Carolina Fugazza[1]

Anatomy of Non-Employment Risk

[1] Università degli Studi di Torino and CeRP-Collegio Carlo Alberto, ESOMAS, c.so Unione Sovietica 218 bis Torino, Italy, E-mail: carolina.fugazza@unito.it

Abstract:
This paper investigates how job separation and job-finding probabilities shape the non-employment risk across ages and working group characteristics. Improving on current methods, I estimate duration models for employment and non-employment separately. I then use the results to derive the individual age profiles of conditional transitions in and out of non-employment as well as the unconditional non-employment risk profile over the whole working life. This approach allows me to apply the decomposition of changes in individual non-employment risk. To date, this type of decomposition has only been used to study aggregate non-employment dynamics. I find that differences in job separation rates across ages underlie the observed age differences in non-employment risk. When differences between working groups are under consideration, the job finding probability is just as important as the job separation probability.

Keywords: non-employment risk, duration analysis, heterogeneity, semi-Markov processes

JEL classification: C53, E24, J64

DOI: 10.1515/bejeap-2018-0070

1 Introduction

Among OECD countries, we observe substantial heterogeneity in the unemployment risk, both along the age and occupational characteristics dimensions. For instance, a young worker has twice the joblessness risk as an older worker.[1] In addition, both job finding and separation rates tend to decline with age (for the United States, see, e. g. Choi, Janiak, and Villena-Roldan 2015; Menzio, Telyukova, and Visschers 2016). The unemployment rate varies greatly across occupational characteristics, too; in the United States, for example, the unemployment rate in construction is about twice the unemployment rate in manufacturing and low-skilled workers are more likely than skilled workers to be jobless. Despite this heterogeneity, the recent crisis has led to a sharp increase in the duration of joblessness for all working groups. In such circumstances, the distinction between long-term unemployed and inactive individuals who are strongly attached to the labor market becomes weak, spurring greater attention to the non-employment risk (see, e. g. Krueger, Cramer, and Cho 2014).

In this paper, I investigate the life cycle dynamics of the non-employment risk for various working groups instead of focusing on the dynamics of the unemployment rate. Importantly, my analysis accounts for duration dependence of both employment and non-employment. My estimates are able to show that the chance of finding a new job diminishes as the length of the non-employment period increases (see, e. g. Shimer 2008; Kroft, Lange, and Notowidigdo 2013) and that the risk of job loss declines with the duration of job tenure (see, e. g. Kiefer, Burdett, and Sharma 1985). This paper thus contributes a two-part method for investigating the anatomy of heterogeneous non-employment 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 well as the implied non-employment risk. Second, I propose a decomposition method to determine the respective contributions of these probabilities to the variation in the non-employment 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 in the years 1985–2004. There are at least two reasons for using this dataset. One is that the dataset provides individual information on Italian labour market outcomes. Italy is an ideal study site because non-employment and long-term unemployment there is structurally high, especially for young workers.[2] A second reason is that the dataset has a panel structure that enables following workers' employment over a substantial portion of their working lives taking into account all possible relevant types of duration dependence in both employment and non-employment (see, e. g. Heckman and Borjas 1980). On the one hand, the duration dependence in non-employment may be due to both observed and unobserved heterogeneity, since workers with low re-employment probability stay unemployed longer. However, the length of non-employment may also reflect pure duration dependence, since being non-employed for long reduces the chances of finding a

Carolina Fugazza is the corresponding author.
© 2019 Walter de Gruyter GmbH, Berlin/Boston.

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

new job, because of the stigma effect, employers may discriminate against those who have been jobless for longer (Eriksson and Rooth 2014; Kroft, Lange, and Notowidigdo, 2013) or because of skill decay (workers lose human capital the longer they are non-employed, Ljungqvist and Sargent 1998). In this paper, I exploit the panel structure of the data set to disentangle the effects of age and other workers' characteristics on labor market transitions from the impact of non-employment duration *per se*. In this way, I identify the groups of workers with potentially high non-employment risk. Duration analysis techniques have been widely used to study the effect of covariates on the conditional probabilities of both job termination and exiting unemployment. In this paper, I go one step further. 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 non-employment. 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 non-employed for all ages, which serves as my measurement of the non-employment 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 non-employed.

Despite their reliability, the main drawback of my data is that they do not allow one to distinguish between unemployment and inactivity, since they collapse both unemployed and inactive individuals into the single category of the non-employed. Consequently, my estimates of the job separation risk may be biased upward, since I cannot distinguish voluntary from involuntary job separation. Symmetrically, my estimates of the job finding risk may be biased downward, since I cannot distinguish between individuals who actively search for a job from the pool of the inactive. Because of these limitations, my results are accurate in terms of the evaluation of the non-employment risk and its determinants, while they should be interpreted as an upper bound estimate for the unemployment risk over the working life. Indeed, the standard measures of unemployment are likely to underestimate the "true" unemployment rate figures since that they do not take into account the non-employed with a strong work force attachment(see, e. g. Jones and Riddell 2006)[3,4]. These measures of unemployment disregard also the group of discouraged job seekers who stop looking for a job. Contini and Grand (2010), for instance, find that in the past 10 years the number of joblessness who are strongly attached to the workforce but who are not actively looking for work has substantially increased in Italy, leading to an actual unemployment rate of 15 % compared to the standard measure of 8 %. I find an implied non-employment probability of about 14 %, on average, across ages and working groups.

In addition, I document substantial heterogeneity in the non-employment risk at an individual level between working groups based on occupational characteristics and across ages. In particular, my results indicate that variation between working groups explains more than two thirds of the total non-employment risk variability. Moreover, consistent with the evidence available for OECD countries, I find that the non-employment risk in the Italian private sector decreases over the working life: for workers younger than 30 years old, it averages 19 %, while for middle-aged workers, it is about 10 % (13 % for workers over 55 years old of age). These dynamics are due to a job separation rate that monotonically declines with age and a job finding rate that falls with age after one's 35th year.[5]

The second contribution of this paper is an evaluation of the relative role of job findings and job separations in shaping the non-employment 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, Janiak, and Villena-Roldan 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 variation in the non-employment 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 60 % of the variability in the non-employment risk on average across ages and occupational characteristics (the contribution of the job finding probability is about 40 %) . I then proceed by explaining age differences and differences between working groups separately.

For the average worker, age differences in the non-employment 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 89 % of the variation of the non-employment risk across ages is due to age differences in job separation probability. These results are in line with the findings of Choi, Janiak, and Villena-Roldan (2015) who document for the United States the prominent role of the job separation risk in determining the higher non-employment 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 72–95 %.

In addition, I focus on differences across working groups characteristics at a given age. I find that the fraction of the variation in the non-employment risk across working groups explained by the variation in the job finding

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

(separation) risk experienced by the different groups is about 56 % (44 %) and that the heterogeneity in the job finding rate is mainly due to differences between Northern and Southern regions.

To my knowledge, very little evidence exists with regard to the relative role of job finding and job separation probabilities in shaping the non-employment risk over the working life. The only exception is Choi, Janiak, and Villena-Roldan (2015), who use U.S. 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, Janiak, and Villena-Roldan (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 Elsby, Hobijn, and Sahin (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 non-employment risk across working groups, while differences in job separation rates between young workers and older workers are at the root of differences in the non-employment 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 non-employment risk. In Section 5, I perform the decompositions to disentangle the relative role of job exit and job finding probabilities in shaping the non-employment 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.[6] The database allows observation of the main episodes of each individual's working career. 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. In particular, WHIP provides personal information on employees (age, gender, place of birth and place of residence) as well as detailed information about their job relationships (starting and ending date, type of occupation and wage) and employers (size of firm, industry and geographic area). Given its richness, its allows one to study the duration of both employment and non-employment spells. However, the main drawback is that WHIP does not allow one to distinguish between unemployment and inactivity. Consequently, WHIP is perfectly suitable for studying the non-employment risk, although some caution should be taken when drawing conclusions for the unemployment risk analysis.

