Unemployment risk over the life cycle under flexible and non-flexible contracts ℵ

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Abstract

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 using a new methodology that takes into account both types of uncertainty faced by workers, i.e. the risk of entering unemployment and of remaining unemployed, and that enables to show how the unemployment risk varies over the life cycle and across different working group categories. Thus, it derives the risk of being unemployed (a stock-related concept) faced at individual level at each stage of the life cycle from the transition probabilities (a flow-related concept) implied by two duration models for individual employment and unemployment spells estimated separately from microdata.

The application of this methodology 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. 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.

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?

This paper deals with the measurement of unemployment risk and its distribution across workers in different age cohort and occupation groups. It derives the probability of being unemployed as a measure of the individual unemployment risk. This measure is obtained taking into account both types of uncertainty faced by workers, and it shows how it varies over the life cycle and among different groups of workers.

At both theoretical and empirical level the two risks (of being 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 Hecman, 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 the employment/unemployment 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. Through Monte Carlo methods I simulate the underlying semi Markov process governing the transitions in and out employment over the life cycle for each representative worker in each working 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 be hump shaped, 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. In particular, 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)[1] and of temporary agency work[2] 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 employement/ unemployment probabilities. Section 5 concludes.

[1]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.

[2] 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. 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. Finallay, the process allows for time dependence, i.e. the transition probabilities depend of the time of entry (through the age at entry in a given state).

The previous literature shows how to derive the stationary distribution of unemployment/employment 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 unemployment/employment probabilities at time *t*, for the case of a non homogeneous Markov process that allows transitions to be time dependent but that do not depend on the elapsed duration in a given state. 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 where transition probabilities are allowed to be both time and duration dependent.

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 (unemployment) spell if the current is unemployed (employed). 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[3]. 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 employment spells I estimate two separate parametric Weibull proportional hazard models[4]. 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[5,6]. According to the adopted approach, the instantaneous hazard rates for unemployment (*u*) and employment (*e*) spells are modelled as following:

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

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

[4] 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.

[5] 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.

[6] 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 rate 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:

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

In simulations, α will be set to 1, thus the survival probabilities in a given state $S(t^j)$, the conditional transition probabilities and the implied unconditional probabilities are 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 life cycle profiles of the unemployment/employment probabilities implied by the estimated transition intensities between states (from employment to unemployment and *vicevesa*).

If the transition process is modeled as a time-homogeneous Markov chain, as the baseline hazard function is constant, than the translation of the regression effects from hazards to survival times and to the stationary probability distribution of states is easy.

However, as discussed in section 2.1, the transition process between the two states of interest (employment and non-employment) is modeled in this paper to allow for duration and lagged duration dependence that turn out to affect significantly the transition process between the two states. Thus, to derive the life cycle profiles tof transition probabilities and the implied profiles of employment/unemployment (unconditional) probability I have to rely on simulation techniques..

In particular, I 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[7]. 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 predicted according the estimated duration models. 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[8]. Thus, I simulate the ongoing spells for which the value of covariates *XB* is endogenously determined being function of the entire past

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

[8]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.

history of the process. For each representative worker, I end up with 5000 simulated sequences of employment and unemployment spells. From each sequence, I can determine the employment status at each age (expressed in months) and by averaging across sequences I can obtain the probability of being employed /unemployed at each point of the life cycle[9]. Thus the simulated Markov model produces the life cycle unconditional probabilities of being employed/unemployed implied by the flows in and out employment and unemployment as well as the time elapsed in each state as predicted from the estimated duration models[10].

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[11], thus what I can study is employment *vs* non-employment probability instead of employment *vs* unemployment probability[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. 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 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

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

[10] 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.

[11] 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.

[12] Flinn and Heckman (1982) find that the transition in and out unemployment and out of the labor force are fundamentally different. Given this limit, due to the lack of information in my data, my results are comparable with Low et al. (2010).

[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.

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 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)[15].

