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Vladislav Flek[a]*, Martin Hála[b] and Martina Mysíková[c]

[a]*Department of International Relations and European Studies, Metropolitan University Prague, Prokopova 16, 130 00 Prague 3, Czech Republic; [b]Department of International Trade, Metropolitan University Prague, Prokopova 16, 130 00 Prague 3, Czech Republic; [c]Research Support Centre, Metropolitan University Prague, Prokopova 16, 130 00 Prague 3, Czech Republic*

We estimate the impact of unemployment duration on exits from unemployment, along with a set of individual and other explanatory variables. The analysis is based on EU-SILC longitudinal data for the period 2007–2010 and involves Spain and the Czech Republic as examples of the two EU countries with remarkably different labour market performance but similar in their totalitarian past, post-transition economies and recent EU entry. Survival functions estimates point uniformly to prolonged unemployment duration and increasing long-term unemployment. However, both these tendencies apply relatively more to the young unemployed. Estimations of hazard models indicate that shorter unemployment spells are more likely to be terminated by finding a job in comparison with spells lasting for more than one year. The hazard ratios are usually higher for prime age unemployed. Finally, we examine education, gender, household size, etc., as determinants of exits from unemployment, with uniform evidence found for university graduates only.

Keywords: duration dependence; EU-SILC; Kaplan-Meier survival functions; labour marginalisation; long-term unemployment; proportional hazard models

JEL classification: C00, E24, J6, P20

1. Introduction

In this paper we are interested in the impact of unemployment duration on job finding prospects of young unemployed in comparison with their prime-age counterparts, and in the evolution of these prospects during the Great Recession (world's economic and financial crisis of 2007–2010). We also examine within both categories of unemployed the role of age, education, gender, family size and other characteristics as determinants of exits from unemployment. In general, factors such as educational mismatch, lack of firm-specific skills and lack of work experience are among the most frequently mentioned causes of high youth unemployment in Europe. The practice of fixed-term labour contracts, seniority-weighted redundancy payments or last-in first-out rules also contributes to high unemployment of young people (Bell & Blanchflower, 2011; ILO, 2013; McGuinness & Wooden, 2009; Quintini & Manfredi, 2009). The Great Recession had amplified all of the already existing difficulties of young people on the

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*Corresponding author. Email: vladislav.flek@mup.cz

labour market, a situation which resulted in further disproportionate increases in youth unemployment rates (ECB, 2012). We intend to contribute to this discussion by reflecting the consequences of the Great Recession on the employability of those currently unemployed.

Labour force marginalisation can be viewed as one of the main factors preventing the unemployed individuals from efficiently competing for jobs: With increasing unemployment duration, job search intensity/efficiency is generally expected to decline as a result of frustration from unsuccessful search, loss of contacts with relevant social networks, and unwillingness of firms to hire those stigmatised by eroded work skills and discipline. With such attitudes marginalised labour force emerges, whose employment prospects are a decreasing function of unemployment duration (Blanchard, 1999; Shimer, 2007). Marginalisation, in turn, leads to social exclusion and polarisation, poor health, child poverty and family problems, to name but some of the most adverse consequences of marginalisation.[1]

Bell and Blanchflower (2011), Brauksa and Fadejeva (2013) or Kelly, McGuinness, O'Connell, Haugh, and Pandiella (2013) point to the possible presence of duration dependence and marginalisation in youth unemployment during the Great Recession. Yet, cross-country comparisons as well as comparisons between the age groups are still rather scarce. Therefore, we offer an additional analysis of these issues for Spain and the Czech Republic. These countries differ substantially in level of aggregate or youth unemployment rates, size of labour markets, institutions and applied policies.[2] Despite substantial differences in national labour markets' functioning and institutional or policy design, youth unemployment rates nearly doubled in both Spain and the Czech Republic during the Great Recession, while the upward aggregate (prime-age) unemployment rate dynamics was relatively less rapid. Within this context, the issue of marginalised young labour force is potentially gaining in relevance for both countries' policies.

For our proposed analysis we explore the Kaplan-Meier survival functions and proportional hazard models (Cox, 1972; Jenkins, 1997; Kaplan & Meier, 1958). These approaches and the specific research questions are formulated in more detail in the following section. In general, our aim is to indicate the extent to which EU countries with remarkably different youth unemployment rates face the same trends and common policy challenges with regard to the presence of long-term young unemployed. The estimation results might differ quantitatively but not necessarily in qualitative terms and policy messages.

Alternatively, our model estimations might point to the necessity of developing purely country-specific approaches towards various activation policy measures aimed at the employability of young people who stay without a job for prolonged periods. This concerns the possible cross-country differences in the lengths of unemployment spells within which the job search of young unemployed is already most/least successful. In such a case, the policy's priorities in each country would have to be formulated differently and target the different groups of young people according to the length of their unemployment episodes. In addition, our analysis of long-term youth unemployment might reveal the different, country-specific risk factors (individual and other characteristics) linked with the poor prospects of leaving unemployment and finding a job.

