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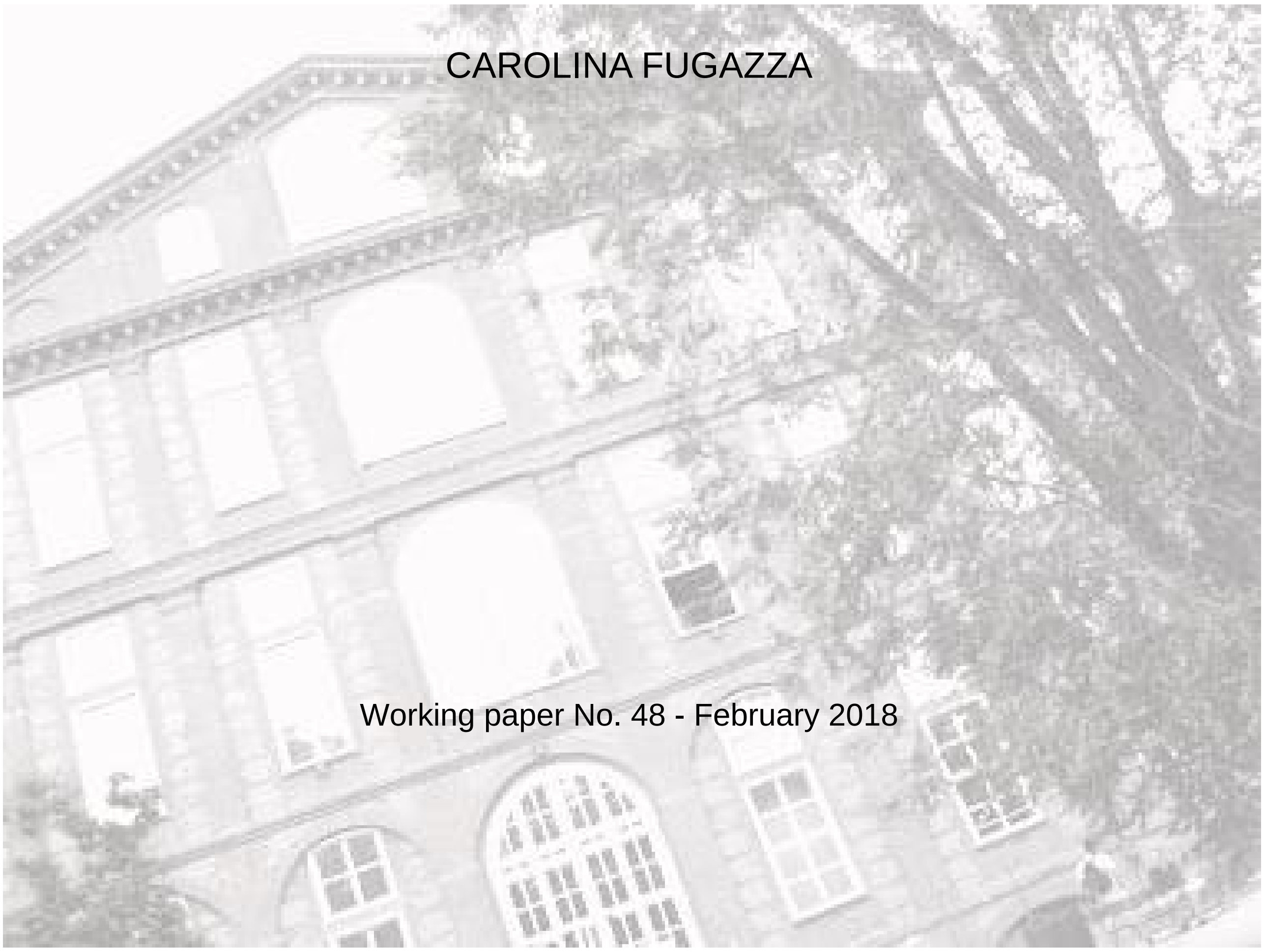
ANATOMY OF UNEMPLOYMENT RISK



CAROLINA FUGAZZA

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Anatomy of unemployment risk[*]

Carolina Fugazza[§]

University of Torino and CeRP (Collegio Carlo Alberto)

Abstract

This paper investigates how job separation and job finding probabilities shape the unemployment risk across ages and working group characteristics. Improving on current methods, I estimate duration models for employment and unemployment separately. I 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 approach allows adapting the decomposition of changes in unemployment risk, which has so far only been used to study aggregate unemployment dynamics (Shimer, 2007 and 2012; Fujita and Ramey, 2009). I find that differences in job separation rates across ages underlie the observed age differences in unemployment risk. When differences between working groups are under consideration, the job findings are just as important as the job separation probability.

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

JEL classifications: C53, E24, J64

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[§]SME, Dipartimento ESOMAS, C.so Unione Sovietica, 218 bis, 10134 Torino (Italy); Tel. +39 011 6706063; email: carolina.fugazza@unito.it

1 Introduction

In OECD countries, a young worker has twice the risk of being unemployed as an older worker.[1] Further, both job finding and separation rates tend to decline with age (e.g., for the United States, see Choi et al., 2015; Menzio et al., 2016). However, whether and how such rates vary across working groups (industry, occupation and geographic area) is unknown. Meanwhile, the unemployment rate displays substantial heterogeneity; for example, in the United States, the unemployment rate in construction is about twice the unemployment rate in manufacturing. My paper investigates the dynamics of job finding and separation rates as well as unemployment risk for different working groups. Importantly, my analysis accounts for duration dependence of both employment and unemployment. Thus, my estimates are able to show that the chance of finding a new job diminishes as the length of the unemployment period increases (e.g., see Shimer, 2008; Kroft et al. 2013) and that the risk of job loss declines with the duration of job tenure (e.g., see Kiefer et al., 1985). This paper thus contributes a method for investigating the anatomy of heterogeneous unemployment risks. First, accounting for duration dependence and unobserved heterogeneity, I show how to use duration analysis results to obtain the whole life-cycle profiles of job separation and job finding probabilities as Ill as the implied unemployment risk. Second, I propose a decomposition method to determine their respective contribution to the variation in the unemployment risk across ages and working group characteristics.

