Universidade do Minho
Escola de Economia e Gestão

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Education and Labour Market Transitions: A Survival Analysis Using Portuguese Data

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Trabalho realizado sob a orientação do
Professor Doutor João Cerejeira
e da
Professora Doutora Carla Sá

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Declaração

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Education and Labour Market Transitions: A Survival Analysis Using Portuguese Data

Abstract

In the recent past, there has been a generalized investment in education across several countries including Portugal; however the rising of educational driven by youths has been followed by an increase in unemployment rate, with especial incidence among youths.

Using a duration analysis framework in continuous time and the Portuguese LFS from 1998 to 2009, we aim to evaluate the role of education in labour market. Namely, we want to access whether education prevents unemployment for those who have a job and whether if it helps unemployed finding a job.

Our results show that more educated individuals, with a high school diploma or higher, have lower hazard of job loss. Among those who lost their job or are looking for their first job, we found evidence that college graduates have higher prospects of finding a job. Those results seem to suggest that employers prefer more skilled workers, in accordance with the idea that education increases the individual's productivity.

Keywords: education, labour market transitions, employment, unemployment, duration analysis

Educação e Transições no Mercado de Trabalho: uma análise de sobrevivência usando dados nacionais.

Resumo

No passado recente, tem havido um aumento generalizado da educação em vários países, incluindo Portugal. Contudo o aumento do nível educacional da população fomentado pelos mais novos tem sido acompanhado por um aumento das taxas de desemprego, com maior incidência sobre os mais jovens.

Usando modelos de duração em tempo contínuo com dados Portugueses do LFS de 1998 até 2009 tentamos avaliar o papel da educação no mercado de trabalho. Nomeadamente, avaliar se a educação previne o desemprego entre aqueles que estão a trabalhar e se ajuda os desempregados a encontrar emprego.

Os nossos resultados mostram que os indivíduos com maior nível de educação, com ensino secundário ou superior, têm menor probabilidade de perder o emprego. Entre aqueles que não têm emprego ou estão à procura do primeiro emprego, encontramos evidência que o ensino superior aumenta a possibilidade de encontrar emprego. Estes resultados parecem sugerir uma maior preferência dos empregados por indivíduos com maior formação, em concordância com a ideia de que a educação aumenta a produtividade dos indivíduos.

Palavras-chave: educação, transições no mercado de trabalho, emprego, desemprego, modelos de duração

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List of abbreviations and acronyms

CIF: Cumulative Incidence Function

EU: European Union

IE: *Inquérito ao Emprego* (Labour Force Survey)

INE: *Instituto Nacional de Estatística* (Statistics Portugal)

LFS: Labour Force Survey

LIFO: Last In First Out

LR: Long-run

NUTS: *Nomenclatura de Unidades Territoriais para fins Estatísticos* (Nomenclature of Territorial Units for Statistics)

OECD: Organisation for Economic Co-operation and Development

PCE: Piecewise-Constant Exponential

PH: Proportional Hazard

PSID: Panel Study of Income Dynamics

SR: Short-run

1 Introduction

In the recent past, there has been a generalized investment in education across several countries including Portugal (OECD, 2009)[1]. The investment in education is guided by the belief that education has positive effects for the individual as well as for the society.

At the individual level, the higher the human capital the higher the potential wage. By investing in education an individual is increasing her human capital and therefore her potential wage in the labour market (Psacharopoulos and Patrinos, 2004). Other individual benefits include lower chances of becoming unemployed, and lower unemployment durations in the event of unemployment. Education is expected to ease transitions in the labour market, and the fact that it improves individual's adaptability to changes[2] is among the possible explanations. The more educated the individual, the higher the opportunity cost of being unemployed or out of labour market (inactive).

The social benefits of education have been broadly study. Several studies highlight the positive impact of education on productivity (Moretti, 2004b), and the causal impact of education on countries' economic growth, especially the quality of education (Barro, 2000; Hanushek and Wößmann, 2007). Additionally, higher levels of education may lead to higher levels of wealth, it may lower the probability that individuals engage in activities that generate negative externalities (such as crime), as well as it may improve the quality of elections and, consequently, the quality of the democracy (Moretti, 2005).

In the current economic context of anaemic growth in combination with higher educational levels and increasing unemployment rates (particularly among the youngsters) makes the study of education and labour market transitions more relevant. A better understanding of the impact of education on the employment-unemployment flows may be useful in designing more effective job policies addressing the labour market participation of the new qualified workers.

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[1] For the OECD countries the education expenditure per student was 24% higher in 2006 than 2000 for non-tertiary level, and 11% higher for tertiary level. Portugal, also registered an increase of 12% and 35% for non-tertiary and tertiary levels, respectively.

[2] The Pedagogy for Employability Group (2012) point many attributes valued by the employers, many of them can be related to education.

