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Employability of young Italian males
after a jobless period, 1989-1998*

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Abstract

In Italy, about 28% of young males starting their first job in the private sector during 1989-1993 left their jobs in the first two years; some of them experienced job to job transitions but the majority of them experienced long jobless periods. A number of empirical studies suggest that the employability of jobless people deteriorates as their joblessness persists as consequence of human capital depreciation, demotivation and/or stigma effects. The aim of this paper is to investigate mechanisms that may produce employer stigmatization, discouragement, and human capital depreciation over the course of joblessness. Therefore, we analyze the existence and the causes of negative jobless duration dependence and the impact of a period of joblessness on wages as an indicator of the depreciation of human capital during joblessness or (to some degree) the wage effect of stigmatization. Sample selection and unobserved endogeneity issues are considered and a measure of jobless loss is suggested. Our results show the presence of a negative jobless duration dependence and a strong negative wage elasticity conted to the length of joblessness. Average jobless loss seems to be large.

Keywords: (to be added)

1. Introduction

In Italy, about 28% of young males starting their first job in the private sector during 1989-1993 left their jobs in the first two years; some of them experienced job to job transitions (about 10%) but the majority of them experienced a jobless period much longer than one month.¹ A number of empirical studies suggest that the employability of jobless persons deteriorates as their joblessness persists (for example, Machin and Manning, 1999). Moreover, the negative relationship between the duration of joblessness and the probability of being rehired does not disappear when selection issues about the heterogeneity of workers are included in the analysis (Van den Berg and Van Ours, 1994 and 1996). This negative relationship can be explained by the depreciation of human capital, the demotivation of the unemployed, and the fact that a long period of joblessness may be interpreted as a signal of a worker's quality at hiring time.

Layoffs have irreversible effects when the workers who lose their jobs have an obsolete skill or find it impossible to make the specific human capital they have accumulated to that point pay off. From an early career perspective, there may exist substantial costs associated with job displacement in the form of missed or delayed opportunities to accumulate general human capital. Wage growth associated with learning about worker ability and job match quality is also put at risk by job displacement. With less labour market experience than older and more established workers, young adults may face a signalling problem associated with job loss (Faber and Gibbons, 1996): an observed displacement may be particularly costly if it is used by prospective and future employers as a bad signal about worker performance. Topel (1990) shows that in the United States in the 1970s and 1980s, after losing a job, workers experience (on average) a wage reduction of between 15% and 40% when they are re-employed. Kletzer and Fairlie (2001) find that the earning and wage costs of job loss for young workers are also large, although somewhat smaller and less persistent than the losses found for older and more established workers. Therefore, the loss of specific human capital when a job is lost seems to be significant.

In this paper, we focus on young Italian workers to assess if their jobless experiences in their very early career have adverse effects and if these effects increase as the length of joblessness increases. Therefore, we investigate the existence of negative jobless duration dependence in order to determine the factors that most affect the declining jobless-to-employment hazard function. This analysis provides the basis for a better understanding of the mechanisms that may produce employer stigmatization, discouragement, and human capital depreciation over the course of a period of joblessness. Then, we analyze the impact of a jobless duration on wages as an indicator of the depreciation of human capital during joblessness or (to some degree) the wage effect of stigmatization. Here, we also address the issues of self

¹ WHIP data

selection into employment and the endogeneity of jobless duration. Finally, we propose a measure of the average jobless loss.

This paper contributes to the existing literature with fresh empirical evidence on the adverse effects of a period of joblessness very early in young people's careers in Italy. We emphasise the importance of a better understanding of which individual characteristics (and/or job attributes) can impact on the duration of a jobless period and we stress the size of the negative wage effects of such jobless duration. This is extremely important in order to design useful policy. Moreover, no previous studies have analysed young worker transitions in the Italian labour market using our framework and WHIP data.

Note that the analysis of early career transitions in the Italian labour market is of special interest. This is due to the particular features of the Italian private labour market: the time necessary to find a new job, after periods out of work, is generally long (and young unemployment rates are high in the period of study); workers transitions to improve their future income (or working conditions) are mainly job-to-job transitions, while jobless periods are often related to periods of unemployment and/or work in the shadow economy (Contini and Villosio, 2001). Therefore, in this context it is particularly interesting to analyze the adverse effect of joblessness during early career phases.

The paper proceeds as follows. Section 2 provides detailed information on the data. In section 3, we illustrate the model used in the subsequent paragraphs. In section 4, we present empirical evidence on negative jobless dependence. Section 5 shows the results on the relationship between wage earned by reemployed workers and the length of the jobless period. Finally, section 6 briefly concludes.

2. Definitions and data

We use information from the 14 years of the Work Histories Italian Panel (WHIP), an employer-employee linked panel database developed by Italian Social Security administrative sources. WHIP covers the years from January 1985 to December 1998. For its institutional purposes, the Italian Social Security Administration collects data both on individual employees and firms (employers). The reference population is made up of all the people – Italian and foreign – who have worked in Italy even if for only a part of their working career. The entire private sector is covered (about 10 million employees and 1.2 million firms per year) and a large representative sample has been extracted from this population. Agricultural workers, individuals who are self-employment and a part of the public administration are also

covered by the Italian Social Security Administration, but data on these sectors are not available or not suitable for the purpose of this study.

We use information about worker age, professional category, sector in which he is employed, dates at which employment spells start and end, the geographical location of employment, the type of the contract held by the worker and real monthly wages². Note that, in administrative archives, information not related to the specific interest of the Italian Social Security Administration (i.e. marriage status, children, etc.) is not present. On the other hand, the coverage and accuracy of administrative archives cannot be found in any other dataset. Also note that we do not have any attrition problems because, once a certain group of individuals is selected, it is possible to follow them over the entire study period.