To accomplish the first aim, I use administrative data on the job careers of Italian men employed in the private sector during 1985-2004. At least two reasons exist for using this dataset. The first is that the dataset provides individual information on the Italian labour market outcomes. Italy is an ideal study site because it is among the countries where long-term unemployment is structurally high, especially for young workers.[2] The second reason is that the dataset has a panel structure that enables following workers' employment over a substantial portion of their working lives. Thus, I can take into account

[1] In the United States 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, approaching 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; 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 were 34% and 35%, respectively (Source: Eurostat).

all possible relevant types of duration dependence in both employment and unemployment to estimate the job separation and job finding probabilities over the entire working life (e.g., see Heckman and Borjas, 1980).[3] Duration analysis techniques have been widely used to study the effect of covariates on the conditional probabilities of job termination and exiting unemployment. In this paper, I go one step further, and relying on the Monte Carlo methods, I simulate the entirety of individual job careers by drawing sequentially from the estimated distributions of durations of employment and unemployment. In this way, I obtain the full age profiles of the conditional job separation and job finding probabilities as well as the unconditional probability of being unemployed for all ages, which serves as my measurement of the unemployment risk. To my knowledge, no previous study has used duration analysis results to derive the full profiles of both the conditional transition rates between labour market states and the unconditional probability of being unemployed.

I document substantial heterogeneity in the unemployment risk at an individual level between working groups based on occupational characteristics and across ages. In particular, my results indicate that the variation between working groups explains more than two thirds of the total unemployment risk variability. Moreover, consistent with the evidence available for OECD countries, I find that the unemployment risk in Italy decreases over the working life: for workers younger than 30 years old, it averages 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 an evaluation of the relative role of job findings and job separations in shaping the unemployment risk across workers. Towards this aim, I adapt common approaches used to study the determinants of aggregate unemployment rate dynamics (e.g., see Shimer, 2007, 2012; Fujita and Ramey, 2009; Petrongolo and Pissarides, 2008; Barnichon, 2012; Choi et al., 2015). These previous studies approximate the unemployment rate with its steady-state value counterpart implied by the job finding and job separation probabilities. They then evaluate the relative contribution of job separation and job finding flows to cyclical fluctuations in unemployment based on their co-movement with the steady-state unemployment rate over time. In this paper, I show that the same methodology can be applied to determine how much of the vari-

[3] My estimates control for both observed and unobserved heterogeneity. Thus my findings on duration dependence are not 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).

ation in the unemployment risk across ages and working group characteristics is due to its co-movement with job separations and job findings, respectively. Overall, I find that fluctuations in the job separation probability account for about 56% of the variability in the unemployment risk on average (the contribution of the job finding probability is about 44%) across ages and occupational characteristics. I then proceed by 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 play only 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, I focus on differences across working group characteristics at a given age. I find that the fraction of the variation in the unemployment risk across working groups explained by the variation in the job finding (separation) risk experienced by the different groups is about 55% (45%).

To my knowledge, very little evidence exists with regard to the relative role of job finding and job separation probabilities in shaping the unemployment risk over the working life. The only exception is Choi et al. (2015), who use data on *aggregate* worker flows in the Current Population Survey 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 United States, 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 Current Population Survey structure precludes following individuals for more than four consecutive months, and it is consequently not possible to account for the impact of duration dependence in both job tenure and joblessness. In contrast, the richness of the administrative data at hand allow me 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.

My study complements the literature that focuses on the determinants of fluctuations in the *aggregate* unemployment risk. For the United States, Shimer (2012) finds that fluctuations in job findings account for most of the cyclical variation in unemployment, while Elbsy et al. (2010) and Fujita and Ramey (2009), for the United States, and Petrongolo and Pissarides (2008) and Gomes (2012), for the United Kingdom, find that the job separation rate is equally relevant to the job finding rate in shaping the cyclicality of unemployment. My 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 workers and older workers 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, I outline the empirical analysis conducted to estimate the job exit and job finding hazard rates. In section 4, I derive the implied life cycle unemployment risk. In section 5, I 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

I 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 full INPS archive. The database includes permanent and temporary employees in the private sector as well as self-employed or retired individuals over the $1985-2004$ period.[5] The database allows observation of the main episodes of each individual's working career.[6]

In this paper, I focus on multiple full-time spells of exclusive employment in the private sector of male individuals whose careers are observed during $1985-2004$.[7] I exclude workers who eventually become self-employed. In particular, I exclusively consider blue- and white-collar employees working full time who are aged between 20 and 60

[5] The dataset has already been used to study various aspects of labour market dynamics (e.g., see 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.

years old.[8] My sample covers about 44,000 workers with a median age of 36 years. 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 re-employment does not occur by the end of 2004, I treat the unemployment spell as censored. Moreover, if retirement occurs during an unemployment spell, then the spell is considered terminated and the worker exits the sample. I treat each job spell interruption as a job separation and do not distinguish among reasons (i.e., resignations, firings and job-to-job mobility) as the difference among them is implicitly reflected in the duration of the subsequent unemployment spell.[9]

The duration of job spells averages about 3 years. It varies widely, with a median of 1.08 years (see Table 1, panel a). The average duration of unemployment is about 1.6 years; however, the median is about 3.9 months. For workers under 25 years old, the median duration of unemployment is about two-thirds 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 beginning 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 non-employed workers to the total number of workers. Figure 1 shows the evolution of the unemployment risk over working life based on the data. According to the data, the unemployment risk faced by Italian workers employed in the private sector is U-shaped with respect to age. In particular, the risk for workers under 25 years old is more than double that for older workers.[10]

The database lacks information on the composition of households, on education and on relevant economic and financial backgrounds outside 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 size, geographic area, type

[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% 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. My measurement of the probability of being unemployed at an older adult age is slightly upward biased given that the data at hand do not distinguish between true unemployment spells and spells out of the labour force.

of occupation (blue and white collar), the logarithms of the daily wage at the beginning of the spell and the length of the previous spell, and the cohort birth year. This set of variables allows identifying a total of $G = 480$ working groups. In Table 1 (panel b, column 2), I 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 1000 employees. The majority of observed job spells are located in the northern regions, with 17% in the central regions and 30% in southern regions. The distribution of unemployment spells by individual and occupation characteristics mirrors the composition of job spells (see Table 1, panel b, 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]

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

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

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

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 of observed individual demographic and occupational characteristics that explain the unemployment and job durations, and ω_i^j (with $j = U, E$) is the error term. The distribution of ω_i^j determines the regression model.

