Heterogeneity in the unemployment risk over the life cycle under standard and flexible contracts*

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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 into heterogeneity in workers' unemployment risk? This paper deals with the measurement of the unemployment risk and its distribution across Italian workers that differ along various dimensions including the type of contract, i.e. standard vs flexible. 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. Our results on Italian data 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. 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.

Keyrwords: Unemployment/Employment risk, Duration, Heterogeneity, Semi-Markov
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 over the individual working life career with fixed distribution of wages in an homogeneous and stationary environment where unemployment length is exponentially distributed. In this framework the exit rate from unemployment and the chance of 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 contrast with the empirical evidence from reduced-form analysis that documents that the job search environment is nonstationary as the hazard from unemployment declines with the unemployment spell length even when unobserved heterogeneity is accounted for (see for example Lancaster, 1979; Flinn and Heckman, 1982; Bover, Arellano and Bentolila, 2002). Thus, in the time dependent environment the optimal solution to the worker's search problem is dynamic over the unemployment spell. However, the reduced-form approach to job search model are unsuitable to detect the sources of nonstationarity, since it does not enable to relate the estimated parameters to the theoretical parameters. Given this ambiguity it is hard to evaluate the impact of the unemployment compensation system using results from the reduced form analysis.

Extensions of the standard job search model have been developed to account for potential sources of nonstationarity (see e.g. Van den Berg, 1990). In addition to this, various other sources of heterogeneity, such as unemployment benefits, stigma, policy reforms or business cycles, 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.

In particular, one issue that has not been fully addressed in the job search theory, neither in the stationary nor in the non-stationary framework, is demographics. Ljungquist and Sargent (2008) show that the stochastic transitions between consecutive age groups affect human capital accumulation implying a non constant unemployment risk over the life cycle that partially rationalizes the evidence of the high-incidence of long-term unemployment among European older workers. While Low, Meghir and Pistaferri (2010) focuses on how different sources of risk, including the employment risk, affect the individual's welfare is affected at various stages of the life cycle.

This paper exploits the detailed information on working careers conveyed by administrative data to measure the unemployment risk and the employment probability over the life cycle across heterogeneous workers in different age cohort and occupation groups. Using a flexible reduced-form model for the hazard rate that easily enable us to account for both observed and unobserved heterogeneity we estimate the risk of entering unemployment and the chance of re-employment over the life cycle allowing for current and lagged duration dependence as well as time dependence. The latter form of dependence allow us to model the impact of the age of the worker on the relevant hazard rates. To our knowledge this is the first work that uses results on transitions in and out employment from a reduced-form model and combine them to derive the implied probability of being unemployed as a measure of the individual unemployment risk over the life cycle.

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, we 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, we 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. To our knowledge, no previous study makes any attempt to document how the two risks combine in shaping the unemployment/employment probability profiles at individual level over the life cycle which turn out to be responsible of the substantial heterogeneity in aggregate employment rates across countries (Jaimovich and Siu, 2009).

In particular, we model a two-state time non-homogeneous semi Markov process that drives the transition from employment to unemployment and *viceversa* which are allowed to be both current and lagged duration dependent as well as time dependent. The transition distributions over the life cycle are obtained estimating two 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. We rely on Monte Carlo techniques to simulate, 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. From the simulated working life careers we derive the age profiles of the probability of being employed, which turn out to display a hump shaped consistently with the observed distribution of the employment across ages.

The empirical analysis is carried using multiple spells data on working histories for a large number of male workers aged between 20 and 60 years old tracked in the panel data INPS which covers the period 1985-2004. Our results document a substantial degree of 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 flexible contracts, namely entrance contracts (apprenticeship contracts and training-on-the-job contracts) and of temporary agency work 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 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 employment/ unemployment probabilities. Section 5 concludes.

2. Methodology

2.1 The semi Markov process

In this paper, we 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

We carry out the parametric analysis of employment and unemployment spells estimating two separate continuous time parametric Weibull models to assess the impact of causal variables on the extent of the duration dependence in employment and unemployment status[1]. We privilege continuous time to discrete time techniques as in the first case results are invariant to the time unit used to record the available data (Flinn and Heckman, 1982) and thus enabling to derive the life cycle profile of the probabilities conditional on whatever length of the employment/unemployment spells. Moreover, since the presence of unmeasured variables could give rise to spurious negative duration dependence (see Heckman, 1991), we take into account the impact of unobserved heterogeneity and we allow for a multiplicative shared frailty distributed as a gamma [2].

According to the adopted approach, the instantaneous hazard rates for unemployment (u) and employment (e) spells are modeled 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, $h^j{}_i(t) = (t^j)^p$ }is the baseline hazard that here takes the Weibull distribution, $\exp(\beta' X_i)$ is a linear combination of observed demographic and occupational characteristics, α^j is the multiplicative effect that captures unobserved heterogeneity. Observed heterogeneity is controlled for by a set of covariates X_i that capture individual and job characteristics.

