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Anatomy of unemployment risk*

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Abstract

This paper investigates the role of job separation and job finding probabilities in shaping the unemployment risk across ages and working characteristics. Improving on current methods, we estimate duration models for employment and unemployment, separately. We then use the duration analysis results to derive the individual age profiles of conditional transitions in and out of unemployment as well as the unconditional unemployment risk profile over the whole working life. This allows to adapt the decomposition of changes in unemployment risk so far used only in the study of aggregate unemployment dynamics (Shimer, 2007 and 2012; Fujita and Ramey, 2009). We find that differences in job separation rates across ages are at the root of the observed age differences in unemployment risk. When looking at differences between working groups, the job findings are just as important as job separation probability.

Keywords: Unemployment Risk, Duration Analysis, Heterogeneity, Semi-Markov Processes

JEL classifications: C53, E24, J64

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1 Introduction

In OECD countries, the risk of being unemployed is twice as high for a young worker,[1] and both job finding and separation rates tend to decline with age (for the US, see, for example, Choi et al., 2015; and Menzio et al., 2016). However, we do not know whether and how such rates vary across working groups (industry, occupation and geographic area). Yet, the unemployment rate does display substantial heterogeneity. For example, in U.S., the unemployment rate in Construction is about twice the unemployment rate in Manufacturing. Our paper investigates the dynamics of job finding and separation rates, as well as unemployment risk, for different working groups. Importantly, our analysis accounts for duration dependence of both employment and unemployment. Thus, our estimates allow to capture the fact that the chance of finding a new job diminishes with the increasing length of the unemployment period (see, for example, Shimer, 2008; Kroft et al. 2013) and that the risk of job loss diminishes with job tenure (see, for example, Kiefer et al., 1985). This paper thus contributes a method for the anatomy of heterogeneous unemployment risks. First, accounting for duration dependence and unobserved heterogeneity, we show how to use duration analysis results to obtain the whole life cycle profiles of job separation and job finding probabilities as well as the implied unemployment risk. Second, we propose a decomposition method to determine their respective contribution to the variation in the unemployment risk across ages and working group characteristics.

To the first aim, we use administrative data on the job careers of Italian males employed in the private sector over the period 1985-2004. There are at least two reasons for using this dataset. The first one is that it provides individual information on the Italian labour market outcomes. Italy is an ideal laboratory since it is among those countries where the incidence of long term unemployment is structurally high, especially for young workers.[2] The second reason is that the dataset at hand has a panel structure which enables workers to be followed in and out of employment over a substantial portion of

[1] In the US in 2017, the unemployment rate among workers aged 20-24 years is about 7.3% while it is about 3.2% for workers aged 45-54; in Europe, the unemployment rate for individuals aged under 25 years old is about 18.7% while it was about 7.5 for individuals aged over 25. The high unemployment rate among young people is a serious problem, especially in Southern Europe, hitting values of around 40% in 2016 in Greece, Italy and Spain.

[2] In Italy, over 60% of unemployed individuals spend more than 12 months searching for a job and the most severely affected are young people, women and those seeking employment for the first time (Source, Italian Labour Force Survey). Moreover, during the period 1995-2013, 40% of unemployed young Italian workers (15-24 years old) were unemployed for over one year (and less than four years), while the corresponding figures for prime-age and older workers are 34% and 35%, respectively (Source: Eurostat).

their working lives. Thus, we can take into account all possible relevant types of duration dependence in both employment and unemployment spells to estimate the job separation and job finding probability over the whole working life (see, for example, Heckman and Borjas, 1980).[3] Duration analysis techniques have been widely used to study the effect of covariates on the conditional probability of job termination and of exiting unemployment. In this paper, we go one step further and, relying on the Monte Carlo methods, we simulate the whole individual job careers by drawing sequentially from the estimated distributions of durations of employment and unemployment. In this way, we obtain the full age profiles of the conditional job separation and job finding probabilities as well as the unconditional probability of being unemployed at all ages, our measurement of the unemployment risk. To our knowledge, no previous study before has used the duration analysis results to derive the full profiles of both the conditional transition rates between labor market states and of the unconditional probability of being unemployed.

We document substantial heterogeneity in the unemployment risk at individual level between working groups formed on the basis of occupational characteristics and across ages. In particular, our results indicate that the variation between working groups explains more than two third of total unemployment risk variability. Moreover, consistently with the evidence available for OECD countries, we find that, for Italy, the unemployment risk decreases over working life: for workers younger than 30 years old, it is, on average, 20%, while for middle-aged workers it is about 10% (14% for workers over 55 years old). These dynamics are due to a job separation rate that monotonically declines with age and a job finding rate that falls with age after 35 years old.[4]

The second contribution of this paper is to evaluate the relative role of job findings and job separations in shaping the unemployment risk across workers. To this aim, we adapt the common approaches used to study the determinants of aggregate unemployment rate dynamics (see, for example, Shimer, 2007 and 2012; Fujita and Ramey, 2009; Petrongolo and Pissarides, 2008; Barnichon, 2012 and Choi et al., 2015). These studies approximate the unemployment rate with its steady-state value counterpart implied by job finding and the job separation probabilities. Then, they evaluate their relative contribution of job separation and job finding flows to cyclical fluctuations in unemployment on the basis of their co-movement with the steady-state unemployment rate over time. In this

[3] Our estimates control for both observed and unobserved heterogeneity so we can exclude that our findings on duration dependence are merely due to the composition of the unemployed pool.

[4] These dynamics for job finding probability in Italy are in line with Italian data on job search intensity over working life (see, for example, Aguiar et al., 2013).

paper, we show that we can apply the same methodology to determine how much of the variation in the unemployment risk across ages and working group characteristics is due to its co-movement with job separations and job findings, respectively. Overall, we find that fluctuations in the job separation probability account on average for about 56% of variability in the unemployment risk (the contribution of the job finding probability is about 44%) across ages and occupational characteristics. We then proceed by focusing on explaining age differences and differences between working groups, separately.

For the average worker, age differences in the unemployment risk are mainly due to age differences in the job separation risk, while differences in the chance of finding a new job only play a minor role. In particular, on average, about 95% of the variation of the unemployment risk across ages is due to age differences in job separation probability. These results confirm the findings of Choi et al. (2015) which document the prominent role of the job separation risk in determining the higher unemployment risk faced by young workers. This result is robust across working groups. In particular, the role of job separation lies in a range of about $80\% - 99\%$.

In addition, we focus on differences across working group characteristics, at a given age. We find that the fraction of the variation in the unemployment risk across working groups explained by the variation in the job finding (separation) risk across groups is about 55% (45%).

To our knowledge, there is very few evidence about the relative role of job finding and job separation probabilities in shaping the unemployment risk over working life. The only exception is Choi et al. (2015) who use data on *aggregate* worker flows in the Current Population Survey (CPS) to estimate the relative role of transition probabilities between employment, unemployment, and inactivity in explaining high youth unemployment. Choi et al. (2015) show that, for the US, differences in unemployment risk across ages are mainly due to age differences in the job separation rate, after controlling for the impact of inflows into inactivity. However, the CPS structure precludes them from following individuals for more than four consecutive months, preventing from accounting for the impact of duration dependence in both job tenure and joblessness. In contrast, the richness of the administrative data at hand allow us to control for both observed and unobserved heterogeneity and to assess how the relative importance of job separation and job finding probabilities varies across working groups.

Our study complements the literature that focuses on the determinants of the fluctuations of the *aggregate* unemployment risk. For the U.S., Shimer (2012) finds that fluctuations in the job findings account for the most part of the cyclical variation in unemployment, while Elbsy et al. (2010) and Fujita and Ramey (2009), for the U.S., and Petrongolo and Pissarides (2008) and Gomes (2012), for the UK, find that the job separation rate is as relevant as the job finding rate in shaping the cyclicality of unemployment. Our results show that both job separations and job findings are relevant in shaping the *heterogeneity* of the unemployment risk across working groups, while differences in job separation rates between young and adults are at the root of differences in the unemployment risk across ages.

The paper is organised as follows. Section 2 describes the data used. In section 3, we outline the empirical analysis conducted to estimate the job exit and job finding hazard rates. In section 4, we derive the implied life cycle unemployment risk. In section 5, we perform the decompositions to disentangle the relative role of job exit and job finding probabilities in shaping the unemployment risk. Section 6 concludes.

2 Data

We use the Work Histories Italian Panel (WHIP) provided by Laboratorio Riccardo Revelli. The WHIP is a panel dataset based on the Italian National Social Security Institute (INPS) administrative records. The panel consists of a random sample of $370,000$ individuals, a dynamic population drawn from the INPS full archive. The database covers permanent and temporary employees in the private sector, self-employed or retired, over the $1985-2004$ period.[5] The database allows for the main episodes of each individual's working career to be observed.[6]

In this paper, we focus on multiple full-time spells of male individuals employed exclusively in the private sector whose job career is observed over the period $1985-2004$.[7] We exclude workers who eventually become self-employed. In particular, we exclusively consider blue and white collar employees working full-time, aged between 20 and 60 years

[5] The dataset has been already used to study various aspects of labor market dynamics (see e.g. Boeri and Garibaldi, 2007; Mussida and Sciulli, 2015).