[11] Technically, I 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. I rely on survival analysis techniques to evaluate the probability of transitioning between employment and unemployment, and *vice versa*.

To allow for lagged duration dependence, I include among the covariates, X_i^U and X_i^E, the time spent in the previous state.[12] I 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, I include explanatory variables whose value is fixed over the current spell and over the life cycle: cohort, type of occupation, industry, firm size and geographic area. [13]

Some remarks on the specification are in order. In many cases, the two approaches, parametric *versus* semi-parametric, produce similar results in terms of the effect of explanatory variables on the hazard rate (e.g., see Petrongolo, 2001). I opt for a parametric rather than a semi-parametric model since I am 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, I favour AFT models over proportional hazard models since the age variable does not have a proportional effect on the risk of terminating the employment and unemployment spells in the data. I 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) individuals would lead to spurious negative duration dependence (see Heckman and Singer, 1984). I account for the impact of unobserved heterogeneity by incorporating a frailty term, α_i, as being equal at the individual level, across discrete (unemployment) spells.[14]

In particular, according to the Akaike information criterion, the distribution that better fits the employment duration data is a log-logistic distribution, while the Weibull distribution appears to better fit the unemployment duration data. I assume that α_i follows the inverted gamma distribution which is widely used in survival analysis because it approximates well a wide class of models (Abbring and Van den Berg, 2007). In this

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

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, I 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, my results are robust to the unobserved heterogeneity.

In Table 2, I report the model estimates for the employment duration. My results support the evidence that the likelihood of a job spell terminating 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 elapsed time in the previous unemployment spell, the greater the negative impact on the current job tenure. These results add to evidence of the scarring effects of unemployment (e.g., see 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 lower the risk of the spell terminating and the longer the job tenure. However, these effects decrease 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 occur more frequently than in the manufacturing and services industries. The northern and central regions are those with longer job relations, while shorter tenures characterise jobs in southern regions. As in the United States (Davis and Haltiwagner, 1992), the probability of separation tends to decrease monotonically with the size of the firm.

Table 3 presents strong evidence of all types of duration dependence considered in unemployment. In particular, a significant negative duration dependence is present in the hazard of exiting the current unemployment spell. In addition, a positive lagged duration

[15] Results are robust across various 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. However, to be directly comparable with existing studies, in this section we discuss the estimation results in term of hazard rates.

dependence is observed: the longer the previous job spell, the higher the chance of exiting the current unemployment spell by becoming employed.

My data show that time dependence is also significant: the higher the age at entry into an unemployment spell, the higher the chance of the spell terminating. However, this pattern reverses at older ages as indicated by the second-order term of the polynomial in age. In my specification, I 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 labour market.

My 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 inherently depends on previous experience. This situation explains why it is necessary to model the careers of each working group to be able to gauge the dynamics of unemployment risk. In the next section, I 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, I use previous results to measure the unemployment risk faced by heterogeneous workers at each stage of their working life. By combining all possible values of the demographic and occupational characteristics, I create a total of $G = 480$ working groups.[17]

I use Monte Carlo methods to simulate the working life career of representative workers from each working group (g). I assume that working life careers start at the age of 20 and extend to 60 years old. At the age of 20, the worker g may be either employed (E) or unemployed (U) with probability that matches the empirical proportion of E to U at the age of 20 in Italy. Then, I simulate a large number N $(= 100,000)$ of possible lengths for the first employment spell ($D^E_{1,g}$) and first unemployment spell ($D^U_{1,g}$) by drawing from

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

the two 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]. I 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, I obtain the entire life-cycle sequences of survival times in unemployment and employment, ($D^U_{1,g}$... $D^U_{S,g}$ and $D^E_{1,g}$... $D^{UE}_{S,g}$, with $g = 1, ..., N$) 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, specifically, 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 , I obtain N simulated working histories (i.e., sequences of employment and unemployment spells). For each working group, g, I average over these sequences to obtain, at each point of the workers' life cycle, a measurement of their unemployment risk, that is, the unconditional probability of being unemployed, $u_{g,t}$, (with $t = 1, ..., T$, where $T = 40$ periods[20]). The unconditional probability of being unemployed is my measure of the unemployment risk.Similarly, from the N sequences of each working group g, I can evaluate, at each age, the conditional probability of job separation, $s_{g,t}$, and job finding, $f_{g,t}$.[21]

In Figure 2, I 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 the 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 also reports the simple average, about 14%, of the unemployment risk across working groups and across ages. As showed in Figure 2, my measurement of the individual unemployment risk matches well with the actual one observed in the data. However, since the dataset at hand covers Italian workers employed in the private sector, my measurement is higher than the unemployment rate observed

[18] In particular, for the representative worker of each working group g ,draw 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 that the total number (S) of employment and unemployment spells experienced up to age 60 may vary across workers, depending on the duration of each spell.

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

among Italian male workers over the period $1985-2004$. Moreover, the average obtained above does not take into account the weigth of each working group in the labour force. Given these limitations, the aim of my analysis in the 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 a 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 workers aged over 40, although about 54% of the gap is recovered by the age of 25. The unemployment risk for older workers (aged over 55 years) is about 13%.

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

According to my results, conditional on being unemployed, the chance of finding a new job within one year is 40% on average, 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 I consider only two market states and disregard inactivity and job-to-job transitions. The risk of job loss declines with age, consistent with the patterns in male job flow transitions found in Choi et al. (2015) and Menzio et al. (2016) in the data for U.S. men.

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

4.2 Heterogeneity across working groups

Figure 4 shows the unemployment risk profiles measured at the working group level. My results show substantial heterogeneity, with the standard deviation of unemployment probability being 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 averaging about 16%, reaching the peak of 8% at young ages. These results are consistent with the evidence of declining unemployment risk with education (e.g., see Mincer, 1991), with the occupation type serving as a proxy for attained education levels. Moreover, workers in southern Italian regions face a higher risk on average (23%) than in north-eastern regions; in particular, the gap is about 30% and 26% at younger ages and at older ages, respectively, confirming available evidence on regional differences in employment opportunities in Italy (e.g., see Viviano, 2003).

