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Skill development patterns and their impact on re-employability:

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Abstract: Our main objective is to assess the impact upon reemployment probabilities of school and/or vocational training attendance during unemployment spells.

According to Weiss' (1986) model return to schooling or training, while unemployed, should have an impact on reemployment probabilities since skill developments not only prevent obsolescence but also contribute to human capital growth. We use duration models to assess the impact of skill dynamics on life cycle trajectories, namely on the probability of getting a job after an unemployment spell.

The dataset used for estimation was selected from the Portuguese quarterly employment surveys (Inquérito ao Emprego) for the period between the 3rd quarter of 2002 and the 4th quarter of 2003.

We present estimates for the Weibull, the Cox proportional hazard (PH) and Prentice and Gloeckler (1978) models assuming continuous-time and discrete-time specifications.

There is no much difference in the estimates from these specifications and they seem to confirm that leaving unemployment becomes easier and/or unemployment spells smaller whenever education and/or training are present to compensate for qualifications obsolescence, all other things being equal (*ceteris paribus*).

We end up with some policy implications that might get support from the present as well as future results of this research.

J.E.L. J64; J24; I28

Key Words: life cycle trajectories; re-employability; duration models

1. INTRODUCTION

Some recent studies analysed skill development patterns along life cycle according to Weiss and his followers contributions to Human Capital theory and their impact on re-employability have been mostly estimated using duration models.

Our main objective in this paper is to study skill development patterns along the life cycle and their impact on life cycle trajectories, namely on reemployment probabilities in the Portuguese labour market. More specifically, we would like to assess the impact upon reemployment probabilities of school and/or vocational training attendance during unemployment spells.

Therefore this paper is organised as follows: section 2 discusses skill dynamics impact on life cycle trajectories on the basis of some of the most important theoretical approaches in this field; section 3 describes the database and the methodological approach; section 4 presents our main conclusions and section 5 raises some further research development topics and policy implications.

2. THEORETICAL FOUNDATIONS

Weiss and his followers' contributions¹ to Human Capital theory questioned Mincer's contribution and main developments, which stated that skills' development occur along life under a continuous and uninterrupted path, following the well known U-shaped curve.

That is the case, for instance, for the omission, along the activity life cycles, of inactivity and unemployment spells, due namely to growing contractual precariousness and recurrent unemployment features, frequently associated with return to schooling and vocational training.

That is why the new approaches on life cycle and human capital theory started to incorporate life cycle breaks and reversibility in their analytical framework.

From Weiss (1986) the stock of human capital growth rate along the life cycle (dK/dt) can be written as:

$$\frac{dK}{dt} = K_0 h g_1(K_t) - \delta g_2(K_t) \quad (1)$$

The first term, in the right hand side, represents the qualification constitution processes, whose strength rises with h , the share of working time associated with occupational qualifying experience, given an initial stock, K_0 ; and the second term has to do with qualification obsolescence, due to unemployment and/or inactivity spells, in

¹ Weiss, (1986); Ashenfelter & Layard (1986); Ashenfelter & Card (1999).

which qualification will depreciate at a rate equal to δ , unless some compensation processes, like schooling and/or vocational training attendance, will take place.

As to g_1 and g_2 , they are defined as follows:

$$g_1(K) > 0, \quad g_1'(K) < 0, \quad g_2(0) = 0, \quad g_2'(K) > 0 \quad (2)$$

meaning that, for a given \mathbf{h} , the human capital growth rate increases with the previously obtained capital stock but at a decreasing rate and that obsolescence is time increasing.

Following this approach, return to schooling or training while unemployed should have an impact on re-employment probabilities since skill developments not only prevent obsolescence but also contribute to human capital growth.

In this paper we use duration models to assess the impact of skill dynamics on life cycle trajectories, namely on the probability of getting a job after an unemployment spell.

According to some authors² duration models assume the duration of a spell, T , as a random variable with distribution $F(t) = P(T \leq t)$ and survivor function $S(t) = P(T \geq t)$ or the equivalent hazard function $h(t) = f(t)/S(t)$ where $f(t)$ is the density of T . Quoting Bollens and Nicaise (1994) the hazard function “represents the instantaneous probability of leaving unemployment at time t , given the individual was unemployed up to time t ”.