Previous studies evidence that transitions between labor market states are affected by time elapsed in the current state but also by time spent in the previous state. (see for example Heckman and Borjas, 1980; Heckman and Flinn, 1982), thus, we allow for both duration and lagged duration dependence as well as time dependence. Among covariates we include age, daily salary which capture the time dependence, as well as the length of the previous employment (non-employment) spell which captures the lagged duration dependence. In addition we consider explanatory variables that are fixed over the spell[3] and over the life cycle and are measured at the beginning of the spell

[1]We 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).

[2] The data that we use convey information on multiple spells per workers, thus allowing for shared frailty entails modeling heterogeneity among workers as a random effect.

[3] In the duration analysis of unemployment spells, the job related covariates are fixed at the value taken at the end of the previous employment spell.

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 Institute) 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[4].

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[5]) and eventually experience unemployment and/or retire[6] over the time span considered. 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)[7]. 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 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)[8]. In the panel data used temporary agency work contracts represent the

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[4] 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.

[5] 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.

[6] 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.

[7]More specifically, 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.

[8] More specifically, 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.

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)[9].

The explanatory variables used in the duration analysis of both employment and unemployment[10] 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.

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

[10] 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 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.

Tables 2 and 4 display the estimated coefficients and the marginal effects for the employment duration model[11] for dataset A and B respectively. According to our results all kinds of the allowed dependence are significant. In particular, we find evidence of negative current duration dependence, i.e. the longer the time elapsed in a job spell the more likely the worker will remain employed. We find that there's significant lagged duration dependence, i.e. the longer the previous unemployment spell the higher the risk of exiting the current employment spell. These results support the evidence that unemployment episodes may have a scarring effect on future labor market histories both in terms of subsequent earnings (Arulampalam, 2001) and in terms of subsequent risk of job separation (Arulampalam et al., 2001 and Gregg, 2001). Moreover, according to the human capital theory explanation the unemployment spell induces a deterioration of individual skills but also lower opportunity to accumulate work experience: the longer an unemployment spell the higher the loss of productivity which induces a higher probability of subsequent job termination. Indeed, the probability of being employed depends on the level of wage at the beginning of the spell which seems to act as a proxy of the workers' level of productivity: the higher the wage at the beginning of the job spell the higher the worker's productivity which contributes to lower the probability of job termination.

Our results support the evidence of time dependence, too. In our specification, time dependence is introduced by controlling for the worker's age at the beginning of the job spells. We find that the older the worker at the beginning of the spell the lower the risk of exiting it and the longer the job tenure. This pattern reverses after reaching the middle age, as evidenced by the (significant) second order term of the polynomial in age. Job interruptions in the construction industry are more frequent than in the manufacturing and the services industries. North- Western and Central regions are those with longer job relations, while shorter tenures characterize jobs in the South and North-East. Not surprisingly, the probability of separation is monotonically decreasing with the dimension of the firm, shorter tenures are more frequent in small firms and become longer as the average dimension increases. In our data, young cohorts face higher job instability than older cohorts, which is not surprising since young cohorts are more affected by fixed-term contracts with respect to the older cohorts.

Tables 3 and 5 show the results for the unemployment duration model for dataset A and B respectively. Our estimates document negative current duration dependence for the unemployment status. In addition, we support the evidence for all kinds of duration dependence. In particular, the longer the past employment spell the higher the chance of exiting the current unemployment spell becoming employed. Negative duration dependence is well documented in literature (see e.g. Heckman and Borjas, 1980; Flinn and Heckman, 1982; and Lynch, 1989). It may be due to the fact that long unemployment durations discourage workers to search a new job (Schweitzer and Smith, 1974). Moreover, it may be due to deterioration of skills (see e.g. Pissarides,

[11] Negative marginal effects (positive coefficients for the hazard rate) indicate that the covariates reduce the duration, while positive marginal effects (negative coefficients for the hazard rate) indicate that the covariates increases the duration.

1992), or it may be signal of unobserved lower productivity (Vishwanath, 1989), or it may be the result of strong competition for jobs among workers. Moreover, duration dependence in unemployment may arise in a framework were job opportunities are spread through an explicitly network of social contacts (Calvó -Armengol and Jackson, 2004). Our evidence supports the view that the longer the employment spell the greater the productivity enhancement from the working experience which may result in a higher probability of terminating the subsequent unemployment spell. Indeed, the probability of remaining unemployed depends on the level of wage at the beginning of the spell. Here, we are analyzing the unemployment duration, thus the wage measured at the beginning of the spell is the last wage received in the previous employment spell. Our result indicates that the level of wage earned upon termination of the preceding job experience taken as a proxy of the level of the workers' productivity may act as a signal affecting the chance of new job finding.

Time dependence is significant also in determining the nature of the unemployment persistence: the higher the age at entry the higher the chance of terminating the current unemployment spell, although this pattern reverses at old ages as indicated by the second order term of the polynomial in age.