We consider the cohorts of young males (between the ages of 16 and 30) starting a jobless period during the period from October 1989 to December 1995. All individuals included in the sample had worked a period of 9 to 23 months (and they had their first working experience³ between January 1989 and December 1993). Note, that we consider only individuals that experienced presumable involuntary separations since we exclude people that experienced job-to-job transitions (with, eventually, a jobless period of less than one month). Individuals that continue their careers in self-employment or with atypical contracts (“*parasubordinati*”) are also not included.⁴ This sample includes 2318 workers and we follow their working history for 36 months. The average elapsed period of joblessness is about 20 months (and about 10 months for the sub-sample of individuals re-employed by the end of the period of study). For more details on sample composition see Table 1.

Finally, our data presents two main problems. First, displaced individuals may receive unemployment benefits, temporary layoff payments and redundancy payments, and we know that benefits can bias our results. Unfortunately, we do not have enough information about the benefits paid to workers. However, note that, in our sample, only individuals working in construction (about 25% of the sample) are eligible, under specific conditions, for unemployment benefits. Some individuals may also be eligible for temporary layoff payments and redundancy

² Monthly wage is computed using information about yearly wage and the number of days worked in that year. In particular, we divide the yearly wage by the number of days worked and, then, we multiply by 26 days. Finally, real monthly wage is computed in the standard way.

³ We assume that we are using the first working experience since the individual is young and he was not recoded by Italian Social Security Administration during the period 1985-1988.

⁴ Of the initial sample of 3199 individuals, about 7% of them are re-employed with atypical contracts and about 16% become self-employed. Therefore, we know that our sample is only representative of the population of young males experiencing jobless periods (after some work experience) that are looking for jobs, mainly in the private sector. The reader has to keep this in mind so as not to miss-understand the results.

payments, but a cross check with the administrative data shows that less than 3% of the individuals in the sample received these payments. Second, workers may appear jobless because they are completing their mandatory military service. Thus, we could observe jobless periods that in reality are not jobless spells, and this could bias our results. However, we do not count jobless spells in correspondence of military service for individuals working in the same firm before and after their military service. Note also, that individuals often complete their military service before they enter into the labour market. Therefore, we believe that the above problems have not significant impact on our results.

3. The Model

Transition out of joblessness

In this section, we analyse the duration of joblessness with a view of investigating the existence of negative duration dependence and of understanding which factors influence the transition path. We use a discrete-time hazard rate model (i.e. Narendranathan and Nickell, 1989; Jenkins and Garcia-Serrano, 2000). In particular, we consider individuals that have just become jobless and are likely to exit thereafter. The probability of person i of being re-employed after t months, given that he has been jobless for $t-1$, is assumed here to be a standard logit hazard function:

$$h_{it} = \exp[\mathbf{x}_{it}'\boldsymbol{\beta} + \gamma(t)] / (1 + \exp[\mathbf{x}_{it}'\boldsymbol{\beta} + \gamma(t)])$$

where \mathbf{x}_{it} is the vector of (time-constant and time-varying) covariates, $\boldsymbol{\beta}$ is a vector of parameters to be estimated and $\gamma(t)$ is some functional form of how the duration of the spell affects the hazard rate (baseline function). For the latter, we initially use a log-time specification. Then, we also use a flexible specification (duration-interval dummies) in order to avoid the potential parameter estimation bias due to the specific assumption of the form of the baseline function (Meyer, 1990). Estimation of the model parameters can be done using standard software applied to a re-organized data set in which each person contributes as many data rows as she is observed at the risk of leaving the jobless state (Allison, 1982; Jenkins, 1995; Jenkins and Garcia-Serrano, 2000).

Individuals might differ in unobserved terms like ability, effort, and taste and these differences could remain constant over time. Allison (1982) points out that, if such unobserved heterogeneity among individuals exists and is temporally stable, the estimated parameters might be inefficient with biased standard errors. Therefore, to account for unobserved heterogeneity, we also include unobserved heterogeneity in the specification of the hazard rate.

Post-joblessness wage analysis

In order to understand the effects of jobless on earnings, we can estimate the wage equation using ordinary least squares (OLS) methods:

$$\log(w_a) = \mathbf{z}_a \boldsymbol{\gamma}_a + \alpha_a \log(t) + \beta_a \log(w_p) + u_a$$

where $\log(w_a)$ is the logarithm of the post-joblessness real monthly wage, \mathbf{z}_a is the vector of the explanatory variables that influence the post-joblessness wages but not the pre-joblessness earnings (i.e. changes in sector, working area and occupation, and actual local unemployment rates), $\log(t)$ is the logarithm of the elapsed joblessness duration (in months) and $\log(w_p)$ is the logarithm of previous job earnings. Note, that the estimation of the above equation raises two main econometric issues: selection issue and endogeneity issue.

First, we can face selection problems since a considerable fraction of the jobless individuals sample was not employed full-time as of December 1998. For such individuals the effects of the determinants of post-joblessness earnings could be systematically different from those of re-employed people. Thus, the selective sample may be unrepresentative of the population and estimation using this sample may result in biased regression parameters. The conventional two-step selectivity adjustment procedure proposed by Heckman (1979) is, therefore, implemented to account for the possibility of selection bias.