The aim of this research is to evaluate how education affects the labour market transitions, namely to check whether more educated individuals have lower risk of job loss (transition from employment to unemployment), and once unemployed, whether it increases the chance of re-employment (transition from unemployment to employment).

The empirical analysis uses data from the Portuguese Labour Force Survey, for the period between 1998 and 2009 (second quarter). The dataset is build based on quarterly data allows for the application of survival analysis techniques. Two models are estimated to analyse the role of education on both, the transition from employment to unemployment and the re-employment probability of the unemployed workers, respectively.

The main contributions of this research relate to its empirical approach. First, we use a panel dataset, which covers a long period of time. Second, we use continuous time survival models, rather than discrete time models as used before. Third, two transitions are analysed, namely from employment to unemployment and from unemployment to employment, which allows for a better understanding of the role of education on labour market transitions.

The remaining of this research is structured as follows. Section 2 discusses the theoretical background and the main results of previous studies. Section 3 introduces the methodology to be used. Section 4 presents the data and empirical model, and Section 5 discusses the estimation results. Finally, Section 6 closes with the main conclusions, the discussion of some limitations of the analysis, and pointing some ways for further work on the topic.

2 Theoretical background

The relationship between labour market outcomes and education has long been of interest for economists. For instance, Mincer (1991) evaluated the impact of education on the unemployment rate for USA, using the PSID (Panel Study of Income Dynamics) dataset from 1976 to 1983. The results showed that the higher the education level, the lower the unemployment rate, the easier to move to another job, and the higher the stability of the current job (measured in terms of its duration).

The individuals take the decision to invest in education (human capital) if they expect its benefits to outweigh the costs, that is, if they expect positive net returns. The existence of positive returns on education is an indicator that education may increase the individuals' productivity, an attribute valued by employers. (See Psacharopoulos, 1985; Psacharopoulos and Patrinos, 2004; Weiss, 1995; and Chevalier, Harmon, Walker and Zhu, 2004).

The benefits that an investment in education brings are not restricted to private returns; we shall consider the existence of social returns as well. From the government point of view, the decision to invest in education is based on the existence of social gains. Moretti (2004a) studied the existence of non-private returns in the US when there is an increase of the labour force share of college graduates within a city. He found a positive spillover effect of college graduates, by comparing similar individuals who work in cities with different shares of college graduates in the labour force. After controlling for unobserved characteristics of the individuals and the cities, he concludes that 1% increase in the proportion of college graduate workers raises the wages of high school dropout workers by 1,9%, of the high school graduates by 1,6% and of the college graduates by 0,4%. The wage increase resulting from an increase in the proportion of college graduates workers is larger for less educated workers as predicted by a demand and supply model.

According to the screening and signalling theories, the educational level observed by the employer reduces the information asymmetry about the unobserved productivity of the potential employee. The more productive individuals invest in education in order to signal their higher productivity and by doing so get a better salary (see Spence, 1973; Stiglitz, 1975; Layard and

Psacharopoulos, 1974; and Weiss, 1995). The crowding-out[3] theory presents itself as an explanation for the lower unemployment rates among the more educated (skilled) workers. Employers have preferences on the abilities of their employees, and the actual and potential workers are ranked accordingly. Therefore, the human capital theory and the screening theory suggest that, on average, the more educated/skilled ones are ranked above the less educated/skilled, being the first, which explain the lower unemployment rate among the former.

Education also may explain the lower unemployment rate by affecting the type of job search methods as well as the searching intensity. In an evaluation for several European countries using European Union Labour Force Survey (EU-LFS) from 2006 to 2008, Bachmann and Baumgarten (2012) apply a ordered logit and a probit model to find out the determinants of job search methods among unemployed workers. They concluded that the more educated and the younger workers search with more intensity[4]. In general, unemployed women search less intensely than man, and family characteristics such as the number of children and the number of elderly living in the household are associated with lower levels of search intensity. They also found the existence of heterogeneity of job search methods among countries. In Mediterranean countries like Spain, Italy and Greece informal search methods are preferred over the public employment office; whereas in the Central and Eastern European countries the workers prefer the direct methods over the public employment office.

Addison and Portugal (2002) use data from the Portuguese LFS (Inquérito ao Emprego) in the 1990s to estimate the effectiveness of job search methods to escape from unemployment. The authors found that search for a job using the public employment service leads to jobs that last and pay less than jobs obtained via other search methods. They also expected to see individuals selecting the job search methods that give them the best chances of finding a new job. The use of direct search methods and informal networks is the most preferred (which contrasts with the results found in the British literature), however, it does assures better chances of finding a job but it is not associated to higher earnings.

Núñez and Livanos (2009) used a multinomial-logit model to access the impact of the education level and the field of study in the short and long run unemployment applied to the EU-15 based

[3] For more details about the crowding-out theory and the job competition model, see Teulings and Koopmanschap (1989), and Thurow (1975), respectively, cited by Wolbers (2000).