Using a proportional hazards model and the Weibull specification for the baseline hazard the survivor function can be written as:

$$h(x, t) = pt^{(p-1)} \cdot e^{-x\beta}$$

Where: p - parameter that indicates duration dependence from the time

profile of the hazard, which is identical to all individuals;

x - vector of individual's characteristics (sex, age, human capital variables – both supply and demand factors);

β - individuals' characteristics parameters.

Duration dependence will be negative if $p < 1$, positive if $p > 1$ and there will be no duration dependence if $p = 1$.

3. Database and methodological approach

Data

In this paper we use the raw dataset from the Portuguese quarterly employment surveys (Inquérito ao Emprego) for the period between the 3rd quarter of 2002 and the 4th quarter of 2003. The survey is a household type survey, conducted and administered by Instituto Nacional de Estatística (INE), the Portuguese statistical authority.

Each quarter the INE inquires a random sample of around 40.000 individuals where 1/6 of the sample is rotated out. For each individual the survey records approximately 150 answers including information about their sex, age, education level, vocational training, household composition, wages, and current and past labour status. At each quarter we know the state occupied by each individual (e.g., unemployed) and its elapsed duration. However, the elapsed duration gives us a biased image of the complete durations, known in the literature as *length biased sampling* [see for example Lancaster (1990)]. This is also known as stock sampling or left truncation. To avoid the complications of this kind of sampling, individuals within a state (unemployment) are followed over a period of up to 6 quarters until a failure or a censor occurs.

Our data comprise all individuals of ages 16-64 who were unemployed in the 3rd quarter of 2002, in a total of 1065.

Methodology and estimation

From a theoretical point of view, unemployment duration is a continuous random variable. However, observations are usually made discretely in time. In our dataset, elapsed durations are recorded in months and the forward unemployment transitions are observed over quarters.

In this paper we present estimates for the continuous and discrete-time models. In the discrete-time model we follow the approach presented in Prentice and Gloeckler (1978) [see also Jenkins (1995)]. The underlying continuous time model is summarized by the proportional hazard rate,

² Bollens and Nicaise (1994)

$$h(t | x) = h_0(t) \exp(x' \beta),$$

where $h_0(t)$ is the baseline hazard, x a vector of k covariates and β a vector of k unknown parameters. Since the available time durations are interval-censored the hazard function at interval j [$j \in (a_{j-1}, a_j]$, $j=0, 1, \dots, L$, with $a_0 = 0$ and $a_L = \infty$] is given by

$$h(j | x) = 1 - \exp[-\exp(\gamma_j + x' \beta)]$$

where

$$\gamma_j = \log \left[\int_{a_{j-1}}^{a_j} h_0(u) du \right],$$

is the integrated baseline hazard. This is also known as the complementary log-log (*cloglog*) model, a form of generalized linear model with the link function,

$$\log\{-\log[1 - h(j | x)]\} = \gamma_j + x' \beta.$$

Supposing random censoring with $\delta_i = 1$ if t_i is a failure (exit from unemployment) and $\delta_i = 0$ if t_i is censored, the likelihood contribution for individual i , still unemployed at the end of interval j , is given by

$$L_i = h(j_i | x_i)^{\delta_i} \prod_{j=1}^{j_i-1} (1 - h(j | x_i)).$$

This would be the likelihood in a random sample of entrants in a state of unemployment (flow sample). However, due to the nature of our sampling design (stock sampling and observation over a fixed interval), the likelihood must be modified. For each individual in the sample, unemployment duration must be conditioned on not having left the state of unemployment before the beginning of the 3rd quarter of 2002 (delayed entry). With delayed entry at u_i for individual i , the corrected likelihood must be divided by survival up to time u_i , i.e., by $P(T_i > u_i)$.

The discrete time-model is an approximation to some underlying continuous-time model. For some authors the grouping of time intervals does not introduce serious aggregation bias [see Bergstrom and Eden (1992) and Jenkins (1990)]. In spite of this we also computed estimations for the Weibull continuous-time model (with gamma

heterogeneity) and for the Cox proportional hazard (PH) model [see for example Kalbfleisch and Prentice (2002)].

