Heterogeneity in the unemployment risk over the life cycle[*]

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Abstract

Unemployment and employment durations display substantial differences across workers belonging to different age groups and employed in different industries, regions and occupations. How do these differences translate in heterogeneity in workers' employment risk?

This paper deals with the measurement of the unemployment risk and its distribution across workers that differ along various dimensions. It measures the individual unemployment risk as the probability of being unemployed, derived taking into account both types of uncertainty faced by workers, i.e. the risk of entering unemployment and of remaining unemployed. The life cycle profiles of the probability of being employed/unemployed are derived taking into account either observable and unobservable heterogeneity which turn out to have great impact in shaping the risk of entering a non-job spell as well as the chance of re-employment.

JEL classifications: C41, J62, J64

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1. Introduction

Unemployment risk is a dynamic concept, that involves the risk of entering unemployment as well as the risk of remaining unemployed (Lauer, 2003); as such, it is intrinsically related to the duration of employment and unemployment spells. Employment and unemployment duration display substantial differences across workers in different age groups, industries, regions and occupations. How do these differences translate into differences in workers' unemployment risk?

The standard model for labor market search addresses the repeated job search with fixed distribution of wages in an homogeneous and stationary environment where unemployment length is exponentially distributed. In this framework the hazard from unemployment and reemployment wages are unrelated to the duration of unemployment spells. In particular, in the stationary framework the individual's expectations are formed independently from time occurrence and from duration dependence. These implications contrasts with the empirical evidence from reduced-form analysis that suggest that the job search environment is nonstationary as the hazard from unemployment declines the with unemployment spell length (see for example Lancaster, 1979; Flinn and Heckman, 1982). However, the reduced-form approach to job search model are unsuitable to detect the sources of nonstationarity, and are not appropriate to evaluate reforms to the unemployment compensation system.

Extensions of the standard job search model have been developed to account for potential sources of nonstationarity (see e.g. Van den Berg, 1990). Moreover, Ljungquist and Sargent (2008) show that the stochastic transitions between consecutive age groups imply a non constant unemployment risk over the life cycle that partially rationarlizes the evidence of the high-incidence of long-term unemployment among European older workers. In addition to this, various other sources of heterogeneity have been examined and advocated as potentially responsible of the fallacies of the standard job search model predictions.

However, due to the fact that the information available in most data sets is insufficient to identify all the parameters the general nonstationary model has not been estimated.

This paper exploits the detailed information on working careers conveyed by administrative data to measure the unemployment risk and its distribution over the life cycle across heterogeneous workers in different age cohort and occupation groups. It derives the probability of being unemployed as a measure of the individual unemployment risk implied in life cycle transitions in and out employment derived by the reduced-form analysis of employment and unemployment spells.

At both theoretical and empirical level the risk of becoming and of remaining unemployed have been considered separately. A lot of studies show how individual consumption and savings behaviors react to uncertainty proxied by the unemployment risk faced by individuals. (e.g., Cochrane, 1991; Carroll et al, 1999, and Guiso et al., 1996). These study use the probability of job loss to measure the uncertainty attached to individual working careers (see e.g. Carroll 1999; Berloffa and Simmons, 2003).

However, there is considerable evidence that the risk of being fired differs from the risk of not finding a job when unemployed and that the differential in these risk can vary with the business cycle; typically the chance of being fired is below the chance of getting an offer when unemployed.

The existing empirical evidence on individual unemployment risk focuses on the two aspects separately. While some empirical studies use duration analysis, others explicitly model the transition among the labor market states as a Markov chain process.

The duration analysis approach focuses on the transitions from unemployment to employment or out of the labor force, as they could play a key role in explaining unemployment dynamics. It is used to detect the individual characteristics and the macro factors that are significant in predicting the transition from employment to unemployment and *viceversa* and in explaining the duration of unemployment. However, little effort in this area has been devoted to detect how it translates in terms of the probability of being unemployed/ employed. Galiani and Hopenhayn (2003), the paper to which mine is more related, estimates a Markov process for transitions from employment to unemployment (and *viceversa*) to derive the conditional distribution of total unemployment time experienced in a 2-year period. However, they do not relate the risk of becoming unemployed and the risk of remaining unemployed to detect a comprehensive measure of unemployment risk at a given stage of the life cycle.

The other econometric approach studies the transitions among labor market states by detecting the individual full probability distribution of labor market states (e.g. the probability of being employed or out of the labor force). However, these studies rely on estimation models that present severe drawbacks: they use time series cross-section dependent data with binary dependent variables that seldom satisfy the independence assumption as the observations are temporally related. Voicu (2005) relies on this approach to provide a methodology that enables to trace a complete picture of labor markets dynamics. His method takes into account the full working histories to estimate a multiperiod multinomial probit that enables to derive the employment/unemployment probabilities over the life cycle. It has the merit of taking into account the dependence of sequential decisions (while the standard multinomial approach is based on the independence assumption). However, this structure disregards the duration dependence of transitions which has been proven to be significant (see the seminal work of Flinn and Heckman, 1982).

In this paper, I use the duration analysis approach to derive the life cycle profile of the probability of being employed/unemployed as a comprehensive measure of the labor market performance. Thus, I measure unemployment risk as the expected probability of being non-employed at a given stage of the life cycle, derived taking into account the risk of entering a non-job spell as well as the chance of re-employment.

The previous literature shows how to derive the stationary distribution of state occupation probabilities in case of time-homogeneous Markov processes, where the unemployment and employment durations are independently and identically distributed. Chesher and Lancaster (1983) derive the distribution of state occupation probabilities at time t, given the initial probability distribution of the two states, for the case of a non homogeneous Markov process that allows for duration dependence. In this paper I use Monte Carlo simulation techniques to derive the distribution of state occupation probabilities associated to a non –homogeneous semi Markov process.

In particular, I estimate two separated continuous time parametric duration models of employment and non-employment spells, allowing for unobserved heterogeneity. The estimated models are used to predict, at each stage of the life cycle, the time varying transition probabilities in and out employment; these are conditional on the time elapsed in each state and on covariates which include the type of occupation, the geographic area of work, the age at the beginning of the spell, the time elapsed in the previous state and the cohort effect. I use the Monte Carlo method to simulate, given the initial probability distribution of the employment and the non employment state, the underlying semi Markov process governing the transition in and out employment over the life cycle for each representative worker in each group, identified by occupation, geographic area and industry types. In particular, assuming that the working life career starts at age 20 and given the initial distribution of being employed, I draw a large number of realizations from the parameterized estimated distribution of the length of time elapsed in the given state (employed/unemployed), i.e. I simulate the durations of the first and the subsequent life cycle employment or unemployment spells. From these simulated working careers I can derive the age profiles of the probability of being employed, which turn out to display a hump shaped profile, consistent with the observed distribution of the employment across ages.

To conduct the duration analysis I prefer continuous time to discrete time techniques as the first are invariant to the time unit used to record the available data, thus, a common set of parameters is available to generate probabilities of events occurring in intervals of different length. This it is particularly useful in this study, as it enables to derive the life cycle profile of the probability of being employed at each age taking into account the length of the employment/unemployment spells (Flinn and Heckman, 1982).