[6] The job relationships are identified on the basis of the social security contributions that workers and employers pay monthly to the INPS. Thus, WHIP does not suffer from attrition problems.

[7] The sample includes workers recruited under standard contracts as well as those recruited under 'entrance' contracts or temporary (agency) contracts. Entrance contracts include apprenticeships and on-the-job training contracts. In our sample, temporary agency work contracts represented 2.12% of the total number of job contracts observed over the period 1985-2004 and their average length was 1.12 years.

old.[8] Our sample covers about 44,000 workers with median age of 36 years.[9] The unemployment spells are defined as starting at the end of a recorded job spell and lasting until re-employment in the private sector (observed in the panel); if we do not observe re-employment by the end of 2004, we treat the unemployment spell as censored. Moreover, if retirement occurs during an unemployment spell, then the spell is considered terminated and the worker exit the sample. We treat each job spell interruption as a job separation and do not distinguish among quits, firings and job-to-job mobility being the difference among them implicitly reflected in the duration of the subsequent unemployment spell.

The duration of job spells is on average about 3 years, it is widely dispersed with a median of 1.08 years and with about 50% of jobs lasting less than one year (see Table 1, panel b). The average unemployment duration is about 1.6 years; however, the median unemployment duration is about 3.9 months. For workers under 25 years old, the median unemployment duration is about two-thirds of the median job duration (6.6 and 9.9 months, respectively); for workers over 25 years old the median job duration is about three times (1 year) their median unemployment duration (3.3 months). The mean age at the entry of job spells and unemployment spells is about 33 years old.

The unemployment risk at each age, i.e. the unconditional probability of being unemployed, is measured on a monthly basis as the ratio of the number of workers who are non-employed over the total number of workers. In Figure 1, we display the evolution of the unemployment risk over working life evidenced by our data. According to our data, the unemployment risk faced by Italian workers employed in the private sector is U-shaped with respect to age. In particular, for workers under 25 years old it is more than double the rate for older workers.[10]

The database lacks information on the composition of households, on education and on the relevant economic and financial background other than occupation-related characteristics. The observed characteristics used to explain the length of employment and unemployment spells are: initial age, initial age squared, working industry, firm dimen-

[8] We focus on full-time employees since the inclusion of part-time workers would mean considering separate labour supply functions to account for differences in factors underlying the decision between the two margins, which is beyond the scope of this study. Part-time workers correspond to 8.9 per cent of the sampled population.

[9] Left truncated job spells account for 16% of the total job spells. We repeated the analysis by excluding them. The results did not change.

[10] The Italian average unemployment rate observed over the period 1998-2004 is about 30% for workers under 25 years old and about 7% for the 26-54 age group. Our measurement of the probability of being unemployed during older adult age is slightly upward biased given that the data at hand does not distinguish between true unemployment spells and spells out of the labour force.

sion, geographic area, type of occupation (blue and white collar), 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 allows us to identify a total of $G = 480$ working groups. In Table 1, panel a, column a) we report the distribution of observed jobs by individual and occupation characteristics. Small and medium sized firms (with 20 or more employees) provide the majority of jobs, while about 7% of observed job relationships are active in firms with more than $1,000$ employees. The majority of observed job spells are located in the northern regions, 17% in the central regions and 30% in the South. The distribution of unemployment spells by individual and occupation characteristics mirrors the composition of job spells (see Table 1, panel a, column 3).

3 Employment and unemployment duration

This section uses duration-based data on employment and unemployment spells to measure the job separation and job finding rates at the individual level.

Previous studies on individual labour market dynamics show that the transition rates depend on the time spent in a given state (current duration dependence) and to a lesser extent on time spent in the previous state (lagged duration dependence), see, for example, Heckman and Borjas (1980).[11]

We model the duration (D) of unemployment (U) and employment (E) using a parametric Accelerated Failure Time Model (AFT, see Lawless 2002). Under this metric, the logarithm of time elapsed in the two states is expressed as

$$\ln\left(D_i^U\right) = \quad \beta^{U\prime} X_i^U + \omega_i^U \tag{1}$$

$$\ln\left(D_i^E\right) = \quad \beta^{E\prime} X_i^E + \omega_i^E \tag{2}$$

where, D_i^U and D_i^E are the elapsed durations in unemployment and employment, respectively; X_i^j (with $j = U, E$) are two sets observed individual demographic and occupational characteristics that explain the unemployment and job durations, and ω_i^j (with $j = U, E$) are the error terms. The distribution of ω_i^j determines the regression model.

[11] Technically, we model the transitions from employment to unemployment (and vice versa) as a two-state time non-homogeneous semi Markov process which allows for various kinds of duration dependence. We rely on survival analysis techniques to evaluate the probability of transitioning between employment and unemployment, and *viceversa*.

To allow for lagged duration dependence, we include among the covariates, X_i^U and X_i^E, the time spent in the previous state.[12] We control for time dependence in job separation including age and daily salary at the beginning of the current employment spell. Time dependence in job finding is controlled by considering age at the beginning of the current unemployment spell and daily salary at the end of the previous job spell. In addition, we include explanatory variables whose value is fixed over the current spell and over the life cycle: cohort, gender, type of occupation, industry, firm dimension and geographic area.[13]

Some remarks on the specification are in order. In many cases, the two approaches, parametric *vs* semi-parametric, produce similar results in terms of the effect of explanatory variables on the hazard rate (see, for example, Petrongolo, 2001). We opt for a parametric rather than as semi-parametric model since we are interested in detecting the patterns of job separation and the job finding profiles and not just in evaluating the difference between hazard rates among workers. Moreover, we favour AFT models over proportional hazard models, since in our data the age variable does not have a proportional effect on the risk of terminating the employment and unemployment spells. We consider the continuous time metric to obtain results that are invariant to the time unit (see Flinn and Heckman, 1982).

Moreover, when the hazard of job separation (job finding) depends on unobserved characteristics (in addition to observables), then individuals displaying frail characteristics exit the employment (unemployment) state relatively soon. Thus, the sample of observed employed (unemployed) would lead to spurious negative duration dependence (see Heckman and Singer, 1984). We account for the impact of unobserved heterogeneity by incorporating a frailty term, α_i, i.e. a random variable whose mean is normalised to *1* and with unknown finite variance which must be estimated. Since the data at hand convey information on multiple employment (unemployment) spells for the same worker, we opt for a shared-frailty model, i.e. we model the unobserved frailty α_i as equal at individual level, across individual (unemployment) spells.[14]

In particular, according to the AIC criterion, the distribution that better fits the

[12] In particular, to account for lagged duration dependence in estimating the hazard job separation (finding), time elapsed in the previous unemployment (employment) spell is included among the covariates.

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

[14] Van den Berg, 1990 shows that models with multiple spells are identified under weaker assumptions than single-spell data.

employment duration data is a Log-logistic distribution, while the Weibull distribution appears to better fit the unemployment duration data. We assume that α_i follows the Inverted Gamma distribution which is widely used in survival analysis since it approximates a wide class of models (Abbring and Van den Berg, 2007). In this respect, under the AFT metric adopted to fit both the employment and unemployment duration models, the interpretation of regression coefficients is unchanged by the frailty.[15]

3.1 Results

In this section, we report the results of the duration analysis.[16] For both employment and unemployment spells, the parameters governing duration dependence are significant. Moreover, 99% of coefficients are significantly different from zero and take a reasonable sign. Importantly, in the case of both employment and unemployment durations, our results are robust to the unobserved heterogeneity.

In Table 2, we report the model estimates for the employment duration. Our results support the evidence that the likelihood of terminating a job spell is strongly dependent on age and exhibits positive duration dependence, both current and lagged. In particular, the time spent in a given job position reduces the probability of separation. In addition, the longer the time elapsed in the previous unemployment spell, the more this negatively affects the current job tenure. These results add to evidence of the scarring effects of unemployment (see, for example, Arulampalam et al., 2000; Arulampalam, 2001; Gregg, 2001; Boheim and Taylor, 2002).

The other evidence aligns with known patterns in the Italian labour market. The older the worker at the beginning of the spell, the higher the risk of terminating it and the longer the job tenure. However, this effect decreases with age, as evidenced by the second order term of the polynomial in age. Young cohorts face higher job instability than older cohorts. Job interruptions in the construction industry are more frequent than in manufacturing and services industries. The Northern and Central regions are those with longer job relations, while shorter tenures characterise jobs in the South. As in the U.S. (Davis and Haltiwagner, 1992) the probability of separation tends to monotonically decrease with the dimension of the firm.

In Table 3, there is strong evidence of all kinds of duration dependence considered in

[15] Results are robust across variuos distributions specifications for ω and α (see Addison and Portugal, 1998),

[16] Given the AFT formulation adopted to model durations, the coefficients provide information on how survival times, in employment or unemployment, are directly affected by the different covariates.

unemployment. In particular, there is a significant negative duration dependence in the hazard of exiting the current unemployment spell. In addition, there is negative lagged duration dependence: the longer the previous job spell, the higher the chance of exiting the current unemployment spell, by becoming employed.