The longitudinal micro data we use were made available to us from Statistics on Income and Living Conditions (EU-SILC). These data are described in Section 3 and then used for computations in the sections to follow. Specifically, in Sections 4 and 5 we estimate the impact of unemployment duration on prospects of exiting

unemployment and becoming employed among the young and prime-age workers, along with a set of additional explanatory variables. The final section concludes.

2.   Estimation methodology

Some studies on duration dependence apply a probit regression model. Albert, Toharia, and Davia (2008) follow this direction when analysing school-to-work transitions in Spain. The probit model has among others also been used by Kelly et al. (2013), who analyse youth transitions from unemployment into employment in Ireland. A probit model is a type of regression model where the dependent variable can take two values (e.g. being 1 in case of 'yes' or 'male' or 0 in case of 'no' or being female). The purpose of the probit model is to estimate the probability that an observation with particular characteristics is going to fall into a specific category. It can be also said that the probit model is a type of binary classification model.

However, as we intend to utilise fully the longitudinal structure of our data, we consider unemployment as a time-related process. This is why, in our case, a duration model is likely to be more appropriate.

This is in line with e.g. Albert et al. (2008), who initially provide probit regression estimates but subsequently turn to a duration model as a better way to capture the time-related process. Other examples of applying duration models include analysis of unemployment durations of young people in France (D'Addio, 1999); retirement decisions in Britain (Disney, Emmerson, & Wakefield, 2006); labour mobility in Latvia (Brauksa & Fadejeva, 2013) or employment decisions after the birth of the first child in Spain (Davia & Legazpe, 2014).

The Kaplan-Meier estimator (Kaplan & Meier, 1958) serves as a preliminary step preceding the estimation of a duration model. It represents a non-parametric estimate of the survival function $S(t)$ that captures the probability of survival past time t. In our analysis, 'survival' means the period of time when an individual remains unemployed; time t is measured in months. Kaplan-Meier estimate of the survival function at any time t is:

$$\hat{S}(t) = \prod_{j|j \leq t} \frac{n_j - d_j}{n_j} \tag{1}$$

where n_j is the number of unemployment spells lasting at least j months, and d_j is the number of such spells transitioning into employment immediately after j months. Using STATA commands and routines, we evaluate point estimates and 95% confidence interval estimates of $S(t)$ for both age groups in countries and periods of our interest. We apply log-rank tests for equality of survival functions. Figure 1 and Table 1 in Section 4 summarise the estimation results and provide a variety of answers to questions related to a diminishing employability of young and prime-age unemployed in the course of the Great Recession.

The estimated survival function (1) could be transformed into a hazard function, defined as d_j/n_j at any time t (see Figure A.1 in the Appendix 1). This function can be treated as preliminary estimate of a baseline hazard function in a duration model but without any explanatory variables. This is further developed and controlled for a set of individual, family and other characteristics further in the present section.

In duration model estimations we build up on a discrete-time proportional hazard model introduced by Cox (1972) and further developed by Prentice and Gloeckler
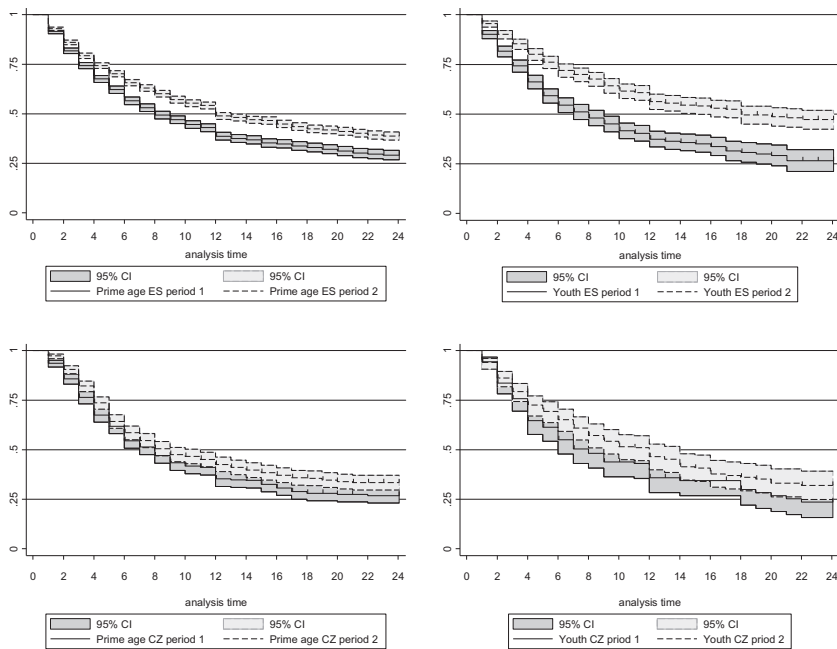
Figure 1.   Probabilities of remaining unemployed over time (Kaplan-Meier survival function esti-
mates for prime-age and young individuals in Spain and the Czech Republic; period 1: 2007–
2008; period 2: 2009–2010).
Sources: EU-SILC LONGITUDINAL UDB 2009, version 4 of March 2013; EU-SILC LONGI-
TUDINAL UDB 2011, version 1 of August 2013. Authors' computations. Note: Analysis time
stands for lengths of unemployment spells in months. Log-rank tests reject the null hypothesis of
equality of survival functions for the two periods in each diagram.