The explanatory variables used in the duration analysis of both employment and unemployment[16] 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.

[15] More precisely, I rely on the flow sampling avoiding the left truncation problem that affect data (Lancaster, 1990).
[16] 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	-0.086	0.008	-10.690	0.000	-0.102	-0.070
Age ^2	0.012	0.001	10.000	0.000	0.009	0.014
Industry						
Manufacturing	-0.688	0.072	-9.520	0.000	-0.830	-0.547
Construction	-0.016	0.073	-0.220	0.828	-0.159	0.127
Trade	-0.852	0.076	-11.240	0.000	-1.001	-0.704
Hotels	0.392	0.076	5.170	0.000	0.243	0.540
Transport	-0.330	0.076	-4.370	0.000	-0.479	-0.182
Financial	-0.578	0.076	-7.570	0.000	-0.727	-0.428
Real estate	ref					
Other services	0.117	0.090	1.300	0.192	-0.059	0.293
Firm size						
0-9	ref					
10-19	-0.167	0.019	-8.600	0.000	-0.205	-0.129
20-199	-0.246	0.018	-13.730	0.000	-0.281	-0.211
200-999	-0.502	0.030	-16.770	0.000	-0.561	-0.444
>1000	-0.928	0.045	-20.730	0.000	-1.016	-0.840
Geographic Area						
North	-0.369	0.020	-18.080	0.000	-0.409	-0.329
Center	-0.289	0.025	-11.550	0.000	-0.338	-0.240
South	ref					
Occupation						
Blue collar	-0.466	0.027	-17.310	0.000	-0.519	-0.413
White collar	ref					
Length of the previous unemployment spell	0.177	0.006	31.960	0.000	0.166	0.188
Log of daily wage at the beginning of the spell	-0.135	0.021	-6.470	0.000	-0.176	-0.094
Birth year						
1930-39						
1940-49						
1950-59	-0.450	0.034	-13.350	0.000	-0.516	-0.384
1960-69	-0.337	0.029	-11.540	0.000	-0.394	-0.280
1970-79	ref					
_cons	2.962	2.962	2.962	2.962	2.962	2.962
/ln_p	0.844	0.006	0.000	0.000	0.834	0.855
/ln_the	1.184	0.008	0.000	0.000	1.169	1.199
p	0.987	0.017	0.000	0.000	0.954	1.022

1/p	-0.086	0.008	-10.690	0.000	-0.102	-0.070
theta	0.012	0.001	10.000	0.000	0.009	0.014

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	0.053	0.004	12.340	0.000	0.044	0.061
Age^2/10	-0.005	0.001	-9.740	0.000	-0.006	-0.004
Industry						
Manufacturing	0.369	0.047	7.790	0.000	0.276	0.462
Construction	0.154	0.048	3.210	0.001	0.060	0.248
Trade	0.306	0.050	6.140	0.000	0.208	0.404
Hotels	0.185	0.050	3.690	0.000	0.087	0.283
Transport	0.457	0.051	9.020	0.000	0.358	0.557
Financial	0.341	0.052	6.560	0.000	0.239	0.442
Real estate	0.119	0.068	1.760	0.079	-0.014	0.252
Other services	ref					
Firm size						
0-9	ref					
10-19	0.088	0.014	6.200	0.000	0.060	0.116
20-199	0.035	0.013	2.640	0.008	0.009	0.060
200-999	-0.013	0.021	-0.630	0.529	-0.053	0.027
>1000	-0.083	0.025	-3.340	0.001	-0.132	-0.034
Geographic Area						
North	0.741	0.016	46.180	0.000	0.710	0.773
Center	0.355	0.020	18.090	0.000	0.316	0.393
sSouth	ref					
Occupation						
Blue collar	0.080	0.019	4.220	0.000	0.043	0.118
White collar	ref					
Length of the previous employment spell	0.135	0.004	32.830	0.000	0.127	0.144
Log of daily wage at the beginning of the spell (i.e. at the end of the previous employment spell)	0.264	0.013	20.250	0.000	0.238	0.289
Birth year						
1930-39	0.711	0.041	17.180	0.000	0.630	0.792
1940-49	0.310	0.037	8.310	0.000	0.237	0.383
1950-59	0.076	0.032	2.360	0.018	0.013	0.139
1960-69	-0.088	0.028	-3.120	0.002	-0.143	-0.033
1970-79	ref					
_cons	-2.771	0.102	-27.200	0.000	-2.971	-2.572