To estimate the two duration models I use continuous time multiple spells data on working histories for a large number of workers tracked in the panel data INPS which covers the period 1985-2004. Thus I cannot distinguish, among the non-employment episodes, the unemployment spells from the out of the labor force spells (Flinn and Heckman, 1982) [1]. I treat equally all the observed job interruptions and consequently, in this paper, the unemployment risk is indeed the chance of not being employed. Given this clarification, hereafter, I use indifferently the term unemployment and non-employment state.

Despite this limit, I think my analysis is still valuable as it provides the age profiles of the chance of being employed/not-employed to be used in all studies where the labor supply is not endogenous.

The empirical analysis is conducted on Italian male workers age between 20 and 65 years old. It evidences that there's substantial heterogeneity in the unemployment risk across various dimensions: age, cohorts and job characteristics (such as type of occupation, firm size and geographic area of working).

The application of this methodology to Italian data enables to highlight the role of entrance contracts (apprenticeship contracts and training-on-the-job contracts)[2] and of temporary agency work[3] in favoring employment among young people. When focusing on standard contracts (open end contracts and fixed term contract and seasonal contracts), younger cohorts face, at each age, a substantial lower probability of being employed than older cohorts, and the probability of being employed when young is much lower than when being middle aged. When the focus is on all types of contracts (including apprenticeship and training-on-the-job contracts as well as temporary agency

[1] Flinn and Heckman (1982) find that the transition in and out unemployment and out of the labor force are fundamentally different.

[2]The apprenticeship contract is a labour contract in which the contracting parties are the young person (aged between 16 and 24) and the employer. Apprenticeship contracts can last from a minimum of 18 months to four years (Law 196/97): within these limits, collective agreements lay down, for each sector, the length of contracts for the various occupational profiles. These type of contracts represent the 4% of job contracts observed in the panel. The average duration is 1.6 years. The training-on-the-job contracts (CFL) (introduced in 1984) are intended to promote the hiring and training of individuals aged between 16 and 32, and can elapse up to 32 months. These type of contracts were introduced by Law No. 863/1984. These type of contracts represent the 9.4 % of job contracts observed in the panel. The average duration is 1.12 years.

[3] Temporary (agency) contracts are temporary employment relationship between a temporary work agency, which is the employer, and a worker, where the latter is assigned to work for and under the control of an undertaking and/or establishment making use of her services (the user company). In the panel data used temporary agency work contracts are observed since 1998 and represent the 2.12% of the total number of job contracts observed in the panel. The average duration is 1.12 years.

work contracts), while, the differences among ages are confirmed, the differences among cohorts tend to be nullified and in some cases overcome.

The paper is organized as follows. In section 2, I detail the methodology followed to conduct the duration analysis of both employment and unemployment spells and to derive the state occupation probabilities. Section 3 is devoted to the description of the data used. In section 4, I present the estimation results and the predicted life cycle employement/ unemployment probabilities. Section 5 concludes.

2. Methodology

2.1 The semi Markov process

I model a two-state time non-homogeneous semi Markov process that drives the transition from employment to unemployment and *viceversa*. At any point in time, a worker may be in either state: employed or unemployed.

This Markov process allows for duration dependence, i.e. the probability of transition from one state to the other varies with the time spent in the state of origin. This happens in both employment and non-employment spells, as the probability of remaining in a given state depends on the time spent in the state. The process also allows for "lagged state duration dependence" as the length of the previous spell affects significantly the probability of remaining in the current state (Heckman and Borjas, 1980). For example, a long unemployment spell may cause a high loss of productivity, which is likely to be reflected in a lower initial wage as well as in a higher probability of termination in the next employment spell.

The previous literature shows how to derive the stationary distribution of state occupation probabilities in case of time-homogeneous Markov processes, where the unemployment and employment durations are independently and identically distributed. Chesner and Lancaster (1983) derive the distribution of state occupation probabilities at time *t*, given the initial probability distribution of the two states, for the case of a non homogeneous Markov process that allows for duration dependence. In this paper I use Monte Carlo simulation techniques to derive the distribution of state occupation probabilities associated to a non –homogeneous semi Markov process.

The procedure is detailed in the following subsections: in 2.2 I present how the transition across the employment and the unemployment state, while 2.3 shows in detail the simulation procedure used to derive the probability distribution.

2.2 Modeling the hazard functions

I use the duration analysis techniques to estimate the impact of individual and job characteristics on the two hazard rates of exiting the two states of interest: unemployment and employment. The process depends on a set of covariates (*X*) that capture individual and job characteristics, including age, cohort, daily salary as well as the length of the previous employment (non-employment) spell if the current is non-employed (employed). The fixed covariates and age are measured at the beginning of each spell and hence are not caused by the length of that spell[4]. In particular, the explanatory variables *X* are of two types. Explanatory variables of type A (*XA*) are fixed over the spell and over the life cycle, they include: cohort, gender, type of occupation, industry and geographic area. Explanatory variables of type B (*XB*) include variables that are fixed over the spell but changing over the life cycle. These include age and wage at the beginning of the current spells as well as the length of previous spell.

To analyse the duration dependence in unemployment and job spells I estimate two separate parametric Weibull proportional hazard models[5]. I privilege continuous time to discrete time techniques as the first are invariant to the time unit used to record the available data, thus, a common set of parameters to generate probabilities of events occurring in intervals of different length. This it is particularly useful in this study, as it enables to derive the life cycle profile of the probability of being employed at each age conditional on whatever length of the employment/non employment spells (Flinn and Heckman, 1982).

Moreover, in order to take into account the impact of unobserved heterogeneity on the elapsed duration in the both models I allow for shared frailty[6][7]. According to the adopted approach, the instantaneous hazard rates for unemployment (*u*) and employment (*e*) spells are modelled as following:

$$h^j{}_i(t^j) = h^j{}_0(t)\exp(\beta' X_i)\alpha^j \qquad \text{with} \qquad j = u, e \tag{1}$$

Where:

t^j is the elapsed duration in a given state

$h_0(t^j)$ is the baseline hazard that here takes the Weibull distribution

$\beta' X_i$ is a linear combination of explanatory variables for individual *I*

α^j is the multiplicative effect that captures unobserved heterogeneity

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[4] When unemployment spells are considered, the job related covariates refers are fixed at their value at the end of the previous employment spell.

[5] I choose this model instead of the widely used semiparametric proportional Cox's model because the latter does not specify a parametric form for the hazard preventing to derive the transition probabilities of interest. In many cases, the two approaches (parametric vs semiparametric) produce similar results in term the effect of explanatory variables on the hazard rate (see e.g Petrongolo, 2001). Moreover, " In parametric analysis, if no failures occur over a particular interval of time, that is informative. In semiparametric analysis, such periods are not informatives" This, because " Semiparamentric analysis is nothing more than a combination of separate binary.outcome analysis, one per failure time, while parametric analysis is a combination of several analyses at all possible failure times" Cleves et al. 2008.

[6] For a deep analysis on the distinction between duration dependence of the hazard rate of exiting unemployment and unobserved heterogeneity, see, e.g., Lancaster 1990; and Devine and Kiefer 1991.

[7] The data convey information on multiple spells per workers, thus allowing for shared frailty entails modelling heterogeneity among workers as a random effect. In fact, a frailty is a latent random effect that enters multiplicatively on the hazard function.

Under the Weibull assumption for the hazard rates distribution, our model is:

$$h^j{}_i(t) = (t^j)^p \exp(\beta' X_i)\alpha^j$$

α, where p and β are the parameters to be estimated.