Table 1.   Mean and median survival time (in months).

	Spain				Czech Republic			
	Youth		Prime-age		Youth		Prime-age	
Period	2007–2008	2009–2010	2007–2008	2009–2010	2007–2008	2009–2010	2007–2008	2009–2010
Arithmetic mean – completed U spells	4.7 (3.8)	6.2 (4.5)	5.1 (4.1)	6.0 (4.8)	5.4 (4.6)	6.1 (4.9)	5.7 (4.3)	6.0 (4.2)
Arithmetic mean – all U spells	6.5 (5.5)	10.0 (7.0)	7.4 (6.2)	9.7 (7.3)	7.0 (6.2)	8.3 (6.9)	8.2 (7.2)	9.1 (7.5)
Kaplan-Meier Restricted mean	11.3 (0.38)	15.4 (0.36)	11.7 (0.19)	13.8 (0.17)	11.3 (0.67)	12.9 (0.58)	11.3 (0.35)	12.5 (0.34)
Kaplan-Meier Extended mean	16.1	30.5	17.4	23.6	15.2	19.6	16.1	19.8
Kaplan-Meier Median survival time	8 (0.56)	18 (–)	8 (0.33)	12 (0.51)	8 (0.99)	12 (1.26)	8 (0.43)	9 (0.70)

Sources: EU-SILC LONGITUDINAL UDB 2009, version 4 of March 2013; EU-SILC LONGITUDINAL
UDB 2011, version 1 of August 2013. Authors' computations.
Note: Standard deviations or standard errors in parentheses.

(1978). Meyer (1990) adapted this model to control for unobserved heterogeneity, while Jenkins (1997) implemented it into a STATA routine, pmghaz. We use a refined version (pmghaz8) authorised by Stephen Jenkins and applied by, for example, Disney et al. (2006); Albert et al. (2008); or Davia and Legazpe (2014).

Hazard models use the concept of a hazard rate $\lambda(t)$. In our case, the hazard rate represents the instantaneous probability of exiting unemployment and moving into employment at time t conditional to having remained unemployed until the moment immediately before t. The general definition of continuous hazard rate is:

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \qquad (2)$$

where T is the duration of an unemployment spell (here the number of months over which a randomly chosen individual remains unemployed).[3] The proportional hazard model assumes that continuous hazard rate for the ith spell bears the following form:

$$\lambda_i(t) = \lambda_0(t) \cdot e^{X_i'(t) \cdot \beta} \qquad (3)$$

In equation (3), $\lambda_0(t)$ stands for the so-called baseline hazard. $X_i(t)$ is a vector of covariates (explanatory variables), such as age of the individual, gender, level of education, etc. β denotes a vector of parameters to be estimated. Finally, the term $e^{X_i'(t) \cdot \beta}$ represents a proportional shifter – the observed explanatory variables shift the entire hazard rate up or down. Note that covariates $X_i(t)$ may generally depend on time. In our analysis all covariates are treated as time-invariant, so we can simplify the notation and write X_i instead of $X_i(t)$.

As our data are grouped by months, we have to use a discrete-time model. Generally, if duration data are grouped into p intervals with the ith interval defined as $[a_{j-1}, a_j]$, the hazard function in the jth interval would represent the conditional probability of leaving unemployment and moving into employment within the interval $[a_{j-1}, a_j]$, given that the duration of the unemployment spell is at least a_{j-1}. In mathematical terms:

$$h_j(X_i) = \Pr(a_{j-1} \leq T < a_j | T \geq a_{j-1}) \qquad (4)$$

When applying previous assumptions and notation, the model we use bears the following general form:

$$h_j(X_i) = 1 - e^{-e^{(X_i' \beta + \gamma_j)}} \qquad (5)$$

where, for each duration interval, the parameter γ_j represents the natural logarithm of the baseline hazard over the relevant interval. In our analysis we use five different duration intervals: $j = 1$ represents first two months of unemployment spell; $j = 2$ denotes a spell lasting 3–4 months; $j = 3$ stands for spells of 5–6 months; $j = 4$ for spells between 7 and 12 months; and finally $j = 5$ represents spells of 13–24 months. The vector of covariates X_i consists of an age variable defined in years; a household size variable defined as the number of household members; a dummy variable for male; two dummies for the highest attained levels of education (secondary and tertiary); and two dummies for densely and medium-populated place of residence.

STATA routine pmghaz8 provides log likelihood estimates of all coefficients of the model and confidence interval estimates. For the sake of better interpretation, the coefficients are transformed into hazard ratios. Estimation results presented later in Table 2 thus mean e^{β} rather than β (standard errors and confidence intervals are also transformed). Suppose for instance that the hazard ratio reported for males takes the value of

Table 2. Hazard ratios of transition from unemployment to employment (not controlled for unobserved heterogeneity unless stated otherwise).