Second, we face an endogeneity problem created by the potentially simultaneous determination of some variables in the model. To account for endogeneity issues, we consider the possibility that acceptance wages and jobless spell length are jointly determined (i.e. Addison *et al.*, 2004). Therefore, the model can be written as

$$\log(w_a) = \mathbf{z}_a \boldsymbol{\gamma}_a + \alpha_a \log t + \beta_a \log(w_p) + u_a \quad (1)$$

$$\log(t) = \mathbf{z}_d \boldsymbol{\gamma}_d + \beta_d \log(w_p) + u_d \quad (2)$$

$$\text{emp} = 1 (\mathbf{z} \boldsymbol{\gamma}_{1e} + \mathbf{x} \boldsymbol{\gamma}_{2e} + \beta_e \log(w_p) + u_e > 0) \quad (3)$$

where emp is a binary variable indicating employment status and \mathbf{z} is the vector of explanatory variables that should influence the jobless duration but not the post-jobless earnings. Kiefer and Neumann (1979) and Hui (1991) suggest that past job experiences affect the distribution and arrival rate of job offers (and, thus, the jobless duration). Therefore, the vector \mathbf{z} may include variables referring to previous job attributes (i.e. occupation, type of contract, sector, working area, year of separation, employment duration). Note that the variable for previous job attributes can also be used as a

vector of explanatory variables in the selection equation. Moreover, in order to identify the selection equation we can also use individual characteristics such as age (these variables are included in the vector x in the selection equation). Thus, $\log(w_p)$, z and z_a represent the exogenous variables and $\gamma_a, \alpha_a, \beta_a, \gamma_d, \beta_d, \gamma_{1e}, \gamma_{2e}, \beta_e$ are the parameters to be estimated. . The first function is the structural equation, the second is the linear projection for the endogenous variable, and the third equation is the selection equation. From the latter, we can compute the inverse Mill's ratios and, then, estimate the structural equation by two stage least squares (2SLS) using the vector z and the inverse Mill's ratio as an instrument. Note that we need to assume u_e distributed as a $N(0,1)$, and orthogonality between the error terms and the variables included in the vector z .

A negative impact of jobless duration on wages can be interpreted as a proxy of poor productivity or as a measure of the depreciation of human capital during joblessness or as an indicator of some stigmatisation effects (Addison *et al.*, 2004; Addison and Portugal, 1989). Also note that a positive sign in the inverse Mill's ratio coefficients may suggest that, controlling for the direct effect of the jobless duration on wages and individual heterogeneity, currently jobless individuals have greater wage losses than their employed counterparts. Note that in the above model we do not account for the possible effects of unobserved job match or individual heterogeneity. We can attempt to control for permanent individual heterogeneity by conditioning the post-jobless wage equation on pre-displacement wages: in practise, we restrict the coefficient on the pre-jobless wage as equal to one (Topel, 1986; Addison and Portugal, 1989). In fact, heterogeneity in pre-jobless wages should reflect observable and unobservable heterogeneity in the characteristics of workers and job attributes.

Measure of jobless loss

If we find a negative elasticity of the post-jobless wages with respect to jobless duration, we can argue that there is a jobless loss. We can estimate the average social cost in euros of the jobless loss attributable to individual i if he is re-employed at time $t=0$ and assumed normally working until retirement:

$$\text{Loss}_i = 12[w_{ai} \eta_i] \sum_{t=0}^{R_i} \delta^t$$

with $\delta = 1/[(1+r)(1+\rho)]$

where $(w_{ai} \eta_i)$ is the instantaneous monthly loss, w_{ai} is the post-jobless fitted wages of individual i , η_i is the estimated elasticity of post-jobless wages to the elapsed jobless duration at point (w_{ai}, t_i) ,⁵ R_i represents the retirement age minus the age at which the worker i has been re-employed, ρ is the depreciation rate and r is the discount rate. Note that the

⁵ w_{ai} and t_i are the exponential of the fitted values respectively of the post-jobless wages and of the elapsed jobless duration (estimated using equation 1-3)

exact elasticity at (w_{ai}, t_i) has been computed using the estimated elasticity of post-jobless wages to the elapsed jobless duration (α_a).

4. Empirical results

Smoothed hazard estimates and cumulative re-employment rates by groups

Figure 1 displays smoothed estimates of the re-employment hazard estimates from the pooled data. The monthly re-employment hazard estimate increases over the first 9 months and then decreases. We can explain this behavior imagining the existence of different groups of individuals: for example, one group of “quickly re-employed” individuals with an increasing hazard estimate while the remainder are “slowly re-employed” individuals. Thus, heterogeneity across individuals could explain the shape of the hazard curve. Using multivariate analysis, we will be able to check if the shape of the hazard is the same once we have controlled for observed individual characteristics.

Table 2 shows estimates of the cumulative proportion of re-employed young males, with breakdowns for groups. We notice that periods out of work in their early careers are indeed rather long. Although one quarter of those out of work had found a job after 6 months, not even one half (40%) had found a job after one year since entry in the jobless state. Only 60% were re-employed after three years.

There are marked differences in cumulative re-employment rates between young individuals working in different geographical areas. Individuals with a previous job working in Northern Italy have the highest cumulative rates: for example, after three years, about 72% of them had been re-hired, whereas the corresponding rate for those working on the Islands is about 51%.

We also find noticeable differences in the cumulative re-employment rates between individuals with work experience longer and shorter than one year. For those with a past experience of 9-12 months the rates are lower than for those with a past experience of 13-23 months (after three years, we have 52% versus 67%).

We also notice that the proportion of people remaining without a job were slightly higher for the young individuals who experienced separations during the 1993 recession.⁶ Moreover, after three years, individuals aged 26 or over on entry

⁶ Differences in cumulative re-employment rates in 1989 and 1995 are due to sample construction

into the jobless state have the lowest cumulative re-employment rates: only about 49% of them had found a job, whereas the corresponding proportion for those aged 16-19 was 67%.

There are also marked differences in the cumulative re-employment rates between previous job sectors, previous occupation and previous working contract. For instance, after three years, cumulative re-employment rates seem to be higher for individuals working in the Industrial and Finance sectors. Moreover, after three years, only 58% of the individuals with permanent contract had been re-employed, but 68% of the individuals with previous training-at-work contracts were re-employed. Similarly, considering former job type, we found that after three years trainers have noticeably higher cumulative re-employment rates (about 67%).