[4] The authors restrict the analysis to active methods relating to dependent employment (Bachmann and Baumgarten, 2012).

on EU-LFS micro-data for the spring quarter of 2005. Both the education level and the field of study are shown to have an effect on the transitions from short-run (SR) unemployment to employment and from SR unemployment to long-run (LR) unemployment. In general, the results suggest that higher education is associated to better chances of finding a job; as well as a more modest effect preventing the LR unemployment. When the effect of getting a higher education diploma is compared among countries, the results are heterogeneous. College graduates in countries like Finland, Belgium and the UK has the strongest positive effect of employment (conditional on being a SR unemployed worker). Conversely, college graduates in countries like Portugal, Italy, and Greece face the lowest likelihood of finding a job (when compared to college graduates in other countries), which may be a signal of labour market problems. Regarding the field of study, the results show unequal employment opportunities across different fields[5]. The fields more successful preventing the SR unemployment are education, engineering, health and welfare, and services and tourism, whereas sciences, biology and environment, computer use, and health and welfare appear to be more effective preventing the LR unemployment.

Riddell and Song (2011a, b) intended to evaluate the relation between education and the labour market using instrumental variables. In Riddell and Song (2011b), the authors studied the existence of a causal effect of education on the probability of re-employment conditional on being unemployed one year earlier. This study was motivated by the idea that more educated and/or skilled individuals make wiser decisions when the *status quo* changes. To test their assumption they used the US Current Population Data (1980-2005) and the 1980 Census. In order to address the education endogeneity problem, they used changes in the compulsory schooling laws and children labour laws as instrumental variables to high-school graduation. To instrument higher education they also used the conscription risk in the Vietnam War[6]. In general, the higher the educational level the higher the chances of re-employment. They found positive non-linear results, with higher effects around 12 and 16 years of schooling, suggesting the presence of sheepskin effect. Regarding the effect of education in unemployment incidence the results show that college graduation is associated to lower prevalence of unemployment, but no causal relationship at the high school was found.

[5] The reference category is social business and law.

[6] During the Vietnam War, males used to enrol in college to defer their conscription in the Armed Service.

The same approach has been implemented using Canadian data such as the LFS (1976-1996), and the Census (1981, 1986, 1991, 1996 and 2001) Public Use Microdata Files. In this case, Riddell and Song (2011a) used changes in the compulsory schooling laws over time and across jurisdictions as instrumental variables for education. Besides the analysis performed to the US presented before, the authors also studied the effect of education on job search intensity. They found evidence that education measured by a dummy for high school graduation or years of schooling has a positive causal effect on job search intensity. Regarding re-employment, the results are in line with the results found with the US data, namely schooling enhances the re-employment chances.

The risk of unemployment can be view under two perspectives: first, there is the risk of job loss, and, second, once unemployed there is a risk of not finding a job. Lauer (2003) analysed both risks in a comparative study for France (*Emploi* survey) and Germany (German Socio-Economic Panel – GSOEP) in the 1990s. The author used a discrete time framework with competing risks hazard rate model with a semi-parametric specification of the baseline hazard function (piecewise constant). He proposes a competing risks model under a discrete time framework using multinomial-logit estimation. In general, the results for both countries show that education lowers the risk of unemployment; the individuals with the lowest level of education and no vocational education have the highest risk of unemployment. *Ceteris paribus*, finishing higher education appears to be more effective protecting individuals from unemployment in France, whereas, in Germany, getting vocational qualification (intermediate level) ensures more protection against unemployment. A common characteristic to both countries is that individuals holding lower tertiary education qualifications show lower risk of job loss than those who have upper tertiary qualifications. A possible explanation may be that lower tertiary degrees are more practical and more oriented to the economy's demand. Education also plays a role by increasing the possibilities of leaving unemployment and finding a job. Higher education graduates show higher probability of re-employment, with a small difference on the re-employment probability between workers with the lower tertiary level and the upper tertiary levels.

Summarizing, in France the risk of job loss is higher[7] than in Germany, for every educational level, as are the re-employment prospects. So, the German workers face a lower risk of unemployment,

[7] The unemployment rate is higher in France than in German, particularly for individuals with basic vocational and intermediate qualifications.

but if unemployed it is harder for them to find a new job. In Germany, holding a vocational qualification (intermediate level) is the best insurance against unemployment, but it is the higher education diploma that enhances the chance of re-employment. In France, the higher education degree is associated with a lower risk of unemployment and a higher probability of exiting from unemployment. These results may explain the higher demand for vocational qualifications in Germany, whereas in France people invest more in higher education qualifications.

Wolbers (2000) intended to understand and test whether less educated workers have higher chances of job loss and experience longer unemployment duration than more educated individuals, as well as to evaluate whether such phenomenon is stronger during recession periods of the labour market. In other words, the author aimed to access the impact of educational level on labour market transitions and if this relation is affected during labour market recessions. To carry out this investigation, he used data from the Labour Supply Panel of Organisatie voor Strategisch Arbeidsmarktonderzoek[8] (OSA) for the years of 1985, 1986, 1988, 1990, 1992 and 1994. He estimated a discrete-time event-history model[9] by means of a logit regression, since the time is measure in months the discrete time comes near a continuous-time model.