In our specification, we evaluate the influence of last job occupation characteristics on the current unemployment duration. Workers who face job interruptions from medium and large size firms have a lower chance of getting a new job. For workers in the Northern regions, especially Eastern ones, the hazard rate of finding a job is higher than in the rest of Italy. These findings, together with the evidence on the duration of job spells support the importance of local conditions in determining the dualistic nature of the Italian formal labor market.

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. Importantly, in case of both employment and unemployment durations, our results are robust to the unobserved heterogeneity.

In the next subsection 4.2 we derive the life cycle employment probabilities derived by simulating the employment and unemployment probabilities predicted according to these estimated hazard functions and results are reported.

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

4.2 Simulating the implied working histories

In this subsection, we outline 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.*

According to results reported in section 4.1 , the transition process between the two states of interest (employment and non-employment) is as a non-homogeneous semi Markov chain. Both duration and lagged duration dependence turn out to affect significantly the transition process between the two states. Thus, to derive the transition probability distributions at each point of the working life we have to rely on MonteCarlo simulation techniques.

In particular, for each representative worker g , we simulate the entire working careers. We assume that working life careers stat at the age of 20 and lasts at the age of 60 years old. At the age of 20, the representative worker may be either employed or unemployed, being the initial probability distribution of the two states is taken from the empirical fraction of employed to non employed at that age. We simulate the survival time T in the initial state employment (unemployment). In particular, we simulate a large number N ($N = 5000$) 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 covariates as well as the estimated coefficients (see Tables 2 to and 5) [12].. As the aim is to generate the working histories for the average representative worker of each group g , the parameter governing the individual heterogeneity α is set to 1. The survival time T is thus function of the individual and job characteristics that remain fixed over the life cycle but also on characteristics that vary over the life cycle: the age and the daily salary at the beginning of the spell and the duration of the previous simulated unemployment (employment) spell[13]. Using the same methodology we simulate the ongoing spells. Thus, for each representative worker, we end up with N simulated working histories, i.e. sequences of employment and unemployment spells. From each sequence, we can determine the employment status at each age and by averaging across sequences we can obtain the both the conditional and the unconditional probability of being employed /unemployed at each point of the life cycle.

4.3 Life cycle employment and unemployment probabilities

In this section, we 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

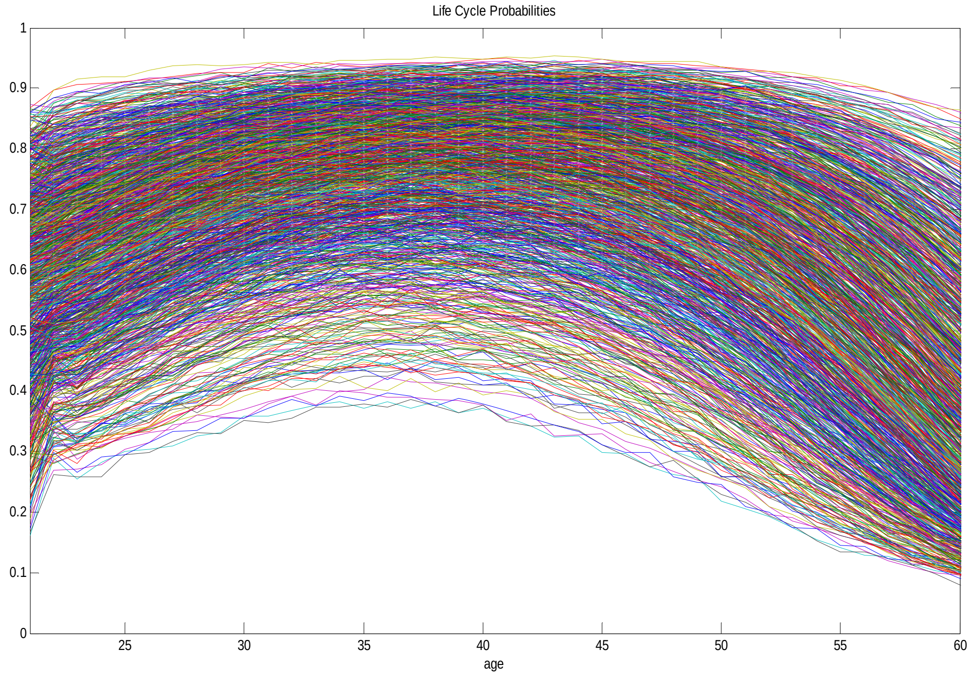
Figure 1 reports the simulated age profiles (1,650 working groups) of the probabilities of being employed at each age for the representative workers of the 1,650 working groups identified according to job characteristics and the birth year cohort. The probabilities are simulated for the model estimated over dataset A, which includes workers hired with standard contracts only. The picture reveals a remarkable

[12] 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.

[13]In simulations, the daily salary at the beginning of the spell is proxied by the average daily salary observed by age, cohort and type of occupation.

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 we 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 2a 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).