Our data show that time dependence is also significant: the higher the age at entry an unemployment spell, the higher the chance of terminating it, although this pattern reverses at older ages as indicated by the second order term of the polynomial in age. In our specification, we evaluate the influence of the last job occupation characteristics on the current unemployment duration. For workers in Northern regions, the unemployment duration is shorter 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 labor market.

Our results indicate that the degree of persistence of both employment and unemployment is substantial and may have a strong impact on subsequent labour market outcomes. Thus, at each point of the working life, the risk of being unemployed depends inherently on previous experience. This is the reason why we need to model the careers of each working group in order to be able to gauge the dynamics of unemployment risk. In the next section, we use the estimates above to derive, at each age, the unconditional probability of being unemployed implied by the conditional transition probabilities in and out of unemployment.

4 Measuring the heterogenous dynamics of unemployment risk

In this section, we use previous results to measure the unemployment risk faced by heterogenous workers at each stage of their working life. By combining all possible values of the demographic and occupational characteristics we form a total of $G = 480$ working groups.[17]

We use the Monte Carlo methods to simulate the working life career of representative workers from each working group (g). We assume that working life careers start at the age of 20 and last until 60 years old. At the age of 20, the worker g may be either employed (E)

[17] The characterisitics are type of occupation, geographic area, industry, firm dimension in addition to birth year of cohort and age.

or unemployed (U) with probability that matches the empirical proportion of E to U at the age of 20 in Italy. Then, we simulate a large number N ($= 100,000$) of possible lengths for the first employment spells ($D^E_{1,g}$) and first unemployment spells ($D^U_{1,g}$) by drawing from the distributions of survival times with shape and scale parameters that depend on the value of the covariates as well as on the estimated coefficients (see Tables $2-3$)[18]. We proceed in the same way, by iterating the subsequent E to U (U to E) transitions, thus simulating all the ongoing spells, $D^U_{s,g}$ and $D^E_{s,g}$, until the age of 60.[19] In this way, for each working group g, we obtain the life cycle sequences of survival times in unemployment and employment, $D^U_{1,g}$... $D^U_{S,g}$ and $D^E_{1,g}$... $D^{UE}_{S,g}$ that are based upon the individual and job characteristics, which remain fixed over the life cycle, but also on characteristics that vary over the life cycle, i.e. age and daily salary at the beginning of the spell and duration of the previous simulated unemployment (employment) spell. Thus, for each representative worker, g, we obtain N simulated working histories (i.e. sequences of employment and unemployment spells). For each working group, g, we average over these sequences to obtain, at each point of their life cycle, a measurement of their unemployment risk, i.e. the unconditional probability of being unemployed (or the unemployment rate), $u_{g,t}$, (with $t = 1, ..., T$, where $T = 40$ periods[20]).[21] Similarly, from the N sequences of each working group g, we can evaluate, at each age, the conditional probability of job separation, $s_{g,t}$, and job finding, $f_{g,t}$.[22]

In Figure 2, we report the life cycle profile of the unemployment risk (solid line), derived from the simulations described above, along with the unemployment rate observed for Italian workers in our data (dashed line), for reference. In particular, the dashed profile plotted in Figure 2 is an average, at each age, of the unemployment risk measured over the G working groups. Figure 2 reports also the simple average, about 14%, of the unemployment risk across working groups and across ages. As showed by Figure 2, our

[18]For the representative worker of each working group g, we simulate the entire working career by drawing iteratively from the distribution of employment and unemployment spells specific to that group by setting the parameter governing the individual heterogeneity α to 1.

[19]Note the total number (S) of employment and unemployment spells experienced up to age 60 may vary across workers, depending on their durations.

[20]For expositional simplicity we let $t = 1$ to corresponds to age 20 and so on till age 60 wich corresponds to $t = 40$.

[21]We measure the unemployment risk as the probability of being unemployed, i.e. number of unemployed workers out of the total number of workers.

[22]At each age, for each working group g, the conditional probability of separation is measured by the number of job spells that terminates at that age out of the total number of job spells ongoing at that age. Similarly, we compute the conditional job finding probability as the number of the unemployment spells that terminates at that age out of the total number of unemployment spells ongoing at that age.

measurement of the individual unemployment risk fits well the actual one observed in the data at hand. However, since the dataset at hand covers Italian workers employed in the private sector, our measurement is higher than the unemployment rate observed among Italian male workers over the period $1985 - 2004$. Moreover, the average obtained above does not take into account the weight of each working group in the labor force. Given this limitations, the aim of our analysis in next sections is to understand the relative role of job finding and job separations in shaping the unemployment risk faced at different ages and across working groups with respect to the average unemployment risk (14%).

4.1 Average life cycle profiles

Overall, the unemployment risk is a convex function of age, reaching the minimum of about 10% at 40 years old. Young workers aged between 20 and 30 years old are about 10% more likely to be unemployed than adults aged over 40, although about 54% of the gap is recovered by the age of 25. The unemployment risk for the elderly (aged over 55 years) is about 13%.

To understand what drives the evidenced life cycle patterns we focus on the differences in transition dynamics in and out of unemployment over life cycles and across groups. In Figure 3, we report the profiles of the average transition probabilities in and out of unemployment.

According to our results, conditionally on being unemployed, the chance of finding a new job within one year is on average 40%, while the average conditional probability of job separation is about 6%. The estimated transition probabilities are higher than in Choi et al. (2015) and Menzio et al. (2016) because we consider only two market states and disregard inactivity and job-to-job transitions. The risk of job loss declines with age, consistently with the patterns in male job flow transitions found in Choi et al. (2015) and Menzio et al. (2016) in the data for US males.

While Choi et al. (2015) and Menzio et al. (2016) show that the job finding rate in the US monotonically decreases over working life, we document that, in Italy, the job finding probability increases with age up to around 33 years old and only after that age does it display a declining pattern. These dynamics are in line with the job search intensity profile evidenced by Aguiar et al. (2013) for Italy. Moreover, the age-increasing job finding probability, early in working life, is consistent with a relatively slower school-to-work transition process observed in Italy compared to the US (see, for example, Pastore, 2012).

4.2 Heterogeneity across working groups

Figure 4 reports the unemployment risk profiles measured at working group level. Our results show substantial heterogeneity, as the standard deviation of unemployment probability is about 15% and about 7%, at younger and older ages, respectively, with a minimum of 3% at mature adult ages. In particular, the type of occupation and the geographic area are at the root of the largest observed differences across working groups (see Figure 4). Blue collar workers experience a higher unemployment risk than white collar workers, with the difference being on average about 16%, reaching the peak of 8% at young ages. These results are consistent with the evidence of declining in education unemployment risk (see, for example, Mincer, 1991), when taking the occupation type as an approximation of attained education levels. Moreover, workers in southern Italian regions face on average a higher risk (23%) than in north-eastern regions; in particular, the gap is respectively about 30% and 26% at younger ages and at older ages, confirming available evidence on regional differences in employment opportunities in Italy (see, for example, Viviano, 2003).

In Figures 5 and 6, we focus on the average transition profiles by occupational characteristics. According to our results, the transitions in and out of unemployment display higher differences according to the type of occupation and geographic area rather than according to firm dimension, types and industry. The difference in the unemployment risk across Italian regions is mainly due to differences in the job finding probability. For example, compared to workers employed in the North-East of Italy, employees in the South face a lower chance, of about 28% on average, of finding a new job and face a higher risk, of about of 14%, of losing a job. Previous studies find that the heterogeneity in the unemployment rate across Italian regions is mainly determined by differences in inflow rates into unemployment (Newell and Pastore, 2000; Pastore, 2012); our results show, on the other hand, that the difference in the job finding rate is mainly due to the observed North-South gap in the unemployment rate.

In the next section, we quantify the relative importance of job finding and job separations in explaining the differences in the unemployment risk faced by Italian workers across occupational characteristics and across different ages.

5 Unemployment risk decomposition

In this section, we assess the role of transition probability distributions in determining the observed differences in the unemployment risk across ages and working groups. To accomplish the analysis we follow two well established methods used in the literature to decompose the cyclical dynamics of the aggregate unemployment rate. The first one is based on the Shimer's pioneering method (Shimer, 2007) and already applied to life cycle unemployment by Choi et al. (2015). The second one is an extension of the approach introduced by Elsby et al. (2013) and Fujita and Ramey (2009).[23] These approaches evaluate the relative contribution of unemployment inflows and outflows assuming that the unemployment rate is well approximated by its steady state value based on worker flow data. Here, we adapt this methodology to evaluate the role of inflow and outflow hazards in shaping the individual unemployment risk over working life and across working groups.

We base the analysis on the approximation of the unemployment risk with its steady-state value counterpart implied by job finding and job separation probabilities:

$$u_{g,t} \approx u_{g,t}^{ss} = \frac{s_{g,t}}{s_{g,t} + f_{g,t}} \tag{3}$$

where, $u_{g,t}$ is the unconditional unemployment probability, $s_{g,t}$ and $f_{g,t}$ are respectively the job separation and job finding probabilities for the working group g at age t (with $g = 1, \ldots, G$ and $t = 1, ..., T$), obtained from Monte Carlo simulations. In (3), $u_{g,t}^{ss}$ is the steady-state unemployment probability for the working group g at age t. In Figure 7, we report the life cycle profiles, averaged across the G working groups, of the "steady-state" unemployment risk computed according to (3). In Figure 7, we also report the profile of $u_{g,t}$ averaged across all the working groups, for reference. The steady-state value approximates well the unemployment rate fitted on data, with the correlation between the two series being about 99%. Thus, we can use the steady-state approximation in (3) to detect the role of transition rates in shaping the observed differences in unemployment risk across ages and across working groups.