Given the estimates of p and β I derive the predicted survival probability in each state:

$$S(t^j) = \exp(-(\lambda^j)t^{j^p})^\alpha$$
$$\lambda^j = \exp(\beta' X) \tag{2}$$

In simulations, α will be set to 1, thus the survival probability in a given state $S(t^j)$ is evaluated for the mean individual in the group identified by the X explanatory variables.

2.3 Simulating the working histories

In this section, I describe the simulation methodology used to obtain the profiles of the expected life cycle working careers from the estimated transition intensities from employment to unemployment and *vicevesa*.

The transition process between the two states of interest (employment and non-employment) is modeled in this paper as a non-homogeneous semi Markov chain. Indeed, both duration and lagged duration dependence turn out to affect significantly the transition process between the two states. Thus, to derive the probability distributions of the two states, I have to rely on simulation techniques so as to generate the survival times in both states as well as the transitions of the process.

In particular, simulate the entire working careers for each representative worker (*g*) of working group *g* identified by the combination of the *X* explanatory variables (i.e. for a representative worker employed as blue collar in the manufacturing sector, in a small size firm, in the north area). The initial probability distribution of the two states is taken from the empirical fraction of employed to non employed at that age[8]. Starting from age 20 I simulate the survival time *T* for the representative worker *g* in the initial state employment (unemployment), i.e. I simulate a large number (5000) of lengths for the first employment (unemployment) spell by drawing from the Weibull distribution with shape and scale parameters that depends on the value of the *XA* and the *XB* covariates as well as the estimated coefficient. As the aim is to generate the working histories for the average representative worker in each group *g*, the parameter governing the individual heterogeneity α is set to 1. The survival time *T* is thus function of the *XA* individual and job characteristics that remain fixed over the life cycle. It depends also on *XB* characteristics that vary over the life cycle: the age and the daily salary at the beginning and the duration of the previous unemployment (employment) spell[9]. Using the same methodology I simulate the ongoing spells for which the value of covariates *XB* is endogenously determined being function of the entire past history of the process. Thus, for each representative worker, I end up with 5000 simulated working histories for each representative worker, i.e. sequences of employment and unemployment

[8] The simulation are initialized at age 15 in order to obtain

[9] Apart from the initial age (set at 20) and daily wage if the first spell is employed, in all other cases the other XB variables are set to zero for the first simulated spell.

spells. From each sequence, I can determine the employment status at each age (expressed in month) and by averaging across sequences I can obtain the probability of being employed /non-employed at each point of the life cycle[10]. Thus the simulated Markov model produces the life cycle probabilities of being employed/non employed which are obtained taking into account the flows in and out employment and unemployment as well as the time elapsed in each state as predicted from the estimated duration models[11].

3. Data

I use the Work Histories Italian Panel (WHIP) provided by Laboratorio Riccardo Revelli. WHIP is a database of individual work histories, based on INPS (the Italian National Social Security Insitute) administrative archives. The panel consists of a random sample (1:180) drawn from the full archive of a dynamic population of about 370,000 individuals (66% men and 34% women) permanently and temporary employed in the private sector or self-employed or retired over the period 1985-2004. The dataset allows observing the main episodes of each individual's working career. The main limit of the analysis is that, as the data source originates from administrative archives, it does not enable to distinguish voluntary from involuntary job interruption spells[12].

In this paper, I focus on multiple-spells working data for two subsamples of male individuals employed in the private sector. The first subsample (here following dataset A) is made of workers who are employed with the so called 'standard' job contracts (open end, fixed term, and seasonal contracts[13]) and eventually experience unemployment and/or retire[14] over the time span considered[15]. In particular, in the first subsample, I exclude those workers who signed at least one atypical contracts (quasi employed –*parasubordinati*) over the period 1985-2004.

The second subsample (here following dataset B) is made by the workers who are hired with standard contracts plus those who are hired with 'entrance' contracts or temporary (agency) contracts. Entrance contracts include apprenticeship and training –on- the- job contracts. The apprenticeship contract is a labor contract for young people (aged between 16 and 24), which can last from a minimum of 18 months to four years (Law 196/97). This type of contracts represents the 4% of the job contracts observed in the panel. The average duration is 1.6 years. The training-on-the-job contracts (introduced by Law No. 863/1984) are intended to promote the hiring and training of individuals aged between 16 and 32, and can elapse up to 32 months. This type of contracts was introduced by Law No. 863/1984, it represents the 9.4 % of job contracts observed in

[10] An alternative method entails to simulate, at the end of each simulated current spell, the transitions across the states taking into account the time spent in the current spell. .

[11] Alternatively, I can simulate the transitions across states taking as given and fixed the time elapsed in each spell. This latter methodology will produce the life cycle probability of being employed at each age when employment and unemployment spell of given duration are considered.

[12] In particular, from data I could precisely detect only involuntary unemployment spells, i.e. those associated to the payment of unemployment benefits. However, to qualify for a benefit (*indennità ordinaria*) a person must have worked at least one year or have made voluntary contributions for two years under open end standard contracts. Thus focusing only on the unemployment benefit related spells would entail the underestimation of the unemployment risk.

[13] Since in the panel a distinction between the three can be made only after 1998, I choose to maintain no distinction through all the sample.

[14] As the panel provide information about the date from which individuals' receive pension benefits, I use this as a proxy of the beginning of retirement period.

[15]

the panel and its average duration is 1.12 years. Temporary agency work, introduced in the Italian Legislation since 1998, are contracts singed between the temporary work agency and worker who is assigned to work for (and under the control of) a firm (the user company). In the panel data used temporary agency work contracts represent the 2.12% of the total number of job contracts observed over the period 1985-2004 and last on average 1.12 years.

The unemployment spells are defined as starting at the end of a recorded job spells and ending at the re-employment in the private sector (observed in the panel), provided the workers does not retire in the period 1985-2004; if re-employment does not happen before the end of 2004 or the worker does note retire I treat the unemployment spell as censored. I exclude from the empirical analysis observations that are left truncated (i.e. we exclude from the analysis job spells that start at the very beginning of the sample: January 1985)[16].

The explanatory variables used in the duration analysis of both employment and unemployment[17] spells are: initial age, initial age squared (/100), working industry, firm dimension, geographic area, type of occupation (blue/white collars), the logarithm of the daily wage at the beginning of the spell and the length of the previous spell and the cohort birth year. The set of variables enable to identify 1,650 working groups.

Table 1 reports the main summary statistics for the dataset A and the dataset B.

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[16] More precisely, I rely on the flow sampling avoiding the left truncation problem that affect data (Lancaster, 1990).

[17] In particular, the job related variables for the unemployment spells,are set at the value recorded in the previous employment spell.