The analysis of transition from employment to unemployment suggested that, in general, the higher the educational level the lower the risk of unemployment, but not in a linear way. Higher education graduates face a higher probability of job loss than the ones with higher vocational education. This suggests that employers may prefer employees with vocational or occupationally specific education. Changes in labour market conditions measured by unemployment rates increase the risk of unemployment mainly for those with lower secondary education. Additionally, the authors found evidence that an increase in unemployment rate rose by 1%, the risk of unemployment in the next month is increased by about 13%. They also found evidence that individuals who enter the labour market at a time of higher unemployment rates, is in worse position thorough her carrier.

Looking at the transition from unemployment to employment, the results suggest that having a diploma of any type increases the chances of finding a job compared to those who have completed primary education. Furthermore, secondary and tertiary education do not differ very much regarding the unemployment protection provided. Individuals with upper secondary education and

[8] Directed translation: Institute for Labour Market Research

[9] Duration models are also addressed as event-history models, mainly by sociologists.

first stage tertiary education are less affected by an increase in the unemployment rates than those with other educational levels. In general, women are less likely than men to find a job, except women holding college degrees who have higher prospects of finding a job than college graduates' men.

Kettunen (1997) used a duration model in a continuous time framework to access how education affects the probability of re-employment. A Weibull model was applied to a Finnish dataset of individuals who lost their job in 1985 and were followed up to 1986. The results show that education, up to 13-14 years of schooling, has a positive effect on re-employment. However this effect turns negative for individuals with master or PhD degrees, who have the lower chances of finding a new job; to author this is due the increase of job selectivity with thee educational level. More educated individuals with specialized education have fewer job offers in their field of training, explaining the decreased employability associated with higher educational level, like master or PhD level.

Summing up, from the existing studies on labour market transitions a few results emerge: First, education do have a positive effect in the protection of unemployment, and for those who are unemployed it seem to increase their chances of finding a new job, possibly due the impact of education on productivity or by acting as a signal mechanism. Second, regarding the transition from unemployment to employment, the intensity of job search seem to play an important role in outcome, with those searching more actively having higher success. Third, some studies point out the importance of family structure, like the presence of young children, in labour market transition, with women being, generally, more penalize in terms of higher unemployment probability and lower chances of find a job. Finally, some cross-country studies show the existence of heterogeneity among countries, in terms of how individuals search for a job or the effect of education, namely the type (vocational or academic education), in the labour market transitions.

3 Duration Analysis

3.1 Single Risks

The labour market is a dynamic place, where several flows take place, as people frequently move between jobs, as well as in and out of the labour force. The aim of this research is to empirically evaluate how education affects labour market transitions. Given the objective of the study and the available information about the duration of employment and unemployment in our dataset, presented in section 4, survival analysis (also known as duration analysis) is adequate. Time[10] to the occurrence of a given event is at the centre of the duration analysis, as well as it allows for the analysis of the determinants of the transition between states. In our particular case, how education affects the risk of unemployment of a worker, given the time she has been employed.

Consider that n stands for the individual and T represents the time an individual spends in a given state, also called the duration of the spell. The duration analysis can be characterized based on several functions of time[11,12]: (i) the density function, $f(t)$; (ii) the cumulative density function, $F(t)$; and (iii) the survival function, $S(t) = 1 - F(t)$, where t is the time since entry in the status at time 0. Given the relation between functions presented above is possible, in principle, to derive one from the other.

Alternatively, the distribution of T can be characterized by means of the hazard function, $h(t,\mathrm{x})$, which measures the instantaneous rate of failure[13]. The hazard rate is the conditional probability that a transition (or a failure) occurs in t, given that the individual have survived up to that moment:

$$\mathrm{h(t)} = \lim_{\Delta \mathrm{t} \to 0} \frac{\mathrm{Pr(t + \Delta t > T > t \,|\, T > t)}}{\Delta \mathrm{t}} \qquad 3.1$$

An important feature of these models is the fact that the presence of a set of explanatory variables (regressors, x) may affect the survival time, and as such have to be modelled. Among the

[10] Continuous or discrete time.

[11] In this research we will use a continuous time frame.

[12] The length of time in a given status is also called spell.