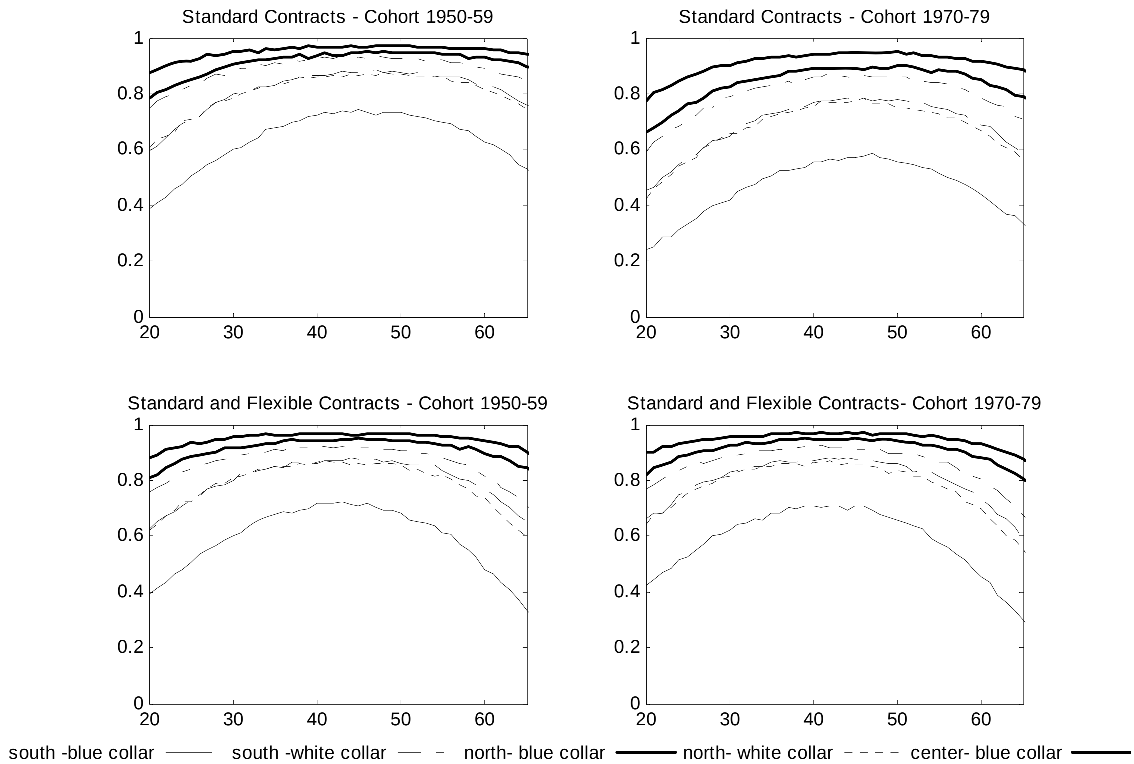
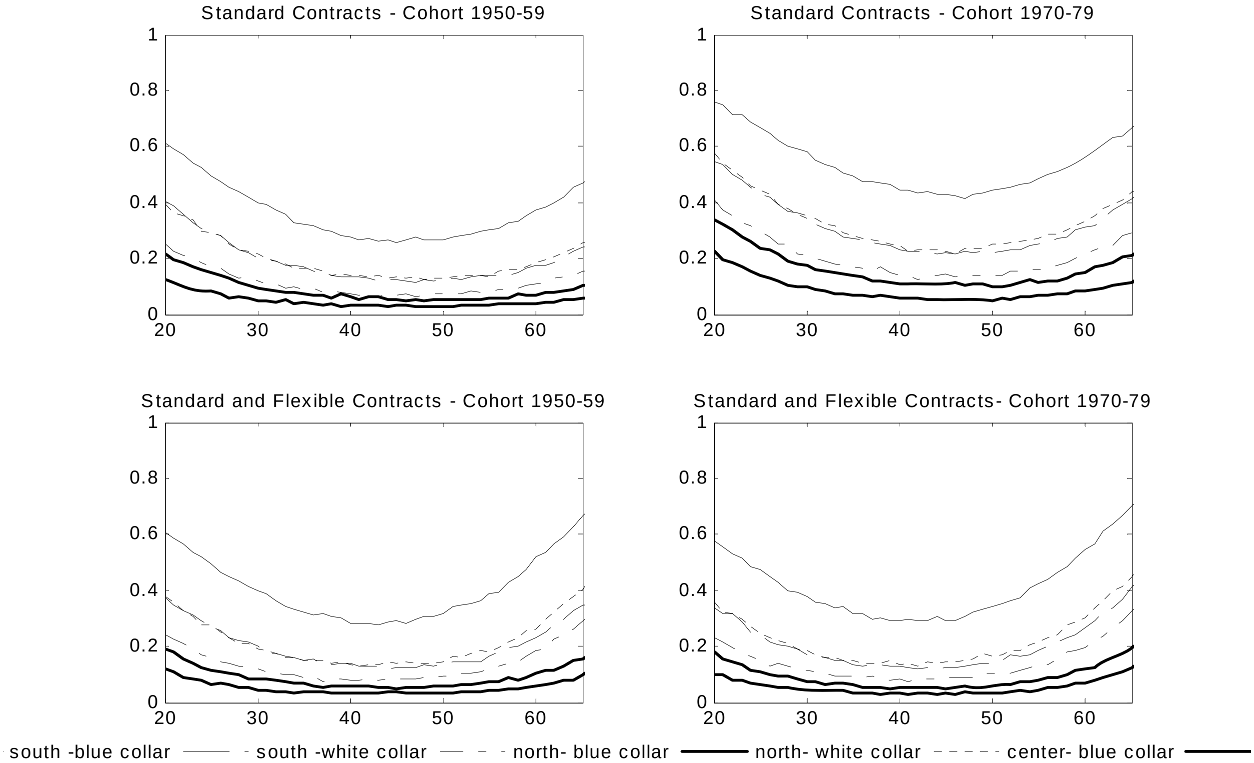