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Table 1 Summary statistics – Dataset A –Standard Labour Contracts

	Dataset A: Standard Contracts				Dataset B: Standard and Flexible Contracts			
	mean	**median**	**p5**	**p95**	**mean**	**median**	**p5**	**p95**
# of job spells	3.51	1	2	10	3.50	2.00	1.00	10.00
duration (years)	2.27	0.04	0.71	10.67	2.10	0.04	0.67	9.66
# of unempl- spells	3.54	1	2	11	3.50	1	2	10
duration (years)	2.23	0	0.47	13.98	1.55	0	0.36	10.13
	freq.	**Percent**			**freq.**	**Percent**		
# of job spells	129,069				271,626			
# of censored job spells	21,844	18.58			48,458	17.84		
# of unempl spells	98,603				216,294			
# of censored unempl spells	21,925	0.17			47,000	0.22		

Explanataory variables

	mean	**median**	**p5**	**p95**	**mean**	**median**	**p5**	**p95**
age at the beginning of job spells	37.25	20.68	36.35	56.60	32.07	17.69	29.35	54.26
age at the beginning of unempl spells	40.64	21.28	40.17	60.04	34.68	18.51	31.61	58.18
Industry	**freq.**	**percent**			**freq.**	**percent**		
Manufacturing	63,542	38.35			120,004	38.64		
Construction	47,658	28.77			73,353	23.62		
Trade	14,470	8.73			32,459	10.45		
Hotels	10,779	6.51			26,520	8.54		
T ransport	14,096	8.51			22,004	7.09		
Financial	9,818	5.93			26,649	8.58		
Real estate	2,554	1.54			4,408	1.42		
Other services	2,757	1.66			5,134	1.65		
Geographic Area								
north	79,872	46.73			168,019	52.89		
center	33,985	19.88			64,164	20.20		
south	57,081	33.39			85,479	26.91		
Firm size								
0-9	46,994	33.1			101,428	37.91		
10-19	20,865	14.69			41,050	15.34		
20-199	43,168	30.4			78,056	29.17		
200-999	14,874	10.48			23,680	8.85		
>1000	16,087	11.33			23,333	8.72		
Occupation								
Blue collars	139,798	81.78			267,123	84.09		
WhiteCollars	31,140	18.22			50,539	15.91		

4. Results

4.1 Estimated hazard functions

In this section I present the estimation results for the duration models introduced in section 2.2.

Table 2 and 3 display the coefficients for the employment and the unemployment duration models estimated over the dataset A. While table 4 and 5 report the correspondent estimates for the dataset B.

The shape parameters governing the duration dependence in the Weibull models are significant in all cases. Also, in all cases there is significant individual heterogeneity. Overall, 99% of coefficients are significantly different from zero and take a reasonable sign.

It is interesting to focus on the effects of the duration of the last spell and of the initial level of wage on the duration of the current spell.

The probability of being employed (unemployed) depends on the duration of the previous unemployment (employment) spell. It is plausible that the longer an unemployment spell is the higher the loss of productivity, thus workers face a higher probability of termination in the subsequent job spell. Seemingly, the longer the employment spell is the greater the productivity enhancement from the working experience is, which results in a higher probability of terminating the subsequent unemployment spell.

The probability of being employed (unemployed) depends on the level of wage at the beginning of the spell which acts as a proxy of the workers' level of productivity. The higher the wage at the beginning of the job spell and thus the higher his productivity which contributes to lower the probability of job termination. For the case of unemployment spells, the high wage perceived at the termination of the preceding job experience convey information about his high probability and thus, the higher the probability of terminating the current unemployment spell.

In the next subsection 4.2 I report the life cycle employment probabilities derived by simulating the employment and unemployment probabilities predicted according to these estimated hazard functions.

Table 2. Duration model for employment spells –Weibull Distribution with Gamma distribution for shared frailty - Marginal effects -

Workers Employed with standard contracts

_t	β	Std. Err.	z	P>z	[95% Conf.	Interval]
Age at the beginning of the spell	-0.106	0.005	-19.530	0.000	-0.117	-0.096
Age ^2	0.013	0.001	19.170	0.000	0.012	0.015
Industry						
Manufacturing	-0.680	0.051	-13.320	0.000	-0.780	-0.580
Construction	-0.136	0.051	-2.640	0.008	-0.236	-0.035
Trade	-0.877	0.054	-16.160	0.000	-0.983	-0.770
Hotels	0.302	0.054	5.640	0.000	0.197	0.407
Transport	-0.389	0.055	-7.130	0.000	-0.497	-0.282
Financial	-0.682	0.057	-12.040	0.000	-0.793	-0.571
Real estate	-0.184	0.076	-2.420	0.015	-0.333	-0.035
Other services	ref					
Firm size						
0-9	ref					
10-19	-0.169	0.016	-10.350	0.000	-0.202	-0.137
20-199	-0.244	0.015	-16.220	0.000	-0.273	-0.214
200-999	-0.458	0.025	-18.430	0.000	-0.507	-0.409
>1000	-0.746	0.035	-21.150	0.000	-0.816	-0.677
Geographic Area						
North	-0.383	0.017	-22.590	0.000	-0.416	-0.350
Center	-0.326	0.021	-15.880	0.000	-0.366	-0.286
South	ref					
Occupation						
Blue collar	0.409	0.022	18.420	0.000	0.365	0.452
White collar	ref					
Length of the previous unemployment spell	0.175	0.005	37.050	0.000	0.165	0.184
Log of daily wage at the beginning of the spell	-0.105	0.018	-5.910	0.000	-0.140	-0.070
Birth year						
1930-39	ref					
1940-49	-0.070	0.033	-2.100	0.036	-0.136	-0.005
1950-59	-0.266	0.038	-7.020	0.000	-0.340	-0.192
1960-69	-0.216	0.042	-5.080	0.000	-0.299	-0.132
1970-79	0.089	0.048	1.840	0.066	-0.006	0.184
_cons	2.559	0.140	18.270	0.000	2.284	2.833
/ln_p	-0.081	0.005	-15.940	0.000	-0.091	-0.071
/ln_the	-0.173	0.015	-11.410	0.000	-0.203	-0.144
p						

1/p	0.923	0.005	0.000	0.000	0.913	0.932
theta	1.084	0.005	0.000	0.000	1.073	1.095

Table 3. Duration model for unemployment spells – Weibull Distribution with Gamma distribution for shared frailty-Marginal effects

Workers Employed with standard contracts

_t	β	Std. Err.	z	P>z	[95% Conf.	Interval]
Age at the beginning of the spell	0.060	0.004	13.980	0.000	0.051	0.068
Age^2/10	-0.006	0.001	-11.300	0.000	-0.007	-0.005
Industry						
Manufacturing	0.268	0.052	5.110	0.000	0.165	0.370
Construction	0.042	0.053	0.800	0.425	-0.062	0.147
Trade	0.199	0.055	3.630	0.000	0.092	0.307
Hotels	0.077	0.056	1.370	0.172	-0.033	0.188
Transport	0.372	0.055	6.720	0.000	0.264	0.481
Financial	0.221	0.056	3.930	0.000	0.111	0.331
Real estate	ref					
Other services	-0.104	0.068	-1.540	0.124	-0.237	0.028
Firm size						
0-9	ref					
10-19	0.753	0.016	47.200	0.000	0.722	0.784
20-199	0.352	0.019	18.040	0.000	0.313	0.390
200-999	0.061	0.019	3.250	0.001	0.024	0.099
>1000	0.142	0.004	34.280	0.000	0.134	0.150
Geographic Area						
North	0.261	0.013	19.950	0.000	0.235	0.286
Center	0.724	0.041	17.600	0.000	0.643	0.805
sSouth	ref					
Occupation						
Blue collar	ref					
White collar	0.061	0.019	3.250	0.001	0.024	0.099
Length of the previous employment spell	0.142	0.004	34.280	0.000	0.134	0.150
Log of daily wage at the beginning of the spell (i.e. at the end of the previous employment spell)	0.261	0.013	19.950	0.000	0.235	0.286
Birth year						
1930-39	0.724	0.041	17.600	0.000	0.643	0.805
1940-49	0.396	0.037	10.730	0.000	0.324	0.469
1950-59	0.105	0.032	3.320	0.001	0.043	0.168
1960-69	-0.106	0.028	-3.840	0.000	-0.161	-0.052
1970-79	ref					
_cons	-2.800	0.105	-26.630	0.000	-3.006	-2.594

