in higher female participation rates.

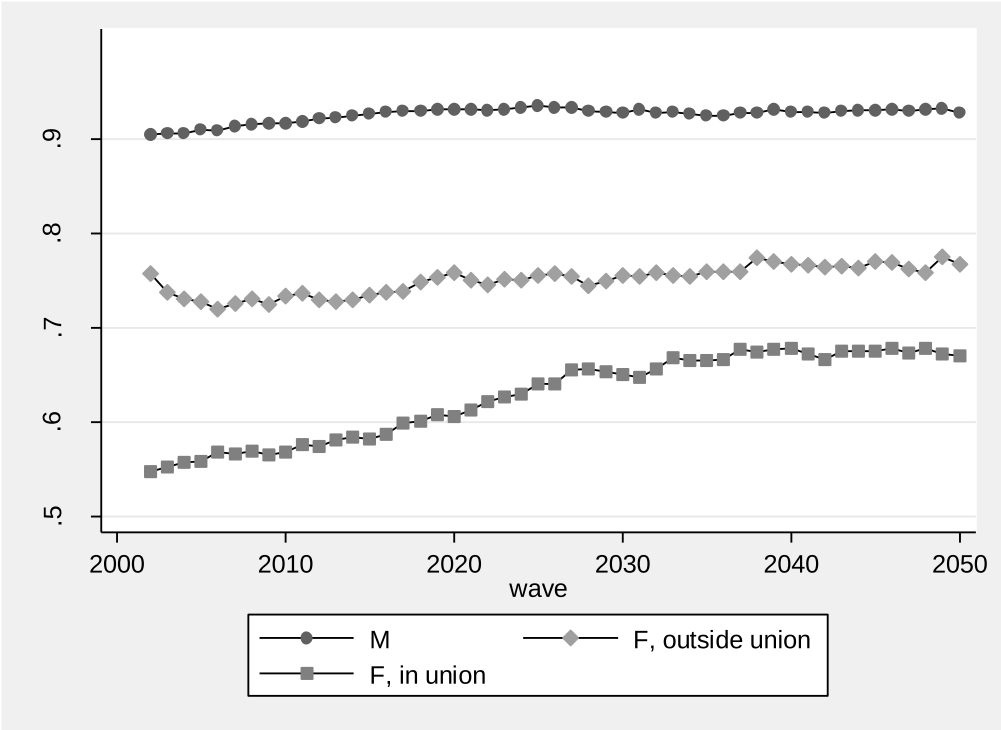

Figure 7. Participation rates by gender (individuals aged 17-54) excluding students