[23] We adopt both approaches, since the Shimer's decomposition has been criticised as the steady state approximation is a non linear functions of transition rates (see Gomes, 2012).

5.1 Shimer's (2007) approach

Following Shimer (2007), we consider for each working group g at age t, the comparison between the steady state unemployment risk, $u^{ss}_{g,t}$, with the counterfactual unemployment risk determined by fixing, one at a time, the job finding and job exiting probability at their average over working life and across working groups.

In particular, to evaluate the role of the job separation probability in shaping the unemployment risk, we fix the job finding rate at its average over working life and across working groups, $\overline{f}$, (i.e. $\overline{f} = \sum_{g=1}^{G}\sum_{t=1}^{T} f_{g,t}$) and take the actual job separation rates, $s_{t,g}$ to determine, for each working group g at each age t, the counterfactual the unemployment risk:

$$u^{s}_{g,t} = \frac{s_{g,t}}{s_{g,t} + \overline{f}} \tag{4}$$

Similarly, to evaluate the role of the job finding probability we fix the job separation at its average over working life and across working groups, $\overline{s}$, (i.e. $\overline{s} = \sum_{g=1}^{G}\sum_{t=1}^{T} s_{g,t}$) and take the actual job finding rates, $f_{t,g}$, to determine the counterfactual the unemployment rate for each group g at each age t:

$$u^{f}_{g,t} = \frac{\overline{s}}{\overline{s} + f_{g,t}} \tag{5}$$

Following Shimer (2007), the contribution of the two transition distributions is evaluated by regressing the two counterfactual unemployment risk series, $u^{s}_{g,t}$ and $u^{f}_{g,t}$, on the steady state approximation of the actual unemployment risk, $u^{ss}_{g,t}$, obtaining:

$$c^{s} = \frac{cov(u^{ss}_{g,t}, u^{s}_{g,t})}{var(u^{ss}_{g,t})};\ c^{f} = \frac{cov(du^{ss}_{g,t}, u^{f}_{g,t})}{var(u^{ss}_{g,t})} \tag{6}$$

where c^{s} and c^{f} are respectively the contributions of variations of job separations and findings across ages and working groups to the heterogeneity of the unemployment risk observed across ages and working groups. According to these computations, reported in Table 4 panel a), first column, fluctuations in the job separation probability account for about 53% of variation in the unemployment risk (the contribution of the job finding probability is about 39%)[24].

[24] The two terms do not sum up to one beacuse of the approximation.

5.2 Fujita and Ramey's (2009) approach

As robustness check, we consider an extension of the approach introduced by Fujita and Ramey (2009).[25] This approach is based on the log-linearization of $u^{ss}_{g,t}$ around its average over ages and across working groups denoted as:

$$\overline{u^{ss}_{g,t}} = \frac{\overline{s}}{\overline{s} + \overline{f}} \tag{7}$$

where $\overline{s}$ and $\overline{f}$ denote the job separation and job finding probabilities averaged over working life and across all working groups. By log-linearizing $u^{ss}_{g,t}$ around $\overline{u^{ss}_{g,t}}$ the following decomposition can be obtained (see Fujita and Ramey, 2009):

$$du^{ss}_{g,t} = \ln \frac{u^{ss}_{g,t}}{\overline{u^{ss}_{g,t}}} = (1 - \overline{u^{ss}_{g,t}}) \ln \frac{s_{g,t}}{\overline{s}} - (1 - \overline{u^{ss}_{g,t}}) \ln \frac{f_{g,t}}{\overline{f}} + \epsilon_{g,t} \tag{8}$$

where $\epsilon_{g,t}$ is a residual term.

Equation (8) shows that deviations of job separation and job finding probabilities from their average (over ages and working groups) contribute separately to deviations of the unemployment risk from its own average (over ages and working groups). Equation (8) is restated as:

$$du^{ss}_{g,t} = du^{s}_{g,t} + du^{f}_{g,t} + \epsilon_{g,t} \tag{9}$$

Fujita and Ramey (2009) show that the linear decomposition can be used to assess quantitatively the effects of the transition rates on unemployment risk variability. Following Fujita and Ramey (2009) we express the contributions through:

$$\beta^{s} = \frac{cov(du^{ss}_{g,t}, du^{s}_{g,t})}{var(du^{ss}_{g,t})};\ \beta^{f} = \frac{cov(du^{ss}_{g,t}, du^{f}_{g,t})}{var(du^{ss}_{g,t})};\ \beta^{\epsilon} = \frac{cov(du^{ss}_{g,t}, d\epsilon_{g,t})}{var(du^{ss}_{g,t})} \tag{10}$$

where $\beta^s + \beta^f + \beta^\epsilon = 1$ (see Fujita and Ramey, 2009). In particular, β^s is the coefficient in a linear regression of $du^{s}_{g,t}$ on $du^{ss}_{g,t}$, which applies correspondingly to the other betas. The betas can be interpreted as the contribution of job separation and job finding probabilities to total variability of the unemployment risk across ages and working group characteristics.

[25] While the Shimer's (2007) approach focuses on explaining differences in unemployment levels over the business cycle, the approach adopted by Elsby et al. (2009) and Fujta and Ramey (2009) focues on explaining percentage differences in unemployement.

We find that the differences in the job finding probability at group level account for 44% of the variation of the unemployment risk while the remaining 56% of the variability is due to differences in separation probability (see table 4, panel b), first column).

According to the two approaches adopted, both the job separation and the job finding probabilities are important in shaping the fluctuations of the unemployment risk across ages and working groups. In the following subsections, we focus on explaining the observed differences across ages and across working groups, separately.

5.3 Differences across ages

In this section, we focus solely on age heterogeneity in the unemployment risk. In particular, we consider at each age t the unemployment risk avearaged across working groups: we aim at determining the respective role o groups characteristics. In particular, we want to determin whether v

$$u_t \approx u_t^{ss} = \frac{s_t}{s_t + f_t} \tag{sst}$$

where $s_t = \sum_{g=1}^{G} s_{g,t}$ and $f_t = \sum_{g=1}^{G} f_{g,t}$.

Shimer's (2007) approach

In this subsection, following Choi et al. (2015), we adapt the Shimer's (2007) approach to explain differences in the unemployment risk across ages. In particular, we consider at each age t the unemployment risk averaged across working groups[26]:

x

To determine the contribution of the job finding and the job separation rates to differences across ages, we compare the unemployment risk at age t, $\overline{u}_t^{ss}$, with the counterfactual unemployment risk determined by fixing, one at a time, the job finding and job exiting probability at their average over working life and across working groups, $\overline{f}$ ($\overline{f} = \sum_{t=1}^{T} f_t$) and $\overline{s}$ ($\overline{s} = \sum_{t=1}^{T} s_t$) , respectively.

In particular, by fixing the job finding at the average over working life and across working groups, $\overline{f}$, and taking the job separation rates at each age averaged across working groups, s_t , we determine the hypothetical life cycle unemployment rate:

$$u_t^s = \frac{s_t}{s_t + \overline{f}} \tag{11}$$

[26]In particular, we consider the unemployment risk implied by the average separation rate and the average finding rate at each age t:

In particular, by fixing the job separation at the average over working life, $\overline{s}$, and taking the job finding rates at each age t averaged across working groups, f_t, we determine the hypothetical life cycle unemployment rate:

$$u_t^f = \frac{\overline{s}}{\overline{s} + f_t} \tag{12}$$

Following Shimer (2007), the contribution of the two transition distributions is measured by the regression coefficients of u_t^s and u_t^f on u_t^{ss}:

$$c^{s(t)} = \frac{cov(\overline{u_t^{ss}}, u_t^s)}{var(\overline{u_t^{ss}})};\ c^{f(t)} = \frac{cov(\overline{u_t^{ss}}, u_t^f)}{var(\overline{u_t^{ss}})} \tag{13}$$

where $c^{s(t)}$ and $c^{f(t)}$ are the contributions of the variability of job separations and findings across ages to the difference of the unemployment risk over working life. According to these computations, reported in Table 4 panel a), second column, fluctuations in the job separation probability account for about 96% of age variations in the unemployment risk (the contribution of the job finding probability is about 3%).