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 the years 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 between 20 and 60 years old.[8] My sample covers about 44,000 workers with a median age of 36 years. The non-employment 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 non-employment spell as censored. Moreover, if retirement occurs during an non-employment 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 non-employment 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 non-employment is about 1.6 years; however, the median is about 5.7 months. Both the employment and the non-employment length distributions are skewed towards longer durations, resulting in average durations that are substantially longer than the median indicating that some workers are re-employed at a slower rate than others, and that this rate decreases the longer the workers remain non-employed.

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

The distributions of the number of employment and non-employment spells observed per worker are similar. In particular, the average number of employment and non-employment spells per worker is 2.8 and the median is 2.

Table 1: Descriptive statistics.

Individual and occupational characteristics	Employment spells	Non-employment spells
Panel a		
Age at entry (average)	33.7	32.8
Daily salary (in euros)	66	60.39
Mean Duration (in years)	3.19	1.6
Median Duration (in years)	1.08	0.48
Average number of spells per worker	2.81	2.8
Median number of spells per worker	2	2
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	0.32
Geographic Area		
Northwest	0.27	0.28
Northeast	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
>1,000	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 non-employment spell. Source: WHIP, Work Histories Italian Panel, years 1985–2004.

For workers under 25 years of age, their median duration of non-employment is about two-thirds the median job duration (6.6 and 9.9 months, respectively). For workers over 25 years of age, the median job duration is about three times (1 year) their median non-employment duration (3.3 months). The mean age at the beginning of job spells and non-employment spells is about 33 years (see Table 1, panel a).

The non-employment risk at each age (i. e., the unconditional probability of being non-employed) 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 non-employment risk over working life based on the data. According to the data, the non-employment 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 of age is more than double that for older workers.[10]

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

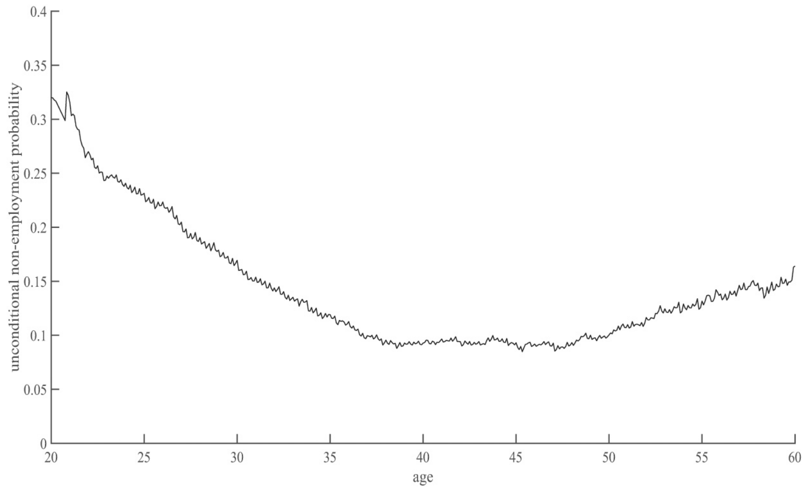

Figure 1: Actual non-employment risk over the life cycle.
The figure reports the non-employment risk faced by Italian workers employed in the private sector. The actual non-employment risk at each age is measured monthly, as the ratio of total non-employed workers over total workers covered by WHIP in a given month. Source: WHIP, Work Histories Italian Panel, years 1985–2004.

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 non-employment spells are initial age, initial age squared, working industry, firm size, geographic area, type 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 non-employment spells by individual and occupation characteristics mirrors the composition of job spells (see Table 1, panel b, column 3).

3 Employment and Non-employment Duration

This section uses duration-based data on employment and non-employment 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, e. g. Heckman and Borjas (1980).[11]

I model the duration (D) of non-employment (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 non-employment and employment, respectively; x_i^j (with $j = U$, E) are two sets of observed individual demographic and occupational characteristics that explain the non-employment 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.

The two models can be restated in terms of the corresponding survivor functions:

$$S(D_i^U|x_i^U) = S_0^U\left\{exp(-\beta^{U\prime} x_i^U) D_i^U\right\} \tag{3}$$

$$S(D_i^E|x_i^E) = S_0^E\left\{exp(-\beta^{E\prime} x_i^E) D_i^E\right\} \tag{4}$$

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

where S_0^j, with $j = U, E$, is the baseline survivor function whose form depends on the distribution of ω_i.

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 age dependence in job separation and job finding including age at the beginning of employment and non-employment spells, respectively. In addition, I consider the following 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] To control for the business cycle, I consider monthly data on the OECD recession indicator for Italy over the period 1985 to 2004.[14]

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 survival times (see, e. g. 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. I favour AFT models over proportional hazard models.[15] I consider the continuous time metric to obtain results that are invariant to the time unit (see Flinn and Heckman 1982).

Moreover, it is well known that when the hazard of job separation (job finding) depends on unobserved characteristics (in addition to observables), then individuals displaying frail characteristics exit the employment (non-employment) state relatively quickly. Thus, the sample of observed employed (non-employed) individuals would lead to spurious negative duration dependence (see Heckman and Singer 1984). The data at hand convey information on multiple non-employment (employment) spells for the same worker. I exploit them to take into account the way the worker's unobserved characteristics affect all of this transitions.[16] In particular, I account for the impact of unobserved heterogeneity by incorporating a multiplicative shared frailty term, α_i, as being equal at the individual level across the employment (non-employment) spells.[17] The frailty term, α_i, is taken as a random variable whose mean is normalised to one and with unknown finite variance, θ, which is estimated and measures the variability of the frailty across individuals. In this case, the survivor function for the two models takes the form:

$$S(D_{ih}^j | x_{ih}^j, \alpha_i^j) = S(D_{ih}^j | x_{ih})^{\alpha_i^j} \tag{5}$$

where j = U, E and the index i denotes the worker (i = 1,..., n) and h denotes the observations on spells available for worker i (h = 1,..., n_i).

Moreover, to take into account that some working groups tend to face high non-employment risk and experience a lot of transitions, I follow the strategy of weighting them according to the inverse of the observed number of spells. In this way, I avoid over-representing those working groups with relatively unstable labor attachment (e. g. younger workers, employees in the construction industry, or small-firm workers), who exhibit a high number of spells but who count relatively few workers. [18]

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 non-employment duration data. I assume that α_i follows the inverted gamma distribution which is widely used in survival analysis because closely 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 non-employment duration models, the interpretation of regression coefficients is unchanged by the frailty.[19]

3.1 Results

In this section, I report the results of the duration analysis. Given the AFT formulation adopted to model durations, the coefficients provide information on how survival times, in employment and in non-employment, are directly affected by the covariates.[20] However, to be directly comparable with existing studies, in this section I discuss the estimation results in term of hazard rates. For both employment and non-employment spells, the parameters governing duration dependence are significant. My results provide evidence that the conditional hazard of non-employment termination is monotonically decreasing the overall spell, since the estimated ancillary parameter, for the AFT Weibull model, γ is lower than 1, while the conditional hazard of employment termination increases at the very beginning of the spell and than it decreases, since the ancillary parameter governing duration dependence, for the log-logistic model, γ is lower than one. Moreover, 99 % of coefficients are significantly different from zero and take a reasonable sign. Importantly, in the case of both employment and non-employment durations, my results are robust to the unobserved heterogeneity.