The Weibull model is a proportional hazard model with a parametric baseline hazard defined by, $h_0(t) = pt^{p-1}$. The Weibull model with gamma heterogeneity has an additional parameter, θ . The Cox PH model is a semiparametric specification, not requiring the specification of $h_0(t)$ to estimate the parameters of interest, β .

4. Results

The estimation results are presented in tables 3 and 4 in the appendix. As pointed out, there is no much difference in the estimates from the discrete and continuous-time specifications which points to the robustness of our results.

For those in education (*in_edu*) there is a positive effect in the hazard function, meaning that they have a higher chance of leaving the state of unemployment compared to those who are not in education. However it is only significant at a 10% level in the cloglog model II (table 3).

Variables *age* and *age square* are also significant and the sign of their estimates points that young unemployed have smaller chances to leave unemployment than older ones but also that this age effect tends to reduce as age increases. For our database age seems to work better as a proxy for a long life experience than *tenure*, which is not significant. This result could also be due to an eventually high turnover rate, especially for the youngsters, preventing Weiss' *h* effect to meaningfully impart on human capital accumulation. In this situation, skills development would depend much more from each workers' general labour market experience than from a given occupation specific experience.

The probability of leaving unemployment at time *t* given that the individual has been unemployed until *t* is smaller for those with 9 years of education compared to those with more than 12 years of education (and we mean formal education). This result agrees with the Weiss model hypothesis according to which more education means an increased stock of human capital whose depreciation is not so fast and so should have a positive impact on reemployment probabilities. The fact that this is the only significant education dummy is due to the fact that 9 years is the compulsory number of years of education in

the Portuguese education system and so most of the individuals in the database have this degree of education³.

Being registered in a Public Employment Agency (*iefp*) seems hopeless for those unemployed. Actually, unemployed people appeal to these agencies' services mainly because they can't receive any unemployment benefit otherwise. This is an obvious sign of the inefficiency of such government services meant to help unemployed to find jobs.

5. Further research development topics and policy implications.

Our research outcomes seem to confirm one of the major hypothesis underlying human capital theories: leaving unemployment becomes more easy and/or unemployment spells smaller whenever education or training are present to compensate for qualifications obsolescence, all other things being equal (*ceteris paribus*).

However, this result needs further and more secure confirmation since the proportion of individuals *in-education* in our sample is rather small (7%). For that we will need a bigger number of cases characterised by simultaneous unemployment and education/vocational training attendance. A deeper insight in our research requires the availability of a larger dataset of unemployed individuals than is possible to obtain from the quarterly employment surveys we use in this paper. We hope that more surveys will be available in the near future.

As can be seen from table 2 there are in our sample some individuals with very long unemployment spells up to 243 months. This happens because we use the ILO unemployment definition and we didn't want to introduce more censoring in our data therefore measuring unemployment as far as it began in the past. However, these cases are very rare and not representative of the actual Portuguese labour market profile. One solution is to restrict the population, considering individuals who enter the state of unemployment in a shorter interval, for instance, between the 2nd Quarter of 1999 and 2nd Quarter of 2002.

Some duration models specify the baseline hazard so that it can detect duration dependence from the time profile of the hazard, which is identical to all individuals. Furthermore this time profile is frequently understood as representing economic cycle

³ The 75% quartile of the age distribution in the database is 45 years which corresponds to individuals for whom 9 years was the compulsory number of schooling years.

effects (v.g. Bollens & Nicaise, 1994). Those effects are supposed to hamper individual qualification outcomes during recession or alternatively to amplify it during expansion thereby affecting individual transitions from unemployment into the labour market, as well. Nevertheless such methodological approach demands a dataset that covers a period long enough to accurately encompass time trends that was not the case in the present research. Once again, we expect that a more suitable **database** will be available that will allow us to go deeper in our research.

In the light of the outcomes outlined, policy measures addressed to foster vocational training and formal education attendance among the unemployed seem to be quite advisable, especially if the skills to be provided are flexible enough and help to redesign industrial restructuring. The larger the unemployment spells and the lower the general qualification level, higher is the need for such qualification policies and programmes in order to compensate for corresponding human capital obsolescence.