| | Spain | | | | | Czech R. | | | |
| | Youth | | | Prime | Age | Youth | | Prime | Age |
Period	2007–2008	2007–2008ˣ	2009–2010	2007–2008	2009–2010	2007–2008	2009–2010	2007–2008	2009–2010
γ_1 (1–2.month)	2.984***	*1.080*	3.123***	3.737***	3.613***	1.323	1.675*	2.714***	1.750***
γ_2 (3–4.month)	3.124***	*1.423*	3.655***	3.571***	3.594***	2.064*	2.009**	4.391***	3.782***
γ_3 (5–6.month)	3.070***	*1.737*	3.329***	3.410***	3.065***	1.416	1.272	3.882***	4.439***
γ_4 (7–12.month)	2.063**	*1.501*	2.625***	2.444***	2.405***	1.541	1.428	2.759***	2.191***
Male	0.982	*0.962*	1.081	1.091*	1.102**	1.511**	0.784	1.100	1.355***
Tertiary education	1.748***	*2.068***	1.338*	1.204***	1.294***	6.247***	2.471*	2.284***	2.905***
Secondary education	1.131	*1.160*	1.159	1.118*	1.032	3.086***	1.605**	1.719***	1.627***
Age	1.046***	*1.079***	1.103***	0.989***	0.991***	0.983	1.026	0.984***	0.989**
Household size	0.893***	*0.838***	0.917**	0.940***	0.932***	0.845**	0.869**	0.978	0.948
Densely populated area	0.914	*0.916*	0.574***	0.743***	0.703***	0.453***	0.517***	0.836***	0.827
Medium-populated area	1.022	*1.087*	0.788	0.682***	0.782***	0.594**	0.628**	0.771**	0.884
Constant	0.019***	*0.038***	0.003***	0.058***	0.040***	0.064***	0.042***	0.038***	0.029***
Log-Likelihood	−1442.1	*−1439.98*	−1252.1	−5631.36	−6862.55	−415.8	−571.9	−1581.8	−1669.25

Sources: EU-SILC LONGITUDINAL UDB 2009, version 4 of March 2013; EU-SILC LONGITUDINAL UDB 2011, version 1 of August 2013. Authors' computations.
x results with controls for unobserved heterogeneity.
Notes:
*significant at 10%
**significant at 5%
***significant at 1%.

'2'. This would indicate a higher 'hazard' of transitioning from unemployment into employment for men than for women. More precisely, the probability that a man moves in a randomly chosen time from unemployment into employment would be, ceteris paribus, twice as high as for a woman.

The model described so far assumes that the set of covariates can capture all the existing individual differences. Such an assumption might be too far-fetched in practice because of the presence of unobserved differences between the individuals; so it is advisable to control for unobserved heterogeneity. The routine pmghaz8 uses the mixed proportional hazard model where the continuous hazard rate is assumed to have the form:

$$\lambda_i(t) = \lambda_0(t) \cdot \varepsilon_i \cdot e^{X_i'(t) \cdot \beta} = \lambda_0(t) \cdot e^{X_i'(t) \cdot \beta + \ln \varepsilon_i} \qquad (6)$$

where ε_i is a gamma-distributed random variable with unit mean and unknown variance which has to be estimated (Jenkins, 1997). Likelihood ratio tests then point to the (in) significance of unobserved heterogeneity in estimated models.

Our methodology is designed to address the following research questions and to compare the results obtained for the young and prime age unemployed: if the coefficients (hazard ratios) for chosen duration intervals γ_{1-4} prove their statistical significance, it would indicate that unemployment duration indeed matters in determining the chances to find a job. In the opposite case it would signal that the impact of the Great Recession on job finding chances has been so destructive that unemployment duration per se plays no significant role.

As for gender differences we test whether unemployed men are more likely to find a job than unemployed women within any given length of unemployment spell. In other words, we intend to find arguments suggesting or rejecting the presence of gender-specific patterns (discrimination) in transitions from unemployment to jobs, associated for example with presumed lower reliability of women as potential employees because of childcare or executing other family or household duties.

We expect to confirm a decisive role of education on transitions from unemployment to employment, with the highest expected positive impact of tertiary education. Investigating the role of age would reveal to which extent the potential employers associate the elderly unemployed with skill obsolescence and deterioration in accumulated human capital. Simultaneously, in case of young unemployed, the impact of age would tell us whether employers tend to hire young unemployed with some previous employment record and accumulation of working experience/discipline, or prefer to hire the unemployed at the very beginning of their working careers.

The coefficient of household size variable, if significant and negative, can be associated with other members (parents) contributing decisively to the common budget, which makes the unemployed feel less pushed to search for a job. The last explanatory variable involved in our analysis is densely populated area. Based on the assumption that bigger cities offer more job opportunities, we intend to test if it really holds that the more densely populated the living area, the higher the probability to exit from unemployment and enter into employment.

3. The data

The longitudinal EU-SILC makes it possible to identify each respondent's labour market status (i.e. employment, unemployment, and inactivity) and its changes on monthly

basis. In addition, this annual survey with retrospectively stated monthly economic activity contains a set of additional variables relevant for our purposes, such as age, gender and education, as well as information on family size, degree of urbanisation, etc.
[4] Monthly information on labour market status can potentially minimise the time aggregation bias, which is inherently present in longitudinal analyses, e.g. European Union Labour Force Survey (EU-LFS) with its quarterly structure of information. The EU statistics on income and living conditions (EU-SILC) is a comparative statistics on income distribution and social inclusion in the EU countries. It was created in 2003 on the basis of a special agreement between Eurostat and Austria, Belgium, Denmark, Greece, Ireland, Luxembourg, and Norway. It was formally launched in 2004 in 15 countries and expanded in 2005 to cover all of the EU Member States (together with Norway and Iceland).

