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Employment Risk over the Life Cycle*

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Abstract

In this paper we focus on the relative role of job finding and job exit in shaping the employment risk over the life cycle. Using Italian labor market data we document that the risk of being fired and the chance of re-employment display substantial heterogeneity depending on age, cohort and occupational characteristics. We show how the two risk combine in shaping the employment risk. Our results evidence that the life cycle employment probability profile is hump shaped with a peak at adult age and that this dynamic is mainly driven by the "U" –age profile of transitions from employment to unemployment. Moreover, we find that differences in job finding probabilities are mainly responsible for the heterogeneity in the employment risk across working groups.

Keywords: Employment risk, Duration, Heterogeneity, Semi-Markov Process
JEL classifications: C41, J62, J64

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1. Introduction

Employment risk is a dynamic concept that involves the risk of exiting employment as well as the risk of remaining out of employment, as such, it is intrinsically related to the duration of both 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?

At both theoretical and empirical level the two risks, that of exiting employment and that of remaining unemployed, have been considered separately. There is considerable evidence that the risk of job loss differs from the risk of not finding a job and that this risk differential can vary over time and across workers. Shimer (2012) focuses on this differential across the business cycle and finds that the chance of exiting unemployment plays much more role than the risk of employment exit in shaping the unemployment rate fluctuations over the business cycle.

In this paper, we exploits the detailed information on working careers conveyed by administrative Italian data and conduct the duration analysis of both employment and unemployment spells. Thus, taking into account both the risk of exiting a job spell as well as the chance of re-employment, we measure the employment risk as the expected probability of being employed at a given stage of the life cycle. We document that the risk of being fired and the chance of re-employment display substantial heterogeneity across workers at different ages and belonging to different cohorts and occupational characteristics. We show how the two risks combine in shaping the employment risk over the life cycle. To our knowledge, this is the first study that makes any attempt to document how the two risks combine in shaping the employment chance profile at individual level over the life cycle which turns out to be at the root of the substantial heterogeneity in aggregate employment rates evidenced across countries (Jaimovich and Siu, 2009).

Existing empirical studies use two alternative approaches to study employment dynamics: the Markov model for transitions among labor market states, and the duration analysis.

The first approach studies the relevant transitions by detecting the full probability distributions of labor market states (e.g. the probability of being employed or out of the labor force). However, estimation techniques used to implement the approach have 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) overcomes these methodological drawbacks to study the employment dynamics over the life cycle in Romania. He relies on panel data to account for the dependence of sequential transitions and thus is able to relax the independence assumption underlying previous studies. 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).

The duration analysis approach focuses mainly on the transitions from unemployment to employment or out of the labor force, 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. Little effort in this area has been devoted to detect how those transitions translate in terms of the chance of being employed. Galiani and Hopenhayn (2003), exploit the information on the length of employment and unemployment the risk of being unemployed over short periods disregarding impact on the employment chance over the life cycle in Argentina.

In this paper, we model labor market transitions in and out employment as a two-state time non-homogeneous semi Markov process allowing for both current and lagged duration dependence as well as time dependent. The transition distributions underlying the process are thus obtained from reduced- form estimations that easily control for both observed and unobserved heterogeneity. The empirical analysis is carried using multiple spells data on working histories for a large number of Italian male workers aged between 20 and 60 years old tracked in the panel data INPS which covers the period 1985-2004. Relying on Monte Carlo techniques we simulate the transitions in and out employment over the life cycle as well as the unconditional probability profile of being employed.

Our results evidence that the employment probability display a hump shaped profile consistently with the observed distribution of the employment across ages. We document a substantial degree of heterogeneity in the employment risk across various dimensions: age, cohorts and job characteristics. The employment probability profiles are hump shaped over the life cycle where this dynamics is mainly driven by the "U" shaped age-profile of job finding probabilities.

Our findings suggest that the shaping of the employment probability over life cycle is explained mainly by the employment exit probability though it is at all ages substantially lower than the job finding probability which is instead responsible of the heterogeneity across groups. This result complements Shimer (2012)' s findings about the relatively stronger role played by job finding fluctuations in explaining the unemployment rate dynamics over the business cycle.

The paper is organized as follows. Section 2 describes the data used. In section 3, we outline the empirical analysis and derive the results about the life cycle employment probabilities. Section 4 concludes.

2. Data

We 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[1].