/ln_p	-0.101	0.003	-39.510	0.000	-0.106	-0.096
/ln_the	0.784	0.008	102.600	0.000	0.769	0.799
p	0.904	0.002	0.000	0.000	0.899	0.908
1/p	1.107	0.003	0.000	0.000	1.101	1.112
theta	2.190	0.017	0.000	0.000	2.157	2.223

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	-0.070	0.005	-13.680	0.000	-0.080	-0.060
Age ^2	0.011	0.001	13.910	0.000	0.009	0.013
Industry						
Manufacturing	-0.949	0.037	-25.920	0.000	-1.021	-0.878
Construction	-0.208	0.045	-4.670	0.000	-0.295	-0.121
Trade	-0.923	0.046	-20.080	0.000	-1.013	-0.833
Hotels	0.356	0.046	7.760	0.000	0.266	0.446
Transport	-0.403	0.047	-8.520	0.000	-0.496	-0.310
Financial	-0.268	0.047	-5.680	0.000	-0.360	-0.176
Real estate	-0.103	0.069	-1.500	0.134	-0.238	0.032
Other services	ref					
Firm size						
0-9	ref					
10-19	-0.136	0.014	-9.760	0.000	-0.163	-0.108
20-199	-0.249	0.013	-19.590	0.000	-0.274	-0.224
200-999	-0.548	0.021	-25.750	0.000	-0.590	-0.506
>1000	-0.622	0.026	-23.480	0.000	-0.673	-0.570
Geographic Area						
North	-0.297	0.015	-19.810	0.000	-0.327	-0.268
Center	-0.255	0.018	-13.930	0.000	-0.291	-0.219
South	ref					
Occupation						
Blue collar	0.512	0.019	27.230	0.000	0.475	0.549
White collar	ref					
Lenght of the previous unemployment spell	0.169	0.004	43.300	0.000	0.161	0.176
Log of daily wage at the beginning of the spell	-0.132	0.015	-8.590	0.000	-0.162	-0.102
Birth year						
1950-59	ref					

1960-69	0.153	0.021	7.270	0.000	0.112	0.194
1970-79	0.398	0.024	16.410	0.000	0.350	0.445
_cons	1.677	0.109	15.380	0.000	1.463	1.891
/ln_p	-0.242	0.005	-49.370	0.000	-0.251	-0.232
/ln_the	-0.072	0.013	-5.600	0.000	-0.097	-0.047
p	0.785	0.004			0.778	0.793
1/p	1.273	0.006			1.261	1.286
theta	0.931	0.012			0.908	0.954

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	26.190	0.000	0.069	0.080
Age^2/10	-0.008	0.000	-20.240	0.000	-0.009	-0.007
Industry						
Manufacturing	0.368	0.037	10.000	0.000	0.296	0.440
Construction	0.163	0.037	4.350	0.000	0.089	0.236
Trade	0.329	0.038	8.610	0.000	0.254	0.404
Hotels	0.144	0.039	3.710	0.000	0.068	0.220
Transport	0.475	0.040	11.980	0.000	0.397	0.552
Financial	0.443	0.040	11.180	0.000	0.365	0.520
Real estate	0.124	0.054	2.280	0.023	0.017	0.231
Other services	ref					
Firm size						
0-9	ref					
10-19	0.092	0.011	8.490	0.000	0.071	0.114
20-199	0.051	0.010	5.130	0.000	0.032	0.071
200-999	0.001	0.016	0.040	0.971	-0.031	0.032
>1000	0.003	0.019	0.160	0.876	-0.034	0.040
Geographic Area						
North	0.805	0.013	63.140	0.000	0.780	0.830
Center	0.429	0.016	27.340	0.000	0.398	0.459
Ssouth	ref					
Occupation						
Blue collar	-0.092	0.015	-6.180	0.000	-0.121	-0.063
White collar	ref					
Length of the previous employment spell	0.118	0.003	37.220	0.000	0.112	0.125