In Table 2, panel (a), 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 non-employment spell, the greater the negative impact on the current job tenure. These results add to evidence of the scarring effects of

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

unemployment on subsequent employability (see, e. g. Arulampalam, Booth, and Taylor 2000; Arulampalam 2001; Gregg 2001; Böheim 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 Haltiwanger 1992), the probability of separation tends to decrease with the size of the firm.

Table 2, in panel (b), presents strong evidence of all types of duration dependence considered in non-employment. In particular, a significant negative duration dependence is present in the hazard of exiting the current non-employment spell.

Table 2: Employment and non-employment duration maximum likelihood estimates.

	(a) Employment duration	**(b) Non-employment duration**
Age	0.105***	−0.119***
	(0.025)	(0.011)
$Age^2/10$	−0.009***	0.019***
	(0.002)	(0.002)
Industry (ref. Services)		
Manufacturing	0.715***	−0.106***
	(0.049)	(0.030)
Construction	−0.154**	0.306***
	(0.062)	(0.038)
Firm size (ref. 1000)		
1–9	−0.649***	−0.300***
	(0.087)	(0.051)
10–19	−0.460	−0.437***
	(0.094)	(0.055)
20–199	−0.336***	−0.363***
	(0.086)	(0.051)
200–999	−0.031	−0.160***
	(0.098)	(0.060)
Geographic area (ref. South)		
North West	0.351***	−1.446***
	(0.058)	(0.040)
North East	0.121*	−1.543***
	(0.053)	(0.043)
Center	0.151**	−0.740***
	(0.068)	(0.045)
Type of occupation (ref. White collar)		
Blue Collar	−0.714***	0.652***
	(0.060)	(0.039)
Length previous non-employment spell	−0.225***	−0.149***
	(0.011)	(0.009)
Cohort (ref. 1970–79)		
Cohort 1940–49	0.369**	−0.181**
	(0.152)	(0.080)
Cohort 1950–59	0.420***	0.748***
	(0.094)	(0.060)
Cohort 1960-69	0.296***	0.636***
	(0.052)	(0.044)
Business cycle indicator, I=1 expansion	0.001	−0.147***
	(0.015)	(0.016)
Constant	−0.499***	2.223***
	(0.110)	(0.197)
γ	0.594***	0.829***
	(0.006)	(0.004)
θ	1.679***	3.700***
	(0.063)	(0.045)
Observations	166,231	134.448

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

Note: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1 Source: WHIP, Work Histories Italian Panel, years 1985–2004. The table reports the maximum likelihood estimates of the AFT log-logistic model with inverted gamma unobserved heterogeneity, for the employment duration and of the AFT Weibull model with inverted gamma unobserved heterogeneity, for the non-employment duration.

My data show that age dependence is also significant: the higher the age at entry into a non-employment 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 non-employment duration. For workers in northern regions, the non-employment 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 for determining the dualistic nature of the Italian labour market.

My results indicate that the degree of persistence of both employment and non-employment 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 non-employed 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 non-employment risk. In the next section, I use the estimates above to derive at each age the unconditional probability of being non-employed implied by the conditional transition probabilities in and out of non-employment.

4 Measuring the Heterogeneous Dynamics of Non-employment Risk

In this section, I use previous results to measure the non-employment 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.[21]

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 non-employed (U) with probability that matches the empirical proportion of E to U at the age of 20 in Italy. I then simulate a large number N (= 100,000) of possible lengths for the first employment spell ($D^E_{1,g}$) and first non-employment spell ($D^U_{1,g}$) by drawing from 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 Table 2).[22] 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.[23] In this way, for each working group g, I obtain the entire life-cycle sequences of survival times in non-employment and employment, ($D^U_{1,g}\dots D^U_{S,g}$ and $D^E_{1,g}\dots D^{UE}_{S,g}$, with $g = 1, \dots, N$) 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 duration of the previous simulated non-employment (employment) spell. Thus, for each representative worker, g, I obtain N simulated working histories (i. e., sequences of employment and non-employment 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 non-employment risk, that is, the unconditional probability of being non-employed, $u_{g,t}$, (with $t = 1, \dots., T$, where $T = 40$ periods[24]). The unconditional probability of being non-employed is my measure of the non-employment 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, $f_{g,t}$.[25]

In Figure 2, I report the life-cycle profile of the non-employment risk (solid line), derived from the simulations described above, along with the non-employment rate observed for Italian workers in the data (dotted line), for reference. In particular, the dashed profile plotted in Figure 2 is an average at each age of the non-employment risk measured over the G working groups. Figure 2 also reports the simple average, about 14 %, of the non-employment risk across working groups and across ages. As showed in Figure 2, my measurement of the individual non-employment risk matches well with the actual one observed in the data. Since the dataset at hand covers only Italian workers employed in the private sector, my measurement is lower than the non-employment rate observed among Italian male workers over the period 1985–2004. However, as emphasised in Contini and Grand (2010), in the last ten years the number of joblessness who do not intensively search for a job has substantially increased in Italy leading to an actual unemployment rate of 15 % compared to standard measure of 8 %. Thus, my measure of the non-employment risk could be a better proxy of the "'true"' individual unemployment risk. 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 non-employment risk faced at different ages and across working groups with respect to the observed average non-employment risk.

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

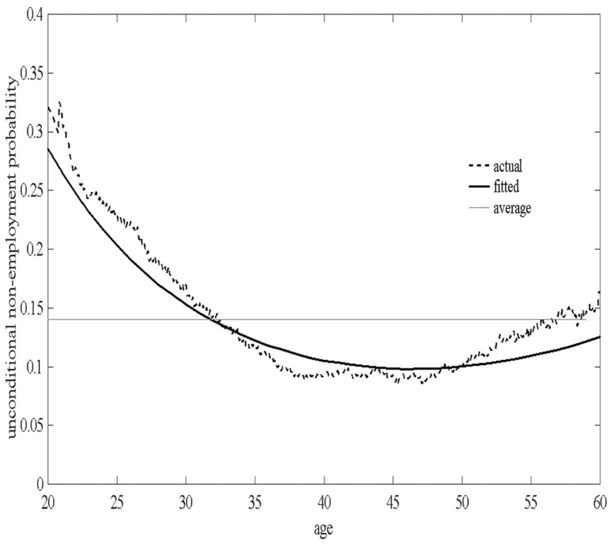

Figure 2: Estimated non-employment risk over the life cycle.
The figure reports the actual non-employment risk (dotted line) and the non-employment risk (solid line) obtained from Monte Carlo simulations of the estimated duration models. The series are averaged over all working groups. In addition, it reports the average unemployment probability across ages and across working groups (grey line).

4.1 Average Life Cycle Profiles

Overall, the non-employment 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 non-employed than workers aged over 40, although about 54 % of the gap is recovered by the age of 25. The non-employment risk for older workers (over 55 years of age) is about 13 %.