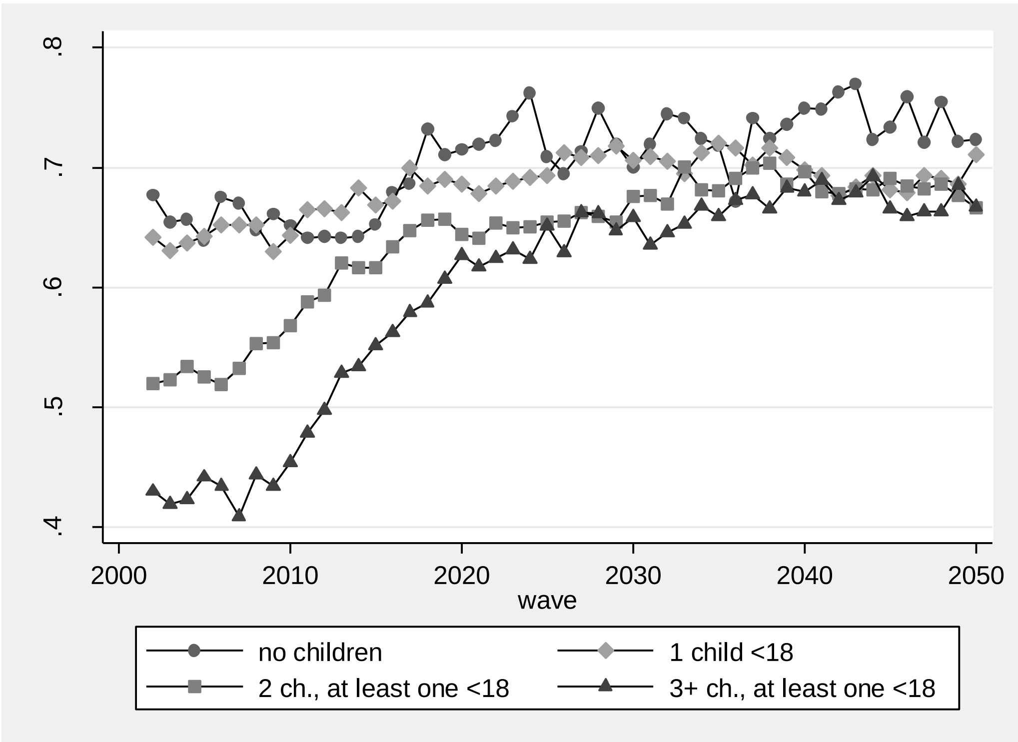

Figure 8. Female participation rates by number of children in the household: individuals aged 17-45 students excluded

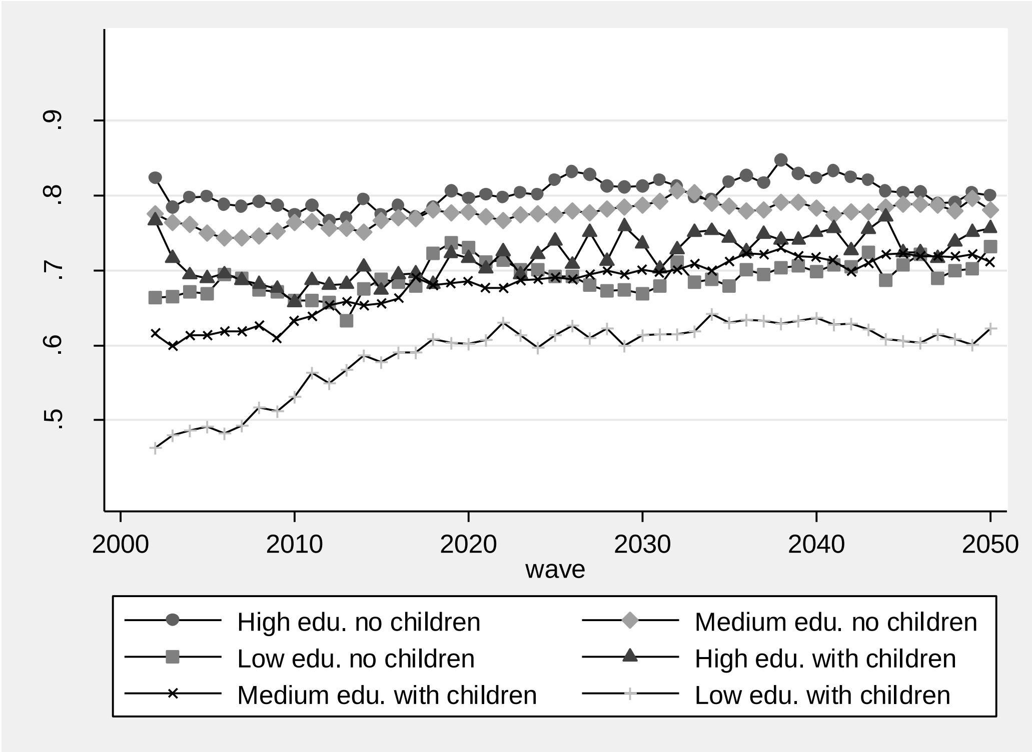

Figure 9. Female participation rates by education: individuals aged 17-54 students excluded