The main advantage of longitudinal EU-SILC is the practical possibility of conducting international comparative analyses of changes in an individual′s labour market status, depending on the duration of the previous status. The use of longitudinal EU-LFS for such international comparative analyses still remains considerably limited since it is not routinely available for research purposes. At the same time, one has to be aware of potential drawbacks of EU-SILC, the retrospective nature of reported economic activity and its self-declared character among others. This may create the well-known calendar bias in the data and also lead to deviation from the ILO definition of unemployment.

The natural option would be to make use of the most recent full four-year panel of EU-SILC 2011 and thus fully exploit the longitudinal element of monthly economic activity for the period 1/2007–12/2010. However, we are particularly interested in a group of young individuals, namely in those aged 16–24 at the beginning of the analysed period, which rules out the possibility to utilise the full four-year panel due to a small number of respondents. Instead, we decide to extract two two-year periods from EU-SILC 2009, which covers monthly economic activity for 1/2007–12/2008, and EU-SILC 2011, which involves the period 1/2009–12/2010. Both of these subsamples contain substantially more respondents than the full four-year panel.

As the reference group prime-age population aged between 25 and 54 at the beginning of both analysed periods was selected. Only those respondents of both age categories who fully participated in these two-year surveys have been subject to further analysis. Thus, our two subsamples (2007–2008, 2009–2010) can be viewed as pure two-year panels. Our subsamples eventually consist of 1757 and 1560 young Czechs and 2391 and 2271 young Spanish for the respective periods. The other groups include 6554 and 5655 Czechs, and 10,198 and 9929 Spanish prime-aged workers.

Our subsamples are further limited to those individuals who experienced unemployment during the observed periods (10–25% of their original sizes in the first analysed period; 13–27% in the second period). Note however that the unit of our analysis is an unemployment spell, not an individual. An individual might experience more than one unemployment spell in the analysed period. Hence, each of her/his unemployment spells enters the analysis as a separate observation (so-called 'multi-episode'). For the sake of clarity, we continue to refer to respondents or individuals, but some of them actually represent more than one observation.

The data used are naturally censored. We call a particular unemployment spell left-censored when it is already in progress at the beginning of the observed period. Right-censored are unemployment spells that do not terminate by the end of the observed period. An additional specific type of right-censoring occurs when an unemployment spell ends in inactivity rather than employment. These types of censoring

cause certain difficulties which we face in our proposed model estimations. If we drop the censored observations from the data, the mean unemployment duration would become downward-biased because longer unemployment spells are more likely to be censored than the short ones.

For this reason we keep all the censored observations in the data-set; yet, by doing so, we face in turn the problem that the actual length of an unemployment spell remains unknown for censored observations. Hence, when building up the estimation models we introduce a censoring indicator which equals 1 if unemployment spell terminates by employment, and 0 in all other cases. The models applied are designed to consider the right-censored data, while left-censoring remains generally unaddressed by estimation techniques available to us.

4.   The results of survival functions estimates

Figure 1 involves a set of diagrams with Kaplan-Meier survival functions. The horizontal axes depict the observed lengths of unemployment spells in months (t), while the vertical axes represent the shares of open spells after t months. All survival curves start from point '1', meaning that all unemployment spells are open at $t = 0$. The slopes are declining over time, in line with the emergence of closed spells.

The survival function is an estimate that reflects the right-censoring mentioned in the previous section. Specifically, one part of right-censored observations is actually distributed above the survival curve and another one below the curve. Yet, for the sake of clarity, we interpret the points at each survival curve as the fraction of those who were unemployed at time $t = 0$ and still have failed to find job until time t. Alternatively, we indicate how many months of unemployment duration are needed for a given fraction of the unemployed to find a job. By doing so we are aware of the fact that our results do not reflect only the values directly observed in the data but also the estimates for right-censored observations.

In all diagrams in Figure 1, the survival functions for 2009–2010 are placed above the functions for 2007–2008. This can be interpreted as an indication of longer unemployment spells (or of a longer time of job search needed to exit from unemployment) in the peaking period of the Great Recession. To illustrate this point, let us look at the following example. In 2007–2008, 35% (45%) of young unemployed in the Czech Republic managed to find a job after an unemployment spell lasting for four (six) months. In the period 2009–2010, the number of months necessary to achieve the same rate of exits of Czech young individuals from unemployment to employment increased to 6 (9) months.

The right upper diagram shows that in this respect the young unemployed in Spain were far worse off: in 2007–2008, 45% of young unemployed in Spain succeeded in finding jobs after an unemployment spell of six months. But in the period 2009–2010, the number of months required to reach the same rate of exits from unemployment to employment increased to 14 months. The prolonged lengths of mean and median unemployment spells between 2007–2008 and 2009–2010 for both countries and age groups of interest are documented in Table 1.