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

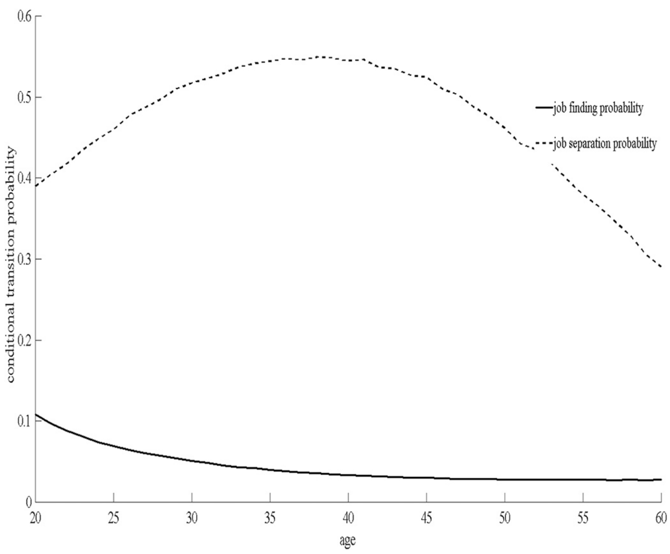

Figure 3: Transition probabilities over working life.
The figure reports the transition probabilities in and out non-employment at each age, obtained from Monte Carlo simulations of employment and non-employment duration models estimated in Table 2, respectively. The plotted age profiles are averages over all the working groups under consideration.

According to my results, conditional on being non-employed, the chance of finding a new job within one year is about 40 % on average, while the average conditional probability of job separation is about 6 %. The estimated transition probabilities are consistent with findings in Macchiarelli and Ward-Warmedinger (2014) who show that the annual average transition rate into employment is about 33.18 % from unemployment and 5.7 % from inactivity, while the overall transition rate out of employment is about 5.5 %.

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

The risk of job loss declines with age, in line with the patterns in male annual job flow transitions found in Choi, Janiak, and Villena-Roldan (2012) in the data for the United States and with the findings evidenced by Baussola et al. (2015) for Italy. As in Baussola et al. (2015) and Choi, Janiak, and Villena-Roldan (2012), I document the fact that the annual job finding probability in Italy is hump shaped in age. These dynamics are in line with the Italian job search intensity profile reported in Aguiar, Hurst, and Karabarbounis (2013) and are consistent with a relatively slow school-to-work transition process observed in Italy (see, e. g. Pastore 2012). Moreover, while the magnitude of the annual job separation rate in Italy is in line with that of the annual job separation rate in the United States, the average annual outflow rate from non-employment, of about 46 %, measured in our data for Italy is about a half than that in the United States (Choi, Janiak, and Villena-Roldan 2012). This evidence suggests that the cross-country differences, between Italy and the United States, in the average non-employment rate over working life are driven by differences in the job finding rate. The comparison with flow rates in the United Kingdom leads to the same conclusion. For the U.K., Elsby, Smith, and Wadsworth (2011) document the fact that the average annual job finding rate is about 55 % (46.4 % for the unemployed and 9.1 % for people who are out of the labor force) and the average job separation rate is about 5 % (4 % into unemployment and 1 % into out of labor force).

4.2 Heterogeneity Across Working Groups

Figure 4 shows the non-employment risk profiles measured at the working group level. My results show substantial heterogeneity, with the standard deviation of non-employment probability being about 18 % and about 9 %, 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, e. g. Figure 4). Blue-collar workers experience a higher non-employment risk than white-collar workers, with the difference averaging about 11 %, reaching the peak of 19 % at young ages. These results are consistent with the evidence of declining non-employment risk with education (see, e. g. 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 (21 %) than in north-eastern regions; in particular, the gap is about 30 % and 15 % at younger ages and at older ages, respectively, confirming available evidence on regional differences in employment opportunities in Italy (e. g. see, e. g. Viviano 2003). Overall, my results are in line with previous findings about the Italian labour market, where young people, low-skilled employees and workers in Southern regions face higher unemployment and non-employment (see, e. g. Barbieri and Mussida 2018).

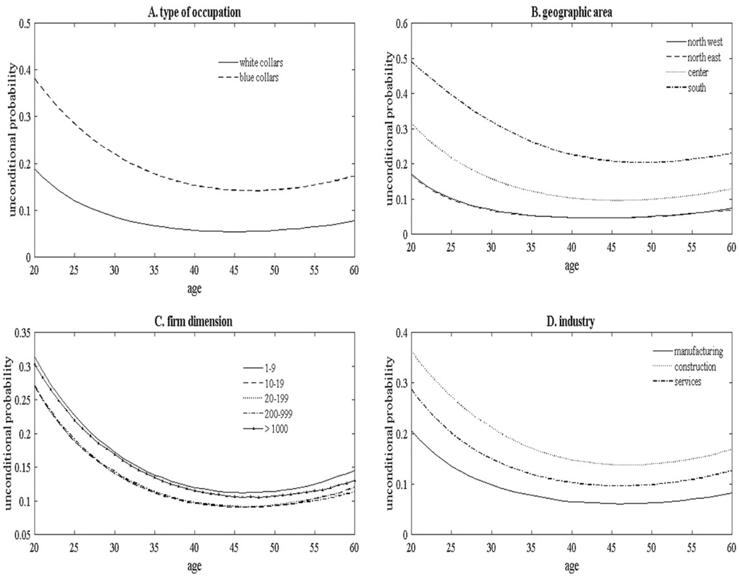

Figure 4: Non-employment risk by occupational characteristics.
The figure reports the simulated average non-employment probability profiles over the life cycle, by working groups.

In Figure 5 and Figure 6, I focus on the average transition profiles by occupational characteristics. According to my results, the transitions in and out of non-employment 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 non-employment risk across Italian regions is mainly due to differences in the job finding probability. For example, compared with workers employed in the north-east 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 9 %, of losing a job. Previous studies find

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

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.

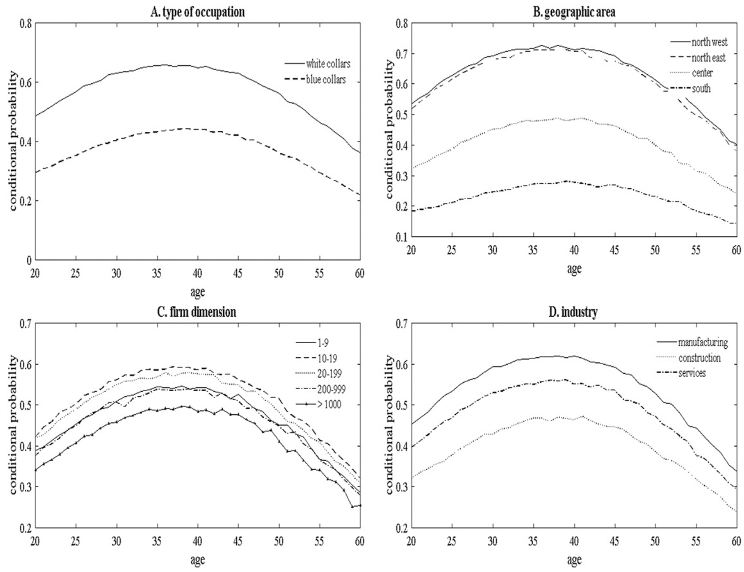

Figure 5: Non-employment risk by occupational characteristics.
The figure reports, by working groups, the simulated average profiles for the transition from non-employment to employment.

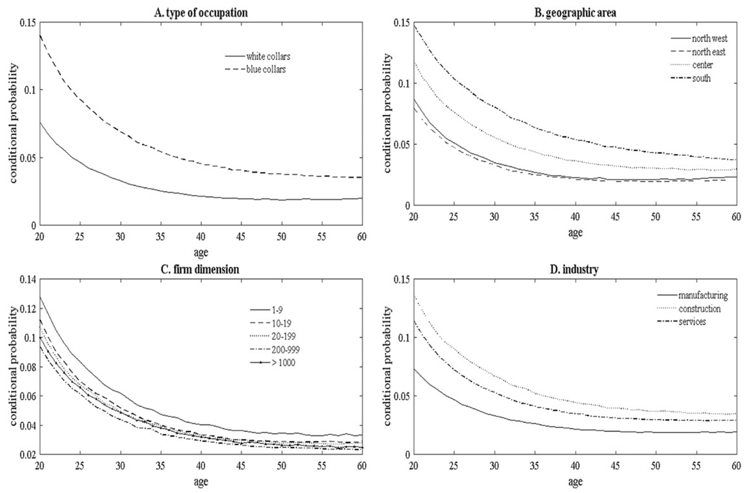

Figure 6: Job loss probabilities by occupational characteristics.
The figure reports the simulated average profiles for the transition from employment to non-employment, by working groups characteristics.