In this paper, we focus on multiple full time-spells in working data of male individuals employed in the private sector. The sample is made by the workers who are hired with standard contracts plus those who are hired with 'entrance' contracts or temporary[2] (agency)

[1] In particular, from data we 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.

[2] 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.

contracts. Entrance contracts include apprenticeship[3]. and training –on- the- job contracts. In the sample considered. temporary agency work contracts represent the 2.12% of the total number of job contracts observed over the period 1985-2004 and their average length is of 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 that the workers does not retire in the period 1985-2004; if re-employment does not happen before the end of 2004 we treat the unemployment spell as censored.

We exclude from the analysis workers who experience part time job spells or who retire over the period covered by the panel data. Moreover, we exclude from the empirical analysis the 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)[4].

The explanatory variables used to explain the length of employment and unemployment[5] 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 210 working groups.

Table 1 reports the main summary statistics for the sample.

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[3] 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: within these limits, collective agreements lay down, for each sector, the length of contracts for the various occupational profiles. These types 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) are intended to promote the hiring and training of individuals aged between 16 and 32, and can elapse up to 32 months. These types of contracts represent the 9.4 % of job contracts observed in the panel. The average duration is 1.12 years.

[4] More precisely, we rely on the flow sampling avoiding the left truncation problem that affects data (Lancaster, 1990).

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

Table 1 Summary statistics

Employment and unemployment spells				
Duration (years)	**mean**	**median**	**p5**	**p95**
employment	3.5	2	1	10
unemployment	3.5	1	2	10
Number of	**freq.**	**Percent**		
employment	271,626			
censored	48,458	17.84		
unemployment	216,294			
censored	47,000	0.22		
Explanatory variables				
	mean	**median**	**p5**	**p95**
age at the beginning of job spells	32.07	17.69	29.35	54.26
age at the beginning of unempl spells	34.68	18.51	31.61	58.18
Industry	**freq.**	**percent**		
Manufacturing	120,004	38.64		
Construction	73,353	23.62		
Trade	32,459	10.45		
Hotels	26,520	8.54		
Transport	22,004	7.09		
Financial	26,649	8.58		
Real estate	4,408	1.42		
Other services	5,134	1.65		
Geographic Area				
north	168,019	52.89		
center	64,164	20.20		
south	85,479	26.91		
Firm size				
0-9	101,428	37.91		
10-19	41,050	15.34		
20-199	78,056	29.17		
200-999	23,680	8.85		
>1000	23,333	8.72		
Occupation				
Blue collars	267,123	84.09		
WhiteCollars	50,539	15.91		

3. Empirical strategy

3.1 Modeling labor market transitions

In this paper, we model the transition from employment to unemployment and *viceversa*, as a two-state time non-homogeneous semi Markov process. 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 empirical analysis to derive the transition distribution driving the semi-Markov process is carried out carry by estimating two separate continuous time parametric Weibull models which enable to assess the impact of causal variables on the extent of the duration dependence in employment and unemployment status[6]. 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 [7].

[6]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).

[7] 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.

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 the 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 and daily salary at the beginning of the spell 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 (measured at the beginning of the spell)[8] and over the life cycle.

3.2 Estimated hazard functions

Table 2 displays the estimated coefficients and the marginal effects for the employment duration model[9]. 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

[8] 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.

[9] 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 increase the duration.

in terms of subsequent earnings (Arulampalam, 2001) and in terms of subsequent risk of job separation (Arulampalam et al., 2001 and Gregg, 2001). Indeed, the length of unemployment spells may induce not only a deterioration of individual skills but also lower opportunity to accumulate work experience: the longer the unemployment spell the higher the loss of productivity which makes the subsequent job termination more likely. According to our results, 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 initial salary the higher the worker's productivity which lowers the probability of job termination.

Moreover, 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. Our findings show 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. Northern and Central regions are those with longer job relations, while shorter tenures characterize jobs in the South. 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.