Fujita and Ramey's (2009) approach

As robustness check, we consider the extended approach based on Fujita and Ramey (2009). Following this approach, we capture the role of age variations in the job finding and job separation rates in explaining the deviations of the unemployment risk faced by the average at each age, $\overline{u_t^{ss}}$, from its own trend $\overline{u^{ss}}$ (i.e. the average unemployment risk across ages):

$$\overline{u^{ss}} = \frac{\overline{s}}{\overline{s} + \overline{f}} \tag{14}$$

where $\overline{f}$ ($\overline{f} = \sum_{t=1}^{T} \overline{f_t}$) and $\overline{s}$ ($\overline{s} = \sum_{t=1}^{T} \overline{s_t}$) denote, for the average worker, the job separation and job finding probabilities averaged over working life. The approach is based on the log-linearization of the average unemployment risk at age t, $\overline{u_t^{ss}}$, around the overall mean, $\overline{u^{ss}}$. From the log-linearisation, the following decomposition can be obtained (see Fujita and Ramey, 2009):

$$d\overline{u_t^{ss}} = \ln \frac{\overline{u_t^{ss}}}{\overline{u^{ss}}} = (1 - \overline{u^{ss}}) \ln \frac{s_t}{\overline{s}} - (1 - \overline{u^{ss}}) \ln \frac{f_t}{\overline{f}} + \epsilon_t = d\overline{u_t^s} + d\overline{u_t^f} + \epsilon_t \tag{15}$$

where ϵ_t is a residual term.

The relative importance of the two transition distributions, s_t and f_t, is expressed through:

$$\beta^{s(t)} = \frac{cov(d\overline{u_t^{ss}}, du_t^s)}{var(d\overline{u_t^{ss}})}; \beta^{f(t)} = \frac{cov(d\overline{u_t^{ss}}, du_t^f)}{var(d\overline{u_t^{ss}})}; \beta^{\epsilon(t)} = \frac{cov(d\overline{u_t^{ss}}, d\epsilon_t)}{var(d\overline{u_t^{ss}})} \quad (16)$$

where $\beta^{s(t)} + \beta^{f(t)} + \beta^{\epsilon(t)} = 1$, $\beta^{s(t)}$and $\beta^{f(t)}$ are the contributions of age variations in job separations and job findings to age differences in the unemployment risk faced by the average worker.

We find that the differences in job separation probability across ages are the main reason for the difference in the unemployment risk at individual level over working life. In particular, about 95% of the rate of change of unemployment probability over the life cycle is due to differences in the job separation probabilities at different ages while differences in job finding probability play a minor role (5%) (see Table 4, panel b), second column).[27]

Our analysis confirms the findings in Choi et al. (2015) who use the Current Population Survey (CPS) to evaluate the impact of transitions between employment, unemployment and inactivity on the unemployment risk over the life cycle. They show that, on average, differences in the unemployment rate across ages are mainly due to differences in the job separation rate, after controlling for the impact of inflows into inactivity. While the CPS structure precludes them from following individuals for more than four consecutive months and accounting for individual and employer characteristics, the panel dimension of the administrative dataset at hand allows us to account for the effects of both observed and unobserved heterogeneity as well as for duration dependence on the transitions in and out of unemployment. Moreover, our results are consistent with Elsby et al. (2010), Gervais et al. (2016) and Hairault et al. (2014) who show that the lower unemployment rate among older workers is determined by their lower probability of job loss.

These patterns support the view that younger workers face higher unemployment risks as they are more likely to separate (the "job shopping" mechanisms, see, for example, Jovanovich, 1979 and Burdett, 1978), despite tending to be involved in a more intensive search to find the best match. Our findings suggest that, to reduce youth unemployment with respect to adults, more emphasis should be placed on labour market policies focusing on reducing the job separation risk. Moreover, given that young workers face higher unemployment risk because of higher job loss probability, our results advocate more generous unemployment benefits for the young given that they have higher incentives to find a job (Michelacci and Ruffo, 2015).

[27] We repeat the analysis for single working groups. Unreported results, available from authors, show that the range of variation for the role of job separation in explaining age variations at working group level is 80%- 99%.

5.4 Differences across working groups

Shimer's (2007) approach

Following the approach of Shimer (2007) and adopted in the previous subsection, we focus on explaining the differences in the unemployment risk across working groups at the same age:

$$\overline{u_g} \approx \overline{u_g^{ss}} = \frac{\overline{s_g}}{\overline{s_g} + \overline{f_g}} \tag{17}$$

where $\overline{s_g} = \sum_{t=1}^{T} s_{g,t}$ and $\overline{f_g} = \sum_{t=1}^{T} f_{g,t}$.

We consider the comparison between the $\overline{u_g^{ss}}$ for the working group g with the counterfactual unemployment risk (17) determined by fixing, one at a time, the job finding and job exiting probability at their average across all working groups and ages.

Firstly, we fix the job finding at the average over all groups and ages, $\overline{f}$ and take the actual job separation rate at group level g, s_g, to determine the hypothetical life cycle unemployment rate:

$$u_g^s = \frac{s_g}{s_g + \overline{f}} \tag{18}$$

Moreover, we fix the job separation at the average across groups, $\overline{s}$, and take the actual job finding rates at group level g, f_g to determine the hypothetical unemployment risk:

$$u_g^f = \frac{\overline{s}}{\overline{s} + f_g} \tag{19}$$

Following Shimer (2007), the contribution of the two transition distributions is measured as the regression coefficients of u_g^s and u_g^f, respectively, on u_g^{ss}:

$$c^{s(g)} = \frac{cov(u_g^{ss}, u_g^s)}{var(u_g^{ss})}\,;\; c^{f(g)} = \frac{cov(u_g^{ss}, u_g^f)}{var(u_g^{ss})} \tag{20}$$

According to our computations, reported in Table 4 panel a), third column, the contribution of fluctuations in the job separation probability account for about 38% of variations in the unemployment risk across working groups (the contribution of the job finding probability is about 54%). Thus, the job finding probability is more important in explaining the differences in the unemployment risk across working groups characteristics other than age.

Fujita and Ramey's (2009) approach

As robustness check, we extend the approach introduced by Elsby et al. (2013) and

Fujita and Ramey (2009). This extended approach is based on the decomposition of the log-linear approximation of u_g^{ss} around the average across working groups and ages, denoted as $\overline{u^{ss}}$ at each age:

$$du_g^{ss} = \ln \frac{u_g^{ss}}{\overline{u^{ss}}} = (1-\overline{u^{ss}}) \ln \frac{s_g}{\overline{s}} - (1-\overline{u^{ss}}) \ln \frac{f_g}{\overline{f}} + \epsilon_{_g} = du_{_g}^{s} + du_{_g}^{f} + \epsilon_{_g} \tag{21}$$

where $\epsilon_{_g}$ is a residual term.

As in the previous subsection, the relative importance of the two transition distributions is assessed by evaluating

$$\beta^{s(g)} = \frac{cov(d\overline{u_g^{ss}}, du_g^s)}{var(d\overline{u_g^{ss}})}; \ \beta^{f(g)} = \frac{cov(d\overline{u_g^{ss}}, du_g^f)}{var(d\overline{u_g^{ss}})}; \ \beta^{\epsilon(g)} = \frac{cov(d\overline{u_g^{ss}}, d\epsilon_g)}{var(d\overline{u_g^{ss}})} \tag{22}$$

where $\beta^{s(g)} + \beta^{f(g)} + \beta^{\epsilon(g)} = 1$, $\beta^{s(g)}$and $\beta^{f(g)}$ are the contributions of the variations in job separations and job findings to differences in the unemployment risk across groups faced at a given age. According to this decomposition, we confirm that the differences in the job finding probability at group level account for 55% of the variation of the unemployment risk observed across groups while the remaining 45% of the variability is due to differences in separation probability (see Table 4 panel b), third column)

Our results show that job finding and job separation rates are almost equally important in shaping the unemployment risk across occupational characteristics at individual level. On the other hand, differences in job separation rates between young adults and more mature adults are at the root of the observed age differences in the unemployment risk at individual level.

Our findings indicate that, in case the policy maker's objective is mitigating the inequality in unemployment between young workers and adults, greater emphasis should be placed on policies designed to reduce the gap in their job separation risk. However, the job finding probability plays a substantial role in shaping the unemployment risk across groups, thus more emphasis should be put on policies aimed at boosting the probability of finding a new job if the objective is to reduce the overall unemployment rate.

6 Conclusions

In this paper, a method to analyse the heterogeneous dynamics of unemployment risk. We use a panel drawn from the Italian Social Security archive to estimate the parameters characterizing duration-dependent (un)employment spells. We show how to use these estimates in Monte Carlo simulations to retrieve the job separation and job finding rates at each age, which depend on prior careers, as well as the implied unemployment risk profile. Thus, we pin down the careers of the representative worker of 481 groups. Finally, we measure the contribution of job finding and separation rates in shaping variations in the unemployment risk across demographics and other working characteristics.

According to our results, the differential in the risk of losing the job across ages explains almost the 95% of differences in the unemployment risk faced by young workers as opposed to older adults. When looking at differences in the unemployment risk across occupational characteristics, the job findings and job separations are almost equally important.

Almost all OECD countries devote substantial resources to implementing labour market policies to foster the employability of young people. Our findings suggest that, to reduce age differences in unemployment risk across workers, greater emphasis should be placed on policies designed to reduce the job separation risk among young workers. Moreover, our results point to age-dependent unemployment insurance policies, with benefits decreasing in age, given the strongest incentive for young workers to search for a job (Michelacci and Ruffo, 2015).