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

5 Non-employment Risk Decomposition

In this section, I assess the role of transition probability distributions in determining the observed differences in the non-employment 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, Janiak, and Villena-Roldan (2015). The second is an extension of the approach introduced by Elsby, Hobijn, and Sahin (2013) and Fujita and Ramey (2009).[26] These approaches evaluate the

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

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 non-employment risk over the working life and across working groups.

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

$$u_{g,t} \approx u^{ss}_{g,t} = \frac{s_{g,t}}{s_{g,t} + f_{g,t}} \tag{6}$$

where, $u_{g,t}$ is the unconditional non-employment 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 $t = 1, \ldots, T$), obtained from Monte Carlo simulations. In (6), $u^{ss}_{g,t}$ is the steady-state non-employment 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" non-employment risk computed according to (6). In Figure 7, I also report the profile of averaged across all working groups, for reference. The steady-state value approximates the non-employment rate fitted on data well, with the correlation between the two series being about 99 %. Thus, I can use the steady-state approximation in (6) to detect the role of transition rates in shaping the observed differences in non-employment risk across ages and across working groups, according to the Shimer's (2007) approach and the Fujita and Ramey's (2009) approach (see Appendix A, for a detailed exposition of the two approaches).

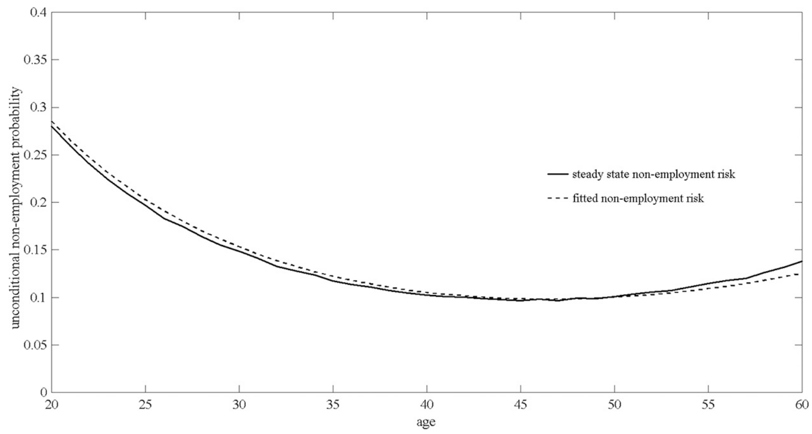

Figure 7: Fitted and steady state non-employment risk over working life.
The figure reports the simulated unconditional non-employment probability profile (solid line) as well as the steady state non-employment probability profile (dashed dot line) implied by the simulated job finding and job separation age profiles. All age profiles are an average across working groups.

Table 3: Non-employment risk decomposition.

	Across ages and working groups	Across ages	Across working groups
(a) Shimer's approach			
Role of job separation	0.54	0.84	0.41
Role of job finding	0.44	0.09	0.52
(b) Fujita and Ramey's approach			
Role of job separation	0.59	0.89	0.44
Role of job finding	0.39	0.13	0.56

The table reports the decomposition of the variation in the steady-state non-employment risk across ages and across working groups. ***Panel (a) reports decompositions according to the Shimer's (2007) 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.

According to my computations, reported in Table 3 (panel a, first column), fluctuations in the job separation probability account for about 54 % of variation in the non-employment risk (the contribution of the job finding probability is about 44 %)[27]. Following the Fujita and Ramey's approach, I find that the differences in the job finding probability at group level account for 39 % of the variation of the non-employment risk while the re-

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

maining 59 % of the variability is due to differences in separation probability (see Table 3, 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 non-employment risk across ages and working groups. In the following subsections, I focus on explaining the observed differences across ages and across working groups, separately.

5.1 Differences Across Ages

Following the methodology detailed in Appendix A.3, I find that the differences in job separation probability across ages are the main reason for the difference in the non-employment risk at the individual level over the working life. In particular, about 84 % of the rate of change of non-employment 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 (0.09 %) (see Table 3, panel a), second column). As robustness check, I consider the extended approach based on Fujita and Ramey (2009). Results reported in Table 3 (panel b, second column), confirm that fluctuations in the job separation probability contribute more to the age variations in the non-employment risk (the contribution of the job finding probability is about 15 %, while the contribution of job separation is about 89 %).[28]

My results are in line with the findings of Choi, Janiak, and Villena-Roldan (2015), who use the Current Population Survey to evaluate the impact of transitions between employment, employment 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 non-employment. Moreover, my results are in line with Elsby, Hobijn, and Sahin (2010), Gervais et al. (2016) and Hairault, Langot, and Sopraseuth (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 non-employment risks as they are more likely to separate (the "job shopping" mechanisms; see, e. g. Jovanovic 1979; Burdett 1978), despite their tendency to be searching more intensively to find the best match.

5.2 Differences Across Working Groups

Following the approaches outlined in Appendix A.4, I focus on explaining the differences in the non-employment risk across working groups. According to my computations, reported in Table 3 (panel a, third column), the contribution of fluctuations in the job separation probability account for about 39 % of variation in the non-employment risk across working groups (the contribution of the job finding probability is about 52 %). Thus, the job finding probability is more important in explaining the differences in the non-employment risk across working group characteristics other than age.

As a robustness check, I extend the approach introduced by Elsby, Hobijn, and Sahin (2013) and Fujita and Ramey (2009). According to this decomposition, the differences in the job finding probability at the group level account for 56 % of the variation of the non-employment risk observed across groups while the remaining 46 % of the variability is due to differences in separation probability (see Table 3 panel b), third column).

Overall, my results show that job finding and job separation rates are almost equally important in shaping the non-employment risk across ages and occupational characteristics at individual level. However, differences in job separation rates between young workers and older workers are at the root of the observed age differences in the non-employment risk at individual level while differences across groups are mainly due to heterogeneity in job finding.

My results indicate that, if the objective of policy-makers is to mitigate the inequality in non-employment between young workers and older workers, greater emphasis should be placed on policies designed to reduce the gap in their job separation risk. The causes of higher separation rates for young workers are various. On the one hand, imperfect skill matching due to information asymmetries weakens the youth employment stability. On the other hand, the atypical contracts[29], especially used for young workers, increase the risk of instability of job relations. Improvements in young people ability to match labour demand could be achieved by enhancing the training system and through policy interventions aimed at increasing job security, such as incentives for firms to hire through permanent job contracts. In addition, the job finding probability plays a major role in shaping the non-employment risk across working groups. Thus, our results suggest that to reduce the overall

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

unemployment and non-employment rates, labour market policies should place greater emphasis on boosting the probability of finding a new job instead of increasing the unemployment benefits, given that generous benefits tend to prolong the duration of unemployment (see e.g. Krueger and Mueller 2010). However, given that young workers face higher non-employment risk because of higher job loss probability, my results support relatively more generous unemployment benefits for younger workers since they have higher incentives to find a job (Michelacci and Ruffo 2015).