Table 3 reports the results for the unemployment duration for which we support evidence for all kinds of duration dependence. In particular, we document negative current duration dependence for the unemployment status. Moreover, the longer the previous 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) and may be due to the fact that long unemployment durations discourage workers to search a new job (Schweitzer and Smith, 1974), to deterioration of skills (see e.g. Pissarides, 1992), or a 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. 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 also significant: 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, 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 3.3 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 –

	b	Std Err	Pvalue	95%Conf interval	
Age at the beginning of the spell	-0.017	0.005	0.001	-0.027	-0.007
Age ^2	0.003	0.001	0.000	0.001	0.004
Industry					
Manufacturing	-0.835	0.097	0.097	-8.590	0.000
Construction	-2.311	0.128	0.128	-18.070	0.000
Trade	-0.179	0.054	0.054	-3.290	0.001
Hotels	-0.920	0.056	0.056	-16.440	0.000
Transport	0.358	0.057	0.057	6.270	0.000
Financial	-0.414	0.057	0.057	-7.250	0.000
Real estate[10]	-0.226	0.058	0.058	-3.910	0.000
Other services	ref				
Firm size					
0-9	ref				
10-19	-0.156	0.015	0.000	-0.186	-0.126
20-199	-0.249	0.014	0.000	-0.276	-0.221
200-999	-0.546	0.023	0.000	-0.591	-0.500
>1000	-0.693	0.030	0.000	-0.751	-0.635
Geographic Area					
north	-0.326	0.016	0.000	-0.357	-0.294
center	-0.278	0.020	0.000	-0.317	-0.239
south	ref				
Occupation					
blue collar	0.581	0.020	0.000	0.542	0.621
white collar	ref				
Lenght of the previous unemployment spell	0.158	0.004	0.000	0.149	0.166
Log of daily wage at the beginning of the spell	-0.127	0.021	0.000	-0.167	-0.087
Birth year					
1940-49	0.052	0.040	0.199	-0.027	0.131
1950-59	-0.232	0.027	0.000	-0.284	-0.179
1960-69	-0.175	0.019	0.000	-0.212	-0.137
1970-79	ref				
_cons	0.887	0.129	6.880	0.000	0.635
/ln_p	-0.167	0.004	0.000	-0.176	-0.159
/ln_the	-0.004	0.014	0.760	-0.031	0.023
p	0.846	0.004	0.000	0.839	0.853
1/p	1.182	0.005	0.000	1.172	1.192
theta	0.996	0.014	0.000	0.969	1.023

[10] This category covers real estate services and professional activity with a focus on providing services to firms.

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

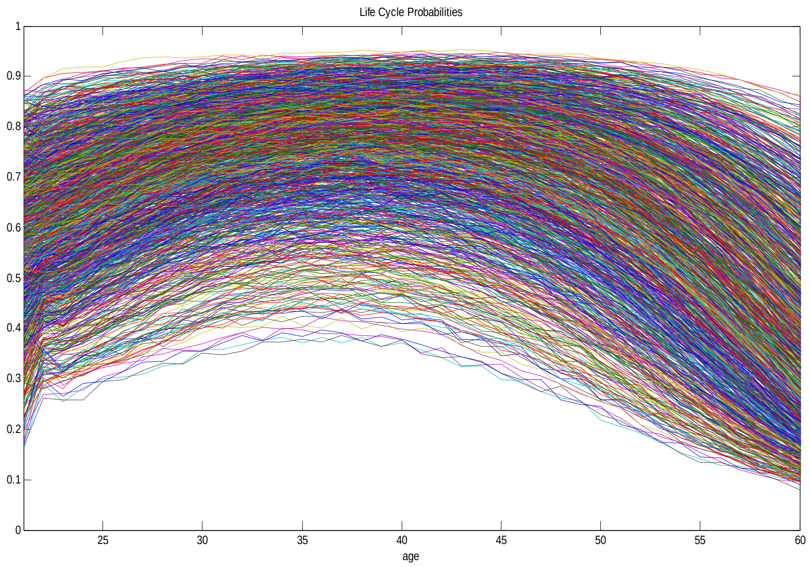
	b	Std Err	Pvalue	95 %Conf interval	
Age at the beginning of the spell	0.105	0.005	0.000	0.096	0.114
Age ^2	-0.014	0.001	0.000	-0.015	-0.013
Industry					
Manufacturing	0.432	0.087	0.000	0.261	0.602
Construction	-0.006	0.130	0.962	-0.261	0.248
Trade	0.320	0.054	0.000	0.215	0.426
Hotels	0.450	0.055	0.000	0.343	0.557
Transport	0.232	0.056	0.000	0.122	0.342
Financial	0.533	0.056	0.000	0.423	0.643
Real estate	0.573	0.056	0.000	0.463	0.684
Other services	ref				
Firm size					
0-9	ref				
10-19	0.091	0.013	0.000	0.065	0.118
20-199	0.030	0.012	0.015	0.006	0.054
200-999	-0.056	0.021	0.008	-0.097	-0.015
>1000	-0.165	0.027	0.000	-0.219	-0.111
Geographic Area					
north	0.757	0.016	0.000	0.725	0.789
center	0.372	0.020	0.000	0.334	0.411
south	ref				
Occupation					
blue collar	-0.176	0.019	0.000	-0.213	-0.139
white collar	ref				
Lenght of the previous unemployment spell	0.087	0.004	0.000	0.079	0.094
Log of daily wage at the beginning of the spell	0.168	0.014	0.000	0.140	0.196
Birth year					
1940-49	-1.017	0.041	0.000	-1.097	-0.937
1950-59	-0.367	0.028	0.000	-0.422	-0.312
1960-69	-0.320	0.021	0.000	-0.362	-0.278
1970-79	ref				
_cons	-2.529	0.110	0.000	-2.744	-2.314
/ln_p	-0.090	0.003	0.000	-0.095	-0.085
/ln_the	0.782	0.008	0.000	0.766	0.798
p	0.914	0.002	0.000	0.909	0.918
1/p	1.095	0.003	0.000	1.089	1.100
theta	2.186	0.018	0.000	2.152	2.222

