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ESTIMATING THE LABOR SUPPLY DYNAMICS OF OLDER WORKERS USING REPEATED CROSS-SECTIONS

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Estimating the Labor Supply Dynamics of Older Workers Using Repeated Cross-sections

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Abstract

The empirical analysis in this paper adopts logit models to study the hazard rate of ceasing from work by the next year for Italian older employees. The specifications are estimated resorting to the framework proposed by Güell and Hu (2006), which extracts information from repeated independent cross-sections to recover the hazard rate of interest at the individual level. The sample is drawn from the ISTAT survey Aspects of Everyday Life and includes employees aged 50-65 in 1993-2002. Our results show that, even conditioning on a wide set of socioeconomic factors, the age profile of the hazard rate is increasing and confirms the low labor market attachment of older workers. Further, the time evolution of the risk of becoming not employed appears to be hump-shaped and achieves its maximum for the cohorts of employees at work in the period 1996-1998, which is characterized by the introduction of important changes in the Social Security system aimed at extending the working life of the elderly.

JEL Codes: C41, J26.

Keywords: Labor supply dynamics, duration analysis, generalized method of moments.

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1 Introduction

The Lisbon and Stockholm agreements plan to modernize the economy of the European Union along the lines of competition, knowledge, sustainable growth and social cohesion. Fulfilling these general purposes requires the achievement of a number of partial goals, such as raising labor market participation at all ages. By 2010 the employment rate should approach 70% for the overall active population and 50% for the population group aged 55-64.

In Italy these targets are far from being fully attained. As reported in Forze di Lavoro (2007) by the Italian National Statistical Institute (ISTAT), during the period 1995-2006 the employment rates of the active population exhibited a clear positive trend but still in 2006 only the labor market attachment of males was in line with the levels recommended by EU. Additionally, just 43.7% of men and 21.9% of women in the age interval 55-64 were at work. Unlike their younger counterparts, elderly individuals who do not carry out a job are likely to be eligible for retirement benefits. Hence, stimulating their employment rates may also translate in complementing the effects brought about by the pension reforms introduced in the last fifteen years, which encourage retirement postponement in order to (i) alleviate the financial burden borne by the National Institute for Social Security (INPS) and (ii) strengthen its long-run sustainability.

The design of effective policies pursuing such a task needs a thorough understanding of the decision process underlying the labor supply dynamics of older workers. This study looks at Italian employees aged 50-65 and performs a discrete-time duration analysis focusing on their hazard rate of stopping working within the next year[1]. In line with Blau (1994) we opt to focus on labor supply dynamics rather than assuming some arbitrary definition of retirement in order (i) to deal with a sample representative of all the employees in the age-range of interest and (ii) to consider any possible trajectory of their employment patterns. Therefore, our strategy takes into account exits from the state of employee occurring for whatever reason, such as following classical retirement routes or experiencing unemployment spells due to firm-downsizings that bridge older workers towards *ad-hoc* early retirement schemes.

Microeconometric investigations probing the transitions between different labor market positions

[1]The choice of this age group is dictated by the wide empirical evidence (See Miniaci, 1998 or Brugiavini and Peracchi, 2003) asserting that the probability of retiring attains its peaks in this population group because of the institutional characteristics of the Italian pension system.

are typically based on longitudinal datasets. They track respondents over time and make it possible to observe the dynamic structure of the process object of study as well as the one of relevant factors supposed to influence its development[2]. However, this kind of data source may present some disadvantages, such as severe attrition affecting the representativeness of the sample, limited cross-sectional dimension or restrictions on information availability[3]. For instance, in the Bank of Italy Survey of Household Income and Wealth (SHIW) less than half of the households interviewed in each wave belong to the panel section[4]. To overcome such limitations, which are common to many other countries[5], we decide to estimate the hazard rate of interest according to an application of the Generalized Method of Moments (GMM) technique proposed by Güell and Hu (2006). This framework turns out to be valuable in a duration context since it allows us to calculate at the *individual level* the likelihood of giving up working only resorting to repeated cross-sections. In other words, despite employees are not tracked over time and their actual employment paths are not observed, this set-up makes us still able to reckon their probability of remaining at work in the future.

Data are drawn from waves 1993-2003 of the ISTAT survey Aspects of Everyday Life[6] (*Aspetti della Vita Quotidiana*). The reasons motivating the adoption of this dataset are manifold. First, each cross-section provides us with a large sample of 20,000 households randomly selected from the whole Italian population. Second, the long time-span covered is well suited to analyze the employment consequences of a long period of institutional changes. Finally, the questionnaire is explicitly designed to describe the socioeconomic status of respondents and allows us to include an exhaustive set of individual and household characteristics in the econometric specifications. Similar research questions could be alternatively addressed using the ISTAT Quarterly Labor Force Survey for the years 1992-2004, which describes in detail both current employment status and past working history but neglects non financial aspects, such as health, which are expected to influence the

[2] Panel datasets are also of fundamental importance to implement econometric methods aimed at controlling for unobserved heterogeneity.

[3] See Heckman and Robb (1985) for further details.

[4] In the wave 1991 of SHIW less then 30% of households have been previously interviewed. This proportion rises to about 40% for all the following waves.

[5] As an example, the Spanish Labor Force Survey does not provide access to family characteristics in its longitudinal version.

[6] The waves 1993-1999 and 2001-2003 of Aspects of Everyday Life are released according to the contract no. 4842 with the Department of Economics and Management, University of Padova. I thank Fausta Ongaro (Department of Statistics, University of Padova) for providing me with the wave 2000 of this survey.

labor market outcomes of the elderly. Moreover, in light of its multipurpose questionnaire and the large sample size, Aspects of Everyday Life compares favorably to the longitudinal datasets currently available for studying the employment patterns of Italian older workers, such as SHIW, the European Community Household Panel (ECHP) and the public releases of the INPS archive.

The structure of this paper is the following. Section 2 describes the principal changes in the Social Security system ongoing in the period considered in this analysis. A brief survey of the related literature is provided in Section 3. Section 4 introduces the GMM estimator adopted. Section 5 presents the dataset used to obtain the main results of this work, which are the focus of Section 6. Finally, Section 7 concludes.

2 Social Security reforms in Italy

The main reforms of the Social Security System passed during the nineties take their names from the Prime Ministers at the time. Specifically, they are the Amato (1992), Dini (1995) and Prodi (1997) acts. Further, minor modifications have been promulgated almost yearly since 1992. All these changes tighten the eligibility criteria and introduce less generous rules for the pension benefit computation in order to stem the runaway growth of the outlays managed by INPS. Such modifications were needed in view of the ageing process characterizing the Italian society, the improved life-expectations of the elderly and the consequent necessity of adjusting the amount of pension benefits granted to the worker during her retirement years to the actual amount of contributions paid to the Social Security throughout her working life.

The Dini reform was the most incisive because it switched the original defined benefit system to the defined contribution method. This conversion was phased in over a long transitional period and affected only the most recent cohorts. In fact, it distinguished between workers with at least 15 years of contribution in 1992 and all other workers. In particular, the former group was totally exempted from the transformation of the scheme and it was exposed only to less radical adjustments in eligibility rules and benefit formulas.

This section concentrates on the legislated changes modifying the old-age and seniority pensions available for employees. In spite of this, it should be remembered that the Social Security system also covers self-employed workers and provides social, survivor and disability benefits[7].

Until 1992 males (females) could claim old-age benefits not before age 60 (55) and conditional on having contributed to the scheme for at least 15 years. The Amato reform gradually increased these requirements in order to grant by 2002 old-age pensions only to males (females) aged at least 65 (60) years old with at least 20 years of contribution.