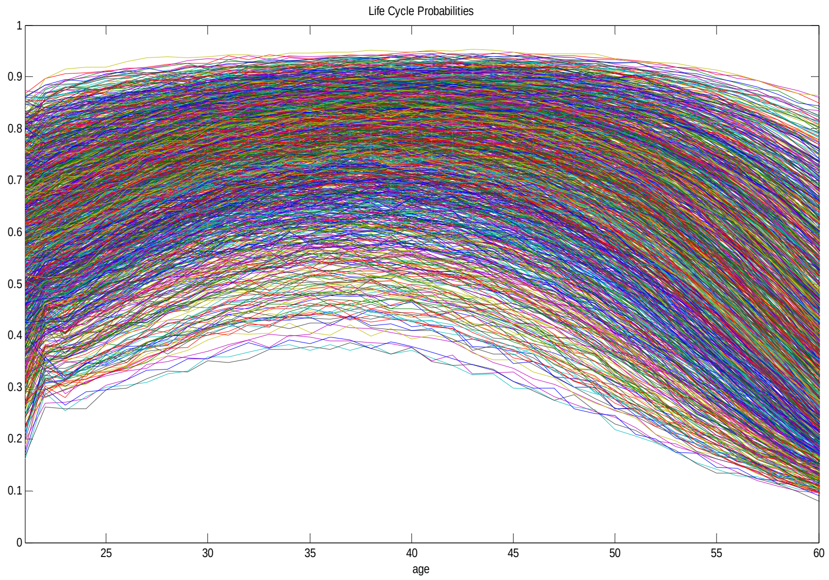
Log of daily wage at the beginning of the spell (i.e. at the end of the previous employment spell)	0.239	0.010	23.810	0.000	0.219	0.258
Birth year						
1930-39	ref					
1940-49	-0.453	0.026	-17.760	0.000	-0.503	-0.403
1950-59	-0.740	0.031	-23.830	0.000	-0.801	-0.679
1960-69	-0.624	0.033	-18.700	0.000	-0.690	-0.559
1970-79	-0.330	0.035	-9.400	0.000	-0.399	-0.261
_cons	-2.301	0.077	-30.020	0.000	-2.451	-2.150
/ln_p	-0.075	0.002	-36.760	0.000	-0.079	-0.139
/ln_the	0.618	0.006	95.780	0.000	0.605	0.681
p	0.928	0.002	0.000	0.000	0.924	0.932
1/p	1.154	1.154	1.154	1.154	1.154	1.154
theta	1.947	1.947	1.947	1.947	1.947	1.947

4.2 Life cycle employment probabilities

In this section, I report the simulated life cycle profiles of the unconditional employment probabilities which specularily mirrors the unconditional unemployment probabilities and which are derived, according to the methodology outlined in section 2.3, from the conditional transitions implied by estimated models.