However, we find also that the job finding probability plays a substantial role in shaping the unemployment risk across working group characteristics. For example, to reduce the unemployment risk in Southern regions and in the Construction industry, more emphasis should be devoted to policies aimed at boosting the probability of finding a new job.

In this paper, we do not consider how the unemployment risk at different ages is affected by business cycle dynamics. Further research along these lines will enhance our understanding of the relative importance of job exit and job finding in shaping the heterogeneous unemployment risk.

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Tables

Table 1: Descriptive statistics

Individual and occupational characteristics	Employment spells	Unemployment spells
	Panel a	
Age at entry (average)	33.7	32.8
Daily salary (euro)	66	60.39
Mean Duration (in years)	3.19	1.6
Median Duration (in years)	1.08	0.48
Num. spells	94,905	63,246
Num subjects	44,737	44,737
	Panel b	
	%	
Industry		
Manufacturing	0.37	0.42
Construction	0.27	0.26
Services	0.36	0.4
Geographic Area		
North West	0.27	0.28
North East	0.22	0.23
Center	0.16	0.18
South	0.35	0.31
Firm size (number of employees)		
1 - 9	0.4	0.4
10 - 19	0.16	0.16
20 - 199	0.3	0.29
200 -999	0.08	0.08
$>$ 1000	0.06	0.07
Type of occupation		
Blue collar	0.88	0.81
White collar	0.12	0.19
Cohort		
1940 - 49	0.12	0.16
1950 - 59	0.2	0.21
1960 - 69	0.39	0.37
1970 - 79	0.29	0.27

Note: Occupational characteristics refer to the last job before the current unemployment spell.Source: WHIP, Work Histories Italian Panel, years 1985-2004.

Table 2: Employment Duration Maximum Likelihood Estimates AFT-Log-logistic model with inverted gamma unobserved heterogeneity

Variables	Coefficients
Age	0.132***
	(0.0123)
Age ^2/10	-0.0246***
	(0.00198)
Industry (ref. Services)	
Manufacturing	0.384***
	(0.0250)
Construction	-0.0181
	(0.0295)
Firm size (ref. >1000)	
1-9	0.000649
	(0.0477)
10 - 19	0.183***
	(0.0505)
20- 199	0.241***
	(0.0470)
200-999	0.375***
	(0.0530)
Geographic area (ref. South)	
North West	0.281***
	(0.0264)
North East	0.0457
	(0.0291)
Center	0.143***
	(0.0312)
Type of occupation (ref. White collar)	
Blue Collar	-0.584***
	(0.0301)
Length previous unemployment spell	-0.224***
	(0.00503)
Log daily salary at the beginning of the spell	0.290***
	(0.0275)
Cohort (ref. 1979- 79)	
Cohort 1940-49	1.186***
	(0.0661)
Cohort 1950 -59	0.545***
	(0.0434)
Cohort 1960-69	0.315***
	(0.0242)
Constant	-3.026***
	(0.221)
Ln(gamma)	-0.673***
	(0.00517)
Ln(theta	.0343366***
	(.0122629)
Observations	166,231

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 Source: WHIP, Work Histories Italian Panel, years 1985-2004.

Table 3: Unemployment Duration Maximum Likelihood Estimates AFT-Weibull model with inverted gamma unobserved heterogeneity

Variables	Coefficients
Age	-0.161***
	(0.00486)
Age ˆ2/10	0.0330***
	(0.000665)
Industry (ref. Services)	
Manufacturing	-0.0743***
	(0.0149)
Construction	0.0711***
	(0.0179)
Firm size (ref. >1000)	
1-9	-0.104***
	(0.0256)
10 - 19	-0.209***
	(0.0271)
20 - 199	-0.153***
	(0.0254)
200-999	-0.0377
	(0.0298)
Geographic area (ref. South)	
North West	-0.784***
	(0.0200)
North East	-0.854***
	(0.0211)
Center	-0.318***
	(0.0223)
Type of occupation (ref. White collar)	
Blue Collar	0.0554***
	(0.0206)
Length previous employment spell	-0.0323***
	(0.00425)
Log daily salary at the end of previous job spell	-0.00456
	(0.00554)
Cohort (ref. 1979- 79)	
Cohort 1940-49	1.223***
	(0.0375)
Cohort 1950 -59	1.581***
	(0.0316)
Cohort 1960-69	1.012***
	(0.0242)
Constant	0.622***
	(0.0931)
Ln(gamma)	-0.170***
	(0.00247)
Ln(theta)	2.104***
	(0.0210)
Observations	134,448

Note: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Source: WHIP, Work Histories Italian Panel, years 1985-2004.

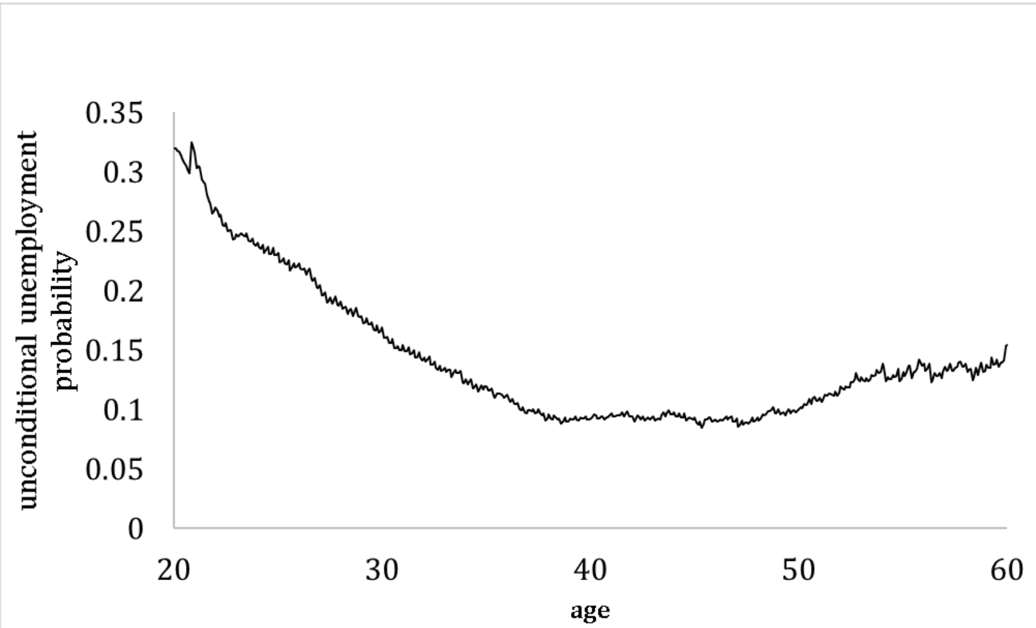
Table 4: Unemployment risk decomposition

	Across ages and working groups	Across ages	Across working groups
a) Shimer's approach			
Cov(uss,us)/var(uss)	0.53	0.96	0.38
Cov($d$uss,$d$uf)/var(uss)	0.39	0.03	0.54
b) Fujita and Ramey's approach			
Cov($d$uss,$d$us)/var($d$uss)	0.56	0.95	0.45
Cov($d$uss,$d$uf)/var($d$uss)	0.44	0.05	0.55

The table reports the decomposition of the variation in the steady-state unemployment risk across ages and across working groups. Panel a) reports decompositions according to the Shimer's (20007) approach. Panel b) reports decompositions according to the Fujita and Ramey's (2009) approach. The first column focuses on heterogeneity along the two dimensions, ages and working groups. The second column focuses on age differences, while the third column focuses on differences between working groups.