The two upper diagrams in Figure 1 suggest the presence of disproportionate increases in long-term unemployment of young people in Spain compared with their prime-age counterparts. Note for instance that the share of young people whose unemployment spells lasted at least for 12 months accelerated dramatically in Spain, namely from 37% in 2007–2008 to 56% in 2009–2010. At the same time, the share of Spanish

prime-age unemployed with unemployment spells lasting at least 12 months increased from 39 to 49%. While it started in 2007–2008 at more or less comparable figures with prime-age unemployed, the situation of young long-term unemployed in Spain has worsened relatively more dramatically.

The two bottom diagrams suggest that the Czech Republic was also suffering from relatively high and disproportionally developing long-term unemployment of young people. The share of young unemployed with unemployment spells lasting at least 12 months jumped from 36% in 2007–2008 to 46% in 2009–2010, while the same figure for prime-age unemployed rose from 35% to 43%. In both countries it is thus likely that the proportion of young long-term unemployed was increasing more rapidly and eventually overtook the prime-age workers.

Table 1 provides a more detailed view on average lengths of unemployment spells. The first row reports arithmetic means of completed (closed) unemployment spells only. When comparing both periods of interest we see a uniform tendency of increasing the mean lengths of unemployment spells in both countries and age groups analysed. Results in the remaining rows tell us in principle the same story, but the figures are much higher compared with those in the first row. This is in line with the assumption that longer unemployment spells are more likely to be censored, and hence, analysing only completed unemployment spells would strongly underestimate the population mean.[5] The disproportions in mean unemployment spells between the prime-age and young unemployed are apparent especially in 2009–2010 when the mean youth unemployment spells were, in general, longer. This finding holds with full uniformity for Spain while for the Czech Republic the results are rather mixed, depending on the mean indicator chosen.

The samples of unemployment spells are usually skewed. Therefore, as an indicator of the central location, the median is more appropriate than the mean. The median survival time is the shortest unemployment spell for which the survival function equals or is less than 0.5. Measured in integer months, in 2007–2008 the median was eight months for both countries and age groups of our interest. When looking at period 2009–2010, the median values rose for both age groups more considerably in Spain than in the Czech Republic. Viewed from another perspective, the median unemployment spells in 2009–2010 were clearly higher for young unemployed than for prime-age ones. In Spain, this gap was much deeper.[6]

5.   Estimation results of proportional hazard models

The first four rows in Table 2 involve the duration intervals γ_{1-4}. The hazard ratios indicate the probability at which each of these four unemployment spells terminate by employment, relative to a chance to find a job within a reference unemployment spell lasting 13–24 months. The remaining rows report the impact of explanatory variables on the probability of moving from unemployment to employment for any past unemployment spell. The highest chance for young unemployed in Spain to find a job arises within an unemployment spell lasting 3–4 months, while the unemployed of prime-age are most likely to become employed within the first two months of their unemployment episodes. However, once controlled for unobserved heterogeneity (the results are shown in Table 2 in italics),[7] the hazard ratios of duration intervals γ_{1-4} become smaller and insignificant for young unemployed in Spain in 2007–2008. This can be interpreted in a way that the employment prospects of Spanish young unemployed deteriorated

enormously in this period, with the effect that the unemployment duration per se plays no significant role.

In both periods in question, young people in the Czech Republic experience the highest probability of transition from unemployment to employment between the third and fourth month of unemployment spell.[8] In other words, the Czech young unemployed are twice as likely to become employed within an unemployment episode lasting 3–4 months than if their unemployment spell lasted 13–24 months. For prime-age unemployed in the Czech Republic, the coefficients for all duration intervals γ_{1-4} are high and significant. Note however that the highest probability of Czech prime-age unemployed to find a job has actually shifted from duration interval γ_2 in 2007–2008 to γ_3 in 2009–2010.

In most cases mentioned above, estimation results tell us that unemployment duration matters as a factor influencing the prospects of finding a job. Marginalisation and even social exclusion thus appear to be a real problem affecting both countries and age groups of interest. As for the young unemployed, our results suggest that they are best able to find a job within unemployment spells lasting between 3–4 months. Activation measures should therefore target with higher intensity those young unemployed with longer unemployment spells.

The analysis of explanatory variables does not confirm with full uniformity that unemployed men are more likely to find a job than unemployed women within any given length of unemployment spell. In Spain, such gender-specific patterns of transitions from unemployment to jobs can be asserted among prime-age unemployed. In the Czech Republic, they apply to young unemployed in 2008–2009 and prime-age unemployed in 2009–2010. Viewed from another perspective, however, this simultaneously means unemployed women are indeed in many cases exposed to lower chances of finding a job than unemployed men.

The hazard ratios indicating the positive impact of tertiary education on transitions from unemployment to employment are significant for both of the countries and the periods as well as age groups analysed. Results in Table 2 suggest that, for example, the prospects of young unemployed university graduates finding jobs are ceteris paribus 1.34–6.25 times higher than for young individuals with primary education. The positive effect fully applies to the unemployed with secondary education in the Czech Republic, too. In contrast, in Spain it is significant only for prime-age unemployed in 2007–2008. So it can be also said that starting from 2009, compared with primary education, secondary education in Spain does not yield any significantly better employment prospects.