Figure 1 reports the simulated age profiles of the probabilities of being employed at each age for the representative workers of 1,200 working groups identified according to job characteristics and the birth years 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 occupation characteristics 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

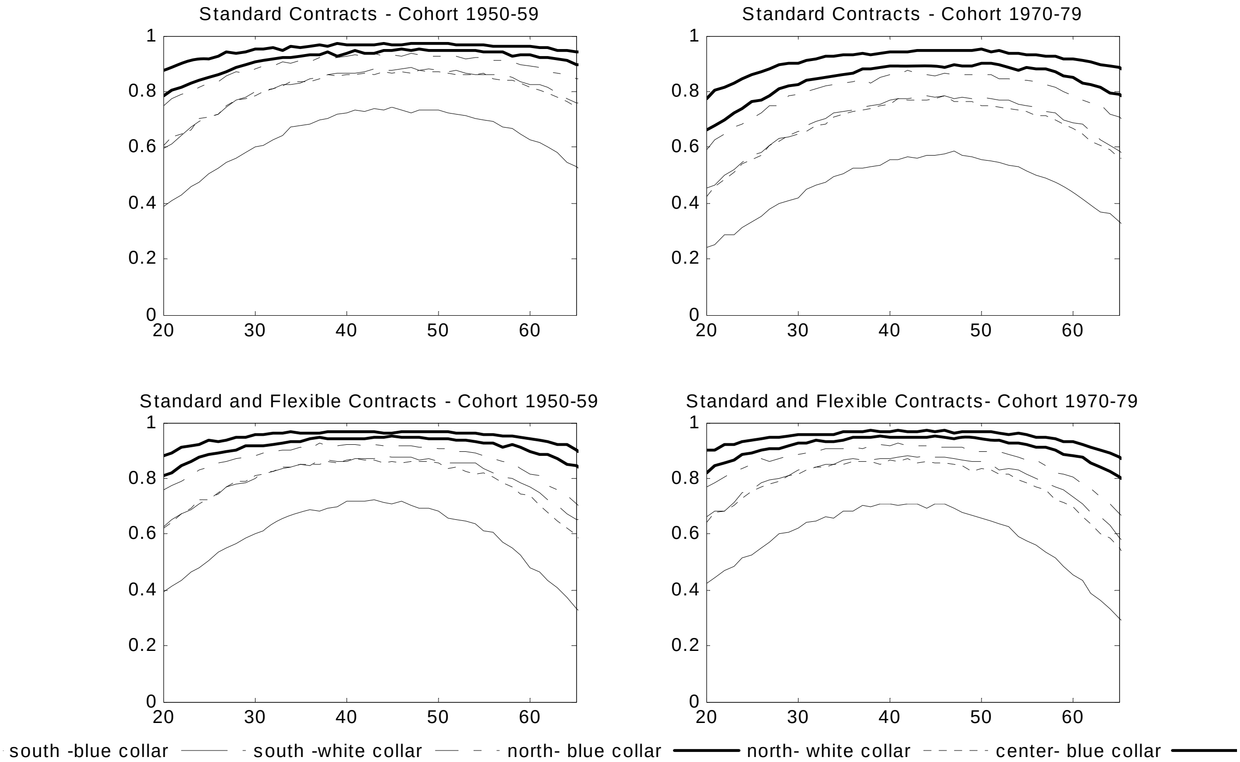


In figure 2 I report the life cycle employment probabilities by age and cohort for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area and birth year cohort (1950-59 and 1970-79). The graphs at 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 cohorts are larger when standard contracts only are considered.