Until 1992 eligibility for seniority pensions differed among sectors of employment. Whereas employees of the private sector had to collect at least 35 years of contribution, this requirement was much looser for public sector workers (20 years of contribution for males and 15 for females). Since 1993 these rules have been tightened and harmonized across sectors of employment. As for male (female) public employees with more than 8 years of contribution, the Amato reform raised to 25 (20) years the minimum length of contributory seniority needed to draw early retirement benefits[8]. For those with lower working careers this requirement was raised to 35 years.

Since 1996, the Dini and, later, the Prodi acts have restricted the access to seniority benefits for all workers and set the eligibility according to two alternative options based on (i) either the attainment of a minimum length of contribution history regardless of current age and (ii) having paid at least 35 years of contribution to the system and fulfilling an age requirement. These changes have been phased in over a long transitional period and were designed to allow early retirement benefits by 2008 only to workers with either at least 40 years of contribution or 57 years of age and 35 years of contribution. Table 1 summarizes the main variations in the eligibility to seniority pensions for employees occurred in the period covered in our analysis[9].

Prior to 1995, in line with the defined benefit schemes, pension amounts were computed according to the formula $r \times N \times P$, where r stands for the rate of return from each year of contribution, N for the number of years of contribution and P indicates pensionable earnings. Although the Dini reform enforces the defined contribution scheme for younger cohorts of workers, the old rules still apply to the computation of a part of their benefits. In general, pensionable earnings result from a weighted sum of past earnings. The reforms of the system basically extended the period taken into account for this computation. While until 1992 only the last 5 years of work were considered, in

[7] See Brugiavini (1999) for further details.

[8] The Amato reform also introduced a penalty in the benefit computation for workers in this category who retire with less than 35 years of contribution.

[9] During the years 1995-1999 the eligibility for seniority pensions was additionally limited by the so-called exit windows, which forced workers to defer retirement by a period between six and twelve months.

2001 this time-interval included (i) the last 10 years for the workers covered by the defined benefit scheme and (ii) the whole working history for those under the defined contribution system. Until 1988 the rate of return r was constant[10], then it became a decreasing function of pensionable earnings. In 1993 the highest pensionable earnings underwent a further reduction in the associated rate of return. Moreover, since the same year, the indexation of all pensions is no longer linked to the earnings growth but depends on the price inflation only.

In conclusion, it should be noted that the Amato reform of 1992 started to provide incentives, through actuarial rewards in the benefit computation, to those workers who decide to postpone retirement even if they are eligible for either old-age or seniority pensions and have contributed to the scheme for more than 40 years.

3 Literature review

The microeconometric analysis of the labor supply dynamics of Italian older workers has received the attention of many studies differing with respect to the theoretical framework, the econometrics and the sample adopted. We recall some contributions to briefly outline the state of the art in this research field[11].

Miniaci (1998) studies individual decisions of retirement through a reduced-form duration analysis. He exploits the retrospective information conveyed by the wave 1995 of SHIW in order to characterize retirement patterns distinguishing between alternative exit routes from the labor market. The sample includes males and females who are, respectively, aged 50-70 or 45-65[12] and household heads or their spouses. The main results come from the estimation of multinomial logit and Cox models. They point out that the probability of quitting employment is highest at the ages of 55, 60 and 65 and that, everything else constant, younger cohorts of workers retire earlier and remain economically inactive for a higher proportion of their lives in view of better life expectancies. Better education and lower replacement ratios increase the likelihood of being at work. *Ceteris paribus*, public sector employees are not shown to retire earlier and no significant differences arise between the North and the South in terms of the probability of applying for invalidity or social benefits.

[10] Pension amounts were subject to a legislated ceiling.

[11] For further details, see also the references quoted in these works.

[12] The inclusion in the sample requires males (females) to become retirees after the age of 50 (45).

Brugiavini and Peracchi (2003) analyze the determinants of the transitions towards retirement using a sample extracted from the INPS archive. Their theoretical framework suggests that at any age individuals decide to keep on working or retire by comparing the expected present values associated with these two outcomes and opting for the employment state producing the highest pay-off. Taking advantage of the detailed income information provided by the data, this work pays great attention to the definition of future earnings, pensionable earnings and social security wealth, which are expected to play a prominent role in this decision. Their sample includes only private sector non-agricultural employees aged 50-69 who have started an employment spell between 1977 and 1996. Reduced-form probit models are used to evaluate the relationship between the transitions towards retirement and a set of explanatory factors including, among others, a full set of age dummies and the above-mentioned income variables. According to their estimates, the actual age-profile of retirement rates is well-replicated and the parameters on the income variables have the expected sign. In particular, the probability of ceasing from work decreases with future labor earnings and rises with higher levels of pension wealth and pensionable earnings. The estimated models are then used to simulate how the retirement rates change under different institutional scenarios that alter both eligibility requirements and pension wealth computation[13].

Spataro (2000) describes retirement decisions according to an option-value model as in Stock and Wise (1990) and imposes specific assumptions on the utility function of individuals. The parameters characterizing agents preferences are estimated exploiting the waves 1991 and 1993 of SHIW and focusing upon individuals aged 45-65 and at work at the end of 1990. Unlike Miniaci (1998), only old-age and seniority retirement routes are considered[14]. Modelling the risk of giving up working with probit specifications, the author obtains the estimates of the structural parameters along with the evolution over age of the hazard rate of interest. The fitted hazard rates are close to the actual ones but, as in comparable studies with American data, they do not entirely capture the peak in the probability of retiring occurring at age 60. In general, Italian workers are more prone to retire earlier and are characterized by a higher risk aversion as well as a lower intertemporal discount rate than their US counterparts. Finally, the comparison between the actual expected retirement

[13] Brugiavini and Peracchi (2001) consider similar research questions and use an older release of the same dataset. Finally, Brugiavini (1999) estimates the impact of social security parameters on actual retirement patterns and on expectations about the retirement age.

[14] This choice also reflects the characteristics of the option value model, which specifies different utility functions for those who are at work and those who retire.

ages and those predicted by the model[15] confirms the predictive power of this framework only for the group of workers aged 51 or over. This limitation may be rationalized by the fact that the retirement option is actually taken into account only by this population group. Hence, the inclusion in the sample of younger workers is likely to introduce bias in the estimates.

Colombino (2003) departs from the focus on the transitions out of employment but still specifies a structural model of retirement. The author follows Gustman and Steinmeier (1986) and assumes that individuals choose their optimal labor market position on the basis of the comparison between the instantaneous utility levels of retiring and being at work. It can be shown that in such a framework the estimation of the structural parameters can be carried out by standard logit analyses of the current employment state. Data are drawn from the wave 1993 of SHIW and the sample considers only the household heads and their spouses who are aged at least 40 years old and are either at work or job pensioners. As Brugiavini and Peracchi (2003), the fitted model permits to simulate the response of individual behaviors to legislated changes to the pension system. The results show that a marginal cut in the benefits ends up in a small but not irrelevant reduction of the number of retirees. On the contrary, dropping the eligibility requirements produces only a slight increase in the proportion of pensioners within the population. This latter evidence suggests that at least in 1993 eligibility constraints were not binding.

The results obtained in our analysis do not go through the development of a structural model of retirement. There is no doubt that recovering structural parameters describing individual preferences is relevant for policy purposes but this comes at the cost of imposing unverifiable assumptions on the utility functions of individuals. Instead, we follow Miniaci (1998) and Brugiavini and Peracchi (2001 and 2003) in order to specify a reduced form approach to estimate the labor supply dynamics of older workers. It is worth remembering that our study complements the contributions listed in this section since it builds upon a dataset that allows us to describe the evolution of the labor market attachment of the elderly in a period characterized by a long series of changes to the pension system.

