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

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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 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 unemployment spells on wages as an indicator of human capital depreciation, or (to some degree) the wage effect of stigmatization. Sample selection and unobserved endogeneity issues are considered. Our results show the presence of a negative jobless duration dependence and a strong negative wage elasticity associated with the length of joblessness.

**Keywords:** joblessness, human capital depreciation, two stage least squares, selection problems

**JEL-codes:** J64, J24

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## 1. Introduction

In Italy, youth employment (20-29) steadily increased since the Sixties till 1990 (from 4.0 million in 1968 to slightly less than 5.0 million in 1990), a consequence of the baby boom, and of the increased participation of young women. The trend dramatically changed its course in the early Nineties before the 1993 recession: in 2002 dependent employment of the young was back to the level of the mid Seventies. Demography had its role – in the mid-Eighties, the baby boom cohorts peaked at 950 000 individuals each year. From then on this number declined steadily, reaching its bottom at 600 000 individuals in 2000. But demography is only one side of the story: while schooling increased, which is good news, the demand for young workers declined in spite of generous subsidies provided by the government, and this is very bad news. The number of new entrants sharply declined, while the cohorts already at work were ageing in absence of generational turnover. The modal age of employment entry hovered around 21 for many years: since the Nineties the outflow of youth workers from employment began to exceed the inflow within 3-4 years from entry. Net employment flows turned negative, indicating that a pattern of labor force utilization that might be called "the disposable commodity model" was already well under way before the cyclical downturn. Young people at the beginning of their working career have had a hard life since then.

Very hard indeed, whether they start as dependent workers (the vast majority, almost 90% of all new entries), or as self-employed. About 28% of young males starting their first job in the private sector as dependent workers 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] Where have all the others gone ? There are four possible non-observable outlets for the young "non-survivors": (i) a return to school; (ii) an outright decision to leave the labour force for whatever reason; (iii) a move in the parallel, hidden economy (unobserved by definition); (iv) a tenured hire from the public sector, and/or a choice of military/police career. The first is a sound choice, but ought to be followed by a re-entry in the labor market some time thereafter (which does not seem to be a frequent case). The second and third are quite possible, but obviously both have strong negative connotations (Contini and Villosio, 2001). The fourth one is the only positive option for a young person's career, but it is a rare event: since the late Eighties there have been no tenured hires of young people in the public sector, all the non-tenured positions being observable in our databases. The choice of a career in the military or police service involves a very small number of individuals each year.

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[1] WHIP data

What is the economic rationale behind these developments? Does a bad start carry negative effects on the following career ? How long do jobless spells impact on employability and future wages? 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 obsolete skills or find it impossible to make their specific human capital 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 labor market experience than older and more established workers, young adults may face a signaling problem associated with job loss (Farber 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 restrict our view to the young Italian workers who have been in employment at least nine months after entry, i.e. those who have had a relatively significant work experience. We assess if their jobless experiences in their 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 selection into employment and the endogeneity of jobless duration.

This paper contributes to the existing literature with fresh empirical evidence on the adverse effects of a period of joblessness in young people's careers in Italy. We emphasize 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 important in order to design useful policy. Moreover, no previous studies have analyzed young worker transitions in the Italian labor market using our framework and WHIP data.

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 wages[2]. 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, at least in

[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.

principle, 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 experience[3] between January 1989 and December 1993). Thus, we select out the least fortunate workers, i.e. those who have had a work experience shorter than 9 months. Such a selection is likely to introducer an "optimistic" bias in our results. Note, also, that we consider only individuals that experienced presumable involuntary separations since we exclude people that experienced job-to-job transitions. Individuals who 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.

Our data present two main problems. Firstly, in Italy displaced individuals may receive unemployment benefits or temporary layoff payments (CIG, Cassa Integrazione Guadagni), and we know that such benefits can bias our results.[5] Unfortunately, we do not have information on the benefits paid to workers. Notice, however, that, in our sample, only individuals working in construction (about 25% of the sample) are eligible, under specific conditions, for unemployment benefits.[6] Some individuals may also be eligible for temporary layoff payments and redundancy payments, but a cross check with the administrative data shows that less than 3% of the individuals in the sample received these payments. Second, we bypass the problem posed by mandatory military service by not counting as jobless spells those of individuals in draft age, employed by the same firm before and after the ten-month period corresponding to mandatory military service. At any rate most individuals complete military service before entering the labour market, and, therefore, this problem should not have a significant impact on our results.

[3] We assume that we are using the first working experience since the individual is young and he was not observed by Italian Social Security Administration database during the period 1985-1988.
[4] Of the initial sample of 3199 individuals, about 7% are re-employed with atypical contracts and 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) who are looking for jobs, mainly in the private sector. This must be kept in mind in order not to misunderstand the results.
[5] On the negative welfare dependent issue see, among the others, Contini and Negri (2005)
[6] Note that we also performed the analysis using the sample that not include individuals working in construction: the main results do not change.