Moreover, individuals with bottom line qualifications already affected by longer unemployment spells, also suffer from the well known ‘chimney effect’ thereby contributing to increase labour market inertia. In the Portuguese labour market, an insufficient demand for higher skills in most industries and occupations forces high qualified individuals to occupy unskilled or semi-skilled jobs thereby pushing downwards the less qualified ones for whom unemployment risk increases. Once in unemployment, reemployment opportunities for these unskilled workers are scarce since they also have very low levels of education and/or vocational training.

Labour market mobility policies should also play a major role in enhancing the reemployment chances. According to a recent study (OEFP, 2000) regional mobility in the Portuguese labour market has been very low.

The same study showed that most of the mobility flows seem to have been voluntarily depicted by individuals whose skills and qualifications are subject to misuse by previous employers which points to the existence of job mismatch. Job mismatch plays indeed a major role in our labour market, as Beveridge curves adjusted by OECD recurrently show⁴. Besides, during recession job mismatch situations risk to turn quickly into unemployment spells whose duration and reversibility strongly depend on each individual’s qualification. Leaving unemployment will therefore heavily depend on

⁴ See, for instance, OECD (2000), *Employment Outlook*.

policies toward better-adjusted job matches as well as policies that activate labor market fluidity on the basis of general qualification upgrading programs.

This paper and further research developments aim to be able to support such policy implications like:

- Assessing and evaluating both 2nd chance education and vocational training programs for the active population that can help decision makers to determine the extension of vocational training and other qualification programmes needed to compensate for unemployment spells' obsolescence;
- Improving the fine-tuning of infra annual flows assessment, be they job-to-job or job-to-unemployment/inactivity and vice-versa on the basis of a more accurate set of turnover indicators.

Furthermore, this approach by allowing the forecast of reemployment probabilities will enable decision makers to address such features as:

- Higher education graduates' reemployment and the corresponding job-matching quality;
- Possible "chimney effects" and the corresponding increase in the eviction of bottom line qualifications which affects long-term unemployment and thereby hysteresis intensity.

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- **Appendix**

Table 1: Variables in the model

| | |
|------------|---|
| Dfam | Number of individuals in the household |
| Age | Age in years |
| Marr | =1 if married; =0 otherwise |
| Male | =1 if male; =0 if female |
| pr_job | =1 if had previous jobs; =0 if searching for 1 st job |
| edu0 | =1 if has less than 4 years of education; =0 otherwise |
| edu4 | =1 if has 4 years of education; =0 otherwise |
| edu9 | =1 if has 9 years of education; =0 otherwise |
| edu12 | =1 if has 12 years of education; =0 otherwise |
| edusup | =1 if more than 12 years of education (graduation, pos-graduation) |
| oth_edu | =1 if has other education |
| in_edu | =1 if is in education; =0 otherwise |
| Tenu | Number of months since start in the first job |
| Iefp | =1 if is registered in a Public Employment Agency; =0 otherwise |
| Iefp_benef | =1 if is registered in a Public Employment Agency and receives benefits |
| Cens | Censoring indicator (=1 if an exit from unemployment; =0 if censored) |
| dur (t) | Unemployment duration in months |

Table 2: Summary of the data

| Variable | Mean | Std. Dev. | Min | Max |
|------------|--------|-----------|-----|-----|
| Dfam | 3.81 | 1.51 | 1 | 11 |
| Age | 34.29 | 13.02 | 16 | 64 |
| Marr | 0.48 | 0.50 | 0 | 1 |
| Male | 0.44 | 0.50 | 0 | 1 |
| pr_job | 0.83 | 0.38 | 0 | 1 |
| edu0 | 0.05 | 0.22 | 0 | 1 |
| edu4 | 0.30 | 0.46 | 0 | 1 |
| edu9 | 0.41 | 0.49 | 0 | 1 |
| edu12 | 0.13 | 0.33 | 0 | 1 |
| edusup | 0.10 | 0.31 | 0 | 1 |
| oth_edu | 0.10 | 0.30 | 0 | 1 |
| in_edu | 0.07 | 0.25 | 0 | 1 |
| Tenu | 197.26 | 185.46 | 0 | 690 |
| Iefp | 0.66 | 0.47 | 0 | 1 |
| iefp_benef | 0.26 | 0.44 | 0 | 1 |
| cens | 0.52 | 0.50 | 0 | 1 |
| dur (t) | 20.25 | 24.08 | 3 | 243 |