Transition out of joblessness: logistic hazard regression model estimates

In this section, we investigate the factors that impact on the speed of transition from jobless to employment. We found that the baseline hazard function exhibits strong negative duration dependence over the period of study (36 months). The latter can be seen in figure 2 where we represent the baseline hazard function without controlling for individual heterogeneity. In tables 3 and 4, we report the estimated duration dependence for an individual possessing sample average characteristics for the non-dichotomous explanatory variables and with reference values for the binary variables. In the former table, we use a $\log(\text{time})$ baseline hazard function and the estimates are presented for the pooling sample and the sample of workers starting jobless spells in period t (with $t=1989$ to 1995) without taking into account for the impact of unobserved heterogeneity. In table 4, we use a non-parametric baseline hazard function (duration-interval dummies) and we also account for unobserved heterogeneity. All our results confirm the existence of strong negative duration dependence. Note that negative duration dependence may be produced by declining job offer arrival rates, increasing reservation wages, or/and from an adversely shifting wage offer distribution (Addison et al. 2004). Alternatively, negative dependence may be explained as a pure sorting of the more employable of the jobless workers as consequence of stigma effects or human capital depreciation. In the following sections, we focus on showing the existence of the latter effects.

Table 5 reports the estimates for the hazard regression model with non-parametric baseline hazard function and unobserved heterogeneity. The reference group includes individuals aged 20-25 years on entry, blue collar workers that had permanent contracts in industry, working in the Northwest and that experienced separations in 1989. There are differences in re-employment probabilities associated with age, previous job occupation and previous job sectors. The oldest individuals (aged 26 or more) have lower re-employment probabilities than the reference group. Individuals

having training-to-work contracts have a higher re-employment probability. Also individuals with a previous occupation as trainers have a higher probability of exiting joblessness. Instead, individuals with formal jobs in the wholesale, automotive, repair, construction, services, research and real estate sectors have lower probabilities to be re-employed than those in the reference group. Note that individuals with previous jobs in construction may be eligible for unemployment benefits and the latter may explain the negative sign of the corresponding coefficient. Individuals with longer job experience have a higher re-employment probability. All of the above results are consistent with those reported in table 2 about cumulative re-employment rates. Finally, note that, as expected, the estimated elasticity of the hazard estimates with respect to the local unemployment rate is statistically significant and negative (about -0.5): re-employment probabilities, as expected, are lower if job availability is lower. Local unemployment rates are highly correlated with the working areas (correlation of about 0.9) and, thus, we include in the regression the local unemployment rates or the area dummies. In the latter specification, we find the same results as above and individuals previously working in Southern Italy or on the Islands (areas with high unemployment rates) have the lowest probability of re-employment.

Post-joblessness wage analysis

Regression estimates for the determinants of post-jobless wages are reported in table 6. Results for the jobless duration regression and for the selectivity equation are respectively provided in Appendix 1 and 2. Different specifications have been considered. First, we estimate the Mincerian wage regression by ordinary least squares (with and without selectivity adjustment). Second, we estimate the model proposed in the previous section (with and without constraint on the coefficient of previous job earnings) by two-step least squares. Two specifications for the jobless duration equation have been considered: the first specification does not allow for the direct effect of post-jobless wages on jobless duration while the second specification includes the post-jobless earnings as explanatory variable.

The ordinary least square (OLS) estimates show that an increase in jobless duration of 10% will lower wages on the subsequent job by 0.23%. Allowing for joint determination of wages and jobless duration (independent of the model specification used) strengthens the negative impact of duration: a corresponding increase in duration reduces wages by about 1.8%. Therefore, such estimated elasticity of the post-jobless wages with respect to duration clearly suggests that, on average, declining reservation wages, human capital depreciation, and stigma effects associated with longer jobless duration dominate productive search outcomes (these results are consistent with the work of Addison and Portugal, 1989, in the USA).

Note that the estimated coefficient of pre-jobless wages (when freely determined) is positive and about 0.4. More notable findings are the positive effects of changes in working area and occupation, probably due to a switch to higher wage areas and occupations. Changes in sector have negative and statistically insignificant effects on wages. Also local regional unemployment rates have no statistical significant effects. The estimated coefficient of the inverse Mill's ratio is positive and significant suggesting that the currently jobless individuals have greater wage losses than their employed counterparts. This result probably indicates that both the duration and the selectivity arguments are capturing a declining reservation wage and human capital depreciation on post-jobless wages.

Estimated jobless loss

We can measure in euro the average jobless loss associated to an average fitted jobless period (that is, 6 months) for an individual 24 years old hired with an average fitted real monthly wage (about 1530 euros) that is assumed normally working from re-employment to retirement. The retirement age is assumed to be 65 years old. Results are presented in Table 7. Note that the estimated loss depends on the values of the discount rate (r) and the depreciation rate (ρ). Therefore, we present results calculated over a range of values of r and ρ on the intervals $[0, 0.10]$ and $[0.05, 0.15]$.⁷ The estimated losses (in 2004 euros) are quite large, even when high values of the discount and depreciation rates are assumed. For example, with a negative elasticity of the post-jobless period with respect to the jobless duration of 17.60%, and the discount and depreciation rates respectively of 0.10 and 0.15, the estimated average jobless loss is about 15,780 euros.