3.3 Life cycle employment and transition 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 the Appendix.

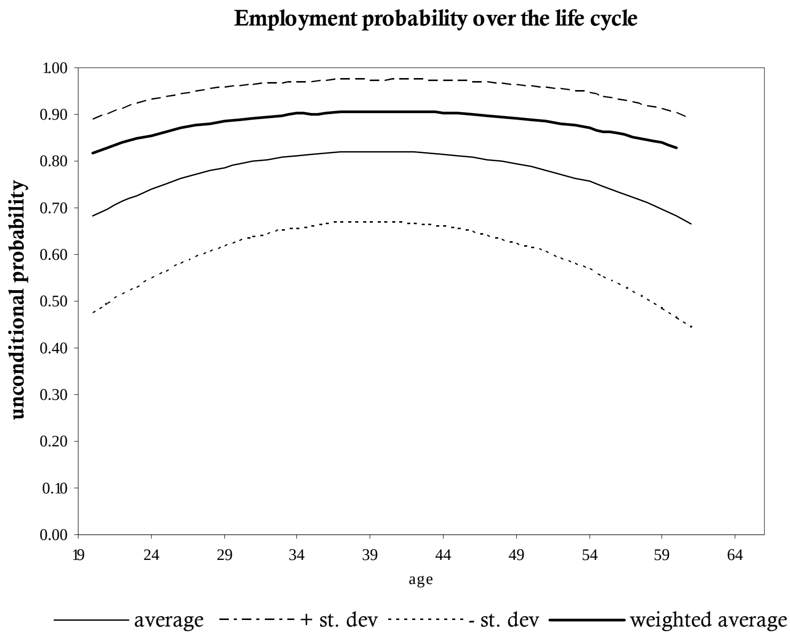
Figure 1 reports the simulated age profiles of the employment probability at each age for the representative workers of the 1050 working groups identified according to job characteristics and the birth year cohort. The picture reveals a remarkable heterogeneity across ages and across working groups defined according the information on the occupational characteristics. The employment probability profiles tend to be hump shaped over the life cycle, a pattern displayed also by the heterogeneity across groups which is higher at younger and older ages and shrinking at mature adult ages.

Figure 1 Life cycle employment probabilities



In figure 2 we report the life cycle profiles averaged across working groups. It draws the simple average profile, the interval profiles determined according the standard deviation across groups and the weighted average profiles obtained by weighting each group's profile by the relative number of workers who exhibit the group specific occupational characteristics.