[13] Durations models are also used to study the time to failure of a machine, that is why the transition from a status to another is also called failure, and the event which causes it is called failure event.

alternative classes of models, the most broadly used in the literature are the Proportional Hazard (PH) models, in which the hazard function is given by

$$h(t, x, \beta) = h_0(t)\, e^{x\beta} \qquad 3.2$$

where $h_0(t)$ is the baseline hazard rate, i.e., the hazard rate that vary in time and is common to all individuals; β is a vector of unknown coefficients associated to covariates vector x (not including a constant); $e^{x\beta}$ is the proportional hazard factor constant over time. The model is proportional given that $e^{x\beta}$ does not depend on time, covariates multiplicatively move the baseline hazard function, and thus the effect is constant over time (proportional). The hazard of subject a is then a multiple of subject's b hazard rate, equation 3.3 presents the hazard ratio between subject a and subject b, constant for all t.

$$\frac{h(t|x_a)}{h(t|x_b)} = \frac{h_0(t)\, e^{x_a\beta''_x}}{h_0(t)\, e^{x_b\beta_x}} = \frac{e^{x_a\beta_x}}{e^{x_b\beta_x}} = e^{x_a - x_b} \qquad 3.3$$

To model the hazard function in equation 3.2 different approaches may be considered: (i) nonparametric[14] models, that we are not going to discuss here; (ii) semiparametric models; and (iii) parametric models. .

Regarding semiparametric models, the most used one is the Cox PH model. Cox (1972) proposed a partial likelihood method to estimate the effect of covariates. The model is semiparametric because the functional form of $h_0(t)$ is not estimated or imposed *a priori*, only the effect of covariates is parameterized. The semiparametric quality of Cox PH model represents an advantage; we do not need to do assumption about $h_0(t)$; this feature is desirable especially when we are not sure about how the hazard evolves over time. On the other hand, we loss efficiency in the estimation of the $\beta s;$ if the functional form of $h_0(t)$ is known we can get better estimates of β by using a parametric model with the right distribution (Cleves, Gutierrez, Gould, & Marchenko, 2010)

In addition to Cox model, another semiparametric model is the Piecewise-Constant Exponential (PCE) model. As in Cox model, also PCE model does not assume a specific form of the baseline hazard function, instead of it, time is divided in M intervals and although the baseline hazard may vary between intervals[15], it is constant within the interval.

[14] For more information about nonparametric models see Kaplan and Meier (1958).

[15] The choice of time intervals must take in account how the hazard function varies, with shorter intervals when the hazard function varies more and wider when the hazard function variation are smaller. (Sá et al., 2007)

$$\text{Piecewise-constant: } h(t, \varphi, x, \beta) = e^{\varphi_m} e^{x\beta}, \qquad \varphi_m = \varphi_1, \dots, \varphi_M \tag{3.4}$$

Contrary to semiparametric models, in parametric models assumptions about the function form of the baseline hazard function are made, by adding π, a vector of ancillary parameters as we can see in equation 3.5.

$$h(t, \pi, x, \beta) = h_0(t, \pi)\, e^{x\beta} \tag{3.5}$$

The added parameters, π, characterize the hazard rate distribution over time where different specifications lead to alternative hazard functions. As in equation 3.2, the term $e^{x\beta}$ is a proportionality factor independent of time that keep the proportionality properties. As previously stated, parametric PH model, allow to better exploit the data and achieve better estimates of β if the right distribution of the failure time is selected. Different distributions can be used for baseline hazard, such as, for instance, Exponential, Weibull; the following equations show the general form of PH model for each one.

$$\begin{aligned} \text{Exponential: } h(t, x, \beta) &= h_0(t)\, e^{x\beta} \\ &= e^{\beta_0} e^{x\beta} \\ &= e^{\beta_0 + x\beta} \end{aligned} \tag{3.6}$$

$$\text{Weibull: } h(t, p, x, \beta) = pt^{p-1} e^{\beta_0 + x\beta} \tag{3.7}$$

The exponential distribution assumes a constant baseline hazard rate, in favour of which is difficult to argue in our case as it implies that the risk is independent of the duration of the spell. Weibull distribution, is monotone increasing or decreasing depending on the value of the ancillary parameter. The Weibull distribution is monotone increasing if $p > 1$ and monotone decreasing if $p < 1$; for $p = 1$ it becomes a particular case of the Exponential distribution.

In duration analysis we are concern about how covariates affect the transition between states, to accomplish it we need observe individual who fail (transit to another state). When we use real dataset, commonly not all individuals under observation fail these situation are called censoring. The most common form of censoring is the right-censoring, this type of censoring occur when the individual fail while it is no longer under observation. In other words, an observation is considered right-censored if during the time an individual is observed the failure event never occur.

Besides censoring, we may also be in the presence of truncation, namely left-truncation also referred as delayed entry. Left-truncation occur when the individual starts to be observed after the onset of risk (enters the status that is in risk of fail), i.e., we start observing the individual in $t > 0$.

3.2 Competing Risks

So far, we have presented single risk models, which apply to the case when there are only two states, the current and another one, but in some cases, more states may exist. The single risk framework can be applied to multi-state scenarios if the states are uncorrelated which is not common. It frequently happens that the occurrence of a given event reduces the subjects at risk of experiencing a competing event. In our case, an individual may move from employment to unemployment or leave the labour market to retirement, and the more individuals retire, the fewer individuals at risk of unemployment. A competing risks framework should then be used. It is called competing events in the sense that only one event can occur first and usually only one event (transition) is observed[16].