Figure 2b Life Cycle Unemployment Probabilities by Cohort - Selected Working Groups

The figure reports the life cycle unemployment 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 unemployment probabilities for the model estimated over dataset A (i.e. workers hired with standard contracts). Right hand graphs report the simulated unemployment probabilities for the model estimated over dataset B (i.e. workers hired with standard and flexible contracts).

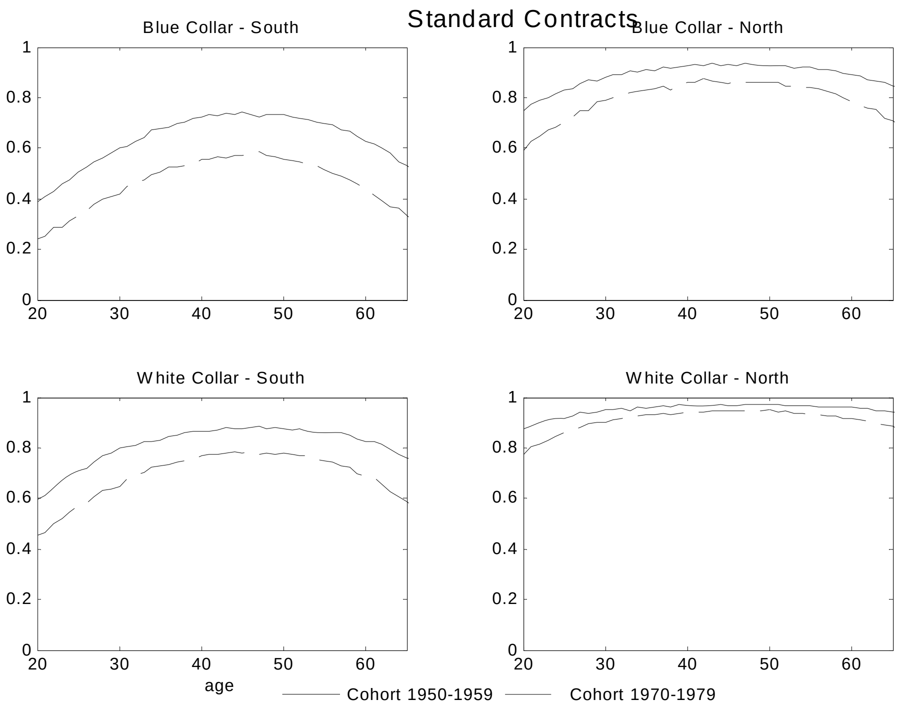


In figure 3 and 4 I report the employment probability profiles for the same selected groups by focusing on the differences across cohorts. In figure 3, I report, profiles obtained when standard contracts only are considered. Workers hired in the manufacturing sector and medium size firms belonging to 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.