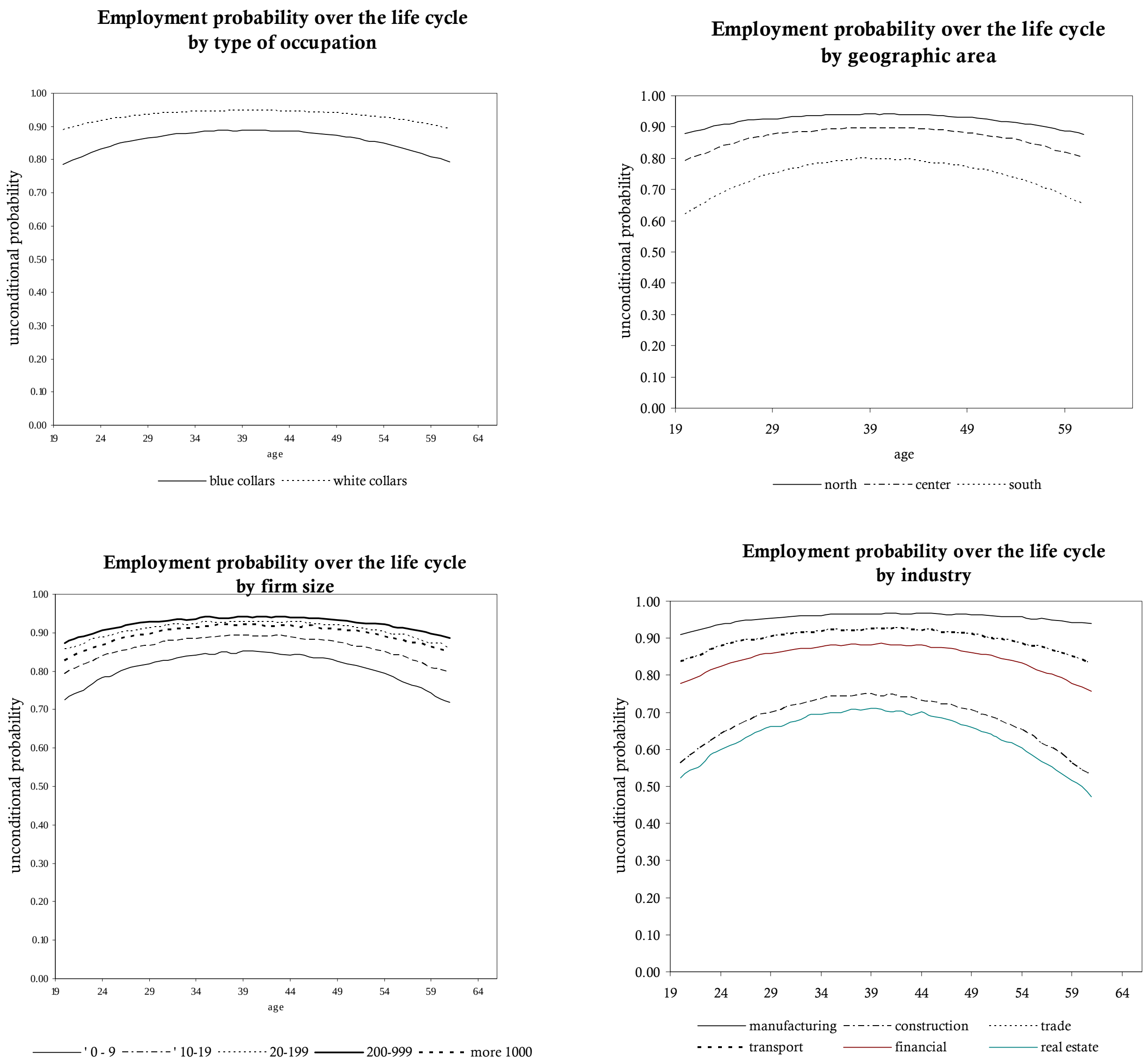
Figure 2 Average Life Cycle Employment Probability



The simple average employment probability across working groups is about 77% over the life cycle, it is a concave function of age and reaches the maximum of about 82% at 39 years old. Young workers aged 20 are about 20% less likely employed than adult aged 39, though the gap is recovered by 504% the age of 25. The confidence interval of one standard deviation from the mean covers about 64% of working groups at young and older ages, while it expands to 75% at mature adult ages. Figure 1 also reports the weighted average employment probability profile obtained taking account the relative importance of each working group. On average, young 20 years old workers are about 11% less likely employed than adult workers and the gap is recovered by 57% at 25 years old. The gap between the simple and the weighted average profiles reflects the relative higher influence of better performing working groups on the overall performance of the Italian labour market. The simple average profile disregards the composition of working groups defined according to the relevant occupational characteristics in the data which turns out to display substantial heterogeneity as outlined in section 2. Thus, to take into account the relative importance of groups, from now on we will refer to weighted average probability profiles. To disentangle what drives the patterns we precede by analyzing the transition dynamics in and out employment over the life cycle and across groups.