In Figures 5 and 6, I focus on the average transition profiles by occupational characteristics. According to my 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 size, type and industry. The difference in the unemployment risk across Italian regions is mainly due to differences in the job finding probability. For example, compared with workers employed in the northeast of Italy, employees in the south face a lower chance, about 28% on average, of finding a new job and face a higher risk, about 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 (NeIll and Pastore, 2000; Pastore, 2012); however, my results show that the difference in the job finding rate is mainly due to the observed north-south gap in the job finding rate.

In the next section, I 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, I 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, I follow two well-established methods used in the literature to decompose the cyclical dynamics of the aggregate unemployment rate. The first is based on Shimer's pioneering method (Shimer, 2007) and has already been applied to life-cycle unemployment by Choi et al. (2015). The second is an extension of the approach introduced by Elsby et al. (2013) and Fujita and Ramey (2009). [22] 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, I adapt this methodology to evaluate the role of inflow and outflow hazards in shaping the individual unemployment risk over the working life and across working groups.

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

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

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), $u^{ss}_{g,t}$ is the steady-state unemployment probability for the working group g at age t. In Figure 7, I report the life cycle profiles, averaged across the G working groups, of the "steady-state" unemployment risk computed according to (3). In Figure 7, I also report the profile of averaged across all working groups, for reference. The steady-state value approximates the unemployment rate fitted on data well, with the correlation between the two series being about 99%. Thus, I 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.

5.1 Shimer's (2007) approach

Following Shimer (2007), I 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 the average values over working life and across working groups.

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

In particular, to evaluate the role of the job separation probability in shaping the unemployment risk, I 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, I 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), I evaluate the contribution of the two transition distributions 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 my 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%)[23].

5.2 Fujita and Ramey's (2009) approach

As robustness check, I consider an extension of the approach introduced by Fujita and Ramey (2009).[24] This approach is based on the log-linearization of $u^{ss}_{g,t}$ around its average

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

[24] While 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) focuses on explaining percentage differences in unemployment.

over ages and across working groups denoted as:

$$\overline{u^{ss}} = \frac{\overline{s}}{\overline{s} + \overline{f}} \tag{7}$$

where $\overline{s}$ and $\overline{f}$ denote the job separation and job finding probabilities averaged over working life and across all working groups (see above). By log-linearizing $u^{ss}_{g,t}$ around $\overline{u^{ss}}$, I obtain the following decomposition (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 quantitatively assess the effects of the transition rates on unemployment risk variability. Following Fujita and Ramey (2009), I express these 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.

I 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 job finding probabilities are important in shaping the fluctuations of the unemployment risk across ages and working groups. In the following subsections, I focus on explaining the observed differences across ages and across working groups, separately.

5.3 Differences across ages

In this section, I focus solely on age heterogeneity in the unemployment risk. In particular, I consider at each age t the unemployment risk averaged across working groups:

$$u_t \approx u_t^{ss} = \frac{s_t}{s_t + f_t} \tag{11}$$

where $s_t = \sum_{g=1}^{G} s_{g,t}$ and $f_t = \sum_{g=1}^{G} f_{g,t}$, are the job separation and the job finding faced by all representative workers on average at age t. The aim is to determine the respective role of job separations and job findings in shaping age differences in the unemployment risk.

Shimer's (2007) approach

In this subsection, following Choi et al. (2015), I adapt the Shimer's (2007) approach to explain differences in the unemployment risk across ages.

To determine the contribution of the job finding and the job separation rates to differences across ages, I compare the average unemployment risk at age t, 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.

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 , I determine the hypothetical life cycle unemployment rate:

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

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, I determine the hypothetical life cycle unemployment rate:

$$u_t^f = \frac{\overline{s}}{\overline{s} + f_t} \tag{13}$$

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}:

$$c^{s(t)} = \frac{cov(u_t^{ss}, u_t^{s})}{var(u_t^{ss})};\ c^{f(t)} = \frac{cov(u_t^{ss}, u_t^{f})}{var(u_t^{ss})} \tag{14}$$

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, I consider the extended approach based on Fujita and Ramey (2009). Following this approach, I 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, u_t^{ss}, from its own trend $\overline{u^{ss}}$ (i.e. the average unemployment risk across ages):

$$\overline{u^{ss}} = \frac{\overline{s}}{\overline{s} + \overline{f}} \tag{15}$$

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 the working life. The approach is based on the log-linearization of the average unemployment risk at age t, 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):

$$du_t^{ss} = \ln \frac{u_t^{ss}}{\overline{u^{ss}}} = (1 - \overline{u^{ss}}) \ln \frac{s_t}{\overline{s}} - (1 - \overline{u^{ss}}) \ln \frac{f_t}{\overline{f}} + \epsilon_t = d\overline{u_t^{s}} + d\overline{u_t^{f}} + \epsilon_t \tag{16}$$

where ϵ_t is a residual term.

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

$$\beta^{s(t)} = \frac{cov(du_t^{ss}, du_t^{s})}{var(du_t^{ss})};\ \beta^{f(t)} = \frac{cov(du_t^{ss}, du_t^{f})}{var(du_t^{ss})};\ \beta^{\epsilon(t)} = \frac{cov(du_t^{ss}, d\epsilon_t)}{var(du_t^{ss})} \tag{17}$$

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.

I 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).[25]

My analysis confirms the findings of Choi et al. (2015), who use the Current Population Survey 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. Although the Current Population Survey structure does not enable following individuals for more than four consecutive months or accounting for individual and employer characteristics, the panel dimension of the administrative dataset at hand allows accounting for the effects of both observed and unobserved heterogeneity as well as for duration dependence on the transitions in and out of unemployment. Moreover, my 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; e.g., see Jovanovich, 1979; Burdett, 1978), despite their tendency to be searching more intensively to find the best match. My findings suggest that, to reduce unemployment among young workers with respect to older workers, more emphasis should be placed on labour market policies that focus on reducing the job separation risk. Moreover, given that young workers face higher unemployment risk because of higher job loss probability, my results support more generous unemployment benefits for younger workers given that they have higher incentives to find a job (Michelacci and Ruffo, 2015).

5.4 Differences across working groups

Shimer's (2007) approach

Following the approach of Shimer (2007) adopted in the previous subsection, I focus on explaining the differences in the unemployment risk across working groups:

$$u_g \approx u_g^{ss} = \frac{s_g}{s_g + f_g} \tag{18}$$

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

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

I consider the comparison between the 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 probabilities at their averages across all working groups and ages.