[15] In SHIW all individuals at work are asked to report the expected age of retirement. The comparison implemented exploits the waves 1991-1995 of the survey.

4 The econometric framework

Let y_i be a binary random variable taking on value 1 if an employee in the age interval 50-65 at time t keeps on working in $t+1$ and 0 if she moves towards not employment for whatever reason. We assume that

$$y_i = 1\left\{x_i'\beta + e_i > 0\right\}, \tag{1}$$

where x_i is a vector collecting explanatory factors of interest, β is the set of parameters we intend to estimate and e_i is a stochastic component following the logistic distribution. As a result, the probability of remaining at work is defined as

$$\Pr(y_i = 1) = \Lambda(x_i'\beta) = \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)}.$$

When the coefficients in β are estimated via the maximization of the standard log-likelihood function

$$y_i \sum_i \log \Lambda(x_i'\beta) + (1-y_i)\sum_i \log(1-\Lambda(x_i'\beta)),$$

we obtain the first-order conditions

$$\underbrace{\sum_i x_i \Lambda(x_i'\beta)}_{\substack{\text{all employees} \\ \text{aged 50-65 at time } t}} \quad = \quad \underbrace{\sum_i y_i x_i}_{\substack{\text{only those still in the sample and} \\ \text{employed at time } t+1}}. \tag{2}$$

On the one hand, the LHS of (2) is the sum of x_i over all the employees in the age range of interest at time t weighted by their conditional probability of remaining at work given x_i. On the other hand, the RHS considers only those still in the sample and employed at time $t+1$. The consistency of the maximum likelihood estimates requires the attrition in the sample to be uncorrelated with the outcome of interest once we condition on x_i.

The implementation of this estimation method crucially relies on the availability of panel data that track individuals over time and allow observing the variable y_i. Güell and Hu (2006) propose an alternative approach that calculates at the individual level the probability of leaving a given initial state using independent cross-sections representative of the same population at different time periods.

Applying this approach to our specific context makes it possible to identify β by exploiting the information provided by (i) an *entry* cross-section collecting employees aged 50-65 at a given time t and (ii) an *exit* cross-section collecting their counterparts aged 51-66 at $t+1$. Claiming that the entry and exit cross-sections are representative of the same population of Italian employees in different time periods is equivalent to saying that the inclusion in the sample should not depend on unobserved factors affecting the labor market position.

Combining these two different datasets, we can mimic equation (2) by the set of moment conditions

$$\underbrace{\sum_i x_{it}\Lambda(x'_{it}\beta)}_{\substack{\text{all employees aged 50-65} \\ \text{in the cross-section of time } t}} = \underbrace{\sum_j x_{jt+1}}_{\substack{\text{all employees aged 51-66} \\ \text{in the cross-section of time } t+1}} . \tag{3}$$

The LHS of (3) is the sum of the vectors of explanatory variables over the sample of employees[16] aged 50-65 at time t weighted by their conditional probability of keeping on working in $t+1$. Instead, the RHS is its unweighted homologue calculated for the entire set of employees aged 51-66 at time $t+1$. The fundamental underpinning for all our results is that individuals aged 51-66 in $t+1$ should behave as their cohort-mates aged 50-65 in t if they were observed and interviewed one year later. We use the employment outcomes and the characteristics of the former group to recover the probability of remaining employed for *each* employee included in the entry cross-section. Finally, since y_i does not show up in (3), reckoning this equation in the sample does not rely on the necessity of following individuals over time[17]. Unlike the FOCs in (2), this way of proceeding circumvents the problems arising from the presence of attrition in longitudinal datasets.

Assuming that the cross-sections of times t and $t+1$ are randomly drawn from the same underlying population, the adoption of the moment conditions (3) can be motivated going through the

[16] Employment condition is defined according to respondents' self-evaluations of their current labor market status.

[17] The indexes i and j in the notation x_{it} and x_{jt+1} intend to emphasize that the cross-sections do not make up of the same set of individuals.

law of iterated expectation,

$$
\begin{aligned}
E[x_{jt+1}\mathbf{1}(t+1)] &= E[x_{jt+1}E[\mathbf{1}(t+1)|x_{jt+1}]] = \\
E[x_{it}E[\mathbf{1}(t+1)|x_{it}]] &= E[x_{it}\Pr(\mathbf{1}(t+1)=1|x_{it})],
\end{aligned}
$$

where $\mathbf{1}(t+1)$ takes on value 1 if the individual is at work in $t+1$ and 0 otherwise. The analogy principle shows easily that $E[x_{jt+1}\mathbf{1}(t+1)]$ is the population analogue of the RHS of (3) after a sample size normalization and the same applies to $E[x_{it}\Pr(\mathbf{1}(t+1)=1|x_{it})]$ and the corresponding LHS.

As pointed out earlier, we draw data from the waves 1993-2003 of the ISTAT survey Aspects of Everyday Life. In order to exploit massively all the available information, the entry cross-section should pool together all the individuals for whom we observe their counterparts one year later, who will be in turn collected in the exit cross-section. Hence, the entry dataset consists of the sample of Italian employees aged 50-65 in 1993-2002, whereas the exit cross-section of their homologues aged 51-66 in 1994-2003. The entry and exit cross sections are by construction not independent as employees aged 51-65 in the years 1994-2002 figure in both these datasets[18].

The GMM estimator $\widehat{\beta}_{GMM}$ results from the minimization of a weighted quadratic function of the vector

$$g(\beta) = \sum_j x_{jt+1} - \sum_i x_{it}\Lambda(x_{it}'\beta).$$

More specifically,

$$\widehat{\beta}_{GMM} = \arg\min_{\beta} g(\beta)W^{-1}g(\beta), \tag{4}$$

where W^{-1} is a symmetric, positive semidefinite weighting matrix.

Given the moment conditions stacked in $g(\beta)$, the efficient GMM estimator requires the weighting matrix W^{-1} to be the inverse of the variance and covariance matrix of $g(\beta)$. Naming n_t and n_{t+1}

[18]To summarize, although the waves 1993-2003 of Aspects of Everyday Life are independent, they are combined in entry and exit cross-sections that are no longer independent as a subsample of respondents is included in both these generated datasets.

the sample size of, respectively, the entry and exit cross-sections, we define

$$W = V\left[\frac{1}{\sqrt{n_t}}\sum_j x_{jt+1} - \frac{1}{\sqrt{n_t}}\sum_i x_{it}\Lambda(x'_{it}\beta)\right] = V\left[\frac{1}{\sqrt{n_t}}\sum_j x_{jt+1}\right] + V\left[\frac{1}{\sqrt{n_t}}\sum_i x_{it}\Lambda(x'_{it}\beta)\right]$$
$$-Cov\left[\frac{1}{\sqrt{n_t}}\sum_j x_{jt+1}, \frac{1}{\sqrt{n_t}}\sum_i x_{it}\Lambda(x'_{it}\beta)\right] - Cov\left[\frac{1}{\sqrt{n_t}}\sum_i x_{it}\Lambda(x'_{it}\beta), \frac{1}{\sqrt{n_t}}\sum_j x_{jt+1}\right] =$$
$$= \frac{n_{t+1}}{n_t}V\left[x_{jt+1}\right] + V\left[x_{it}\Lambda(x'_{it}\beta)\right] - \frac{n^c_{t,t+1}}{n_t}Cov[x_{jt+1}, x_{it}\Lambda(x'_{it}\beta)] - \frac{n^c_{t,t+1}}{n_t}Cov[x_{it}\Lambda(x'_{it}\beta), x_{jt+1}]. \quad (5)$$

The weighting matrix W^{-1} reflects the sample design of our analysis generating not independent entry and exit cross-sections. In fact, the information conveyed by the set of $n^c_{t,t+1}$ individuals showing up in both the datasets leads to the presence of the covariance matrices in (5)[19].