In figure 3 we report the weighted profiles by focusing on the occupational characteristics that, according to the empirical analysis of section 3.2, turned out to affect significantly the employment and unemployment spells' duration: type of occupation, geographic area, firm size and industry.

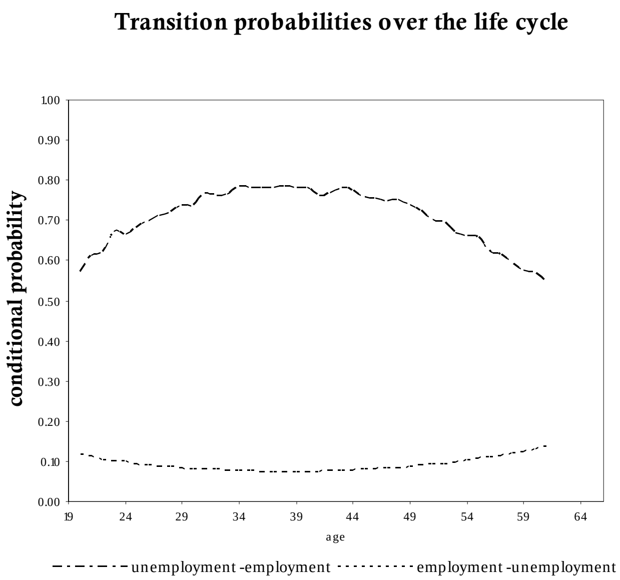
Figure 3 Life Cycle Employment Probabilities by Occupational Characteristics



According to our simulations, blue collars experience higher job instability over the life cycle whit respect to white collars, the difference is on average the difference about 7% reaching the peak of 10% at young and older ages. Workers in the southern regions face on average a higher risk (+18% and +12%) than in northern and central regions, in particular the gap is respectively about 26% and 18% and young ages and 22% and 15% at older ages, while is of about 15% and 10% at 38-40 years old. Working in medium large firms dimension firms is associated to a lower employment risk at all ages. Industries such as construction and real estate are characterized by substantial more employment risk than the manufacturing, trade and transport and financial industries. The average employment probability is on average 23% lower in the construction industry than in manufacturing, with the peak of about 35% at young and old ages.

The life cycle employment probability profiles are determined by the dynamics of the transition profiles in and out of employment, in figure 4 we report their weighted average.

Figure 4 Life Cycle Employment and Unemployment Transition Probabilities



These transition probabilities measure the average probability that workers find a job and loose it, respectively, at each age. According to the simulations of the estimated transitions we find that, across ages, the chance of getting a job is on average 70% while the average probability of becoming unemployed is about 9%. The transition probability out of employment is "U" shaped over ages while the transition out of unemployment is inverted "U" shaped with respectively a minimum of 7.3% and maximum of about 78 % reached at 38 – 40 years old. Over the life cycle, the dynamics of outflows from employment to unemployment are stronger than those of inflows. According to our simulations, the risk of loosing a job is at 20 years old on average 55% higher than the risk faced at 38-40 years old, while at 20 years old the chance of getting a new job is 26% lower than at adult ages.

In figure 5 and 6 we focus on the average transition profiles by occupational characteristics.

Figure 5 Unemployment to Employment Life Cycle Transition Probabilities by type of occupation, geographic area, firm size and industry