/ln_p	-0.090	0.003	-35.300	0.000	-0.095	-0.085
/ln_the	0.730	0.008	94.390	0.000	0.715	0.746
p						
1/p	0.914	0.002	0.000	0.000	0.909	0.918
theta	1.095	0.003	0.000	0.000	1.089	1.100

Table 4. Duration model for employment spells - Weibull Distribution with Gamma distribution for shared frailty –Marginal effects

Workers Employed with standard and flexible contracts

_t	β	Std. Err.	z	P>z	[95% Conf.	Interval]
Age at the beginning of the spell	-0.085	0.004	-22.740	0.000	-0.092	-0.077
Age ^2	0.012	0.001	23.430	0.000	0.011	0.013
Industry						
Manufacturing	-0.798	0.041	-19.580	0.000	-0.878	-0.718
Construction	-0.195	0.041	-4.740	0.000	-0.276	-0.115
Trade	-0.879	0.043	-20.620	0.000	-0.963	-0.796
Hotels	0.373	0.043	8.710	0.000	0.289	0.457
Transport	-0.372	0.044	-8.490	0.000	-0.458	-0.286
Financial	-0.284	0.044	-6.460	0.000	-0.370	-0.198
Real estate	-0.151	0.062	-2.430	0.015	-0.273	-0.029
Other services	ref					
Firm size						
0-9	ref					
10-19	-0.320	0.013	-23.830	0.000	-0.347	-0.294
20-199	-0.290	0.016	-17.770	0.000	-0.322	-0.258
200-999	-0.467	0.017	-27.580	0.000	-0.500	-0.434
>1000	0.167	0.004	46.900	0.000	0.160	0.174
Geographic Area						
North	-0.116	0.014	-8.280	0.000	-0.143	-0.088
Center	0.065	0.040	1.620	0.106	-0.014	0.144
South	ref					
Occupation						
Blue collar	ref					
White collar	-0.467	0.017	-27.580	0.000	-0.500	-0.434
Lenght of the previous unemployment spell	0.167	0.004	46.900	0.000	0.160	0.174
Log of daily wage at the beginning of the spell	-0.116	0.014	-8.280	0.000	-0.143	-0.088
Birth year						
1930-39	ref					
1940-49	0.044	0.033	1.330	0.184	-0.021	0.108

1950-59	0.000	0.037	-0.420	0.673	-0.088	0.057
1960-69	0.065	0.040	1.620	0.106	-0.014	0.144
1970-79	0.286	0.042	6.740	0.000	0.203	0.369
_cons	2.318	0.094	24.580	0.000	2.133	2.502
/ln_p	-0.167	0.004	-40.140	0.000	-0.175	-0.159
/ln_the	-0.158	0.012	-13.420	0.000	-0.181	-0.135
p	0.846	0.004			0.839	0.853
1/p	1.182	0.005			1.172	1.191
theta	0.854	0.010			0.834	0.874

Table 5. Duration model for unemployment spells -Weibull Distribution with Gamma distribution for shared frailty–Marginal effects

Workers Employed with standard and flexible contracts

_t	β	Std. Err.	z	P>z	[95% Conf.	Interval]
Age at the beginning of the spell	0.075	0.003	26.290	0.000	0.069	0.081
Age^2/10	-0.008	0.000	-20.340	0.000	-0.009	-0.007
Industry						
Manufacturing	0.366	0.037	9.980	0.000	0.294	0.438
Construction	0.153	0.037	4.110	0.000	0.080	0.226
Trade	0.323	0.038	8.470	0.000	0.248	0.398
Hotels	0.136	0.039	3.500	0.000	0.060	0.211
Transport	0.483	0.039	12.230	0.000	0.406	0.560
Financial	0.421	0.040	10.660	0.000	0.344	0.499
Real estate	0.108	0.054	1.980	0.047	0.001	0.215
Other services	ref					
Firm size						
0-9	ref					
10-19	0.814	0.013	64.230	0.000	0.789	0.839
20-199	0.428	0.016	27.470	0.000	0.398	0.459
200-999	0.000	0.000	0.000	0.000	0.000	0.000
>1000	0.123	0.003	38.640	0.000	0.117	0.129
Geographic Area						
North	0.233	0.010	23.230	0.000	0.214	0.253
Center	-0.365	0.025	-14.340	0.000	-0.415	-0.315
Ssouth	ref					
Occupation						
Blue collar	-0.079	0.015	-5.380	0.000	-0.108	-0.050

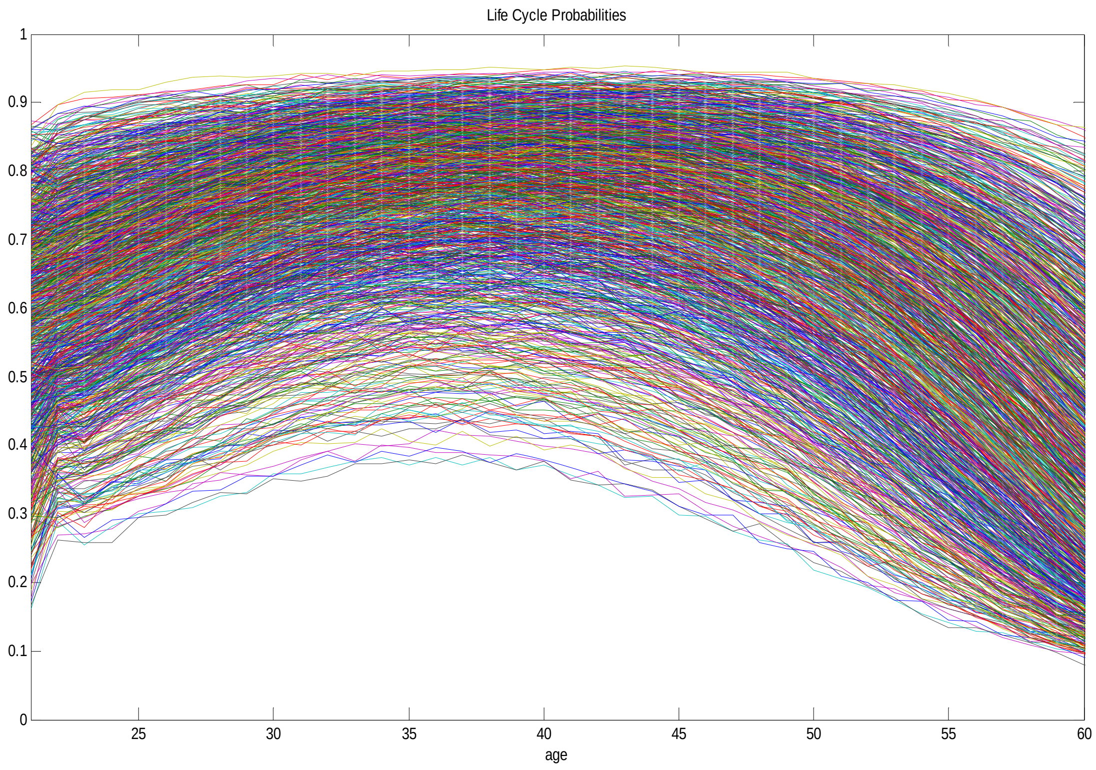
White collar	ref					
Length of the previous employment spell	0.123	0.003	38.640	0.000	0.117	0.129
Log of daily wage at the beginning of the spell (i.e. at the end of the previous employment spell)	0.233	0.010	23.230	0.000	0.214	0.253
Birth year						
1930-39	ref					
1940-49	-0.365	0.025	-14.340	0.000	-0.415	-0.315
1950-59	-0.714	0.031	-23.120	0.000	-0.775	-0.654
1960-69	-0.657	0.033	-19.760	0.000	-0.722	-0.592
1970-79	-0.358	0.035	-10.230	0.000	-0.426	-0.289
_cons	-2.279	0.077	-29.780	0.000	-2.429	-2.129
/ln_p	-0.067	0.002	-33.040	0.000	-0.071	-0.063
/ln_the	0.575	0.007	88.350	0.000	0.562	0.588
p	0.935	0.002			0.931	0.939
1/p	1.070	0.002			1.065	1.074
theta	1.777	0.012			1.754	1.800