Following Newey and McFadden (1994), we have

$$\sqrt{n_t}(\widehat{\beta}_{GMM} - \beta) \simeq \left[\frac{1}{n_t}\sum_i \Lambda(x'_{it}\beta)(1-\Lambda(x'_{it}\beta))x_{it}x'_{it}\right]^{-1} \cdot \left[\sqrt{\frac{n_{t+1}}{n_t}}\frac{1}{\sqrt{n_{t+1}}}\sum_j x_{jt+1} - \frac{1}{\sqrt{n_t}}\sum_i x_{it}\Lambda(x'_{it}\beta)\right] \quad (6)$$

While the first term between brackets in the right-hand-side of (6) converges to

$$A = E\left[\Lambda(x'_{it}\beta)(1-\Lambda(x'_{it}\beta))x_{it}x'_{it}\right],$$

the second term is asymptotically distributed as a normal random variable with zero mean and variance-covariance matrix equal to W. As a result,

$$\sqrt{n_t}(\widehat{\beta}_{GMM} - \beta) \simeq N(0, (A'W^{-1}A)^{-1}).$$

The variance and covariance matrix of $\widehat{\beta}_{GMM}$ can be estimated by replacing A and W with

[19] In Güell and Hu (2006) the moment conditions specified are uncorrelated and produce a diagonal weighting matrix.

their sample analogues.

As usual, the implementation of the efficient GMM estimator needs a set of starting values $\widetilde{\beta}$ coming from a consistent estimator of β. We obtain them by running the GMM machinery and assuming W to be the identity matrix. This choice is suggested by the fact that GMM estimators are always consistent regardless of the weighting matrix adopted. Building upon this set of first-stage GMM estimates, we calculate the sample analogue of W and plug it in (4) to get the optimal GMM estimates.

Duration analysis

Our study develops a duration analysis where the time elapsed in the initial state is indicated by the age at which employees are at work. As written above, the probability $\Lambda(x'_{it}\beta)$ indicates the likelihood of remaining employed in the future given the characteristics included in the vector x_{it}. For comparability with the literature, in the remainder of the paper the outcome of interest will be $1 - \Lambda(x'_{it}\beta)$, which identifies the hazard rate of exiting employment within the next year. Unlike proportional hazard models, the logit specifications used in this analysis allow the effect on the hazard rate of a given explanatory variable to change with the values taken on by all the other covariates. Therefore, as long as age is included among the regressors, the impact of the other explanatory variables is duration dependent.

The choice of the moment conditions in (3) implicitly assumes that for the individuals in our sample the exit from employment is not followed by reverse transitions[20]. Building upon this hypothesis, we describe the exit from employment as an absorbing state and formally exclude that individuals at work in $t + 1$ were not employed in t. This assumption follows from our claim that the entry and exit cross-section are representative of the same population at times t and $t + 1$. Employees aged 51-66 in $t + 1$ are assumed to be at work in t as their counterparts aged 50-65 included in the entry cross-section.

If we recovered the parameters of interest in a standard maximum likelihood framework as that described by the first order conditions (2), the information contained in the matrix of covariates x_i would be used both in the LHS, which refers to employees at time t, and in the RHS, which considers only those who remain at work in $t + 1$. Our set-up does not make use of panel datasets

[20] In SHIW only 4.3 (2.2) percent of males (females) not at work in wave 2000 are found employed in wave 2002.

and then the matrix of covariates for the workers in the entry cross-section (employees at time t) cannot be associated with their counterparts in the exit cross-section (employees at time $t+1$). Indeed, while the left-hand side of moment conditions (3) refers to the matrix x_{it}, the right-hand side considers the information conveyed by x_{jt+1}.

We assume that the distribution of the covariates in x_{it} and x_{jt+1} may vary only due to the exit from the initial state of employee. However, since the age distribution in the entry and exit cross-sections differs by construction[21], the age of individuals at work in $t+1$ is dated back to the previous year. This way of proceeding follows from the set of moment conditions used. Let us suppose for simplicity to include only age among the explanatory variables. If the workers in $t+1$ are on average older than their counterparts in t, the probability $\Lambda(x_{it}'\beta)$ cannot weight the observations of the entry cross-section to enforce the validity of (3) in the sample. In fact, on average the summation in the RHS will be always higher than its weighted homologue in the LHS. From a more intuitive standpoint, by dating back age we conform to the standard ML logit model, where age as of time t (if available) is used in both sides of the first order conditions[22].

5 Data and descriptive statistics

The series of repeated cross-sections called Aspects of Everyday Life have been collected yearly by ISTAT from 1993 to 2003. This multipurpose survey draws a representative sample of the Italian population and gathers detailed information about individual and household characteristics, such as education, accommodation, employment, health and utilization of medical care services[23].

Table (2) describes the explanatory variables that will be used in the empirical analysis while Table (3) presents their summary statistics as well as the sample size of the entry and exit cross-sections.

As noted earlier, while the entry cross-section collects the observations referring to workers aged 50-65 in 1993-2002, the exit cross-sections include their counterparts aged 51-66 in 1994-2003. However, it should be kept in mind that the age of individuals in the exit cross-sections is dated

[21] The employees in the exit cross-section are on average one year older than those in the entry cross-section.

[22] The same holds for variables indicating calendar years. Employees in the entry cross-section are at work in the period 1993-2002, those in the exit cross-section refer to the period 1994-2003.

[23] However, since Aspects of Everyday Life is not explicitly designed for labor supply analyses it misses out information on characteristics, like income and built-up pension wealth, expected to affect the employment status. A discrete classification of the household income is available only for waves 1996 and 1997.

back to the previous year to allow the estimation of the moment conditions in the sample. Table (3) summarizes the age distribution in both the entry and exit cross-section using the same age-class labelling. In this way we indicate the proportion of workers in the former dataset actually in each age-class as well as the proportion of their counterparts one year older included in the exit cross-section. For instance, if we look at the age class 50-52 in Table (3), we notice that 37.8 percent of workers of the entry cross-section are in this age interval, while the observations about their counterparts one year older amount to 40.1 percent of the exit cross-section. At the same way, 6.2 percent of workers in the entry cross-section are aged 62-65, while their counterparts one year older constitute 4.9 percent of the exit cross-section[24].

If we look at the age distribution in the entry cross-sections, we find that more than 50 percent of employees at work during the period 1993-2002 are aged at most 54, whereas less than 18 percent of individuals in the sample are aged 59 or over. This raw evidence highlights the low labor market participation of the elderly in Italy[25]. In addition, we find that about 80 percent of male employees live in a household with at least three members and this proportion falls to less than 65 percent for females. The probability of being hospitalized is less than 6 percent for both males and females. Since this variable is an indicator of the overall health status, it suggests the expected positive relationship between health conditions and labor market attachment. Most of individuals in our sample have either a middle or a high school degree, are homeowners, white-collars and live in the North or in the Centre of Italy. Finally, more than 50 percent of males are employed in the private sector, whereas most of women are at work in the public sector.