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

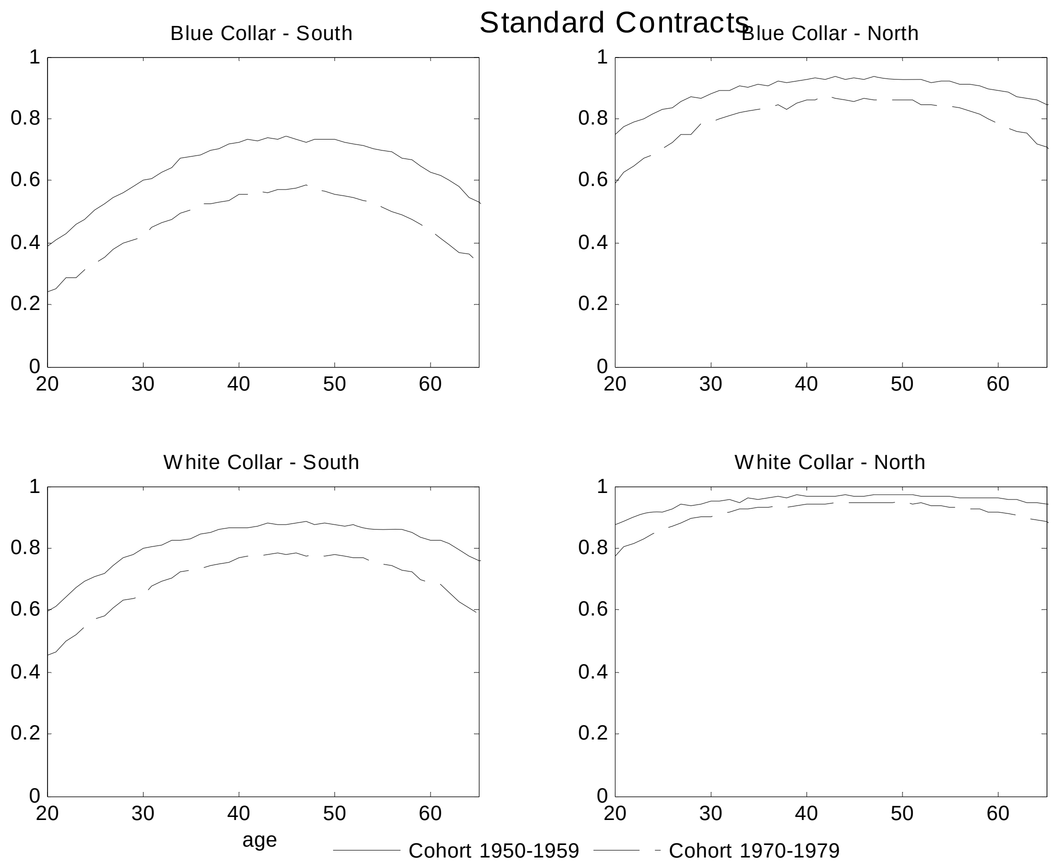
The figure reports the life cycle employment probabilities for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area and birth year cohort (1950-59 and 1970-79). Left hand graphs report the simulated 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 between cohorts 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