Firstly, I 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:

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

Moreover, I 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:

$$u_g^f = \frac{\overline{s}}{\overline{s} + f_g} \tag{20}$$

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}:

$$c^{s(g)} = \frac{cov(u_g^{ss}, u_g^s)}{var(u_g^{ss})}\,;\, c^{f(g)} = \frac{cov(u_g^{ss}, u_g^f)}{var(u_g^{ss})} \tag{21}$$

According to my computations, reported in Table 4 (panel a, third column), the contribution of fluctuations in the job separation probability account for about 38% of variation 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 group characteristics other than age.

Fujita and Ramey's (2009) approach

As a robustness check, I 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 $\overline{u^{ss}}$:

$$du_g^{ss} = \ln \frac{u_g^{ss}}{\overline{u^{ss}}} = (1 - \overline{u^{ss}}) \ln \frac{s_g}{\overline{s}} - (1 - \overline{u^{ss}}) \ln \frac{f_g}{\overline{f}} + \epsilon_g = du_g^s + du_g^f + \epsilon_g \tag{22}$$

where ϵ_g is a residual term.

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

$$\beta^{s(g)} = \frac{cov(du_g^{ss}, du_g^{s})}{var(du_g^{ss})};\ \beta^{f(g)} = \frac{cov(du_g^{ss}, du_g^{f})}{var(du_g^{ss})};\ \beta^{\epsilon(g)} = \frac{cov(du_g^{ss}, d\epsilon_g)}{var(du_g^{ss})} \tag{23}$$

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, I confirm that the differences in the job finding probability at the 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)

My 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 workers and older workers are at the root of the observed age differences in the unemployment risk at individual level.

My findings indicate that, if the objective of policy-makers is to mitigate the inequality in unemployment between young workers and older workers, 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, if the objective is to reduce the overall unemployment rate, policies should place greater emphasis on boosting the probability of finding a new job.

6 Conclusions

In this paper, a method is proposed to analyse the heterogeneous dynamics of unemployment risk. I use a panel drawn from the Italian Social Security archive to estimate the parameters characterizing duration-dependent (un)employment spells. I 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, I pin down the careers of representative workers for groups. Finally, I measure the contribution of job finding and separation rates in shaping variations in the unemployment risk across demographics and other working characteristics.

According to my results, the differential in the risk of losing the job across ages explains almost the of difference in the unemployment risk faced by young workers as opposed to older workers. When differences in the unemployment risk across occupational characteristics are considered, 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. My 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, my results point to age-dependent unemployment insurance policies, with benefits decreasing with age, given that young workers have the strongest incentive to search for a job (Michelacci and Ruffo, 2015).

However, I also find 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, I do not consider how the unemployment risk at different ages is affected by business cycle dynamics. Further research along these lines will enhance the 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 ˆ2/10	-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.

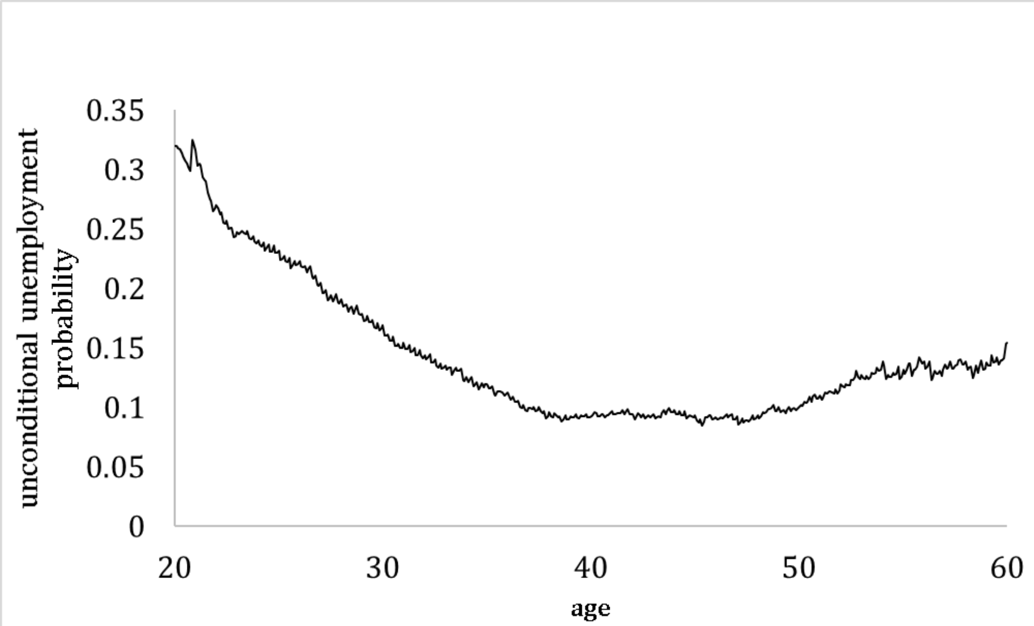
Table 4: Unemployment risk decomposition

	Across ages and working groups	Across ages	Across working groups
a) Shimer's approach			
role of job separation	0.53	0.96	0.38
role of job finding	0.39	0.03	0.54
b) Fujita and Ramey's approach			
role of job separation	0.56	0.95	0.45
role of job finding	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.