In Figure 3-6, we study respectively the relationship between elasticity of the post-jobless fitted wages with respect to the fitted jobless duration at point (w_{ai}, t_i) versus fitted wages and versus fitted jobless duration, and the relationship between jobless loss versus fitted wages and versus fitted jobless duration. Note that we assume an estimated elasticity of the post-jobless period with respect to the jobless duration of 17,60%, a discount rate equal to 0.15 and a depreciation rate equal to 0.10. We find that exact elasticity at point (w_i, t_i) seems to decrease in the post-jobless fitted wage and to slightly increase in the fitted jobless duration. Finally, note that the relationship between estimated individual jobless losses and fitted jobless durations is linear.

⁷ These intervals are normally used in the literature on human capital - for example, see Hamermesh (1987)

5. Conclusions

In this paper, we show that young Italian males experiencing jobless periods in their very early careers experience re-employment wage losses. These losses increase with the duration of joblessness. Moreover, their probability of re-employment decreases when the elapsed jobless period increases. Therefore, we find evidence that supports the thesis that a negative jobless duration dependence can be explained as a pure sorting of the more employable of the jobless workers as consequence of stigma effects or human capital depreciation.

We find that the estimated elasticity of the post-jobless wages with respect of duration is about 18% when joint determination of post-jobless wages and jobless duration is allowed (and sample selection problems corrected). It clearly shows that, declining reservation wages, human capital depreciation, and stigma effects associated with longer jobless duration dominate productive search outcomes.

Finally, we measure the average jobless loss for individuals assumed to be working normally from re-employment to retirement. We find that such loss (even when high discount and depreciation rates are considered) is large. Therefore, our analysis indicates that this is an extremely important policy issue and shows that policy makers need to develop policy that helps to avoid the negative effects for jobless periods and the subsequent jobless losses.

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Figure 1. Smoothed hazard estimate

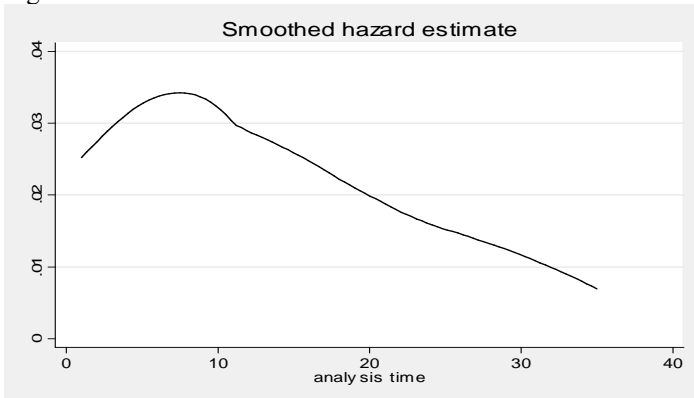


Figure 2. Kaplan-Meier survivor function (survivor in joblessness)