As with gender and education, no uniform effect of age has been confirmed. As shown in Table 2, age plays a significant but relatively modest negative role when we look at prime-age unemployed, in a sense that the older the unemployed person, the lower her/his chance to move into employment. This common tendency recorded for both countries is most likely due to skill obsolescence and deterioration in accumulated human capital, which potential employers associate with this group of unemployed. This is not too surprising for a high unemployment country such as Spain. Perhaps more surprisingly, the Czech labour market also appears to be relatively hostile to those unemployed who are gradually approaching retirement age.[9] In Spain, the significant impact of age has also been noticed for the young unemployed in both analysed periods and in direct contrast to prime-age population, this impact is now slightly positive. This could be interpreted in a way that employers in Spain prefer to hire relatively more mature young unemployed, presumably with a previous employment record and accumulation of some working experience/discipline.

Household size has a significant and slightly negative impact on entering employment in most cases except for the prime-age unemployed in the Czech Republic. For the young unemployed in both countries this can be associated with the fact that other members of respondents' households (parents) contribute decisively to the household budget and the young unemployed therefore feel less pushed to search for a job. Interpretation of such a result for prime-age unemployed in Spain is analogous – it is most likely linked with relying on partner's income and therefore again with lower incentives for intensive job search.

The last explanatory variable involved in our analysis is densely populated area. Perhaps surprisingly, in some cases the coefficients are significant and suggest that the more densely populated the living area, the lower the probability to exit from unemployment and enter into employment. Notwithstanding the general assumption that bigger cities provide more job opportunities and, hence, entering into employment is easier here,[10] our results suggest, at least partially, the opposite. This could be partly explained by the fact that the coefficients evaluate the significance of the area of residence and not of the actual workplace. Another explanation would be that larger cities constitute places with harsh labour market competition and lack of well-paid jobs, while the city dwellers expect to find jobs with remuneration above average (the notorious problem in both Spain and the Czech Republic when many young people simply do not want to do hard and physically-demanding jobs that might be well-paid, but are rather looking for office jobs and jobs with no particular attire and responsibilities but are well-paid).

6   Conclusions

Survival functions depicted in Kaplan-Meier diagrams generally indicate higher long-term unemployment, prolonged unemployment spells and more time needed for job search in the peaking period of the Great Recession for both age categories and the countries analysed. Our results also suggest that long-term unemployment of young people constitute, at least in relative terms, an even more urgent policy challenge than in the case of prime-age unemployed. The same finding concerns the median survival time as the key indicator of the length of an unemployment episode that has increased in both countries and age groups, but with much higher dynamics among the young unemployed.

Proportional hazard model estimations confirm in most cases that the probability of finding a job is higher if the unemployment spells lasts less than one year. The most important exemption from this tendency concerns the young unemployed in Spain in the initial period of the Great Recession when their employment prospects deteriorated so much that unemployment duration per se played no significant role. In terms of specific youth unemployment policy messages, our proportional hazard model estimation results for the peaking period of the Great Recession show quite uniformly that the various activation measures designed for the young unemployed should probably be shifted beyond the horizon of 3–4 months, since within this interval they have the best chances of finding a job.

A detailed analysis of explanatory variables attempts to detect the main factors affecting the transitions from unemployment to employment. In line with expectations it shows with a full uniformity that the probability of finding a job among unemployed university graduates is higher than that of lower education groups. This holds, even if with lower frequency, also for the unemployed with secondary education. Note in

particular that starting from 2009, compared with primary education, secondary education in Spain does not yield any significantly better employment prospect.

The impact of other explanatory variables on the probability of finding a job, such as gender, age, family size, etc., differs across countries, periods and age groups analysed. Even so, unemployed women are relatively frequently exposed to lower chances of finding a job than unemployed men. Furthermore, for the prime-age unemployed in both countries we found evidence suggesting that the older the unemployed person, the lower her/his chances of moving into employment. As for the impact of age among the young unemployed, employers in Spain are likely to hire the relatively more mature young unemployed, thus favouring the possible previous employment record and accumulation of some working experience/discipline.

Except for prime-age unemployed in the Czech Republic, estimation results prove quite uniformly the negative impact of family size on the probability of leaving unemployment and becoming employed. Parental (or partner) income thus appears to function as a significant disincentive for a more intensive job search. Finally, our results are likely to challenge the view established in the literature concerning the best employment prospects associated with living in big cities. In some cases we found the opposite evidence, meaning that unemployed individuals living in bigger cities may have higher reservation wages as well as other requirements linked with the quality of potential jobs. These specificities may make them more reluctant to accept 'second-rate' jobs compared with the unemployed living in less densely populated areas. However, verification of such assumptions would obviously require further research.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. The individual's exposure to social exclusion is unequally distributed within contemporary societies, depending on various age, gender, education, and other characteristics: Esping-Andersen (2009) identifies particularly the young people and women as highly exposed groups while Ejrnaes and Boje (2011) belong to those who stress the exposure of low-skilled men.
2. OECD (2013, 2014) deal with typical features of Spanish or Czech labour markets with regard to the period covered by our analysis. Among other specificities Spain is characterised as a country with a dual labour market consisting of a sector of highly protected permanent employees, along with a relatively very large sector of unprotected temporary workers. Young people are among those whose stable employability is likely to be most adversely affected by this dual labour market structure. Spain is also believed to suffer from a relative lack of childcare facilities, from short parental leave and from the bi-modal employment pattern for young women (quick returns to employment or prolonged separations from

employment). See, inter alia, also Ejrnaes and Boje (2011) for discussion. In contrast, in the Czech Republic such labour market fragmentations are still less apparent.