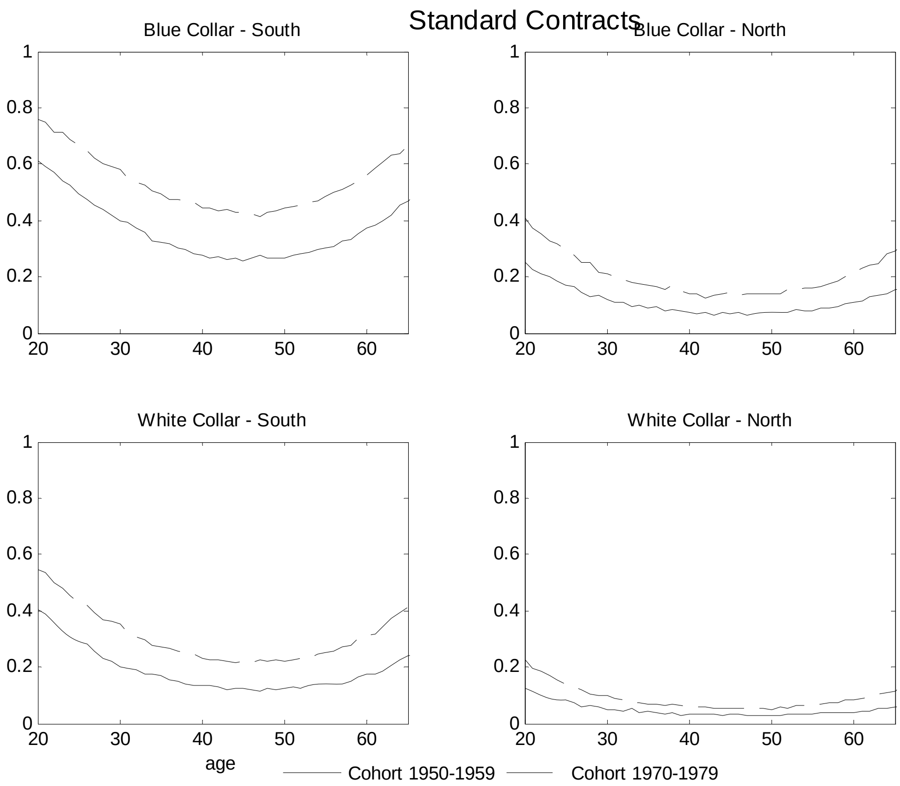
Figure 3 Life Cycle Employment and Unemployment Probabilities by Cohort - Standard contracts - Selected Working Groups

The figure reports in panel a) the life cycle employment probabilities and in panel b) the life cycle unemployment 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).

a)



b)

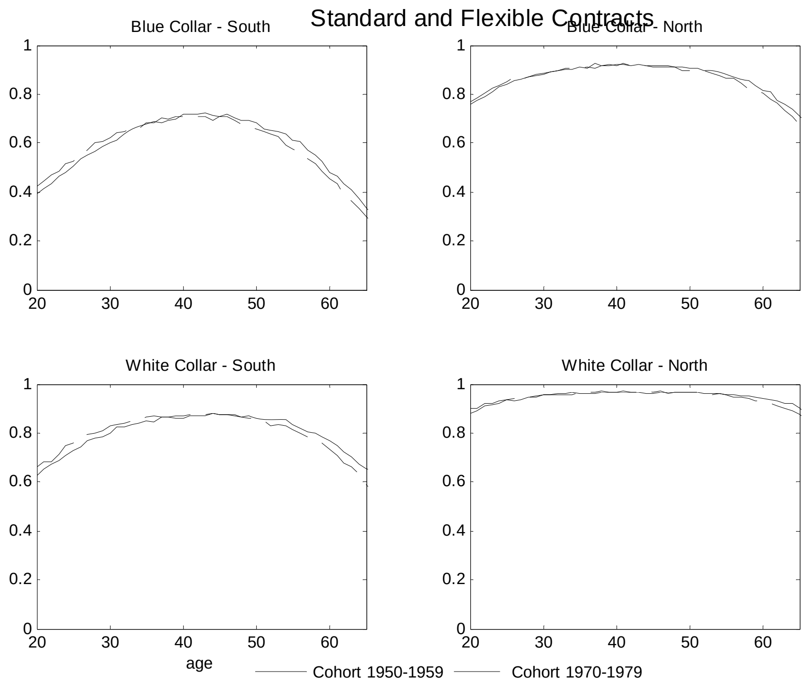


In figure 4, I report, for the same selected working groups, the life cycle the profiles of employment probabilities obtained when all types of contracts (standard and flexible) are considered. In this case, the differences among cohorts tend to be overcome. In all cases, young cohorts display higher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

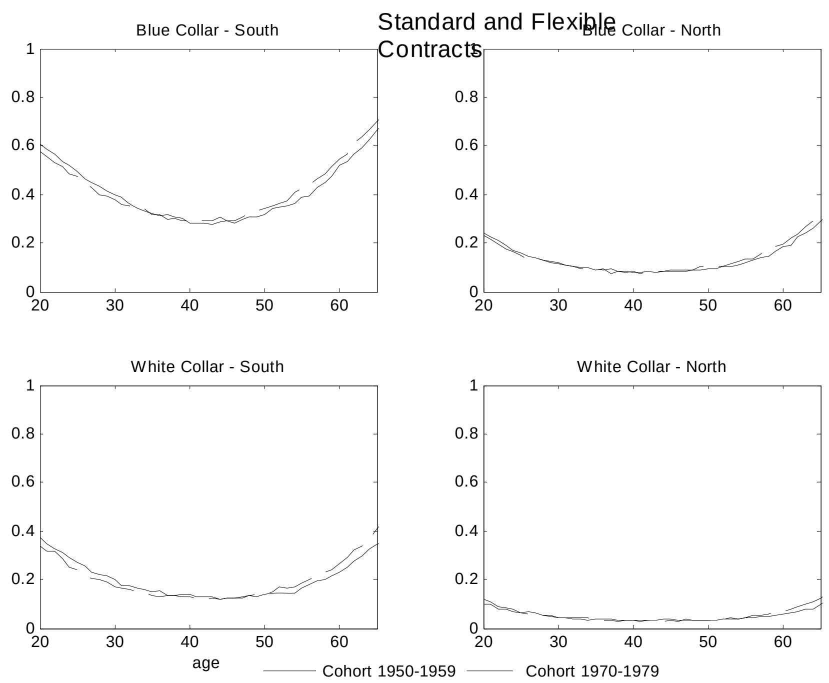
Figure 4 Life Cycle Employment Probabilities by Cohort – Standard and flexible contracts - Selected Working Groups