6 Results

6.1 Age and cohort profiles of the hazard rate

We consider employees aged 50-65 in 1993-2002 and calculate the age-profile of their hazard rate of becoming not employed within the next year. The hazard rate is allowed to vary across age classes and over time by distinguishing among individuals at work in different calendar years. As

[24] Analogous explanations are valid for calendar years variables. While in the entry cross-section 31.6 percent of male employees are at work in the period 1996-1998, 30.4 percent of observations in the exit cross-section refer to their counterparts one year older at work in the years 1997-1999.

[25] The three groups of calendar years appear to be evenly distributed in the sample.

reported in Table (2), we define three groups of calendar years, 1993-1995 (baseline), 1996-1998 and 1999-2002, as well as six age classes, 50-52, 53-54, 55-56, 57-58, 59-61 and 62-65.

The interpretation of the parameters on the year dummies should be cautious. On the one hand, these variables may capture the impact of the reforms of the Social Security system but also reflect whatever macro-change occurred in the Italian economy during the period of reference. On the other hand, they are also allowed to pick up cohort fixed-effects, namely the variations on the hazard rate due to the variability in the socioeconomic conditions characterizing individuals at the same stage of their life-cycle but born in different years.

The columns labeled *Baseline* in Table (4) report the coefficient estimates for males and females. We first carry out a formal Wald test maintaining the null hypothesis that the hazard rate does not exhibit either time or age variation. This test is to be interpreted as a basic goodness of fit measure since if the null hypothesis is accepted, age and time dummies should be replaced with a more parsimonious specification including only an intercept term. The statistics follow a chi-squared distribution with 7 degrees of freedom and strongly suggests the rejection of the null hypothesis for both males and females.

The hazard rate computed according to these sets of estimates are plotted in Figure (1) and Figure (2). The time trend of the hazard rate is hump-shaped for both genders since, conditional on age, the cohorts of employees at work in 1996-1998 present the lowest likelihood of keeping on working in the future. The estimates in Table (4) illustrate that this difference is statistically significant.

As for the age-profile, our results suggest that males aged 53-54 present on average a significantly higher probability of exiting employment than their younger counterparts[26]. The hazard rate remains constant in the age interval 53-58 and significantly increases for individuals aged 59-61 and 62-65. Overall, significant increments in the exit probability for the age classes 53-54, 59-61 and 62-65 appear to be consistent with the related literature, which document peaks in the likelihood of quitting employment around ages 55, 60 and 65[27]. When looking at Figure (2), we find that female employees in the age-class 50-52 present on average a hazard rate of ceasing from work in line with that of their counterparts aged 53-54 and lower than those aged 55-56. In addition, female

[26] Results of the tests used to analyze variations in the hazard rate across age classes are available upon request.
[27] See Miniaci (1998) or Brugiavini and Peracchi (2003).

employees aged at least 59 years old are the most likely to quit employment.

6.2 Allowing for further explanatory variables

Our specifications are enriched by a more exhaustive set of regressors including household size, hospitalization during the last twelve months, homeownership, education, job characteristics, sector of employment and region of residence. The results are displayed in the *Covariates* columns in Table (4). Overall, the goodness of fit of the specifications adopted benefits from the inclusion of this additional set of covariates since the hypothesis of their joint insignificance is not supported by the data.

Parameters on year of employment variables still assert that, even conditioning on further explanatory factors, the evolution over time of the hazard rate is hump-shaped. Maintaining the cohorts of employees in 1993-1995 as benchmark, the risk of becoming not employed within the next year significantly rises for those at work in 1996-1998 and falls for the youngest cohorts.

Our estimates suggest the puzzling evidence that the cohorts of employees with the highest propensity towards leaving employment are those at work during 1996-1998, which is the period just the after the introduction of the Dini reform (1995) and characterized by the implementation of the Prodi act (1997). It is worth noting that our estimation strategy does not allow us to carry out a tight impact evaluation of the pension reforms passed by the Parliament during the nineties as the year dummies may reflect cohort effects and changes in the general macro-economic conditions. However, our results suggest that the probability of exiting employment is higher for the cohorts of employees at work in a period characterized by two major legislated changes aimed at lowering the generosity of the pension system and, in particular, at making the requirements for seniority benefits eligibility more severe. Workers facing an unstable institutional set-up may have opted to retire as soon as they became eligible in order to avoid further coercive extensions of their working life and poorer pension benefits, *ceteris paribus*.

The considerations made above for the age-profile of the hazard rate are still valid and prove once again the small incentives to remain employed provided to the elderly by the Italian labor market institutions. This evidence might represent not only a genuine age effect indicating that the disutility of work rises with age but it can also be driven by the higher levels of pension wealth built-up by older workers, which makes the retirement option more favorable.

Our findings also point to a negative relationship between household size and the probability of keeping on working. Living in larger families may entail a heavier burden of non-market activities, such as looking after elderly parents, which are associated with a higher propensity towards exiting the labor market, *ceteris paribus.*

Hospitalization is a proxy for the overall health status. Consistently with what suggested by the literature[28], those who have been admitted to a hospital during the last twelve months present higher hazard rates of ceasing from work. As for education, males with an upper school degree and females with an university degree are those more likely to exit employment[29]. Homeownership is associated with a reduction in the probability of exiting employment only in the case of female employees. In addition, it should be noted how, *ceteris paribus*, both working in the public sector and living in the South are associated with a drop in the hazard rate of becoming not employed. This latter evidence is at least partly due to the less favorable economic conditions distinguishing this region from the rest of Italy. Indeed, at a given age, workers in the South are less likely to have accumulated the necessary years of contribution needed to claim old-age or seniority pensions because of the higher difficulties in finding and preserving a job as compared to those living in the North and in the Centre.

6.3 Simulations

Building upon this latter set of estimates, we plot the hazard rate for males and females belonging to an arbitrarily chosen reference category of employees, namely white-collars of the primary or industry sectors, homeowners, with an upper secondary school degree, not having been hospitalized during the last twelve months, living in the North in a household with three components. In other words, we simulate how the hazard rate of the hypothetical employees in this reference category varies across age classes and over time.

If we look at the results for males described in Figure (3) we find that the probability of transiting out of employment within the next year presents negligible differences at all ages for individuals at work in the periods 1993-1995 and 1999-2002, while it is much higher for those at work in the period

[28] See Lumsdaine and Mitchell (1999) for a survey.

[29] We argue that the result for females is driven by the high percentage of women in our sample with an university degree and at work in the public sector. As described in Section 2, public sector workers are faced with more generous pension schemes.

1996-1998. These differentials are more evident than in the baseline case. In general, regardless of the year of employment, the risk of ceasing from work is less than 10 percent until age 52. Then, for those at work in the period 1996-1998, the hazard rate is slightly less than 20 percent between 53 and 58 years of age, whereas it is around 10 percent for the remaining two groups. In all groups the hazard rate steadily increases with age. For males at work between 1996 and 1998, it is about 30 percent in the age interval 59-61 and to more than 50 percent in the oldest age class. Among those aged 59 or over, the cohorts of workers in 1993-1995 and 1999-2002 are still about 10 percentage points more likely to remain at work in the future, everything else constant.

Turning our attention to the results for females in Figure (4), we notice that until age 58 the hazard rate of exiting employment for employees at work in the period 1996-1998 doubles that of the other two groups. For later ages, the differentials shrink in relative terms but remain still sizeable. In the age interval 59-65 the probability of exiting employment is higher than 70 percent for those at work between 1996 and 1998, while it is around 50 percent for the remaining female employees in the sample.