### 3. The Model

*Transition out of joblessness*

In this section, we analyze 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 all individuals from the moment they 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, for each person, there are many data rows as there are time intervals at risk of the event occurring for each person. (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. It is well known 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 impact of joblessness on earnings of those individuals who re-enter the job market, we 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 of industry, 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 must face selection problems since a considerable fraction of the jobless individuals sample was not re-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 acceptance wages and jobless spell length (i.e. Addison *et all*., 2004). Therefore, the model can be written as

$$\log(w_a) = \mathbf{z_a}\,\boldsymbol{\gamma_a} + \alpha_a \log t + \beta_a \log(w_p) + u_a \qquad (1)$$

$$\log(t) = \mathbf{z}\,\boldsymbol{\gamma_d} + \beta_d \log(w_p) + u_d \qquad (2)$$

$$emp = 1\,(\mathbf{z}\,\boldsymbol{\gamma_{1e}} + \mathbf{x}\,\boldsymbol{\gamma_{2e}} + \beta_e \log(w_p) + u_e > 0) \qquad (3)$$

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, $\log(w_p)$, $\mathbf{z}$ and $\mathbf{z}_a$ represent the exogenous variables and $\boldsymbol{\gamma}_a, \alpha_a$, $\beta_a$, $\boldsymbol{\gamma}_d$, $\beta_d$, $\boldsymbol{\gamma}_{1e}$, $\boldsymbol{\gamma}_{2e}$, $\beta_e$ 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 $\mathbf{z}$.

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 stigmatization effects (Addison *et all.*, 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.

## 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. This pattern can be explained the existence of different groups of individuals: for example, one group of "quickly re-employed" individuals with an increasing hazard estimate, and another group of "slowly re-employed" individuals. Thus, heterogeneity across individuals could explain the shape of the hazard curve: this will be checked once controlling 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 differences in cumulative re-employment rates betweens young individuals working in different geographical areas. Individuals with a previous job working in Northern Italy have the highest re-employment rates: for example, after three years, about 72% of them had been re-hired, whereas the corresponding rate for those working in the Islands is about 51%.

We also find noticeable differences in the 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%).

The proportion of people remaining without a job were slightly higher for the young individuals who experienced separations during the 1993 recession.[7] Moreover, after three years, individuals aged 26 or over on into the jobless state have the lowest 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 joblessness 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(time) baseline hazard function and the estimates are presented for the pooled 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 all. 2004). Alternatively, negative dependence may be explained as a pure sorting of the more employable of the jobless workers as

[7] Differences in cumulative re-employment rates in 1989 and 1995 are due to sample construction

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 a more realistic 1.8%. For example, this implies that the doubling of a jobless spell duration (on average, from 6 to 12 months) will reduce the wage at re-employment by about 18%: for the average individual, it means a wage reduction from 1565 euros to 1283 euros. Therefore, such estimates suggest that, on average, there is an declining reservation wages / human capital depreciation/ stigma effects associated with longer jobless duration.

Note that the estimated elasticity of pre-jobless wages (when freely determined) is positive and about 4%. More notable findings are the positive effects of changes in working area (+16 %) and skill level (+ 29%), due to a switch to higher wage areas and higher qualification. Changes in sector have negative and statistically insignificant effects on wages. Also local regional unemployment rates have no direct statistical significant effects, although they indirectly will, via their impact on the duration of the jobless spell. 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.

## 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 1.8% 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.

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Figure 1. Smoothed hazard estimate

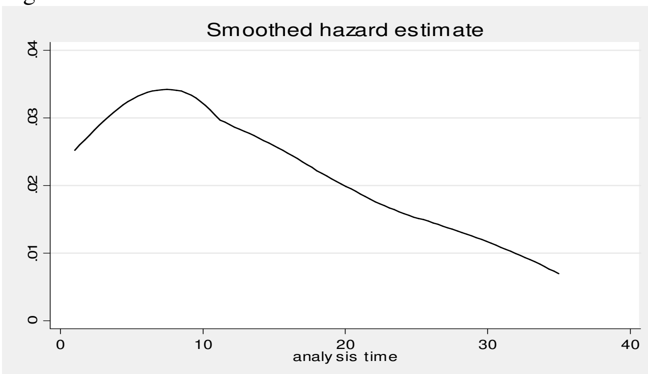


Figure 2. Kaplan-Meier survivor function (survivor in joblessness)

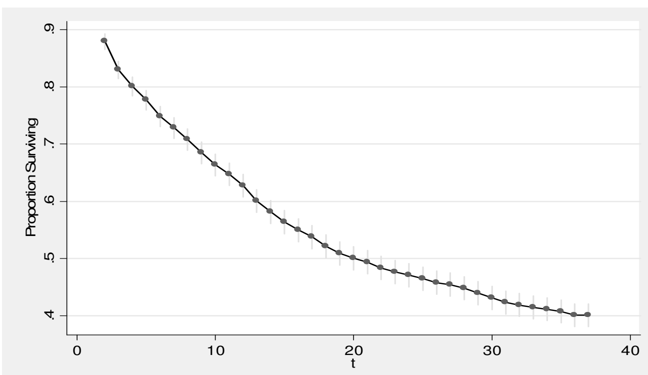


Table 1. Descriptive statistics

| | | | |
|---|---|---|---|
| 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 | 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)

| | Model A | | | Model B | | |
|---|---|---|---|---|---|---|
| Variables | 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

**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: trasportation, 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 2**. 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: trasportation, 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 | | |