Let I be the possible competing event that range from 1 to k; T represents the random duration variable. In this research, we only consider one spell or transition, when a spell ends the individual has fail (transit to one of the k states) or is censored. Additionally, the competing events are defined to be mutually exclusive. Then, for each subject observed the observed failure time is $\mathrm{T} = \min(\mathrm{T_1}, \dots, \mathrm{T_k}, \mathrm{T_0})$[17]. Regardless of the assumption of independence between the k events the total hazard rate is the sum of k sub-hazard rates, $h(t, \mathrm{x}) = \sum_{i=1}^{k} h_i(t, \mathrm{x})$, and the probability of failure from cause i is given by $h_i(t, \mathrm{x})/h(t, \mathrm{x})$. The sub-hazard rates are designated as cause-specific hazard and are similar to hazard rate function in single risk setting.

$$\mathrm{h_i(t, x)} = \lim_{\Delta \mathrm{t} \to 0} \frac{\mathrm{Pr(t + \Delta t > T > t, I = \; i \,|\, T > t, x)}}{\Delta \mathrm{t}} \qquad 3.8$$

Equation 3.8 keeps the proportional hazard properties and can be estimated using the semiparametric PH Cox model (equation 3.9) as well as a fully parametric approach.

$$\mathrm{h_i(t, x, \beta_i) = h_0(t)\; e^{x\beta_i}} \qquad 3.9$$

The results from cause-specific hazard have similar interpretation to the single risk hazard rate; the estimation of cause-specific hazard for cause i is simple, as it considers the competing events of i as censored.

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[16] Studies on the cause of dead are good examples as only one event is observed: dead by infection, accident, heart attack.

[17] T_0 is the observed time for censored observations.

Coefficients are estimated using a likelihood procedure, and the general log-likelihood function applied to competing risks is expressed in the following equation:

$$ln\, L = \sum_{i=1}^{k}\left[\sum_{n=1}^{N} d_n\, ln\, f(t_n, \beta_i, \mathrm{x}_i, \theta_i) + \sum_{n=1}^{N}(1-d_n)\, ln\, S(t_n, \beta_i, \mathrm{x}_n, \theta_i)\right] \qquad 3.10$$

When we are in the presence of competing risks, we also should pay attention to cumulative incident function[18] (CIF), this function generalizes the concept of failure function to competing risks: The CIF_i at time t is the probability of failure from cause i before (or up to) time t given that other failure cause has not happen yet. Therefore, $\mathrm{CIF_i(t)} < 1$ given that compete events can occur as well. Formally:

$$\begin{aligned} \mathrm{CIF}_i(t) &= F_i(t) \\ &= \Pr(T \leq t, \text{failure cause } i) \\ &= \int_0^t h_i(\mathrm{x})\, S(\mathrm{x})\, d\mathrm{x} \end{aligned} \qquad 3.11$$

The overall cumulative failure function is the sum of CIF of k competing events then:

$$\mathrm{F(t)} = \textstyle\sum_1^{\mathrm{k}} \mathrm{F_i(t)}, \textit{ where } \mathrm{F}(\infty) = 1$$

from which we conclude that CIF gives the proportion of individuals that fail from cause i without forgetting that they may had fail from other $\mathrm{k}-1$ events (see equation 3.12). Consequently, the CIF_i depends not only on the hazard of event i, but also on the $k-1$ hazards. Portela and Schweinzer (2013) suggest that the efficient and correct CIF analysis is through a competing risks regression model, and implement a competing risks regression following the model of Fine and Gray (1999).

$$\mathrm{CIF_i}(\infty) = \Pr(\text{failure event } \mathrm{I} = \mathrm{i}) \qquad 3.12$$

According to Fine and Gray (1999), the cause-specific hazard does not offer a straightforward interpretation in terms of survival probabilities for a given failure event; and they propose a model for the CIF of the failure event under analysis (or sub-distribution). Contrary to cause-specific hazards, sub-distribution hazard and CIF have a direct correspondence for the same event; i.e., the CIF for event i is a function of sub-distribution of event i, only. As in Cox regression, covariates

[18] Also referred as sub-distribution.

affect the sub-distribution in a proportional way. The authors propose a transformed Cox model associated with a direct transformation of the CIF.

A more detailed presentation of duration analysis, namely competing risk, is out of the scope of this work. For a more detailed analysis about duration analysis and competing risks framework, see among others Cleves, Gutierrez, Gould, and Marchenko (2010); Cox (1959, 1972); Fine and Gray (1999); Jenkins (2005); Lancaster (1990); Portela and Schweinzer (2013); Rabe-Hesketh and Skrondal (2012); Sá, Dismuke, and Guimarães (2007).