6.4 Robustness checks

At the moment our specifications control for time and age effects but do not include interaction terms between these two sets of variables. Since we are estimating logit models, the effect of a given explanatory factor changes with the values taken on by the other covariates. This implies that the effect of the year of employment is not constrained to be age-invariant[30] and that the dummies for the years of employment do not produce parallel shifts in the hazard rate common to all age classes, as illustrated in Figures (1)-(4). This issue should not be neglected in an economic context characterized by several pension reforms because these changes concentrate their effects on workers at specific ages[31]. Nevertheless, there is no doubt that interaction terms between age and time dummies may introduce additional flexibility in our specifications and increase the overall goodness of fit.

We carry out formal Wald tests to assess whether allowing for interaction effects between age and time dummies improves the explanatory power of our models. Our previous specifications are

[30] As discussed in Section 4, parameters on explanatory factors are duration dependent.

[31] Table (1) displays the variations of the age requirements needed to obtain seniority benefits after 35 years of contribution.

enriched by a full set of interactions in order to explicitly let the effect of each age class vary over each group of calendar years. Testing the joint insignificance of the parameters on the interactions between time and age dummies is equivalent to testing whether our previous restricted specifications are flexible enough to capture the variability of the hazard rate over time and across age-classes. As shown in Table (5), the null hypothesis is always not rejected suggesting that the specifications of Table (4), albeit more parsimonious, are appropriate to analyze how the probability of transiting out of employment has evolved for the employees in our sample.

7 Conclusions

Italy has engaged in aligning domestic employment rates with the targets set by the European Council in the Lisbon and Stockholm agreements. However, labor market participation is globally below the levels settled by EU, especially when we look at the employment outcomes of the elderly. As most older individuals not at work are eligible for retirement benefits, their labor market attachment is strictly related to the characteristics of the Social Security system, which has undergone several modifications since the early nineties aimed at ensuring its financial sustainability in the long-run and postponing the retirement of older workers. In particular, three important reforms, Amato (1992), Dini (1995) and Prodi (1997), modify the eligibility rules and the computation of pension benefits lowering the overall generosity of the system. After more than a decade from the first organic reform, we want to assess whether the labor market attachment of older workers has evolved along the lines pursued by Social Security reforms.

Typically, empirical investigations studying labor market transitions extract information from longitudinal datasets. In spite of their widespread utilization, panel data may present some disadvantages, such as attrition affecting the representativeness of the sample, small sample dimension and absence of variables relevant to describe the phenomenon of interest. Nevertheless, independent cross-sections filling the above-mentioned gaps of panel datasets are usually discarded when analyzing changes in the employment status as they do not follow individuals over time. To overcome this limitation, Güell and Hu (2006) develop an econometric framework able to recover at the individual level the probability of leaving a given initial state by combining independent cross-sections representative of the same population in different time periods. Our empirical analysis follows this approach in order to estimate the hazard rate of ceasing from work within the next year for Italian employees aged 50-65 in 1993-2002. Data are drawn from the repeated ISTAT cross-sections Aspects of Everyday Life.

As expected, age, household size, health, sector of employment and the region of residence are significantly associated with the labor supply dynamics of both genders. In particular, the increasing age-profile of the hazard rate denotes the absence of incentives that can make the elderly willing to prolong their working life. Hence, the Italian institutional background is shown to be not in line with EU recommendations, which instead urge the adoption of policies in order to raise the labor market participation of this population group.

The time trend of the hazard rate is hump-shaped. Conditional on age, the cohorts of employees at work in 1996-1998 present a higher risk of becoming not employed by the next year as compared to their counterparts at work in 1993-1995 and 1999-2002. Although an impact evaluation of the pension reforms of the nineties is beyond the scopes of this study, our results suggest that the cohorts of employees at work in the period following the introduction of the Dini reform (1995) and characterized by the implementation of the Prodi act (1997) are the most likely to retire. This pattern is consistent with the dynamics of the financial burden afforded by the Social Security system. In fact, if we look at the time series of the public pension expenditure as percentage of GDP between 1989 and 2003, we notice that it first rises to achieve its highest levels in the period 1997-1999 and then diminishes[32]. This reduction may be explained by (i) the phasing in of tighter eligibility criteria, (ii) rates of return from each year of contribution decreasing with pensionable earnings as well as (iii) the indexation of pension benefits to price inflation only and no longer to earnings growth.

The GMM estimator developed in this work can be additionally implemented using the waves of surveys consisting of both a longitudinal and a refresher component, such as SHIW and the Survey of Health, Ageing and Retirement in Europe (SHARE). The advantage of our approach over classical panel data models lies in the fact that it exploits the information coming from the whole dataset and not from its longitudinal section only. If each wave is cross-sectionally representative, this framework circumvents the problems arising from potential attrition in the sample and avoids complicating

[32] See the report released in 2006 by the Government Commission at the Ministry of Labor for the Evaluation of Pension Expenditure.

the estimation method to explicitly account for this issue. Combining independent cross-sections to investigate labor market transitions is a new way to complement the evidence obtained with traditional panel data techniques by taking advantage of alternative sources of information relevant to understand the labor supply dynamics of older workers.

References

[1] Blau D.M. (1994), Labor Force Dynamics of Older Men, Econometrica, 62(1): 117-156.

[2] Brugiavini A. (1999), Social Security and Retirement in Italy, in Social Security and Retirement around the World, Eds. Gruber J. and Wise D.A., The University of Chicago Press.

[3] Brugiavini A. and Peracchi F. (2001), Micro Modelling of Retirement Behavior in Italy, in Social Security and Retirement Around the World: Micro-estimation, Eds. Gruber J. and Wise D.A., The University of Chicago Press: 345-399.

[4] Brugiavini A., Peracchi F. and Wise D.A. (2002), Pensions and Retirement Incentives: a Tale of Three Countries: Italy, Spain and the USA, Il Giornale degli Economisti e Annali di Economia, 61(2): 131-169.

[5] Brugiavini A. and Peracchi F. (2003), Social Security, Wealth and Retirement Decisions in Italy, Labour (Special Issue), 17: 79-114.

[6] Colombino U. (2003), A Simple Intertemporal Model of Retirement Estimated on Italian Cross-section Data, Labour (Special Issue), 17: 115-137.

[7] Government Commission at the Ministry of Labor for the Evaluation of Pension Expenditure (2006), Gli Andamenti Finanziari del Sistema Pensionistico Obbligatorio, downloadable from the web-site of the Italian Ministry of Labor, www.lavoro.gov.it.

[8] Güell M. and Hu L. (2006), Estimating the Probability of Leaving Unemployment Using Uncompleted Spells from Repeated Cross-section Data, Journal of Econometrics, 133: 307-341.

[9] Heckman J.J. and Rob Jr. J. (1985), Alternative Methods for Evaluating the Impact of Interventions, in Longitudinal Analysis of Labor Market Data, Eds. Heckman J.J. and Singer B., Econometric Society Monographs, 10, Cambridge University Press.

[10] Inglese L. (2003), Early Retirement in Italy: Recent Trends, Labour (Special Issue), 17: 79-114.

[11] ISTAT (2007), Forze di Lavoro - Media 2006, Rome.

[12] Lumsdaine R.L. and Mitchell O.S. (1999), New Developments in the Economics of Retirement, in Handbook of Labor Economics, Volume 3, Chapter 49, Eds. Ashenfelter O. and Card D., Elsevier Science.

[13] Miniaci R. (1998), Microeconometric Analysis of the Retirement Decisions: Italy, OECD, Working Paper, 205.

[14] Newey W.K. and McFadden D.L. (1994), Large Sample Estimation and Hypothesis Testing, in Handbook of Econometrics, Volume 4, Chapter 36, Eds. Engle R.F. and McFadden D.L., Elsevier Science.

[15] Spataro L. (2000), Le Scelte di Pensionamento in Italia: Un'applicazione (ed estensione) del Modello "Option Value", Studi Economici, 72: 25-54.