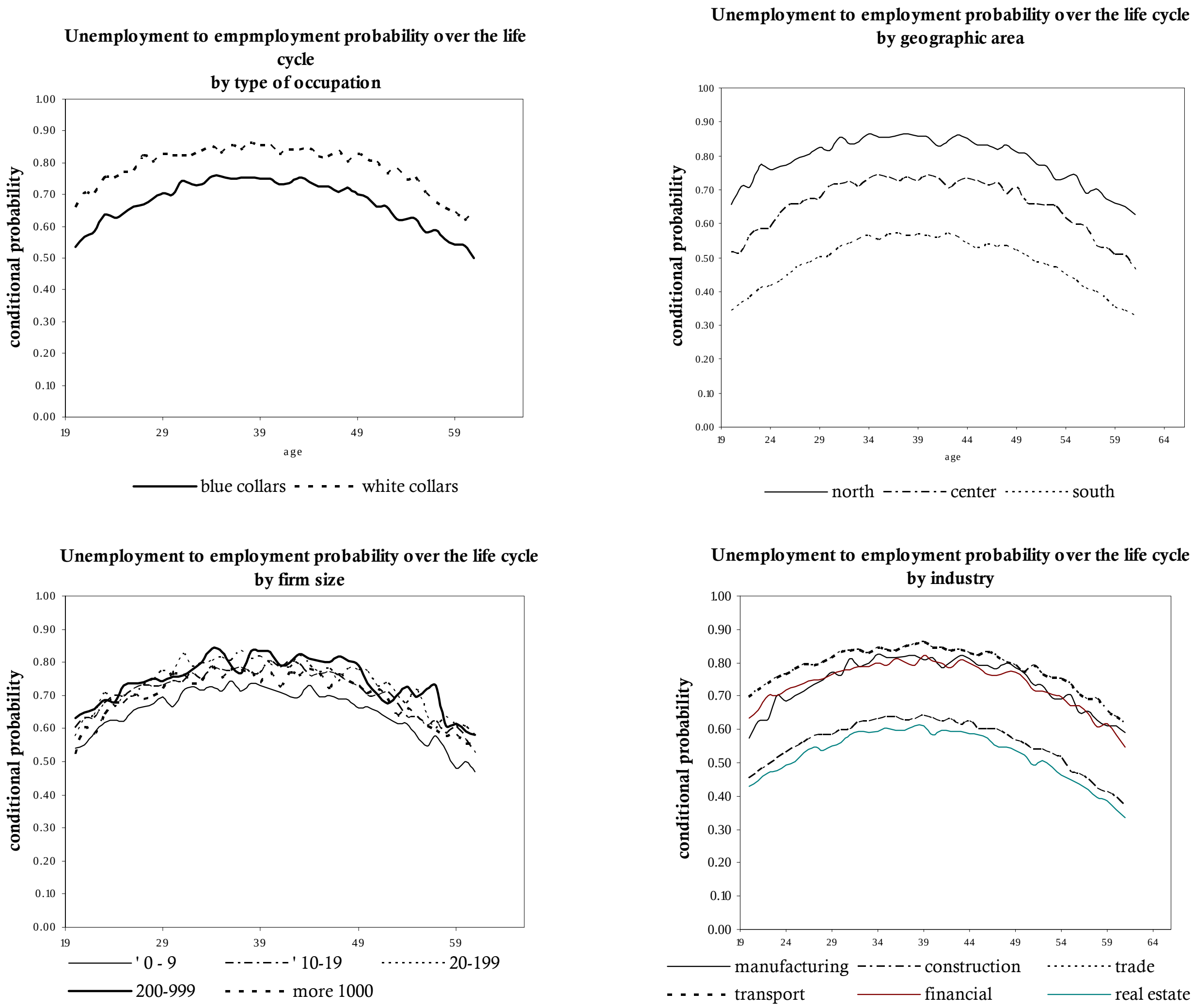
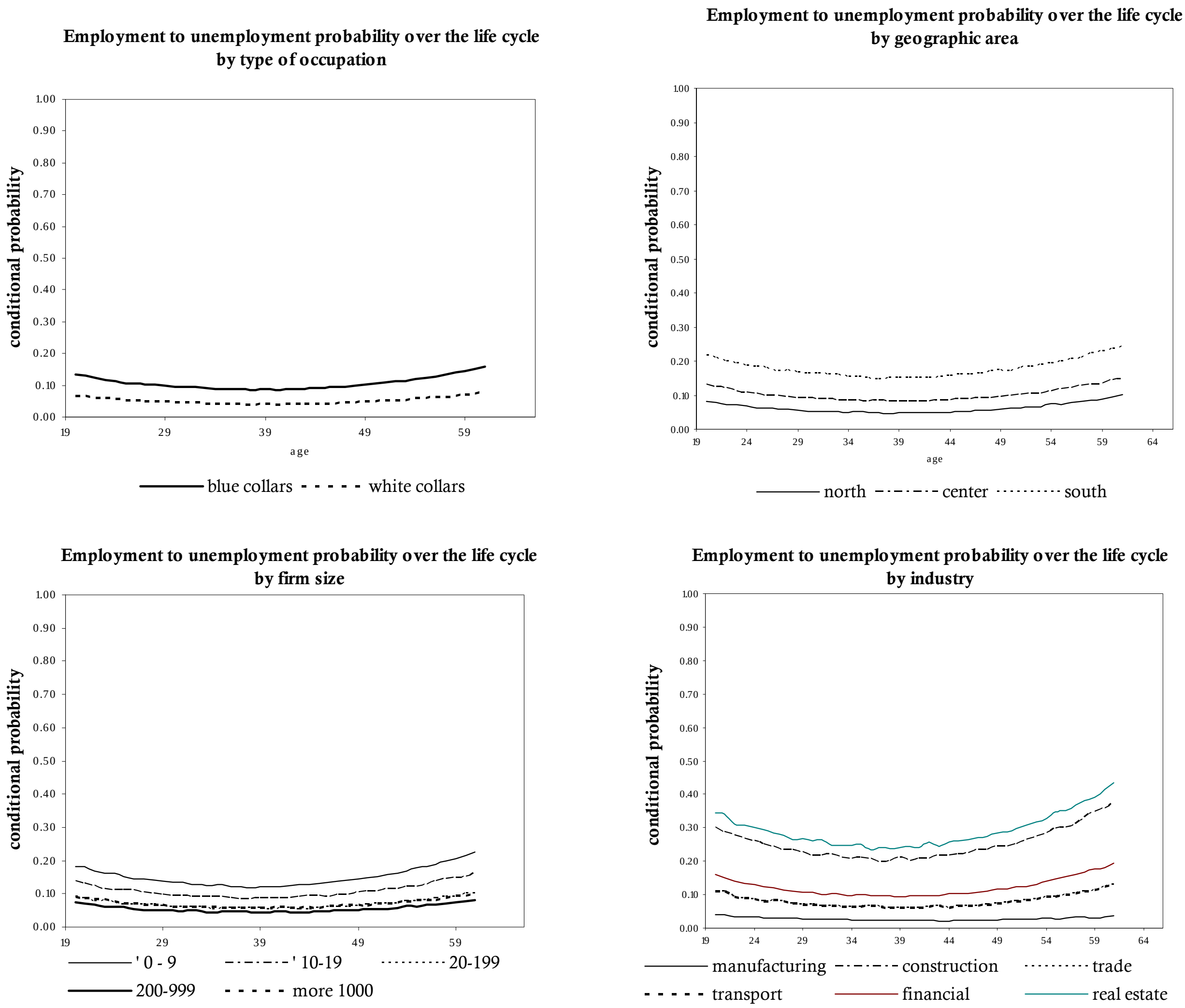