3.3 Stratified Proportional Hazard Model

An extension of the proportional hazard model is the stratified proportional hazard model. In the proportional hazard model framework the stratification may be useful because it allows the shape of the baseline hazard function to differ between stratum while the effect (scale) of covariates in the model remain constant for all stratum.

Mathematically the hazard rate function is given by:

$$h(t|x_n) = h_{0,s}(t)\, e^{x_n \beta}, \text{ if individual } n \text{ is in stratum } s \qquad 3.13$$

The effect of covariates (vector x) is equal for all stratum, but the baseline hazard is allowed to vary between stratum.

Stratified analysis can also be used to guarantee the proportionality of hazard rates; if the true baseline hazard function shape differs between stratums the proportionality assumption may be violated. Hence, the stratification presents itself as a possible solution, see Singer and Willett (2003).

In our analysis we perform a stratified analysis based on Portuguese statistical classification of economic activity[19] for models concerning the transition from employment to unemployment. For a more detailed discussion, see appendix B.

[19] The Portuguese classification system is called CAE and it is similar to the Statistical Classification of Economic Activities in the European Community, also known as NACE from the French *Nomenclature statistique des activités économiques dans la Communauté européenne*.

4 Data and model specification

4.1 The data

The methodology discussed above will be implemented using data from the Portuguese LFS, the *Inquério ao Emprego (IE)* carried on by the Statistics Portugal (INE) for the period between 1998 and 2009[20]. The aim of the LFS is to characterize the labour market situation of the population.

The data are collected by means of a quarterly survey and the used data range from the first quarter of 1998 (1998-1Q) up to the second quarter of 2009 (2009-2Q), the most recent available data at the time we conduct this research. The sample is obtained from a sample database called *Main-Sample*[21]; in the period of analysis there were two *Main-Samples*, one created from 1991 Census and updated in 1996 (AM-1996) and the other from 2001 Census containing nearly 500.000 households in their main residence. Thus, the individuals in the LFS result from a two-stage sample selection: the first step corresponds to the selection to the *Main-Sample* and the second stage is the selection of households from the *Main-Sample*.

The LFS data has a panel format with a rotation system, where each household (individual) is observed during six consecutive quarters, after which it (she) is replaced by a new household (individual). In other words, the sample is composed by six rounds, and in each quarter the oldest round is replaced by a new one after being observed for six consecutive quarters. The withdrawal households are replaced by households from the same geographical area, meaning that the representativeness of the geographic areas is fixed over time. The construction of the LFS using such a rotation scheme allows for a longitudinal analysis, as it is possible to observe, and follow, the same household (individuals) over six periods of time by the mean of a unique identification number for individuals.

From 1998-1Q to 2002-4Q, the LFS is composed by 20.747 households from AM-1996; and from 2004-2Q the LFS is composed by 22.554 households from AM-2001. In order to prevent a disruptive between the two *Main-Samples*, there was a transition period from 2003-1Q to 2004-1Q, both inclusive. Thus, in 2003-1Q, about 5/6 of the LFS were households taken from the older sample and 1/6 from the newer; in 2003-2Q, about 4/6 of the LFS were households taken from

[20] A new series of the labour force survey starts in 1998 and ends at 2010.

[21] From the Portuguese "Amostra-Mãe".

the older sample and 2/6 from the newer, and so forth. Finally, in 2004-2Q it was replaced the last 1/6 from the older sample and the first households from the new sample, i.e., two rotations were replaced.

The data are collected using direct individual interviews (microdata) where all individuals in the household are interviewed. The information collected allows for a detailed characterization of the individuals in respect to several topics[22], namely:

- Economic and sociodemographic variables: age, gender, geographic area of residence and work, education/training, and income;

- Employment Status: employed, unemployed or inactive (out of labour market);

- Job attributes: full or part-time, type of contract, and occupation;

- Others: field of study, and job search methods.

To accomplish the aims of this research using the described methodology in chapter 3 required us to harmonize the data[23] in a way that make it possible to compare variables and individuals over time.

The most frequent changes observed are in the answer alternatives, usually implying the aggregation or separation of some categories. In those cases, we adopt a least common denominator rule to maximize the comparability and to reduce the loss of information/detail.

As explained before, all members of the household are interviewed; as it is frequent in survey data there was some record errors that show inconsistencies that need to be corrected. Given the panel format of LFS, the majority of corrections are related to inconsistency of recorders between quarters.

The household members' interview is mandatory and there is the possibility that other apt family member answers in place of other family members. We have decided to exclude those individuals whose records (the number of interviews) were incomplete, since we have no information that justify or explain the missing quarter. A record was considered incomplete if between the first and the last interview, for a given individual, there was a quarter with no available data. Individu-

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[22] The survey is created respecting the criteria defined by Eurostat imposed by the need of comparability of national data within European countries to compose the European Labour Force Survey. To ensure the European comparability and follow the International Labour Organization (ILO), the survey is subject to regular modifications concerning to sampling, dimension and rotation of the sample and also the questionnaire structure.