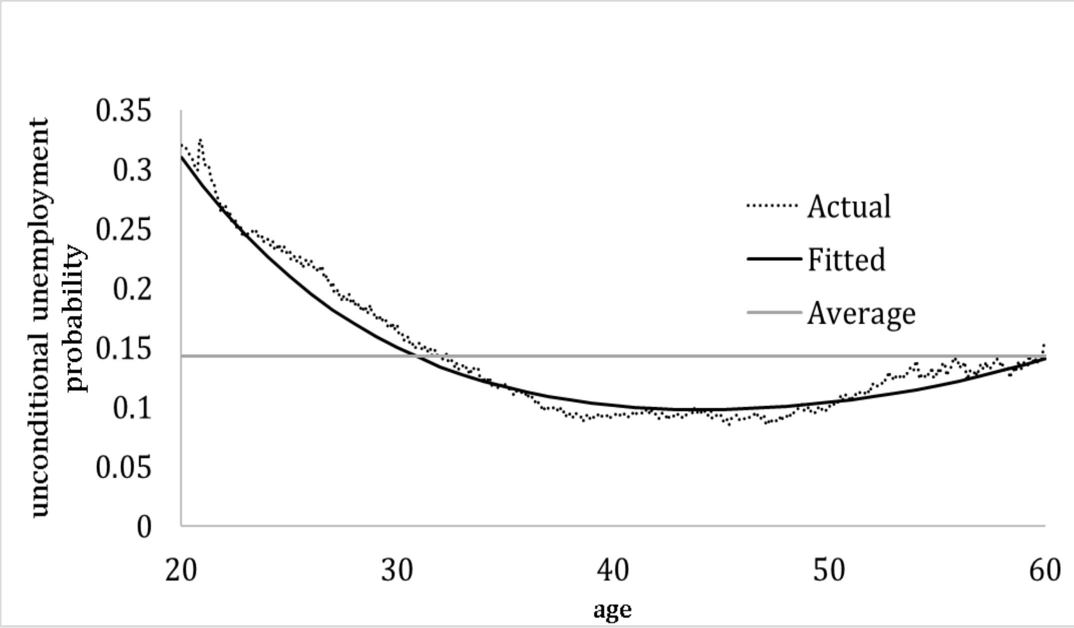
Figures

Figure 1: Actual unemployment risk over the life cycle



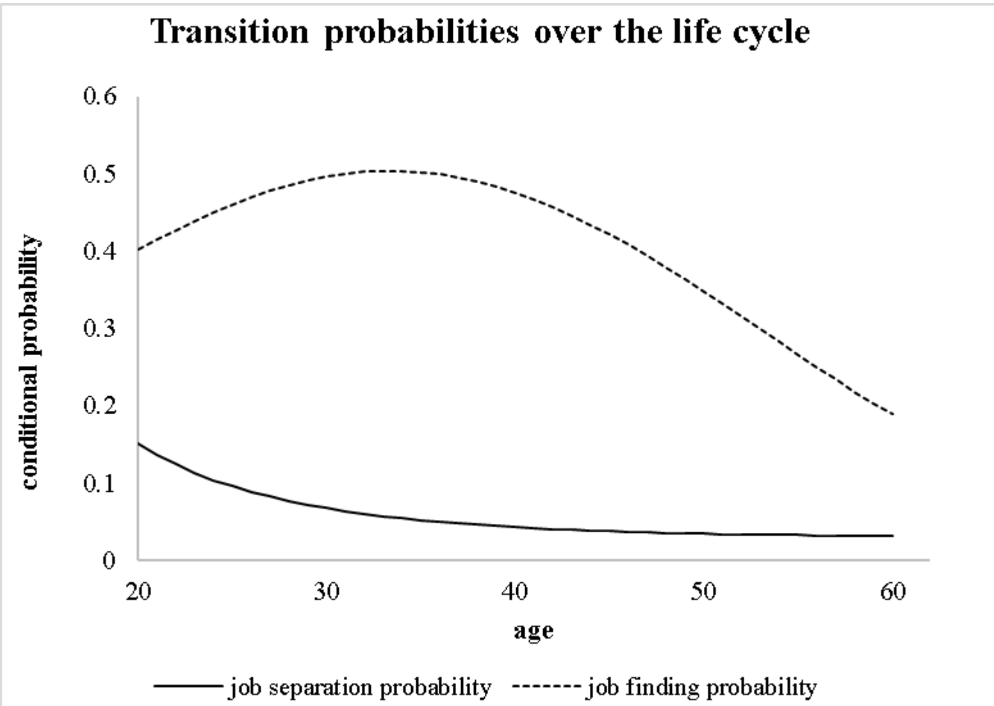
The figure reports the unemployment risk faced by Italian workers employed in the private sector. The actual unemployment risk at each age is measured monthly, as the ratio of total non-employed workers over total workers covered by WHIP in a given month. Source: WHIP, Work Histories Italian Panel, years 1985-2004.

Figure 2: Estimated unemployment risk over the life cycle



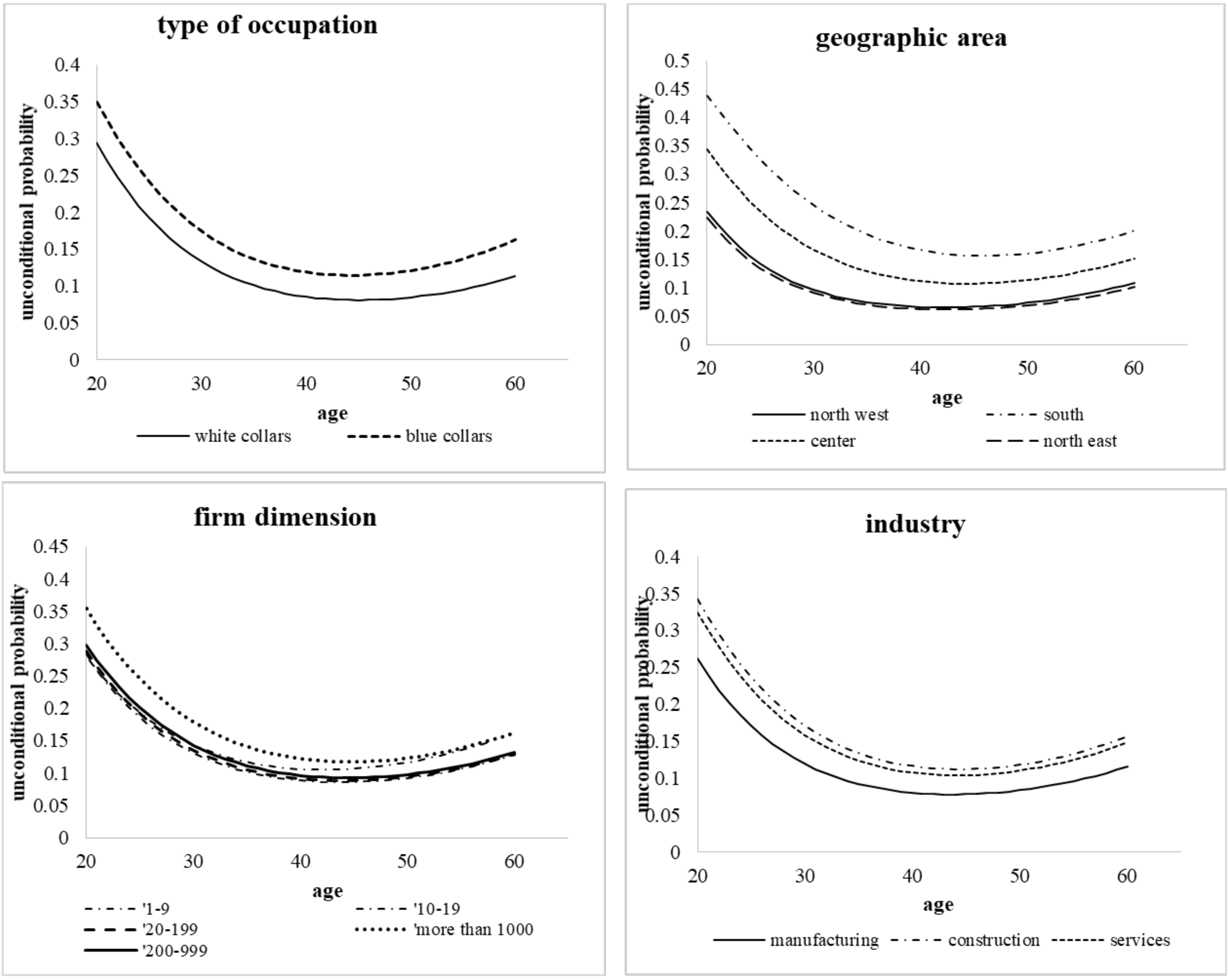
The figure reports the actual unemployment risk (dashed line) and the unemployment risk (solid line) obtained from Monte Carlo simulations of the estimated duration mdoels. The series are averaged over all working groups. In addition, it reports the average unemployment probability across ages and across working groups (grey line).