Table 3: Discrete-time model (cloglog)

| Variables | Model (*) | |
|------------|-------------------------|-------------------------|
| | I | II |
| P1 | ... | -1.065155 (.4993474) |
| P2 | ... | .3307893 (.4746939) |
| log(t) | .1289084 (.0415882) | ... |
| dfam | .0520994 (.029371) | .0568617 (.0294466) |
| age | -.0796888 (.0251373) | -.0820132 (.0248809) |
| age2 | .0008886 (.000317) | .0009317 (.0003157) |
| male | -.0864233 (.0899642) | -.1103594 (.0901428) |
| marr | .1501023 (.1087117) | .1460944 (.1082413) |
| pr_job | .1819433 (.1433075) | .1805144 (.1426429) |
| tenu | .0007796 (.0006786) | .0008076 (.0006766) |
| edu0 | -.1655696 (.2384279) | -.2541978 (.2383566) |
| edu4 | -.3196548 (.1762485) | -.3829298 (.1743898) |
| edu9 | -.342324 (.1586327) | -.413958 (.1576962) |
| edu12 | -.350194 (.1833168) | -.3941944 (.1822714) |
| in_edu | .272352 (.1722402) | .3195659 (.1718554) |
| iefp | -.5147694 (.1012892) | -.5567614 (.1005394) |
| iefp_benef | -.223616 (.1236875) | -.2749514 (.1233267) |
| _cons | -.2147277 (.4712049) | ... |
| | | |
| Log lik | -1385.2707 | -1353.4734 |

(*) Model I has a parametric baseline hazard given by $\log(t)$. It is comparable to the Weibull specification in the continuous-time case. Model II has a flexible baseline defined as a step function where $P1=1$ if $t \leq 3$ and $P2=1$ if $t > 3$.

Table 4: Continuous-time model (Cox PH and Weibull)

| Variables | Model (**) | | |
|------------|-------------------------|-------------------------|-------------------------|
| | III | IV | V |
| dfam | .0578979 (.030218) | .0546252 (.0294552) | .0924403 (.0437501) |
| age | -.0762119 (.0257768) | -.0805354 (.0252115) | -.1006554 (.0371744) |
| age2 | .0009338 (.0003227) | .0009412 (.0003183) | .0011308 (.000449) |
| male | -.1010887 (.0911607) | -.0776618 (.0899766) | -.1244181 (.1272112) |
| marr | .1023166 (.1102448) | .1593185 (.1085944) | .1896877 (.1508482) |
| pr_job | .0713924 (.1466027) | .1769711 (.1433933) | .237645 (.1962403) |
| tenu | .0006415 (.0006625) | .0005723 (.0006657) | .0008998 (.0009282) |
| edu0 | -.1162371 (.2438753) | -.1903521 (.237305) | -.2176584 (.3304322) |
| edu4 | -.2023219 (.1806197) | -.2645565 (.1756571) | -.2970827 (.2385502) |
| edu9 | -.2576134 (.1622508) | -.2951356 (.1581801) | -.4318796 (.2193326) |
| edu12 | -.2484499 (.1855899) | -.3104589 (.1828876) | -.2708281 (.2399607) |
| in_edu | .2084327 (.1725296) | .2676762 (.1716945) | .3560805 (.2219991) |
| iefp | -.4829205 (.1033244) | -.5129379 (.1014807) | -.769218 (.1620667) |
| iefp_benef | -.2537148 (.1257258) | -.2358012 (.123633) | -.3331793 (.1700479) |
| _cons | ... | -1.077815 (.4719587) | -1.591991 (.6583935) |
| p | ... | 1.100285 (.0428436) | 1.531782 (.1987087) |
| theta | ... | ... | .2738681 (.1422805) |
| Log lik | -2652.1724 | -468.83764 | -463.21828 |

(**) Model III is the Cox PH model. Model IV is the Weibull model with parameter p and Model V is the Weibull with gamma heterogeneity with parameter theta.