[16] Stock J.H. and Wise D.A. (1990), Pensions, the Option Value of Work and Retirement, Econometrica, 58: 1151-1180.

Table 1: Eligibility rules for seniority benefits in the period 1996-2003. Before 1996 workers with 35 years of contribution history could apply for early retirement benefits at any age.

	Private sector				Public sector	
	Blue collars (*)		White collars			
	Age (with 35 years of contribution)	Years of contribution (at any age)	Age (with 35 years of contribution)	Years of contribution (at any age)	Age (with 35 years of contribution)	Years of contribution (at any age)
1996	52	36	54	36	53	36
1997	52	36	54	36	53	36
1998	53	36	54	36	53	36
1999	53	36	55	37	53	37
2000	54	36	55	37	54	37
2001	54	36	56	37	55	37
2002	55	36	57	37	55	37
2003	55	36	57	37	56	37

Note: (*) Blue collars category also includes individuals who started to work before 19 years of age and those who receive redundancy payments. Source: Brugiavini et al. (2002), Inglese (2003) and Laws 335/1995 and 449/1997. The whole pension scheme provisions (in Italian) can be downloaded from the Ministry of Labor web-site, www.lavoro.gov.it.

Table 2: Description of the explanatory variables used in the regressions.

Variable	Description
Calendary year	
year9395	dummy=1 if the person is at work in the period 1993-1995 (baseline)
year9698	dummy=1 if the person is at work in the period 1996-1998
year9902	dummy=1 if the person is at work in the period 1999-2000
Age	
age5052	dummy=1 if the person is aged 50-52
age5354	dummy=1 if the person is aged 53-54
age5556	dummy=1 if the person is aged 55-56
age5758	dummy=1 if the person is aged 57-58
age5961	dummy=1 if the person is aged 59-61
age6265	dummy=1 if the person is aged 62-65
Household size	
hh_mem1	dummy=1 if one household member
hh_mem2	dummy=1 if two household members
hh_mem3	dummy=1 if three household members
hh_mem4	dummy=1 if four household members
hh_mem5	dummy=1 if at least five household members (baseline)
Health status	
hospitalized	dummy=1 if the person has been hospitalized during the last twelve months
Education	
university	dummy=1 if the person has an university degree
high_school	dummy=1 if the person has a high school degree
middle_school	dummy=1 if the person has a middle school degree
low_educ	dummy=1 if the person has at most a primary school degree (baseline)
Homeownership	
homeowner	dummy=1 if the person is homeowner
Job characteristics	
white_collar	dummy=1 if the person is white collar
Sector of employment	
primary_industry	dummy=1 if the person is employed in the sectors of agriculture, hunting, fishing, industry, mining and construction
services	dummy=1 if the person is employed in the sectors of trade, lodging and catering, transport, communication and renting services and other business activities
public_sector	dummy=1 if the person is employed in the public sector (baseline)
Macro region of residence	
north	dummy=1 if the person lives in the North
centre	dummy=1 if the person lives in the Centre
south_islands	dummy=1 if the person lives in the South or Islands (baseline)

Table 3: Summary statistics of the explanatory variables used in the regressions.

Variable	Males		Females	
	Entry	Exit	Entry	Exit
Calendar year				
year9698	0.316	0.304	0.316	0.299
year9902	0.396	0.407	0.440	0.457
Age				
age5052	0.378	0.401	0.430	0.451
age5354	0.196	0.196	0.212	0.219
age5556	0.147	0.148	0.146	0.142
age5758	0.107	0.106	0.098	0.092
age5961	0.110	0.101	0.074	0.063
age6265	0.062	0.049	0.040	0.034
Household size				
hh_mem1	0.062	0.065	0.124	0.134
hh_mem2	0.145	0.155	0.240	0.250
hh_mem3	0.288	0.290	0.306	0.307
hh_mem4	0.350	0.344	0.228	0.231
Health status				
hospitalized	0.055	0.049	0.043	0.038
Education				
university	0.120	0.123	0.157	0.153
high_school	0.276	0.282	0.323	0.331
middle_school	0.254	0.248	0.209	0.211
Homeownership				
homeowner	0.781	0.782	0.790	0.795
Job characteristics				
white_collar	0.516	0.520	0.609	0.617
Sector of employment				
primary_industry	0.396	0.392	0.201	0.194
services	0.286	0.279	0.269	0.259
Macro region of residence				
north	0.372	0.360	0.408	0.399
centre	0.200	0.279	0.232	0.230
Sample size	18,305	16,073	8,658	7,769

Source: ISTAT, Aspects of Everyday Life 1993-2003. Note: The number of individuals in common between entry and exit cross-sections ($n^c_{t,t+1}$) amounts to 14,299 for males and 6,748 for females.

Table 4: Italy, employees aged 50-65 in 1993-2002. GMM logit model estimates of the effects on the hazard rate of leaving employment within the next year. For each parameter we report the point estimate and the standard error within brackets.

Variable	Males		Females	
	Baseline	Covariates	Baseline	Covariates
year9698	0.350**	0.542***	0.490*	0.917***
	(0.155)	(0.172)	(0.261)	(0.344)
year9902	-0.173	-0.023	-0.403	-0.227
	(0.144)	(0.157)	(0.268)	(0.323)
age5052	-2.669***	-3.369***	-2.820***	-3.238***
	(0.163)	(0.253)	(0.270)	(0.482)
age5354	-1.989***	-2.579***	-2.545***	-2.685***
	(0.172)	(0.251)	(0.375)	(0.575)
age5556	-2.072***	-2.562***	-1.935***	-1.766***
	(0.195)	(0.273)	(0.301)	(0.508)
age5758	-1.984***	-2.397***	-1.789***	-1.368***
	(0.214)	(0.286)	(0.313)	(0.509)
age5961	-1.494***	-1.784***	-1.145***	-0.304
	(0.143)	(0.227)	(0.239)	(0.449)
age6265	-0.876***	-0.898***	-1.139***	-0.152
	(0.129)	(0.218)	(0.244)	(0.467)
hh_mem1	/	-1.580***	/	-3.707***
		(0.278)		(0.628)
hh_mem2	/	-1.804***	/	-2.696***
		(0.208)		(0.339)
hh_mem3	/	-0.953***	/	-1.731***
		(0.120)		(0.251)
hh_mem4	/	-0.413***	/	-0.924***
		(0.105)		(0.219)
hospitalized	/	0.772***	/	1.502***
		(0.123)		(0.273)
university	/	-0.226	/	1.450***
		(0.192)		(0.373)
high_school	/	-0.104	/	0.505
		(0.147)		(0.330)

See the next page

Variable	Males		Females	
	Baseline	Covariates	Baseline	Covariates
middle_school	/	0.334***	/	0.300
		(0.117)		(0.252)
homeowner	/	0.001	/	-0.429**
		(0.101)		(0.193)
white_collar	/	0.095	/	-0.263
		(0.121)		(0.286)
primary_industry	/	0.417***	/	1.311***
		(0.127)		(0.280)
services	/	0.480***	/	1.092***
		(0.123)		(0.246)
north	/	1.031***	/	1.000***
		(0.112)		(0.237)
centre	/	0.876***	/	0.668***
		(0.120)		(0.247)
Explanatory factors $[\chi^2_{14}]$	/	217.66***	/	100.87***
Goodness of fit	257.47***	357.89***	119.88***	129.45***
Sample size				
Entry cross-section	18,305	18,305	8,658	8,658
Exit cross-section	16,073	16,073	7,769	7,769

Source: ISTAT, Aspects of Everyday Life 1993-2003. Note: *Goodness of fit* reports the results of Wald tests maintaining the null hypothesis that the whole set of explanatory factors can be replaced with an intercept term. It follows a chi-squared distribution with 7 (21) degrees of freedom for the *Baseline* (*Covariates*) specifications.