The figure reports in panel a) the life cycle employment probabilities and in panel b) the life cycle unemployment 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).

a)



b)

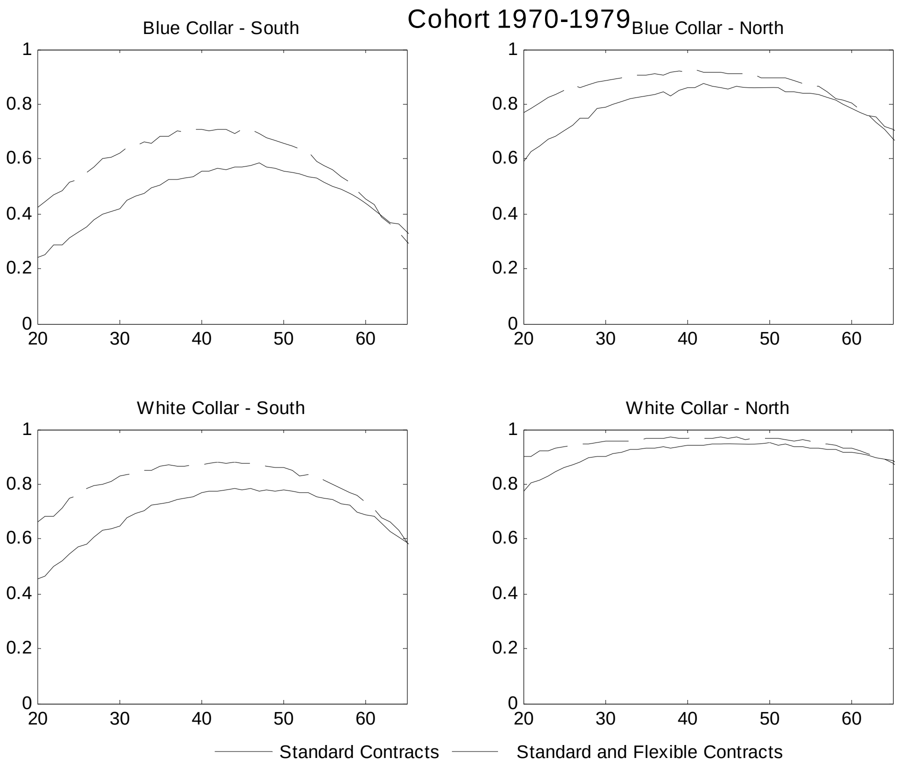


Our results, based on the employment and unemployment duration observed over the period 1985-2004, reveal that the Italian cohorts do not display remarkable differences in terms of the life cycle employment probabilities. The employment probability for young people is enhanced by using flexible contracts, 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)[14].

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

The figure reports in panel a) the life cycle employment probabilities and in panel b) the life cycle unemployment 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.

a)



[14] 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.

b)