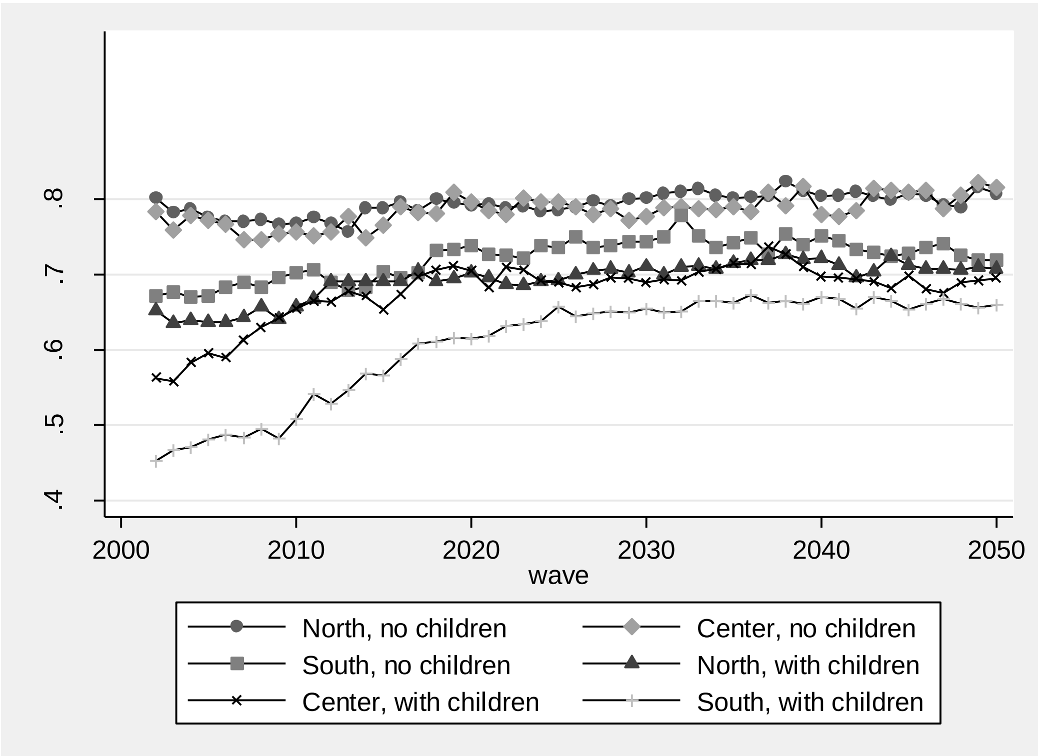

Figure 10. Female participation rates by area: individuals aged 17-54 students excluded

8. Conclusions

In this paper we have dealt with the problem of assigning unobserved individual effects to the simulation sample, when new individuals enter the simulation with a history of previous outcomes. The only theoretically sound methodology in this case is sampling from the conditional distributions, which might be impossible or very difficult to derive analytically and very computationally demanding to sample from empirically. Using a dynamic microsimulation model of labor supply in Italy as a testbed, we have shown that neglecting the problem (*i.e.* assigning a null effect to all individuals) implies a forecasting bias in discrete choice models, due to nonlinearity of the probit/logit transformations. Sampling from the unconditional estimated distributions of the individual effects prevent the forecasting bias, hence getting cross-sectional statistics right, but introduces unnatural breaks in individual trajectories at the moment of imputation, therefore getting longitudinal statistics wrong. The same applies if simple specifications without unobserved heterogeneity are used. We have then provided a first empirical application of a new method that greatly reduces the complexity of sampling from conditional distributions. Our results have been validated on out-of sample data, albeit admittedly short. Correctly imputing individual effects allows to remain on track with observed data both cross-sectionally and longitudinally.

Finally, from a substantive point of view, our microsimulation documents the existence of a marked though slow process of convergence in the activity rates of different subgroups of the Italian population: between men and women, between women with children and women without children, between the North and the South of Italy.

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