4.2 Life cycle employment probabilities

In this section, I report the simulated life cycle profiles of the employment probabilities based on the survival times predicted from the estimated models and derived according to the methodology outlined in section 2.3

Figure 1 reports the simulated age profiles (1,650 working groups) of the probabilities of being employed at each age for the representative workers of the 1,650 working groups identified according to job characteristics and the birth year cohort. The probabilities are simulated for the model estimated over dataset A, which includes workers hired with standard contracts only. The picture reveals a remarkable heterogeneity across ages and across the defined groups of workers. In particular, the heterogeneity is higher at younger and older ages, while it shrinks over central ages.

Figure 1 Life cycle employment probabilities

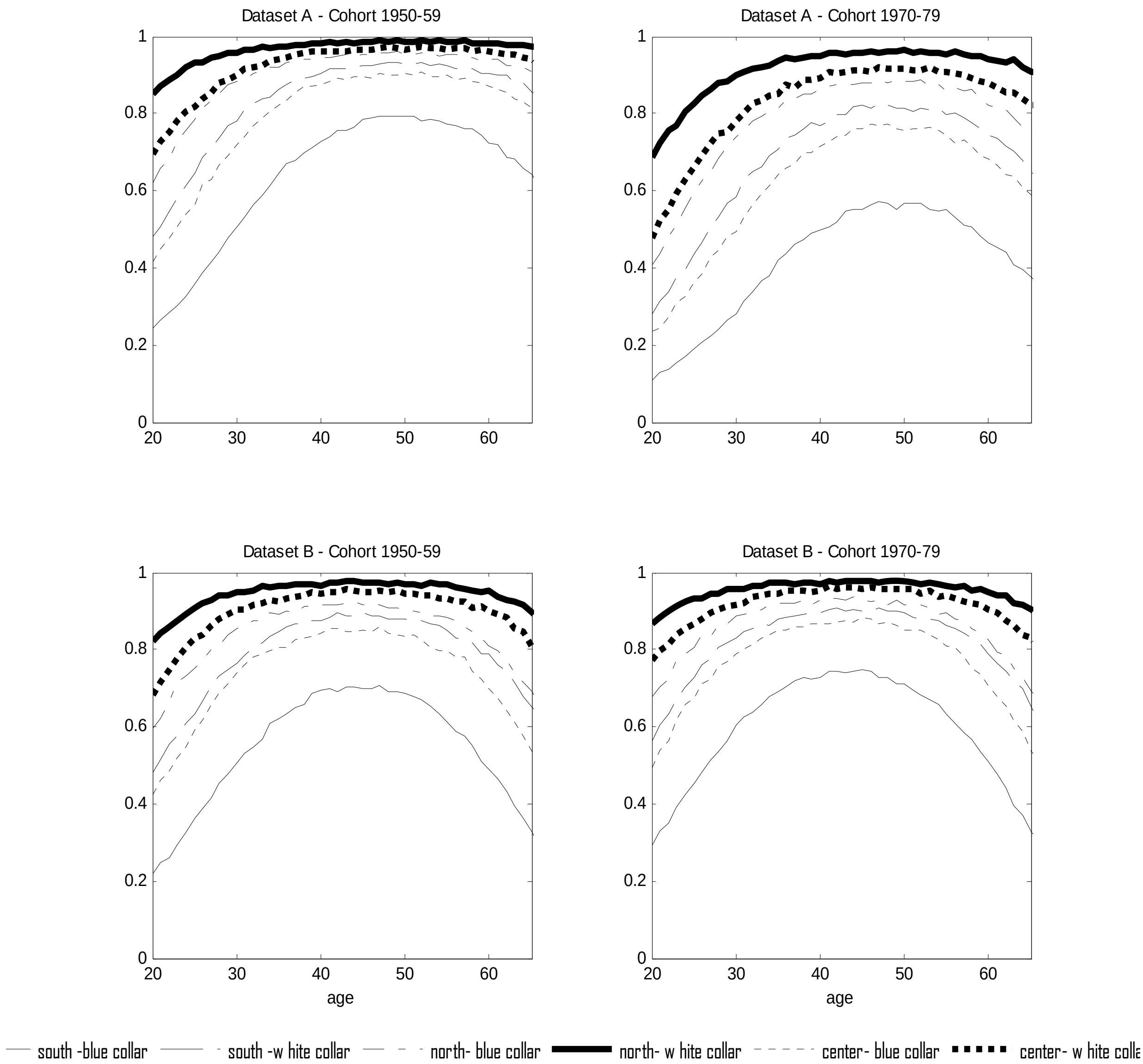


In figure 2 I report the life cycle employment probabilities by age and cohort for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area and birth year cohort (1950-59 and 1970-79). The graphs at the top report the simulated employment probabilities for the model estimated over dataset A (i.e. workers hired with standard contracts). The graphs at the bottom report the simulated employment probabilities for the model estimated over dataset B (i.e. workers hired with standard and flexible contracts).

The employment probabilities are concave functions of age, though to a different degree across working groups. The heterogeneity in the employment probability is higher at younger and older ages, while it shrinks over central ages. Workers in the northern side of the country and white collars have higher employment probabilities at all ages and for any cohort. The differences, in particular across ages and cohorts are larger when standard contracts only are considered.