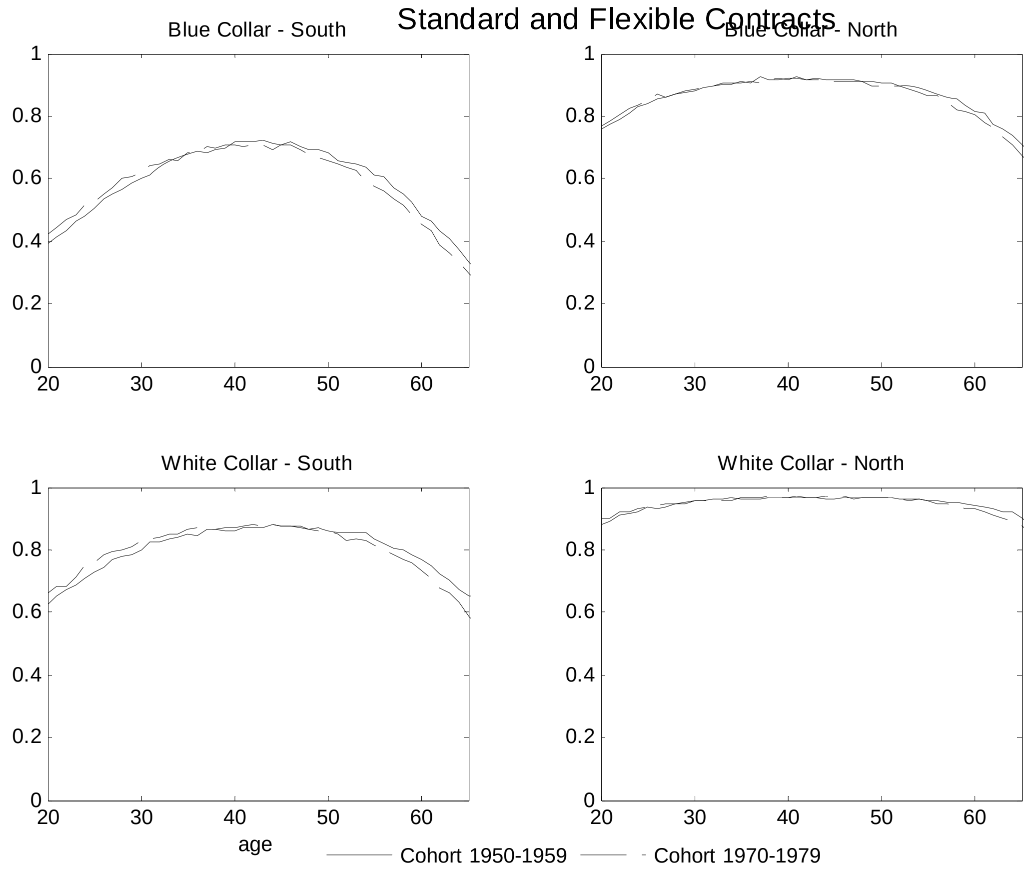
The figure reports the life cycle employment probabilities for the representative workers hired by medium size firms (20-199) operating in the Manufacturing industry distinguishing by type of occupation and geographic area (south on the left hand graphs, north on the right hand graphs) and birth year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

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)[17].

According to my results, the introduction of flexible contracts enhances the probability of being employed at young ages for younger cohorts, while reduces the probabilities of being employed at old ages for older cohorts, suggesting that the evolution of the labor market performance has been mainly driven by the demand side of the market.

[17] 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.