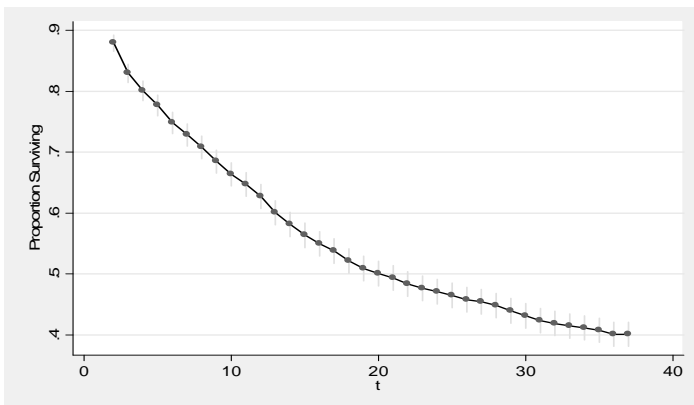


Figure 3. Elasticities at point (w_i, t_i) versus fitted wages

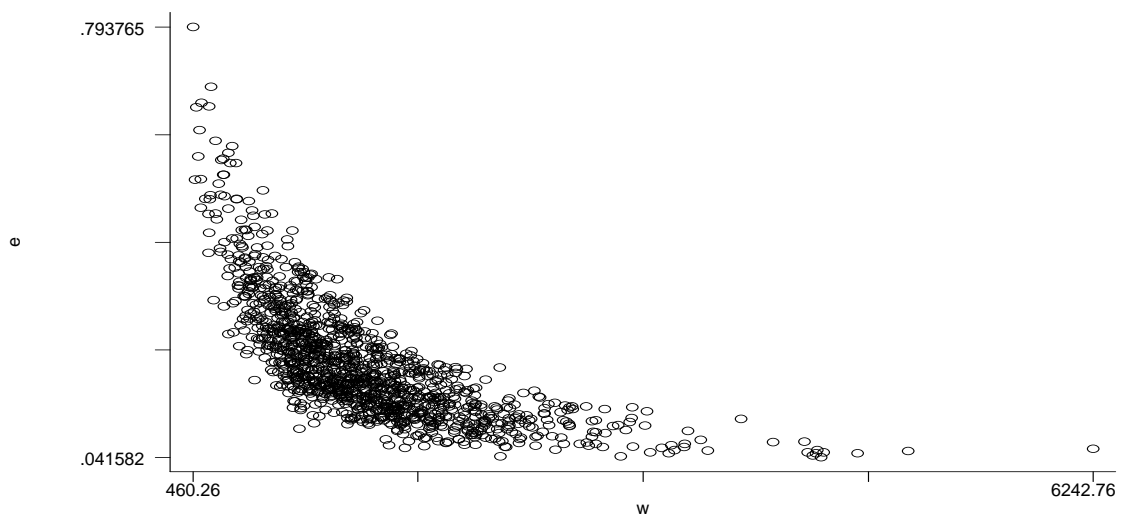


Figure 4. Elasticities at point (w_i, t_i) versus fitted jobless duration

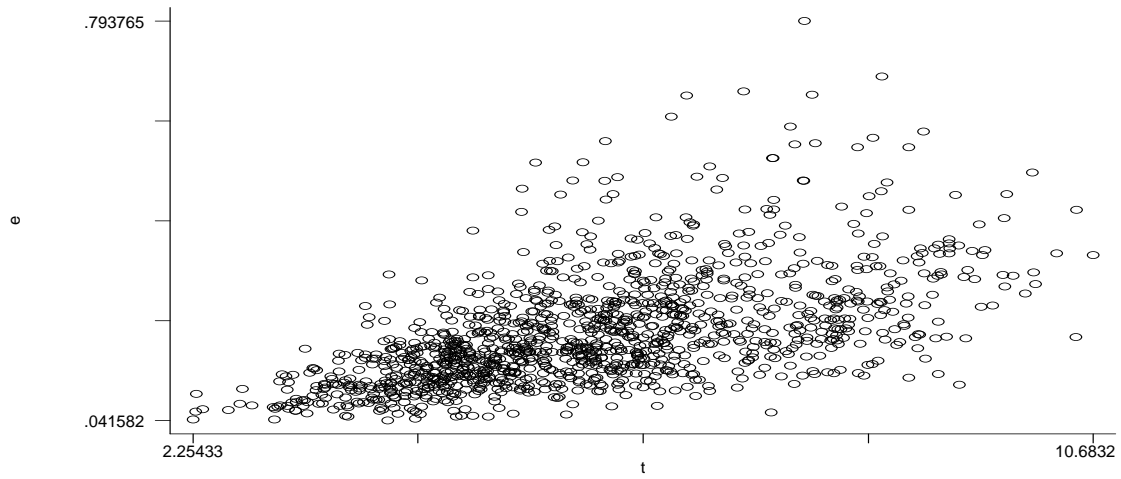


Figure 5. Estimated individual losses versus fitted wages

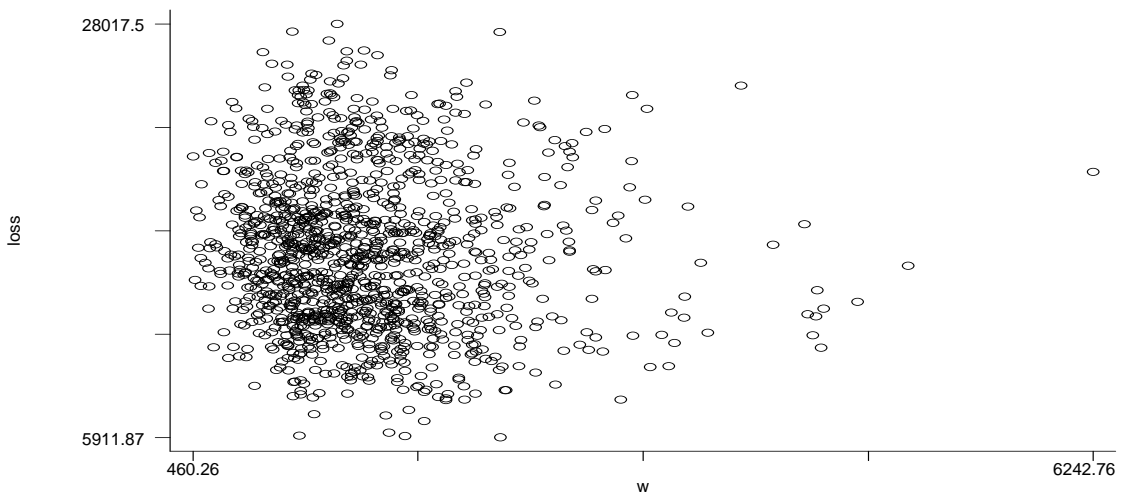


Figure 6. Estimated individual losses versus fitted jobless duration

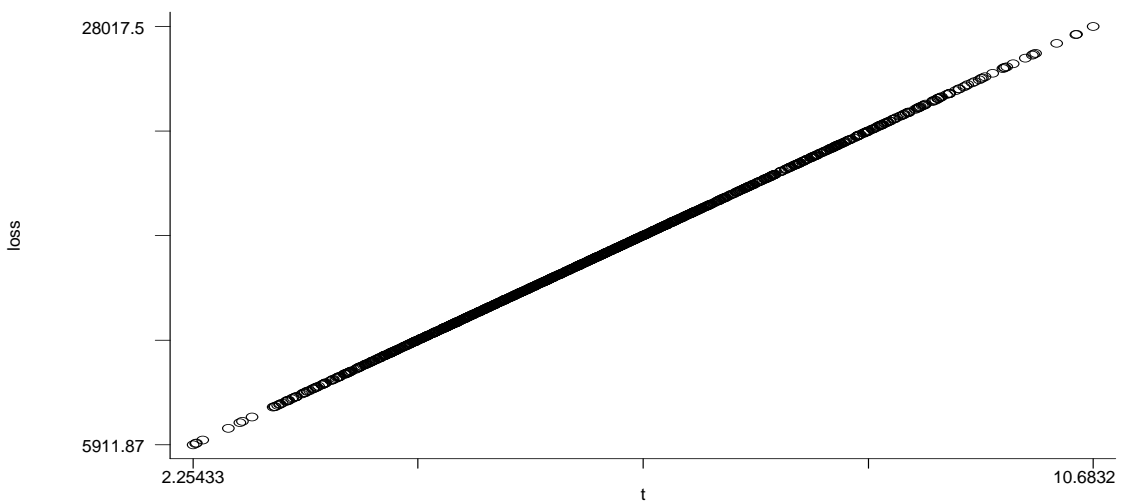


Table 1. Descriptive statistics

Number of observations	2318	Previous job sector	
Area		industry	42.84
Northwest	25.33%	construction	24.81
Northeast	15.32%	wholesale. automotive and repair	17.3
Centre	20.85%	entertainment	6.21
South	26.07%	transportation. communication	2.29
Islands	12.43%	finance	0.91
Cohort		services. research and real estate	5.65
1989	4.31%	Previous job contract	
1990	19.28%	permanent	79.26%
1991	23.47%	training-at-work	20.74%
1992	21.48%	Previous job occupation	
1993	18.29%	trainer	31.79%
1994	10.48%	blue collar	53.15%
1995	2.67%	white collar	15.06%
Age at initial period		Previous job experience	
16-19 years	37.62%	9-12 months	45.90%
20-25 years	41.50%	12-23 months	54.10%
26 or more years	20.88%	real monthly wage: mean (std dev)	1318 (449)