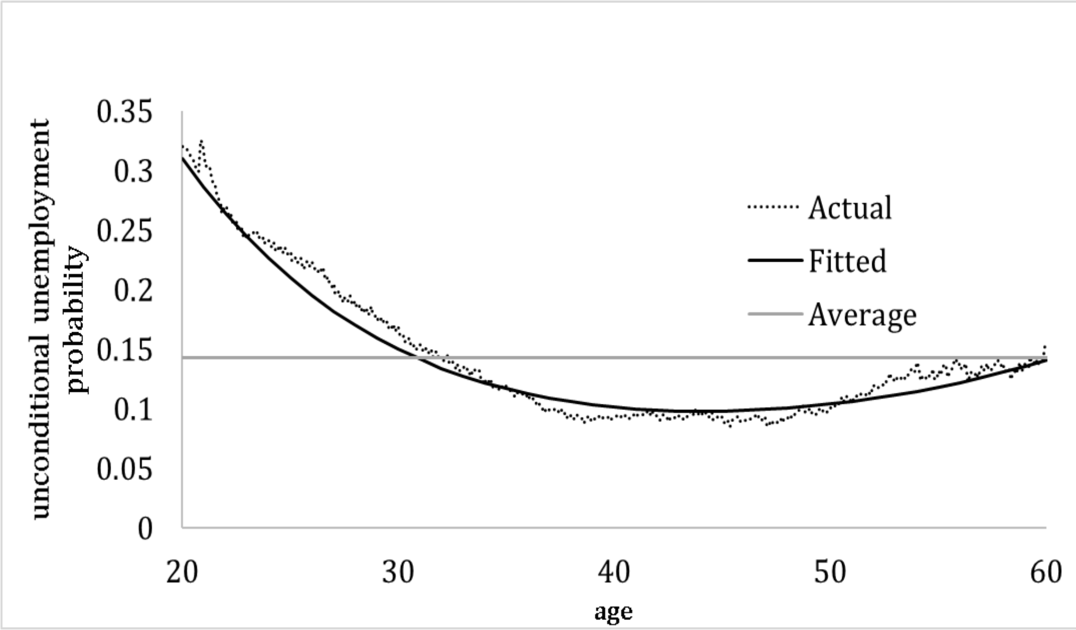
Figures

Figure 1: Actual unemployment risk over the life cycle



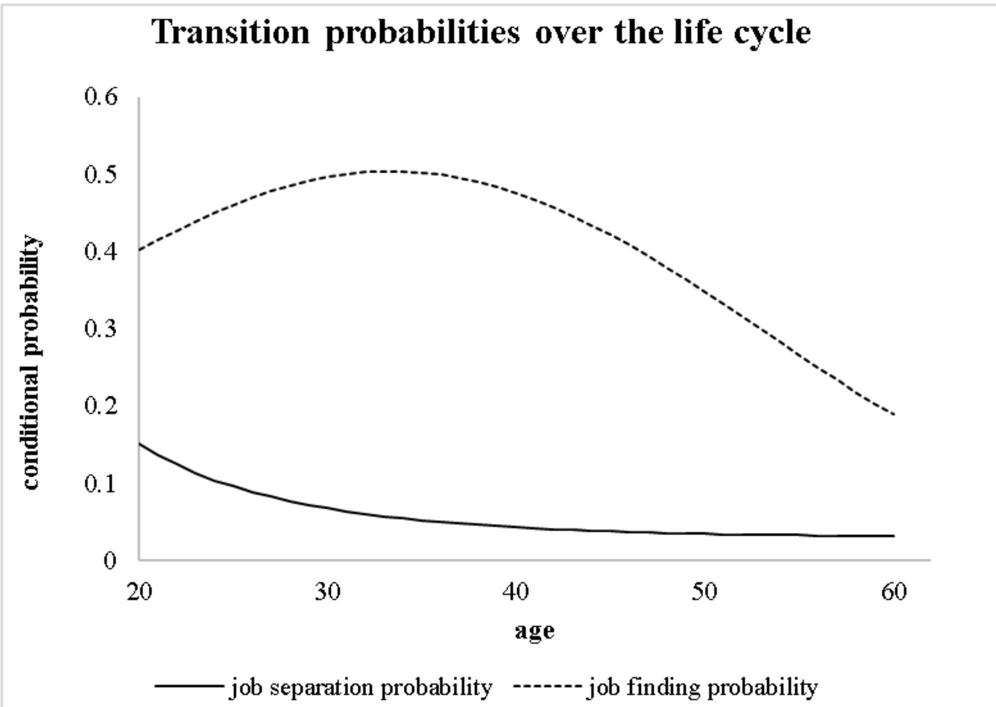
The figure reports the unemployment risk faced by Italian workers employed in the private sector. The actual unemployment risk at each age is measured monthly, as the ratio of total non-employed workers over total workers covered by WHIP in a given month. Source: WHIP, Work Histories Italian Panel, years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

Figure 2: Estimated unemployment risk over the life cycle



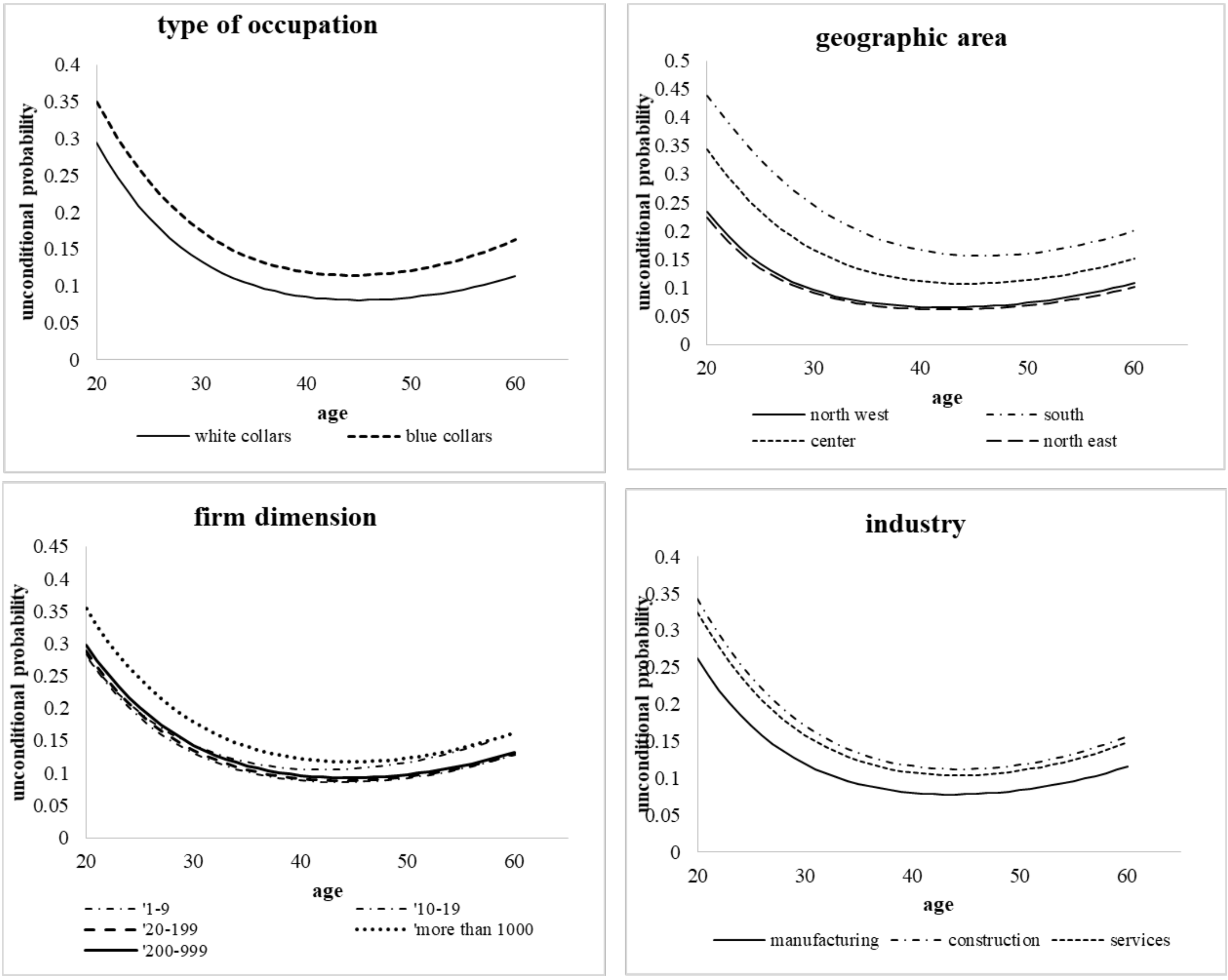
The figure reports the actual unemployment risk (dashed line) and the unemployment risk (solid line) obtained from Monte Carlo simulations of the estimated duration mdoels. The series are averaged over all working groups. In addition, it reports the average unemployment probability across ages and across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