3. It can be derived that $\lambda(t) = \frac{f(t)}{S(t)}$, where $f(t)$ is the probability density function of T, and $S(t)$ is the survival function.

4. Employment definition in EU-SILC includes employees and self-employed (including family workers) working part-time or full-time. Unemployment is self-defined according to person's own perception. Inactivity comprises students, further training, unpaid work experience, retirement and early retirement, permanently disabled, military service, fulfilling domestic tasks and care responsibilities, and other inactive persons.

5. Indeed, the arithmetic mean of all unemployment spells is much higher in all cases. However, even this indicator still underestimates the population mean, as it considers only a fraction of the actual length of incomplete unemployment spells. The restricted mean survival time is estimated as the area under the Kaplan-Meier survival curve. It also underestimates the population mean, as the survival function is limited to 24 months in our data. The extended mean is based on an exponential imputation of the right tail of the Kaplan-Meier survival function so that the survival function curve eventually reaches zero.

6. D'Addio (1999) reports lower figures for France at the beginning of the 1990s, namely the median unemployment spells based on the Kaplan-Meier estimator for roughly 5 months for young men and 7 months for young women. Brauksa and Fadejeva (2013) record for the sample of all unemployed in Latvia the median unemployment spell lasting about 11 months in 2005–2008, with an increasing tendency in more recent periods (12 months for 2008–2010, and more than 15 months for 2010–2011, respectively).

7. Likelihood ratio tests suggest that unobserved heterogeneity is insignificant in all estimated models except for Spanish youth in 2007–2008. In all remaining cases, the results are almost identical, regardless of controlling or not for unobserved heterogeneity. Thus, Table 2 displays as a rule only the results *without* controlling for unobserved heterogeneity. Just for Spanish youth in 2007–2008, the results *with* controlling for unobserved heterogeneity are also added.

8. Our results for young unemployed differ from findings presented by D'Addio (1999), where the French young people had at the beginning of the 1990s the highest chances of finding jobs within the first two months of unemployment.

9. This tendency is confirmed by Flek and Mysíková (2015), who report the presence of a positive net flow of Czech elderly workers from employment to unemployment even at times of the pre-recession expansionary period when the aggregate unemployment rate was declining. For the other age categories of Czech workers this net flow was negative during the same period.

10. Such effect was found, for example, by Brauksa and Fadejeva (2013) for Latvia where the unemployed people living in the capital have the highest probability to find job.

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Appendix: 1

Estimated Kaplan-Meier hazard functions

Figure A1
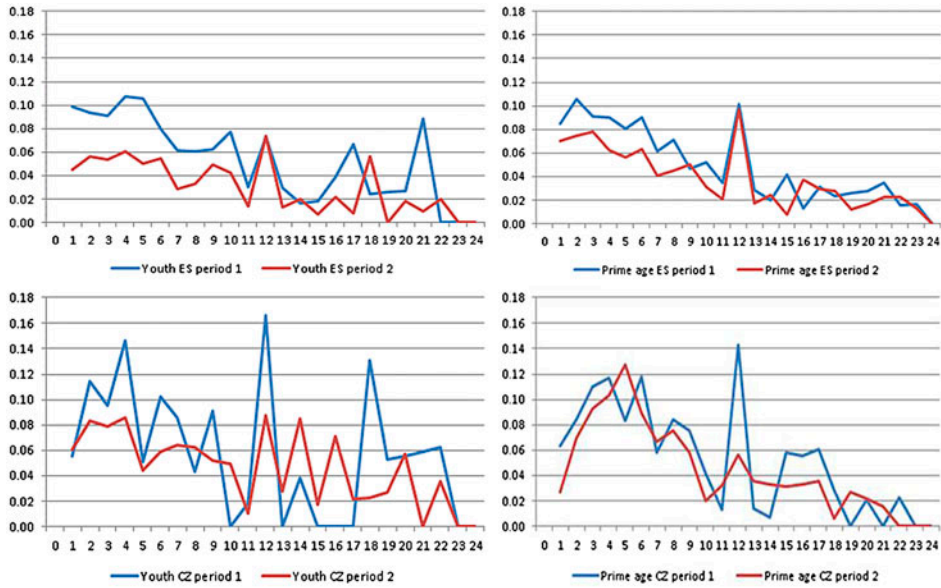
Sources: EU-SILC LONGITUDINAL UDB 2009, version 4 of March 2013; EU-SILC LONGI-TUDINALUDB 2011, version 1 of August 2013. Authors' computations.

Note: Period 1: 2007–2008. Period 2: 2008–2009. The diagrams assign the probability of leaving unemployment and moving into employment in percent (vertical axis) to each month of unemployment duration (horizontal axis).