6 Conclusions

In this paper, a method is proposed to analyse the heterogeneous dynamics of non-employment risk. I use a panel drawn from the Italian Social Security archive to estimate the parameters characterising duration-dependent employment and non-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 non-employment risk profile. I thus 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 non-employment risk across demographics and other working characteristics.

According to my results, the differential in the risk of losing one's job across ages explains almost of the difference in the non-employment risk faced by young workers as opposed to older workers. When differences in the non-employment risk across occupational characteristics are considered, the job finding probability is the most 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 non-employment and unemployment risk, 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 non-employment risk across working group characteristics. For example, to reduce the non-employment 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 model the feedback effects from macroeconomic conditions to individual risks. Further research along these lines will enhance the understanding of the relative importance of job exit and job finding in shaping the heterogeneity in unemployment and non-employment risk.

Acknowledgements

I would like to thank Christian Bartolucci, John.V. Duca, Chirstopher Flinn, Stefan Hochguertel, Francis Kramarz, Costas Meghir, Claudio Michelacci, Raffaele Miniaci, Giovanna Nicodano, Lia Pacelli, Nicola Pavoni, Roberto Quaranta, Alessandro Sembenelli, Konstantinos Tatsiramos, Benjamin Villena-Roldan, Claudia Villosio and Mathis Wagner for their helpful discussions and comments. I would also like to thank the participants at Cognetti's Lunch Seminar, the Institute for Employment Research (IAB) Workshop, the ESPE 2011 Annual Congress, the AIEL 2011 Annual Congress, IFS and IZA workshops. Grateful thanks are given for the financial support from CINTIA-Italy and the Piedmont Region. The usual disclaimers apply.

A Non-employment Risk Decompositions

A.1 Shimer's (2007) Approach

Following Shimer (2007), I consider for each working group g at age t, the comparison between the steady state non-employment risk, $u^{ss}_{g,t}$ (see eq. (6) in the text), with the counterfactual non-employment 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.

In particular, to evaluate the role of the job separation probability in shaping the non-employment risk, I fix the job finding rate at its average over working life and across working groups, $\bar{f}$, (i.e. $\bar{f} = \sum_{g=1}^{G}\sum_{t=1}^{T} f_{g,t}$) and

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

take the actual job separation rates, $s_{t,g}$ to determine, for each working group g at each age t, the counterfactual the non-employment risk:

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

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, $\bar{s}$, (i.e. $\bar{s} = \sum_{g=1}^{G} \sum_{t=1}^{T} s_{g,t}$) and take the actual job finding rates, $f_{t,g}$, to determine the counterfactual the non-employment rate for each group g at each age t:

$$u^{f}_{g,t} = \frac{\bar{s}}{\bar{s} + f_{g,t}} \tag{8}$$

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

$$c^{s} = \frac{cov(u^{ss}_{g,t}, u^{s}_{g,t})}{var(u^{ss}_{g,t})};\ c^{f} = \frac{cov(du^{ss}_{g,t}, u^{f}_{g,t})}{var(u^{ss}_{g,t})} \tag{9}$$

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 non-employment risk observed across ages and working groups.

A.2 Fujita and Ramey's (2009) Approach

As robustness check, I consider an extension of the approach introduced by Fujita and Ramey (2009).[30] This approach is based on the log-linearisation of $u^{ss}_{g,t}$ around its average over ages and across working groups denoted as:

$$\overline{u^{ss}} = \frac{\bar{s}}{\bar{s} + \bar{f}} \tag{10}$$

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

$$du^{ss}_{g,t} = \ln \frac{u^{ss}_{g,t}}{\overline{\overline{u^{ss}_{g,t}}}} = (1 - \overline{u^{ss}_{g,t}}) \ln \frac{s_{g,t}}{\bar{s}} - (1 - \overline{u^{ss}_{g,t}}) \ln \frac{f_{g,t}}{\bar{f}} + \epsilon_{g,t} \tag{11}$$

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

Equation (11) shows that deviations of job separation and job finding probabilities from their average (over ages and working groups) contribute separately to deviations of the non-employment risk from its own average (over ages and working groups). Equation (11) is restated as:

$$du^{ss}_{g,t} = du^{s}_{g,t} + du^{f}_{g,t} + \epsilon_{g,t} \tag{12}$$

Fujita and Ramey (2009) show that the linear decomposition can be used to quantitatively assess the effects of the transition rates on non-employment risk variability. Following Fujita and Ramey (2009), I express these contributions through

$$\beta^{s} = \frac{cov(du^{ss}_{g,t}, du^{s}_{g,t})}{var(du^{ss}_{g,t})};\beta^{f} = \frac{cov(du^{ss}_{g,t}, du^{f}_{g,t})}{var(du^{ss}_{g,t})};\beta^{\epsilon} = \frac{cov(du^{ss}_{g,t}, d\epsilon_{g,t})}{var(du^{ss}_{g,t})} \tag{13}$$

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 non-employment risk across ages and working group characteristics.

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

A.3 Differences Across Ages

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

$$u_t \approx u_t^{ss} = \frac{s_t}{s_t + f_t} \tag{14}$$

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 non-employment risk.

Shimer's (2007) approach

In this subsection, following Choi, Janiak, and Villena-Roldan (2015), I adapt the Shimer's (2007) approach to explain differences in the non-employment risk across ages.

To determine the contribution of the job finding and the job separation rates to differences across ages, I compare the average non-employment risk at age t, u_t^{ss}, with the counterfactual non-employment 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, $\bar{f}\,(\bar{f} = \sum_{t=1}^{T} f_t)$ and $\bar{s}\,(\bar{s} = \sum_{t=1}^{T} s_t)$, respectively.

By fixing the job finding at the average over working life and across working groups, $\bar{f}$, and taking the job separation rates at each age averaged across working groups, s_t , I determine the hypothetical life cycle non-employment rate:

$$u_t^{s} = \frac{s_t}{s_t + \bar{f}} \tag{15}$$

By fixing the job separation at the average over working life, $\bar{s}$, and taking the job finding rates at each age t averaged across working groups, f_t, I determine the hypothetical life cycle non-employment rate:

$$u_t^{f} = \frac{\bar{s}}{\bar{s} + f_t} \tag{16}$$

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}:

$$c^{s(t)} = \frac{cov(u_t^{ss}, u_t^{s})}{var(u_t^{ss})};\; c^{f(t)} = \frac{cov(u_t^{ss}, u_t^{f})}{var(u_t^{ss})} \tag{17}$$

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 non-employment risk over working life.

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 non-employment risk faced by the average at each age, u_t^{ss}, from its own trend $\overline{u^{ss}}$ (i.e. the average non-employment risk across ages):

$$\overline{u^{ss}} = \frac{\bar{s}}{\bar{s} + \bar{f}} \tag{18}$$

where $\bar{f}\,(\bar{f} = \sum_{t=1}^{T} \bar{f_t})$ and $\bar{s}\,(\bar{s} = \sum_{t=1}^{T} \bar{s_t})$ denote, for the average worker, the job separation and job finding probabilities averaged over the working life. The approach is based on the log-linearisation of the average non-employment 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):

$$du_t^{ss} = \ln \frac{u_t^{ss}}{\overline{u^{ss}}} = (1 - \overline{u^{ss}}) \ln \frac{s_t}{\bar{s}} - (1 - \overline{u^{ss}}) \ln \frac{f_t}{\bar{f}} + \epsilon_{t} = \overline{du_t^{s}} + \overline{du_t^{f}} + \epsilon_t \tag{19}$$

where ϵ_t is a residual term.