Figure 3: Transition probabilities over working life



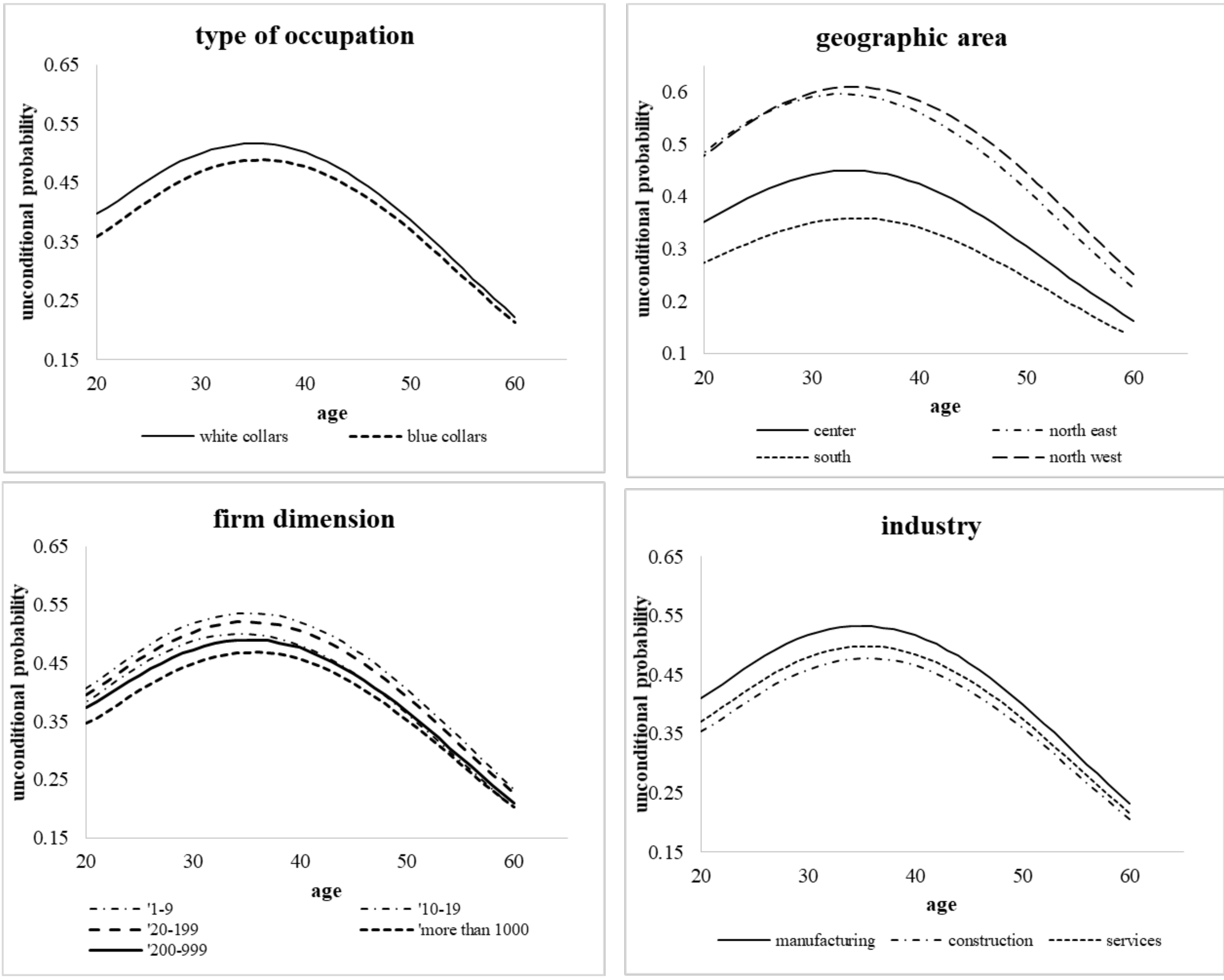
The figure reports the transition probabilities in and out unemployment at each age, obtained from Monte Carlo simulations of employment and unemployeemnt duration models estimated in Tables 2 and 3, respectively. The plotted age profiles are averages over all the considered working groups.