Figure 2 Life Cycle Employment Probabilities by Cohort - Selected Working Groups

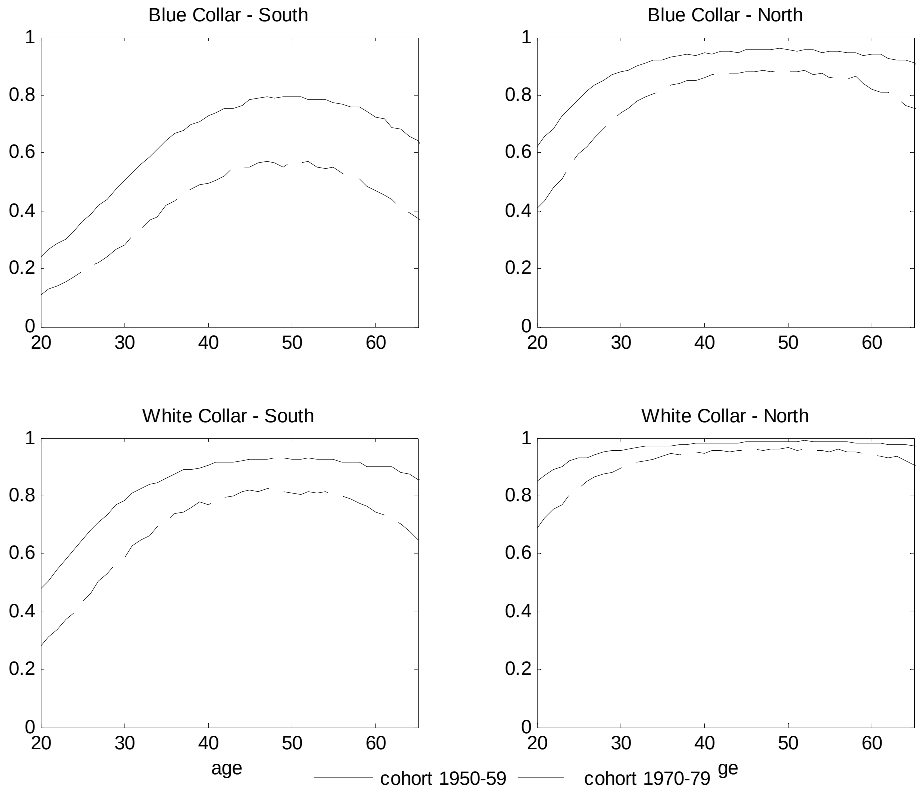
The figure reports the life cycle employment probabilities for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area and birth year cohort (1950-59 and 1970-79). Left hand graphs report the simulated employment probabilities for the model estimated over dataset A (i.e. workers hired with standard contracts). Right hand graphs report the simulated employment probabilities for the model estimated over dataset B (i.e. workers hired with standard and flexible contracts).



In figure 3 and 4 I report the employment probability profiles for the same selected groups by focusing on the differences across cohorts. In figure 3, I report, profiles obtained when standard contracts only are considered. Workers hired in the manufacturing sector and medium size firms belonging to the cohort 1970-79 faces on average a lower probability (11%) of being employed than those belonging to the cohort of 1950-1959. In general, the difference by cohort in the chance of being employed is higher for workers in southern (20%) and central (10%) Italian regions than for those employed in the northern (7%) part of the country.

Figure 3 Life Cycle Employment Probabilities by Cohort - Standard contracts - Selected Working Groups

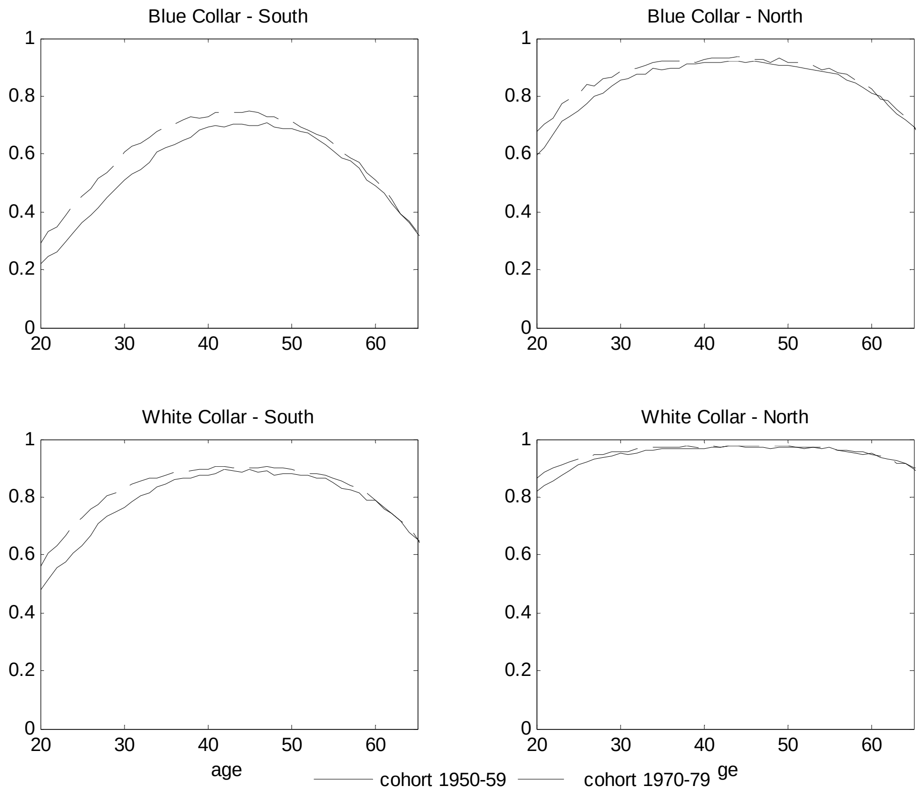
The figure reports the life cycle employment probabilities for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area (south on the left hand graphs, north on the right hand graphs) and birth year cohort (1950-59 and 1970-79).



In figure 4, I report, for the same selected working groups, the life cycle the profiles of employment probabilities obtained when all types of contracts (standard and flexible) are considered. In this case, the differences among cohorts tend to be overcome. In all cases, young cohorts display higher employment probabilities than old cohorts at the beginning of the life cycle, while later on the difference tend to disappear.

Figure 4 Life Cycle Employment Probabilities by Cohort – Standard and flexible contracts - Selected Working Groups

The figure reports the life cycle employment probabilities for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area (south on the left hand graphs, north on the right hand graphs) and birth year cohort (1950-59 and 1970-79).



Our results, based on the employment and unemployment duration observed over the period 1985-2004, reveal that the Italian cohorts do not display remarkable differences in terms of the life cycle employment probabilities. The employment probability for young people is enhanced by using flexible contracts, which is more evident in figure 5 which reports, for the cohort 1970-79, the life cycle profiles by type of contract. However, when considering the older cohorts (e.g. the cohort 1950-59), it turns out that the flexible contracts reduce the probability of being employed especially at older ages (see figure 6)[18].

[18] For the case of the older worker, the relevant flexible contract are the temporary (agency) work contracts, since age limit to sign apprenticeship and training contracts are 29 and 32 years respectively.

Figure 5 Life Cycle Employment Probabilities by Type of Contracts - Selected Working Groups - Cohort 1970-79

The figure reports the life cycle employment probabilities for the representative workers belonging to the cohort 1970-79 hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area (south on the left hand graphs, north on the right hand graphs). The profiles are reported by type of contract.