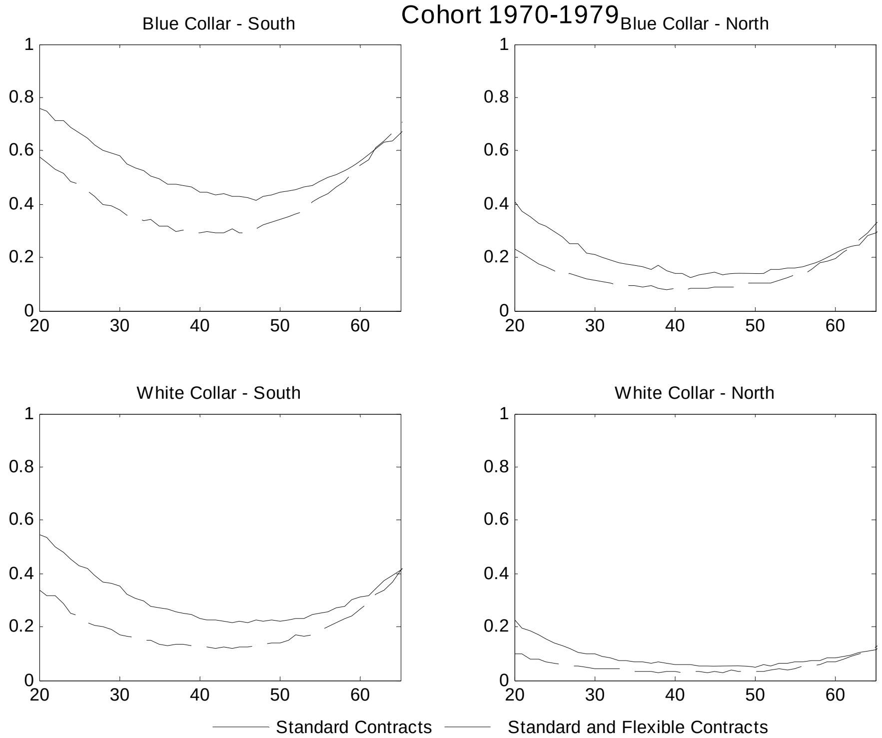
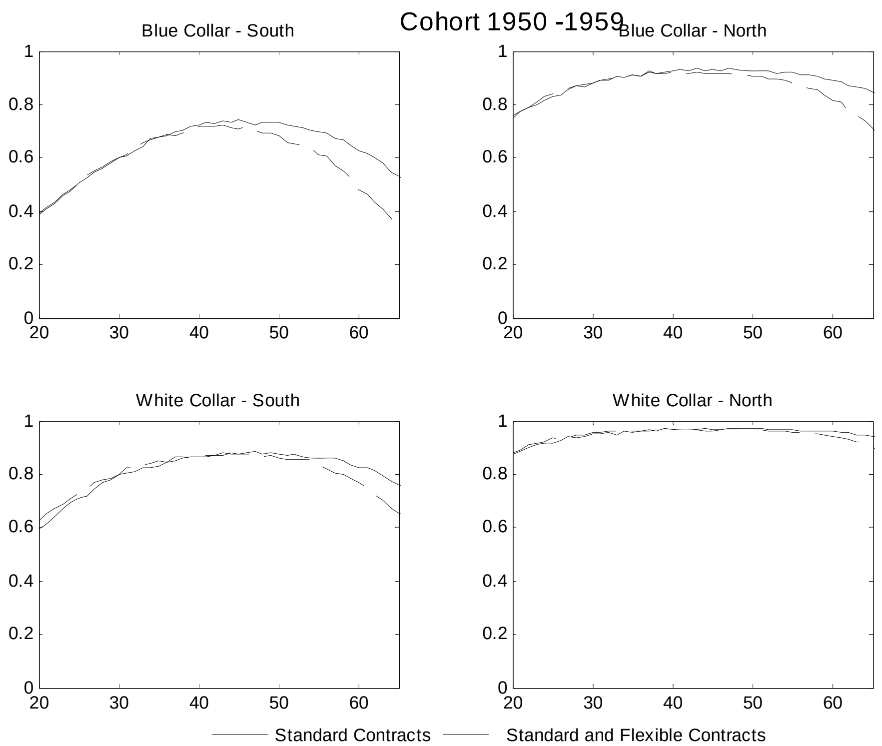


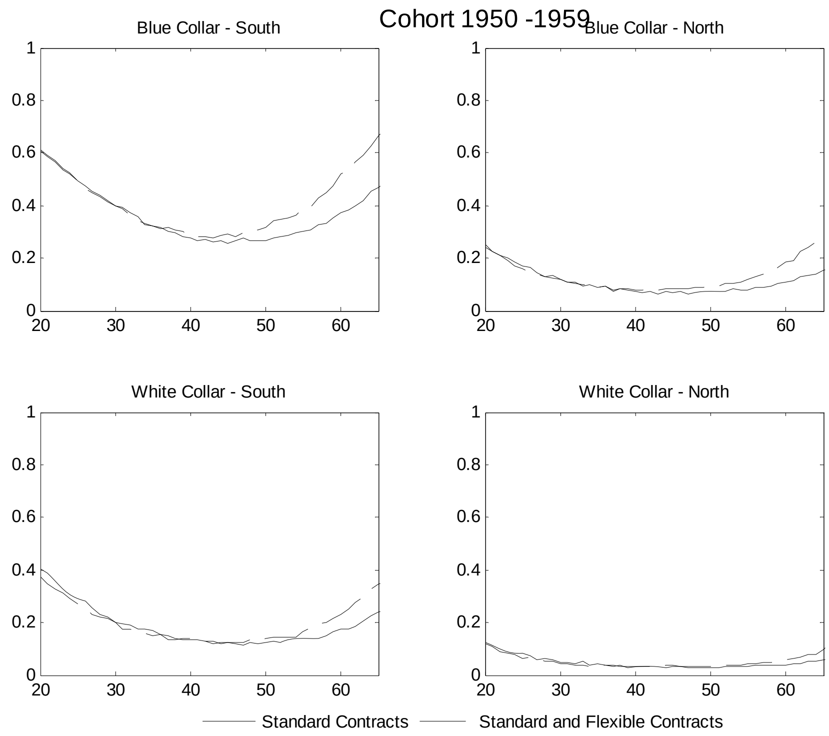
Figure 6 Life Cycle Employment Probabilities by Type of Contracts - Selected Working Groups - Cohort 1950-59

The figure reports in panel a) the life cycle employment probabilities and in panel b) the life cycle unemployment 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.

a)



b)



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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