Figure 6 Employment Life Cycle Transition Probabilities by Occupational Characteristics



Our results evidence that transitions from unemployment to employment display higher heterogeneity according to type of occupation and geographic area than according to firm size types and industry. For all occupational characteristics, the life cycle dynamics of outflows from employment to unemployment are stronger than those of inflows. According to our simulations, the risk of loosing a job for a blue collar is at 20 and at 60 years about 53% and 80% higher than the risk faced at 38-40 years, while at 20 and at 60 years the chance of getting a new job is 28% and 33% lower than at adult ages. For white collars 20 and at 60 years old the risk of loosing a job is +67% and +96% higher than at the ages of 38-40; the chance of exiting unemployment at 20 and 60 years is 22% and 24% less than the chance faced at the adult age of 38-40. Similar patterns over life cycle are evidenced for transitions by the remaining occupational characteristics. According to our findings, the employment probability profile over life cycle is mainly explained by the differential in the risk of loosing the job though, at all ages, it is substantially lower than the job finding probability which turns out to be instead at the root of the heterogeneity across groups. This evidence complements the Shimer (2012)'s findings about the relatively stronger role played by job finding fluctuations in explaining the unemployment rate dynamics over the business cycle.

5. Conclusion

In this paper, we derive the life cycle profile of the probability of being employed/unemployed as a comprehensive measure of the labor market performance. We measure the employment risk implied by the predicted transitions in and out employment which in turn account for time elapsed in each state.

Our findings highlight the different role of the job exit *vs* job finding in shaping of the employment risk over life cycle and across working groups. Job exit is mainly responsible of differences across ages while job finding explain much of the difference in the employment risk across occupational characteristics.

In this paper we do not take into account how the employment risk at different ages is affected by business cycle dynamics nor we consider the role of different institutional settings. Further research according these lines ought to enhance our understanding of the relative role of job exit and finding in shaping the individual employment risk.

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Appendix

In this Appendix, 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 *viceversa.*

According to results reported in section 3.2 , 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 Monte Carlo 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 ($=5000$) 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 – 3) [11]. 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[12]. 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.

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

[12] In 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.