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

$$\beta^{s(t)} = \frac{cov(du_t^{ss}, du_t^{s})}{var(du_t^{ss})};\; \beta^{f(t)} = \frac{cov(du_t^{ss}, du_t^{f})}{var(du_t^{ss})};\; \beta^{\epsilon(t)} = \frac{cov(du_t^{ss}, d\epsilon_t)}{var(du_t^{ss})} \tag{20}$$

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 non-employment risk faced by the average worker.

Automatically generated rough PDF by ProofCheck from River Valley Technologies Ltd

A.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 non-employment risk across working groups:

$$u_g \approx u_g^{ss} = \frac{s_g}{s_g + f_g} \tag{21}$$

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 non-employment risk (22 and 23) 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, $\bar{f}$ and take the actual job separation rate at group level g, s_g, to determine the hypothetical life cycle non-employment rate:

$$u_g^{s} = \frac{s_g}{s_g + \bar{f}} \tag{22}$$

Moreover, I fix the job separation at the average across groups, $\bar{s}$, and take the actual job finding rates at group level g, f_g to determine the hypothetical non-employment risk:

$$u_g^{f} = \frac{\bar{s}}{\bar{s} + f_g} \tag{23}$$

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}:

$$c^{s(g)} = \frac{cov(u_g^{ss}, u_g^{s})}{var(u_g^{ss})}\,; c^{f(g)} = \frac{cov(u_g^{ss}, u_g^{f})}{var(u_g^{ss})} \tag{24}$$

Fujita and Ramey's (2009) approach

As a robustness check, I extend the approach introduced by Elsby, Hobijn, and Sahin (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 $\overline{u^{ss}}$:

$$du_g^{ss} = \ln \frac{u_g^{ss}}{\overline{u^{ss}}} = (1 - \overline{u^{ss}}) \ln \frac{s_g}{\bar{s}} - (1 - \overline{u^{ss}}) \ln \frac{f_g}{\bar{f}} + \epsilon_g = du_g^{s} + du_g^{f} + \epsilon_g \tag{25}$$

where ϵ_g is a residual term.

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

$$\beta^{s(g)} = \frac{cov(du_g^{ss}, du_g^{s})}{var(du_g^{ss})};\ \beta^{f(g)} = \frac{cov(du_g^{ss}, du_g^{f})}{var(du_g^{ss})};\ \beta^{\epsilon(g)} = \frac{cov(du_g^{ss}, d\epsilon_g)}{var(du_g^{ss})} \tag{26}$$

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 non-employment risk across groups, faced at a given age.

Notes

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 under 25 years old of age is about 18.7 %, while it was about 7.5 % for individuals over 25. High unemployment rate among young people is a serious problem, especially in Southern Europe, it approached 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 more than one year (and fewer than four years), while the corresponding figures for prime-age and older workers were 34 % and 35 %, respectively (source: Eurostat).

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

3 Jones and Riddell (2006) use the Canadian Labour Force Survey to study the labor market transitions of unemployed and inactive individuals. Their results point at including individuals classified as inactive but strongly attached to the labor market in supplementary measures of unemployment.
4 Brandolini, Cipollone, and Viviano 2006, show that in the European Community Household Panel the job finding rate among unemployed individuals and inactive individuals engaged in some degree of job searching is not statistically different.
5 These dynamics for job finding probability in Italy are in line with Italian data on job search intensity over working life (see, e. g. Aguiar, Hurst, and Karabarbounis 2013).
6 This dataset has already been used to study various aspects of labour market dynamics (see, e. g. Boeri and Garibaldi 2007; Mussida and Sciulli 2015).
7 The sample includes workers recruited under standard contracts as well as those recruited under "entrance" contracts or temporary (atypical) contracts. Entrance contracts include apprenticeships and on-the-job training contracts. In my 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.
8 I 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. I repeated the analysis by excluding them. The results did not change.
10 The average Italian non-employment rate observed over the period 1998–2004 is about 30 % for workers under 25 years of age and about 7 % for the 26–54 age group.
11 Technically, I model the transitions from employment to non-employment (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 non-employment, and *vice versa*.
12 In particular, to account for lagged duration dependence in estimating the risk job separation (finding), I include time elapsed in the previous non-employment (employment) spell among the covariates.
13 In the analysis of non-employment spells, the job-related covariates are fixed at the value taken at the end of the previous employment spell.
14 Source Fred Economic Data, Federal Reserve Bank of St. Louis.
15 In proportional hazards models, the effect of a unit increase in a covariate is uniformly multiplicative with respect to the hazard rate. If this assumption is reasonable and in my data holds for working groups characteristics such as type of occupation, geographic area and firm size it may not hold for the age of the worker since a unit increase in age at the beginning of the spell does not affect the hazard of employment termination in a uniform proportional way throughout the spell. In this case, the AFT model is preferable since it is more flexible and does not rely on the proportionality assumption.
16 Van den Berg (1990) shows that models with multiple spells are identified under weaker assumptions than single-spell data.
17 Shared frailty models are the survival-data analog to panel data random-effects models. In shared frailty models the frailties are not observation specific, but instead are shared across groups of observations. In my case, the frailty is shared across the multiple spells observed at worker level. I therefore allow the observations on non-employment (employment) for the same worker to be correlated.
18 I thank an anonymous referee for this point.
19 Results are robust across various distributions specifications for ω and α (see Addison and Portugal 1998).
20 For example, a positive coefficient indicates a positive effect on the duration and thus a negative effect on the hazard.
21 The characteristics are type of occupation, geographic area, industry, firm size in addition to birth year of cohort and age.
22 In particular, for the representative worker of each working group g , I draw from the distribution of employment and non-employment spells specific to that group by setting the parameter governing the individual heterogeneity α to 1.
23 Note that the total number (S) of employment and non-employment spells experienced up to age 60 may vary across workers, depending on the duration of each spell.
24 For expositional simplicity I let $t = 1$ to corresponds to age 20 and so on untill age 60 which corresponds to $t = 40$.
25 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 non-employment spells that terminate at that age out of the total number of non-employment spells ongoing at that age.
26 I adopt both approaches, since Shimer's decomposition has been criticised because the steady state approximation is a non-linear function of transition rates (see Gomes 2012).
27 The two terms do not sum up to one because of the approximation.
28 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 the working group level is 72–95 %.
29 Atypical contracts in Italy are characterized by lower duration and separation costs as well as lower social security costs and reduced protection.
30 While Shimer's (2007) approach focuses on explaining differences in unemployment levels over the business cycle, the approach adopted by Fujita and Ramey (2009) focuses on explaining percentage differences in unemployment.

References

Abbring, I. H., and G. J. Van Den Berg. 2007. "The Unobserved Heterogeneity Distribution in Duration Analysis." *Biometrika, Biometrika Trust* 94 (1): 87–99.

Addison, J. T., and P. Portugal. 1998. "Some Specification Issues in Unemployment Duration Analysis." *Labour Economics* 5 (1): 53–66.

Aguiar, M., E. Hurst, and L. Karabarbounis. 2013. "The Life-Cycle Profile of Time Spent on Job Search." *The American Economic Review*: Papers and Proceedings, 111–116.

Arulampalam, W., L. Booth, and M. P. Taylor. 2000. "Unemployment Persistence." *Oxford Economic Papers* 52: 24–50, Oxford University Press.

Arulampalam, W. 2001. "Unemployment Really Scarring? Effect of Unemployment Experiences on Wages." *The Economic Journal* 111: 585–606.

Barbieri, L., and C. Mussida. 2018. "Structural Differences Across Macroregions: An Empirical Investigation." *Empirica* 45: 215–46.