Table 2. Cumulative proportion of re-employed individuals

	Months			
	6	12	24	36
All	0.27	0.4	0.53	0.6
Area				
Northwest	0.33	0.45	0.62	0.68
Northeast	0.4	0.54	0.66	0.72
Centre	0.24	0.38	0.51	0.57
South	0.19	0.32	0.44	0.52
Islands	0.18	0.32	0.45	0.51
Cohort				
1989	0.1	0.17	0.27	0.27
1990	0.3	0.43	0.6	0.66
1991	0.31	0.44	0.57	0.6
1992	0.29	0.4	0.52	0.61
1993	0.21	0.35	0.49	0.56
1994	0.25	0.4	0.54	0.65
1995	0.31	0.5	0.66	0.71
Age at initial period				
16-19 years	0.26	0.41	0.59	0.67
20-25 years	0.28	0.4	0.52	0.59
26 or more years	0.27	0.37	0.45	0.49
Previous job sector				
industry	0.3	0.44	0.59	0.66
construction	0.22	0.36	0.48	0.54
wholesale, automotive and repair	0.26	0.37	0.51	0.57
entertainment	0.28	0.41	0.54	0.58
transportation, communication	0.26	0.4	0.47	0.47
finance	0.33	0.48	0.67	0.67
services, research and real estate	0.25	0.37	0.47	0.54
Previous job contract				
permanent	0.25	0.38	0.52	0.58
training-at-work	0.34	0.46	0.62	0.68
Previous job occupation				
trainer	0.28	0.42	0.59	0.67
blue collar	0.26	0.38	0.5	0.56
white collar	0.3	0.44	0.55	0.59
Previous job experience				
9-12 months	0.22	0.32	0.46	0.52
12-23 months	0.31	0.44	0.6	0.67

Table 3. Estimated duration dependence: log(time) baseline hazard function

Regression for each Cohort:	Estimated duration dependence	Unobserved heterogeneity	Covariates
1989	-0.381* (0.189)	no	yes
1990	-0.532** (0.057)	no	yes
1991	-0.713** (0.052)	no	yes
1992	-0.543** (0.055)	no	yes
1993	-0.440** (0.064)	no	yes
1994	-0.439** (0.080)	no	yes
1995	-0.498** (0.159)	no	yes
Pooling sample	-0.567** (0.026)	no	yes

Note: the covariates are the same variables used in table 5

Table 4. Estimated duration dependence: non-parametric baseline hazard function

Pooling sample	Estimated duration dependence	Estimated duration dependence
Unobserved heterog	no	yes
Covariates	yes	yes
months 1-6	-4.048** (0.840)	-4.189** (0.970)
months 7-12	-4.583** (0.841)	-4.621** (0.971)
months 13-18	-4.671** (0.841)	-4.637** (0.970)
months 19-24	-5.257** (0.844)	-5.171** (0.972)
months 25-30	-5.229** (0.843)	-5.117** (0.971)
months 31-36	-5.736** (0.848)	-5.595** (0.976)

Note: the covariates are the same variables used in table 5

Table 5. Transition from joblessness to employment (non-parametric baseline hazard function)

Variables	Model A		Model B	
	Coef.	Std.Err.	Coef.	Std.Err.
age16_19	-0.170	0.090	-0.172	0.090
age26plus	-0.298 **	0.087	-0.307 **	0.087
Previous job occupation: trainers	0.345 **	0.104	0.350 **	0.104
Previous job occupation: white collars	0.095	0.104	0.106	0.104
Previous job contract: training-at-work	0.337 **	0.087	0.348 **	0.087
Previous job sector: construction	-0.209 *	0.085	-0.204 *	0.085
Previous job sector: wholesale, automotive, repair	-0.222 *	0.095	-0.211 *	0.095
Previous job sector: entertainment	-0.083	0.140	-0.051	0.142
Previous job sector: transportation, communication	-0.173	0.239	-0.164	0.240
Previous job sector: finance	0.157	0.344	0.145	0.345
Previous job sector: services, research, real estate	-0.364 *	0.157	-0.361 *	0.158
Previous job experience: ln(months)	0.495 **	0.115	0.488 **	0.115
Previous job earnings: log(real monthly wage)	0.002	0.123	-0.001	0.124
log(regional unemployment rate)	-0.505 **	0.064	---	---
Previous working area: Northeast	---	---	0.211 *	0.100
Previous working area: Centre	---	---	-0.331 **	0.096
Previous working area: South	---	---	-0.511 **	0.092
Previous working area: Islands	---	---	-0.530 **	0.118
cohort 1990	1.255 **	0.226	1.271 **	0.226
cohort 1991	1.147 **	0.226	1.145 **	0.226
cohort 1992	1.110 **	0.226	1.097 **	0.226
cohort 1993	0.965 **	0.230	0.956 **	0.230
cohort 1994	1.130 **	0.240	1.090 **	0.240
cohort 1995	1.363 **	0.292	1.323 **	0.293
Baseline hazard function: month 1-6	-4.189 **	0.970	-5.090 **	0.965
Baseline hazard function: month 7-12	-4.621 **	0.971	-5.526 **	0.966
Baseline hazard function: month 13-18	-4.637 **	0.970	-5.548 **	0.965
Baseline hazard function: month 19-24	-5.171 **	0.972	-6.088 **	0.967
Baseline hazard function: month 25-30	-5.117 **	0.971	-6.038 **	0.966
Baseline hazard function: month 31-36	-5.595 **	0.976	-6.517 **	0.971
sigma_u	0.655 **	0.138	0.655	0.139
rho	0.115 **	0.024	0.115	0.024
log-likelihood	-5820.07		-5816.77	

Note: ** means statistical significant at 1% level; * means statistical significant at 5% level.