Table 5: Italy, employees aged 50-65 in 1993-2002. GMM logit model estimates of the effects on the hazard rate of leaving employment within the next year. For each parameter we report the point estimate and the standard error within brackets.

Variable	Males		Females	
	Baseline	Covariates	Baseline	Covariates
year9698	-0.054	-0.048	-0.415	-0.237
	(0.300)	(0.348)	(0.681)	(0.911)
year9902	-0.161	-0.157	-0.259	-0.200
	(0.253)	(0.296)	(0.500)	(0.679)
age5052	-2.868***	-3.589***	-3.500***	-4.104***
	(0.454)	(0.511)	(1.175)	(1.392)
age5354	-1.995***	-2.570***	-3.098***	-3.317**
	(0.299)	(0.362)	(1.188)	(1.371)
age5556	-1.906***	-2.418***	-1.241***	-0.866
	(0.300)	(0.362)	(0.318)	(0.558)
age5758	-2.265***	-2.717***	-1.676***	-1.195
	(0.506)	(0.562)	(0.523)	(0.734)
age5961	-1.368***	-1.659***	-1.245***	-0.187
	(0.220)	(0.296)	(0.395)	(0.643)
age6265	-0.749***	-0.645**	-0.910***	0.270
	(0.189)	(0.270)	(0.338)	(0.583)
age5052_year9698	0.765	0.984	2.057	2.571
	(0.627)	(0.668)	(1.425)	(1.694)
age5354_year9698	0.240	0.401	1.893	2.333
	(0.524)	(0.576)	(1.441)	(1.681)
age5556_year9698	0.166	0.367	-1.224	-1.430
	(0.538)	(0.591)	(1.391)	(1.669)
age5758_year9698	0.867	1.129	0.400	0.608
	(0.660)	(0.716)	(0.980)	(1.265)
age5961_year9698	0.274	0.475	0.982	1.157
	(0.451)	(0.513)	(0.894)	(1.205)
age5052_year9902	0.100	0.277	-0.304	0.072
	(0.650)	(0.685)	(1.930)	(2.119)
age5354_year9902	0.134	0.264	0.059	0.299
	(0.462)	(0.506)	(1.674)	(1.862)
age5556_year9902	-0.284	-0.072	-0.456	-0.373
	(0.575)	(0.620)	(0.719)	(0.930)
age5758_year9902	0.248	0.436	0.153	0.291
	(0.725)	(0.777)	(0.855)	(1.099)
age5961_year9902	-0.269	-0.132	0.057	-0.130
	(0.482)	(0.540)	(0.798)	(1.071)

See the next page

Variable	Males		Females	
	Baseline	Covariates	Baseline	Covariates
hh_mem1	/	-1.585***	/	-3.865***
		(0.278)		(0.648)
hh_mem2	/	-1.819***	/	-2.817***
		(0.209)		(0.371)
hh_mem3	/	-0.957***	/	-1.867***
		(0.120)		(0.290)
hh_mem4	/	-0.416***	/	-1.004***
		(0.106)		(0.248)
hospitalized	/	0.785***	/	1.647***
		(0.127)		(0.327)
university	/	-0.220	/	1.522***
		(0.193)		(0.389)
high_school	/	-0.111	/	0.541
		(0.148)		(0.341)
middle_school	/	0.330***	/	0.328
		(0.117)		(0.266)
homeowner	/	0.002	/	-0.473**
		(0.102)		(0.205)
white_collar	/	0.095	/	-0.270
		(0.122)		(0.298)
primary_industry	/	0.419***	/	1.378***
		(0.128)		(0.298)
services	/	0.482***	/	1.129***
		(0.124)		(0.259)
north	/	1.032***	/	1.022***
		(0.112)		(0.248)
centre	/	0.874***	/	0.692***
		(0.120)		(0.257)
Interaction terms [χ^2_{10}]	4.33	4.91	10.42	9.31
Additional covariates [χ^2_{14}]	/	215.83***	/	84.83***
Goodness of fit	277.02***	367.18***	93.33***	109.45***
Sample size				
Entry cross-section	18,305	18,305	8,658	8,658
Exit cross-section	16,073	16,073	7,769	7,769

Source: ISTAT, Aspects of Everyday Life 1993-2003. Note: *Goodness of fit* reports the results of Wald tests maintaining the null hypothesis that the whole set of explanatory factors can be replaced with an intercept term. It follows a chi-squared distribution with 17 (31) degrees of freedom for the *Baseline* (*Covariates*) specifications.

Figure 1: Hazard rate for male employees.

Figure 2: Hazard rate for female employees.

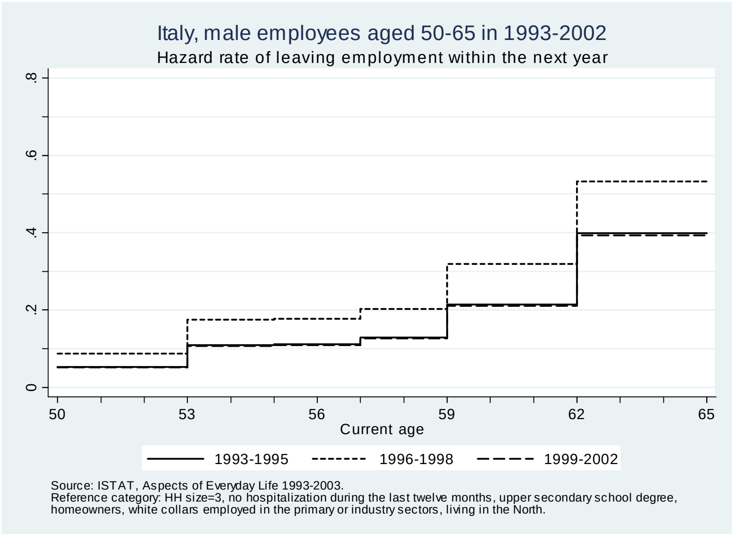

Figure 3: Hazard rate for male employees in the reference category.

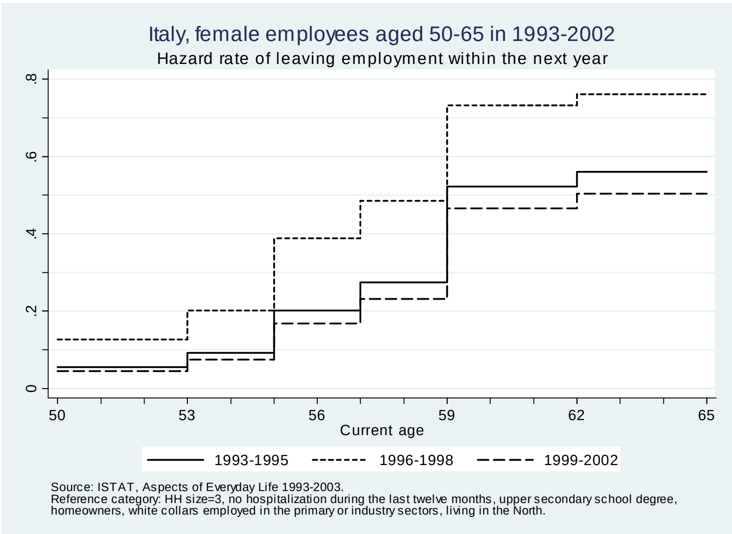

Figure 4: Hazard rate for female employees in the reference category.