Figure 4: Unemployment risk by occupational characteristics



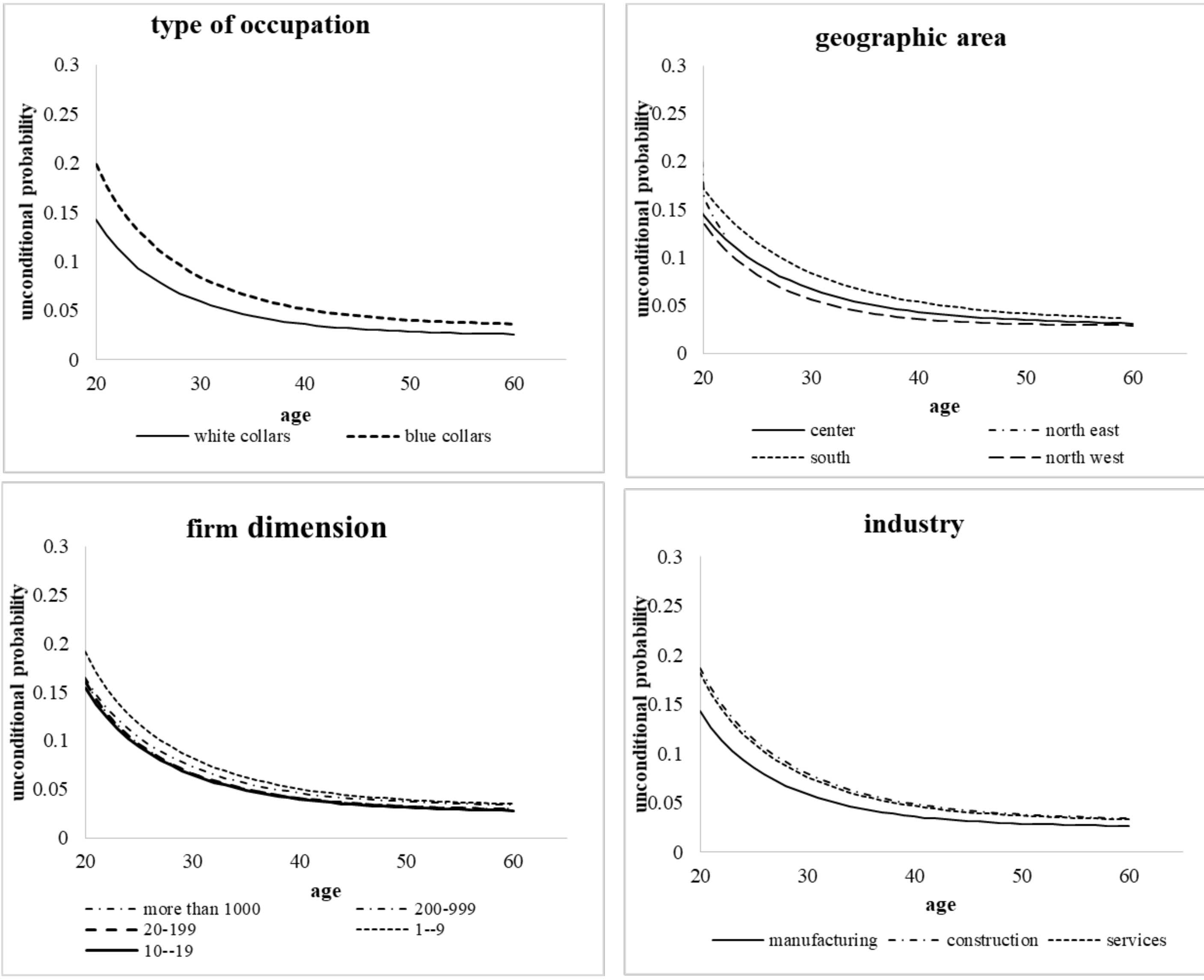
The figure reports the simulated average unemployment probability profiles over the life cycle, by working groups.

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



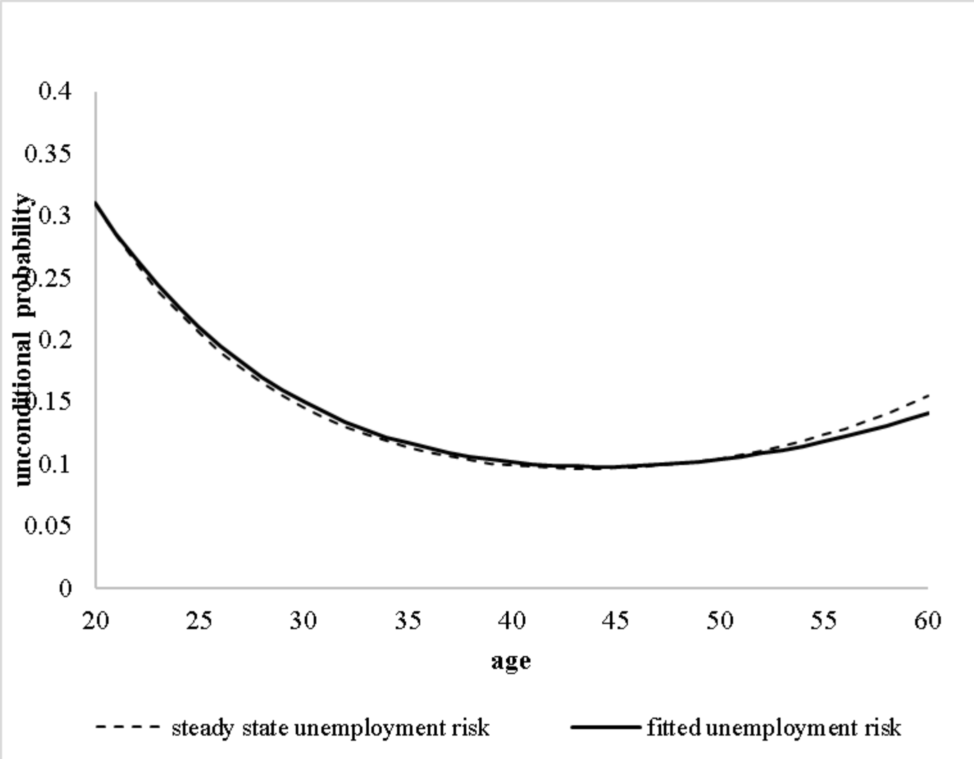
The figure reports, by working groups, the simulated average profiles for the transition from unemployment to employment.

Figure 6: Job loss proabablities 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



The 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 working groups.

DEPARTMENT OF ECONOMICS AND STATISTICS
UNIVERSITY OF TORINO
Corso Unione Sovietica 218 bis - 10134 Torino (ITALY)
Web page: http://esomas.econ.unito.it/