Table 6. The determinants of post-joblessness wages

log(post-jobless wage)	OLS			OLS		
	Coef.	Std.Err.		Coef.	Std.Err.	
Elapsed jobless duration: log(months)	-0.0230 **	0.0076		-0.0232 **	0.0076	
Previous job earnings: log(real monthly wages)	0.3892 **	0.0263		0.3690 **	0.0269	
Dummy: change in working area	0.1363 **	0.0316		0.1228 **	0.0318	
Dummy: sector change	0.0091	0.0186		-0.0046	0.0190	
Dummy: occupational change	0.1347 **	0.0199		0.1449 **	0.0200	
log(regional unemployment rate)	0.0127	0.0168		-0.0220	0.0196	
lambda	---	---		0.1687 **	0.0501	
constant	4.4723 **	0.1896		4.5961 **	0.1924	

log(post-jobless wage)	2SLS			2SLS		
	Coef.	Std.Err.		Coef.	Std.Err.	
Elapsed jobless duration: log(months)	-0.1870 **	0.0479		-0.1760 **	0.0544	
Previous job earnings: log(real monthly wages)	0.3741 **	0.031		1		
Dummy: change in working area	0.1949 **	0.0427		0.1567 **	0.0484	
Dummy: sector change	-0.0002	0.0222		-0.0215	0.0252	
Dummy: occupational change	0.2038 **	0.0288		0.2900 **	0.0323	
log(regional unemployment rate)	0.0452	0.0301		0.0623	0.0342	
lambda	0.1825 **	0.0569		0.0113	0.0639	
constant	4.6647 **	0.2252		0.2585 **	0.0623	

Note: the 2SLS estimates area not statistically different from the 2SLS estimates obtained adding post-jobless wages as an explanatory variable in the jobless duration regression

Table 7. Jobless lost for the average individual assumed to be working normally from re-employment until retirement

a=17.6%	r		
ρ	0.05	0.1	0.15
0	60478	35700	25273
0.05	34968	24576	19231
0.1	24576	19042	15780

Note: retirement age = 65 years; average individual age is 24 years old; average fitted elapsed jobless duration is 6 months; average fitted real monthly wage is 1565 euro.

Appendix 1. First step estimation: elapsed jobless duration determinants

Elapsed jobless duration: log(months)	Coef.	Std. Err.
Previous job occupation: trainers	-0.0378	0.1175
Previous job occupation: white collars	-0.2951 **	0.1057
Previous job contract: training-at-work	-0.1498	0.108
Previous job sector: construction	0.0392	0.0944
Previous job sector: wholesale, automotive, repair	0.1475	0.1004
Previous job sector: entertainment	-0.0843	0.1384
Previous job sector: transportation, communication	-0.3303	0.2369
Previous job sector: finance	0.3023	0.3361
Previous job sector: services, research, real estate	0.1655	0.1798
Previous working area: Northeast	-0.247 *	0.1007
Previous working area: Centre	0.1375	0.1063
Previous working area: South	0.3844 **	0.1149
Previous working area: Islands	0.323 *	0.138
Displacement year: 1990	-0.4107	0.3251
Displacement year: 1991	-0.5433	0.3012
Displacement year: 1992	-0.2675	0.3072
Displacement year: 1993	-0.1956	0.2979
Displacement year: 1994	-0.294	0.3274
Displacement year: 1995	-0.5636	0.3679
Tenure: log(months)	-0.2874 *	0.131
Previous job earnings: log(real monthly wage)	0.0733	0.1209
Post-jobless earnings: log(real monthly wage)	---	---
Lambda	-0.4491	0.368
Constant	2.5924 *	1.1176

Appendix 3. Selection equation

Probit Estimation (emp=1)	Coef.	Std. Err.
Age	-0.0553 **	0.0097
Previous job occupation: trainers	0.0835	0.0914
Previous job occupation: white collars	0.0599	0.0898
Previous job contract: training-at-work	0.2594 **	0.0767
Previous job sector: construction	-0.1799 *	0.0736
Previous job sector: wholesale, automotive, repair	-0.1449	0.0816
Previous job sector: entertainment	-0.0388	0.1197
Previous job sector: transportation, communication	-0.1524	0.1887
Previous job sector: finance	0.1882	0.3074
Previous job sector: services, research, real estate	-0.2893 *	0.1305
Previous working area: Northeast	0.1568	0.0941
Previous working area: Centre	-0.2430 **	0.0838
Previous working area: South	-0.3053 **	0.0796
Previous working area: Islands	-0.3786 **	0.0979
Displacement year: 1990	0.9038 **	0.1549
Displacement year: 1991	0.7217 **	0.1539
Displacement year: 1992	0.7746 **	0.1541
Displacement year: 1993	0.6537 **	0.1570
Displacement year: 1994	0.8393 **	0.1709
Displacement year: 1995	0.8549 **	0.2320
Tenure: log(months)	0.3361 **	0.1011
Previous job earnings: log(real monthly wage)	0.0910	0.1053
Constant	-0.6957	0.8101
log-likelihood	-1375.15	