Figure 3: Transition probabilities over working life



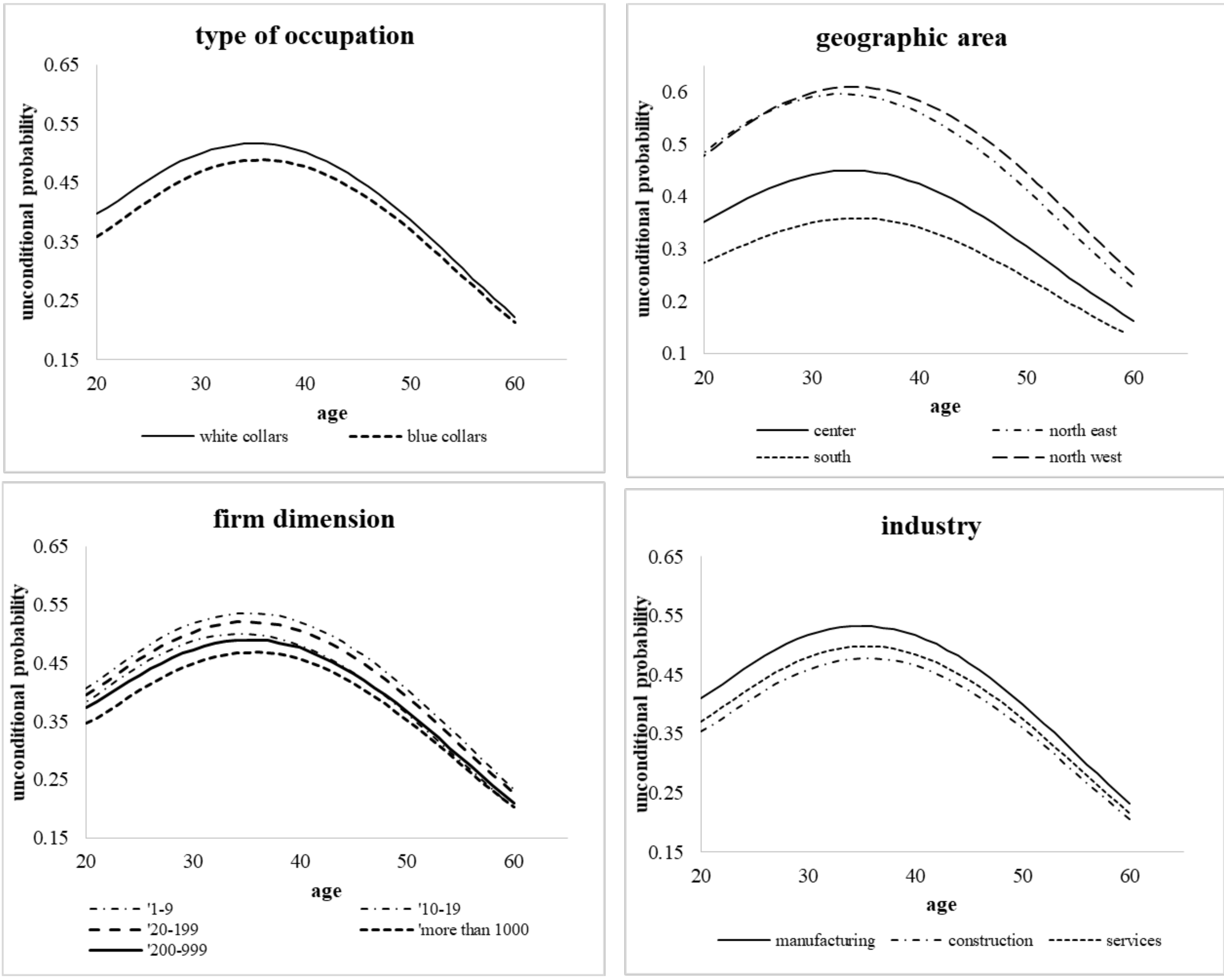
The figure reports the transition probabilities in and out unemployment at each age, obtained from Monte Carlo simulations of employment and unemployeemnt duration models estimated in Tables 2 and 3, respectively. The plotted age profiles are averages over all the considered working groups.

Figure 4: Unemployment risk by occupational characteristics



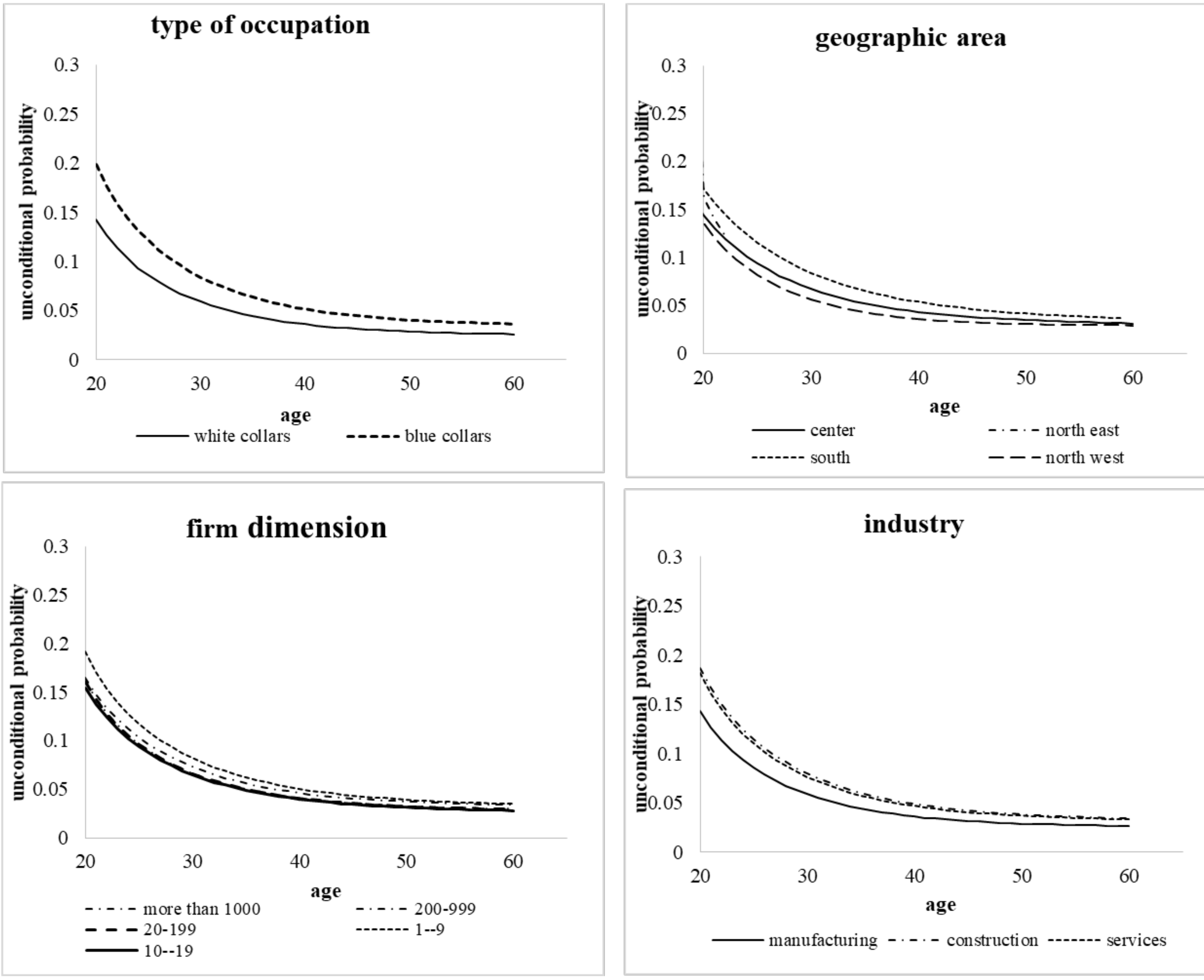
The figure reports the simulated average unemployment probability profiles over the life cycle, by working groups.

Figure 5: Job finding transition rates by type of occupation, geographic area, firm size and industry



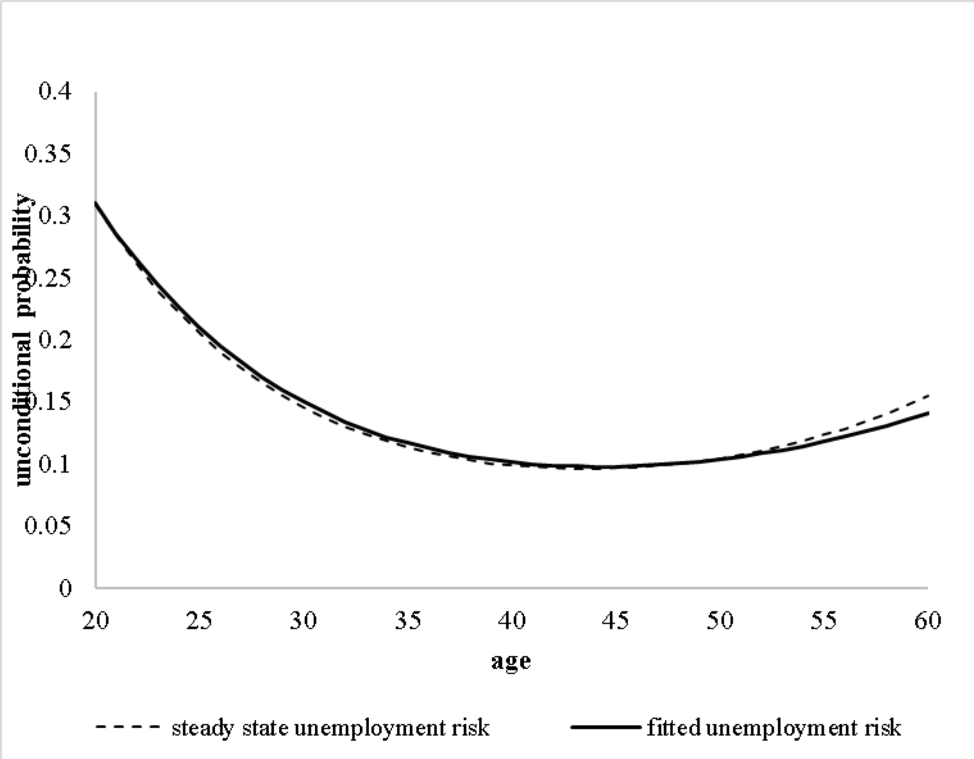
The figure reports, by working groups, the simulated average profiles for the transition from unemployment to employment.

Figure 6: Job loss proababilities by occupational characteristics



The figure reportsthe simulated average profiles for the transition from employment to unemployment, by working groups characteristics.

Figure 7: Fitted and steady state unemployment risk over working life



he figure reports the simulated unconditional unemployment probability profile (solid line) as well as the steady state unemployment probability profile (dashed dot line) implied by the simulated job finding and job separation age profiles. All age profiles are an average across the considered working groups.