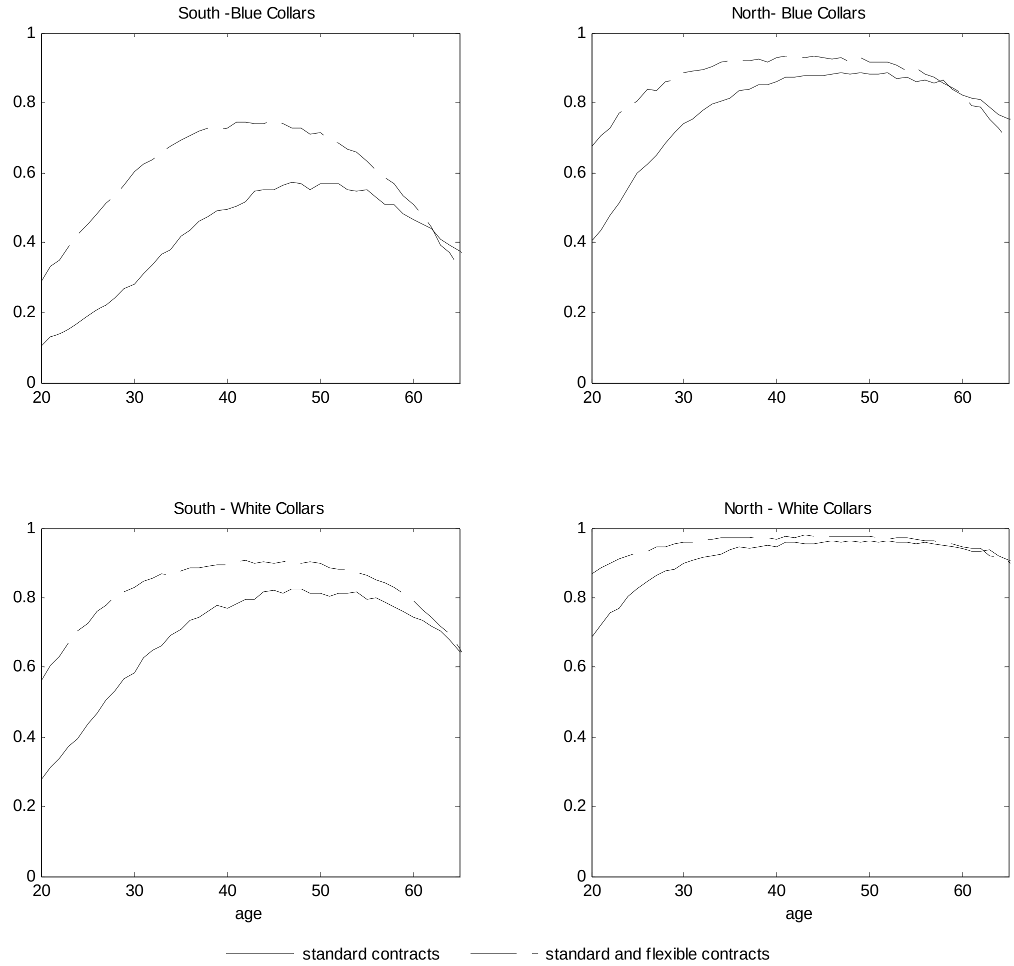
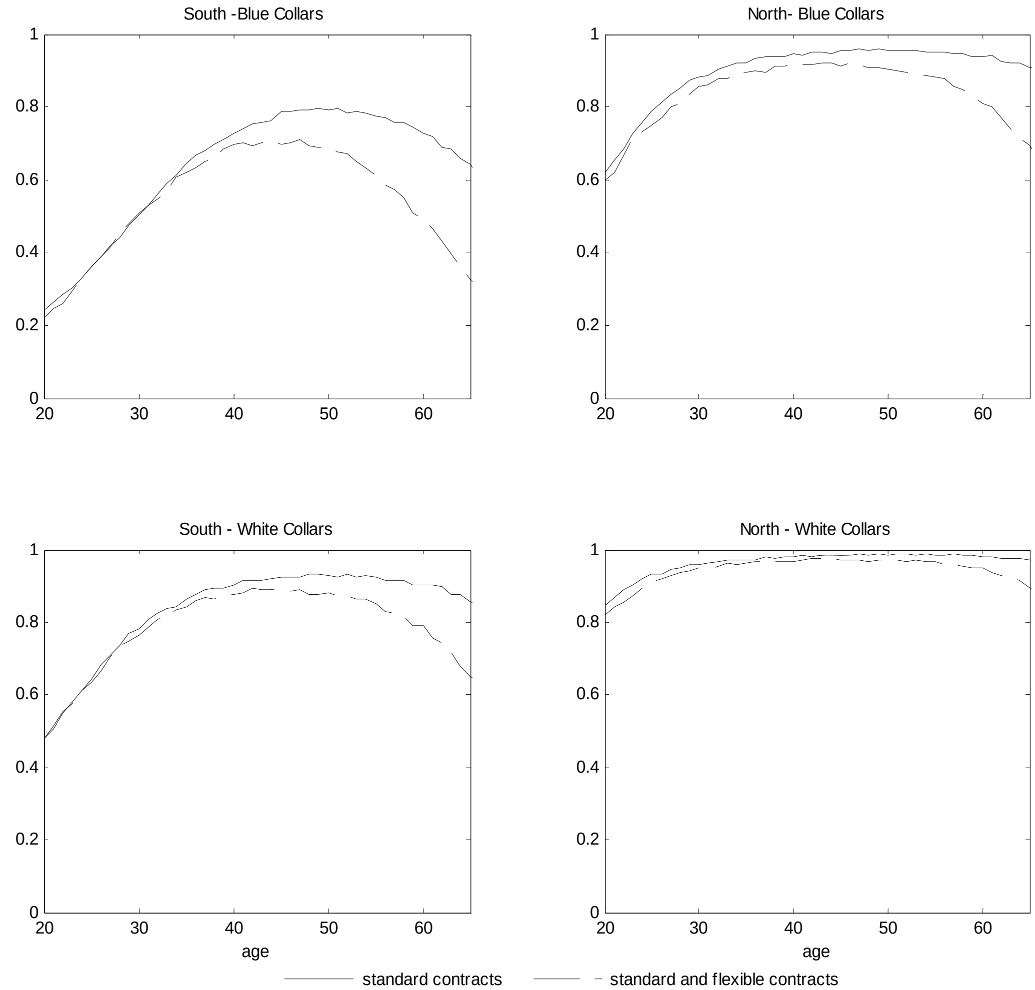


Figure 6 Life Cycle Employment Probabilities by Type of Contracts - Selected Working Groups - Cohort 1950-59

The figure reports the life cycle employment probabilities for the representative workers belonging to the cohort 1950-59 hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area (south on the left hand graphs, north on the right hand graphs). The profiles are reported by type of contract.



5. Conclusion

In this paper, I use the duration analysis approach to derive the life cycle profile of the probability of being employed/unemployed as a comprehensive measure of the labor market performance. Thus, I measure unemployment risk as the expected probability of being non-employed at a given stage of the life cycle, derived taking into account the risk of entering a non-job spell as well as the chance of re-employment.

The methodology applied to Italian data enables to highlight the role of entrance contracts (apprenticeship contracts and training-on-the-job contracts) and of temporary agency work in favoring employment among young people. In particular, when focusing on standard contracts (open end contracts and fixed term contract and seasonal contracts), younger cohorts face, at each age, a substantial lower probability of being employed than older cohorts, and the probability of being employed when young is much lower than when being middle aged. When the focus is on all types of contracts (including apprenticeship and training-on-the-job contracts as well as temporary agency work contracts), while, the differences among ages are confirmed, the differences among cohorts tend to be nullified and in some cases overcome.

In this paper the effect of the business cycle in shaping the employment and unemployment duration is not taken into account. Moreover, I do not consider that the hazard of job spells and unemployment can be affected by the type of contract, an issue that could be taken into account by estimating a competing risk model. Further research on this area accommodating for these topics ought to enhance our understanding of the relationship between flows and stocks in labor markets and their implication for the expected outcomes at individual levels.

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