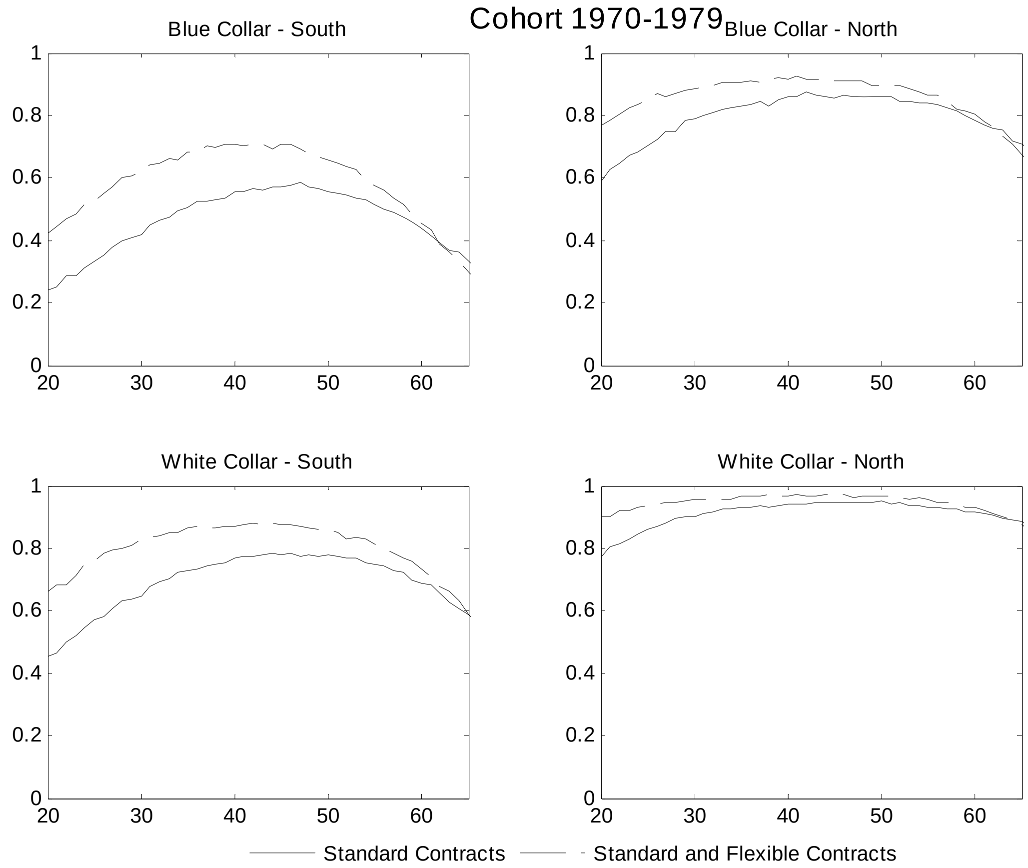
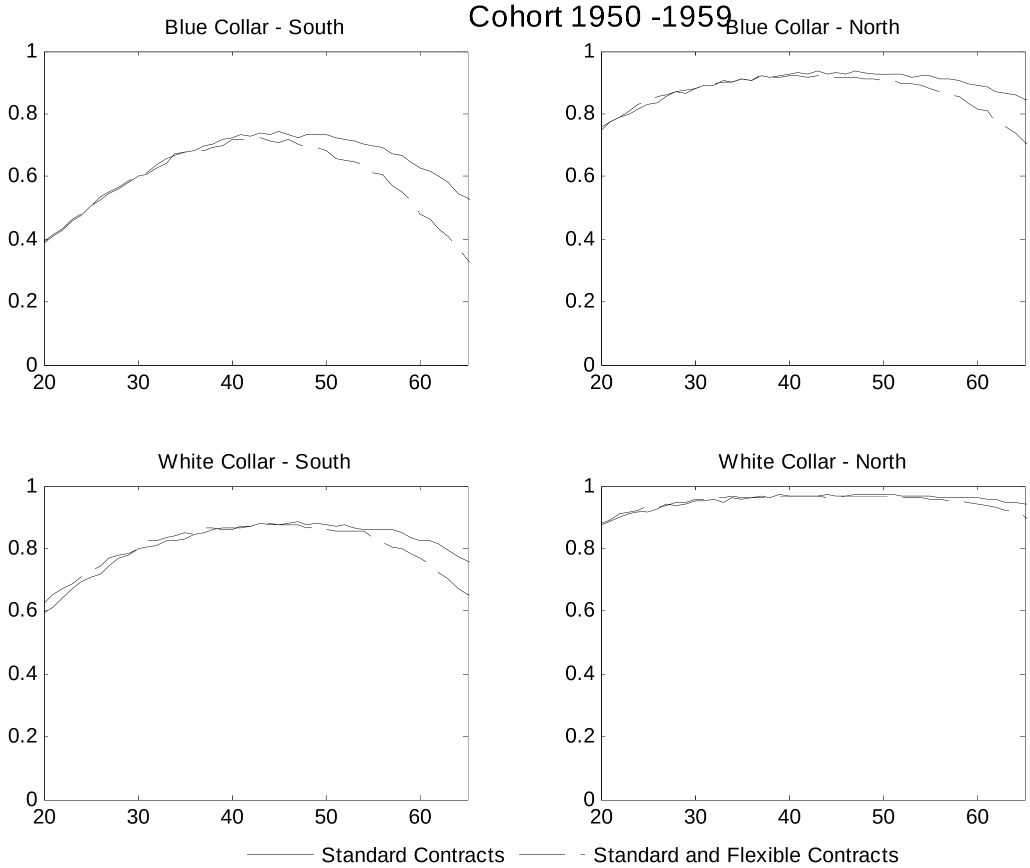


Figure 6 Life Cycle Employment Probabilities by Type of Contracts - Selected Working Groups - Cohort 1950-59

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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