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd

Barnichon, R. 2012. "Vacancy Posting, Job Separation, and Unemployment Fluctuations." *Journal of Economic Dynamics and Control* 36 (3): 315–30.
Baussola, M. L., J. Jenkins, C. Mussida, and M. Penfold. 2015. "Determinants of the Gender Unemployment Gap in Italy and the United Kingdom: A Comparative Investigation." *International Labour Review* 154 (4): 537–62.
Boeri, T., and P. Garibaldi. 2007. "Two Tier Reforms of Employment Protection: A Honeymoon Effect?" *The Economic Journal* 117: 357–85.
Böheim, R., and M. P. Taylor. 2002. "The Search for Success: Do the Unemployed Find Stable Employment?" *Labour Economics* 9 (6): 717–35.
Brandolini, A., P. Cipollone, and E. Viviano. 2006. "Does the ILO Definition Capture All Unemployment?" *Journal of the European Economic Association* 4 (1): 153–79.
Burdett, K. 1978. "A Theory of Employee Job Search and Quit Rates." *The American Economic Review* 68 (1): 212–20.
Choi, S., A. Janiak, and B, Villena-Roldan. 2012. "Unemployment, Participation and Worker Flows Over the Life-Cycle." Working Papers 617, Barcelona Graduate School of Economics.
Choi, S., A. Janiak, and B, Villena-Roldan. 2015. "Unemployment, Participation and Worker Flows Over the Life-Cycle." *The Economic Journal* 125: 1705–33.
Contini, B., and E. Grand. 2010. "Disposable Workforce in Italy" IZA Discussion Paper No. 4724.
Davis, S., and J. Haltiwanger. 1992. "Gross Job Creation, Gross Job Destruction and Job Reallocation." *Quarterly Journal of Economics* 107: 819–63
Elsby, M., B. Hobijn, and A. Sahin. 2010. "The Labor Market in the Great Recession." *Brookings Papers on Economic Activity* 41 (1): 1–48.
Elsby, M., J. C. Smith, and J. Wadsworth. 2011. "The Role of Worker Flows in the Dynamics and Distribution of UK Unemployment." *Oxford Review of Economic Policy* 27 (2): 338–63.
Elsby, M., B. Hobijn, and A. Sahin. 2013. "Unemployment Dynamics in OECD countries." *The Review of Economics and Statistics* 95 (2): 530–48.
Eriksson, S., and D.-O. Rooth. 2014. "Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence from a Field Experiment." *American Economic Review* 104 (3): 1014–39.
Flinn, C. J., and J. J. Heckman. 1982. "Models for the Analysis of Labor Force Dynamics." NBER Working Papers 0857.
Fujita, S., and G. Ramey. 2009. "The Cyclicality of Separation and Job Finding Rates." *International Economic Review* 50 (2): 415–30.
Gervais, M., N. Jaimovich, Siu H. E., and Y. Yedid-Levi. 2016. "What Should I be When I Grow Up? Occupations and Unemployment Over the Life Cycle." *Journal of Monetary Economics* 83: 54–70.
Gregg, P. A. 2001. "The Impact of Youth Unemployment on Adult Unemployment in the NCDS." *The Economic Journal* 111 (475): 626–53.
Gomes, P. 2012. "Labour Market Flows: Facts from the United Kingdom." *Labour Economics* 19 (2): 165–75.
Guvenen, F., F. Karahan, S. Ozkan, and J. Song. 2017. "Heterogeneous Scarring Effects of Full-Year Nonemployment." *American Economic Review* 107 (5): 369–73.
Hairault, J.-O., F. Langot, and T. Sopraseuth. 2014. "Why is Old Workers' Labor Market More Volatile? Unemployment Fluctuations over the Life-Cycle." IZA Discussion Papers 8076.
Heckman, J. J., and G. J. Borjas. 1980. "Does Unemployment Cause Future Unemployment? Definitions, Questions and AnsIrs from a Continuous Time Model of Heterogeneity and State Dependence." *Economica* 47 (187): 247–83.
Heckman, J. J., and B. Singer. 1984. "Econometric Duration Analysis." *Journal of Econometrics* 24 (1–2): 63–132.
Jones, S. R. G., and W. C. Riddell. 2006. "Unemployment and Nonemployment: Heterogeneities in Labor Market States." *The Review of Economics and Statistics* 88 (2): 314–23.
Jovanovic, B. 1979. "Job Matching and the Theory of Turnover." *Journal of Political Economy* 87 (5): 972–90.
Karahan, F., S. Ozkan, and J. Song. 2017. Sources of Inequality in Earnings Growth over the Life Cycle." Unpublished.
Kiefer, N. M., K. Burdett, and S. Sharma. 1985. "Layoffs and Duration Dependence in a Model of Turnover." *Journal of Econometrics* 28: 51–69.
Kroft, K. F. Lange, and M. J. Notowidigdo. 2013. "Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment." *Quarterly Journal of Economics* 128 (3): 1123–67.
Krueger, A., and A. Mueller. 2010. "Job Search and Unemployment Insurance: New Evidence from Time Use Data." *Journal of Public Economics* 94 (3): 298–307.
Krueger, A., J. Cramer, and D. Cho. 2014. "Are the Long-Term Unemployed on the Margins of the Labor Market? Brookings Papers on Economic Activity." *Brookings Papers on Economic Activity* 94 (3): 298–307.
Lawless, J. F. 2002. *Statistical Models and Methods for Lifetime Data*, 2nd ed. Hoboken: Wiley Series in Probability and Statistics.
Ljungqvist, L., and T. J. Sargent. 1998. "European Unemployment Dilemm". *IZA Journal of Political Economy* 106 (3): 514–50.
Macchiarelli, C., and M. Ward-Warmedinger. 2014. "Transitions in Labour Market Status in EU Labour Markets". *IZA Journal of European Labor Studies* 3 (17): 1–25.
Menzio, G., I. Telyukova, and L. Visschers. 2016. "Directed Search Over the Life-Cycle." *Review of Economic Dynamics* 19: 38–62.
Michelacci, C., and H. Ruffo. 2015. "Optimal Life Cycle Unemployment Insurance." *The American Economic Review* 105 (2): 816–59.
Mincer, J. 1991. "Education and Unemployment of Women." NBER Working Paper No. w3837.
Mussida, C., and D. Sciulli. 2015. "Flexibility Policies and Re-Employment Probabilities in Italy." *B E Journal of Economic Analysis and Policy* 15 (2): 621–51.
Neill, A., and F. Pastore. 2000. "Regional Unemployment and Industrial Restructuring in Poland." IZA Discussion Paper no. 194.
Pastore, F. 2012. "Primum Vivere Industrial Change, Job Destruction and the Geographical Distribution of Unemployment." *IZA Journal of European Labor Studies* 1 (1): 1–15.
Petrongolo, B. 2001. "Reemployment Probabilities and the Returns to Matching." *Journal of Labor Economics* 19 (3): 716–41.
Petrongolo, B., and C. A. Pissarides. 2008. "The Ins and Outs of European Unemployment." *The American Economic Review* 98 (2): 256–62.
Shimer, R. 2007. "Reassessing the Ins and Outs of Unemployment." NBER Working Papers, 13421.
Shimer, R. 2008. "The Probability of Finding a Job." *The American Economic Review: Papers & Proceedings* 98: 268–73.
Shimer, R. 2012. "Reassessing the Ins and Outs from Unemployment." *Review of Economic Dynamics* 15: 127–248.
Van den Berg, G. 1990. "Non Stationarity in Job Search Theory." *Review of Economics Studies* 57: 255–77.
Viviano, E. 2003. "Un'analisi critica delle definizioni di disoccupazione e partecipazione in Italia." *Politica economica* il Mulino (1): 161–90.

Automatically generated rough PDF by *ProofCheck* from River Valley Technologies Ltd