[23] Raw data were presented in quarterly databases, which had to be put together and harmonized.

als whose records register a sex change, an age decrease or an increase of more than one year between quarters were eliminated.

Regarding the education level we have discarded individuals if it decreases; when the education level increases, we opt for a more careful approach due the existence of governmental programs designed to promote education among low educated adults. We compare the initial educational level and the highest educational level achieved, and we eliminated records that fall in any of the following situations[24]: (i) the individual education level increases for three or more consecutive quarters for those with three or more interviews (records); (ii) the individual ends with an education level higher than a graduate degree (like a master degree or PhD) and started without a graduate degree; (iii) the individual ends with a tertiary education degree and started with the primary education level; (iv) the individual ends with a high school diploma and started with no educational; (v) the individual is less than 18 years old that ends with the *basic 3* level[25] and started with *basic 1* level[26] *or less*; (vi) the individual is less than 18 years old that ended with the *basic 2* level and started with no educational level.

In duration analysis the most important variable is time. In our particular case it refers to the employment and unemployment durations. Regarding employment, the beginning of employment (onset of risk) is the date (mm/01/yyyy) at which the individual started working in the current job or occupation. The duration of employment at quarter t for individual n is given by the time between the onset of risk and the last day of the reference week (mm/dd/yyyy) of quarter t for individual n. Regarding unemployment, the beginning of unemployment (onset of risk) is the most recent of two dates: (i) the date (mm/01/yyyy) at which the individual left the last job or occupation; (ii) the date (mm/01/yyyy) at which the individual started to looking for a job. The duration of unemployment at quarter t for individual n is given by the time between the onset of risk and the last day of the reference week (mm/dd/yyyy) of quarter t for individual n.

If an individual who was employed (unemployed) at quarter $t-1$, is now unemployed (employed) at quarter t, we consider that the transition occurred at the last day of the reference week, although technically the transition occurred in a prior date we believe that this difference do not affect the quality of our estimates.

[24] We shall remember that subjects are followed during one and half years (six quarters).

[25] Corresponding to the third cycle of primary school: nine years of schooling.

[26] Corresponding to first cycle of primary school: four years of schooling.

Some errors and outliers regarding the measure of time (duration) had to be dealt with; appendix A presents the rules that have been used to remove what we considered errors and/or outliers.

4.2 Model Specification

This section is divided in two parts. Section 4.2.1 presents the model applied to the transition from employment to unemployment, whereas section 4.2.2 presents the model used to study the transition from unemployment to employment.

In both cases, to implement our analysis we restrict our sample to men and women aged between 15 and 64, interviewed between the first quarter of 1998 and the second quarter of 2009. For those who experience more than one transition in the labour market we split those records in spells, treating each spell (transition) as different individual, i.e, we do not use multi-spell analysis.

Concerning the analysis on the transition between employment to unemployment, we restrict our sample to individuals who work in Portugal, excluding workers in military service (either conscripted or not), self-employed and workers without pay. Some individuals experience job-to-job transition between interviews, when this happen we have no information about that transition, namely we do not know when the individual left the previous job, for how long he was unemployed, or whether it is an actual job-to-job transition without and unemployment spell (the worker may have left the previews job with a job offer). In those cases, we discard previous observation to the last job-to-job transition and keep the forward observation.

4.2.1 From employment to unemployment

The duration variable of employment, T, for individual n at quarter t is given by the time since the individual started working in the current job or occupation (set on risk) up to the reference week, and it is the dependent variable.

The independent variable with the greatest interest is education, specifically, the highest level of formal education attained and completed by the individual. The variable enters the model by means of a set of dummy variables, as presented in Table 1, which allows a more refine evaluation of education's effect for the different educational levels.

We also added some individual characteristics like gender (female) and the civil status (married or not married) where both covariates are equal to one if the individual is female or married, respectively. We also control for the age of the individuals by means of a set of categorical variables (the age groups are presented in Table 1, and its definition is similar to the one used by INE, and by Núñez and Livanos, 2009).

Regarding the family structure, we include covariates for the number of children and elderly (either parents or parents-in-law) in the household (see Bachmann and Baumgarten, 2012). We also added variables for gender and marital status. Given the differences in social positions of men and women, and to better understand the effect of family structure, we interact covariates child1, child2, elderly, and married with female (dummy variable) to better capture the differences between genders, if exist.

Labour market conditions are not static, like economic activity it changes over time. To capture that, we use, as a proxy, two unemployment related variables: rate in two dimensions, at a NUTS-II and national level using variables NUTS-W and NAT-W (see Table 1). In the period of analysis, national unemployment rate had an increasing trend with a minimum of 3.7% in 2000 and a maximum of 9.1% in 2009; the added covariates allow us to control this increasing pattern.

The variables in the model are in equation 4.1:

$$\begin{aligned} \mathrm{x}\beta = {} & \beta_1 Female + \beta_2 Married + \beta_3 Child1 + \beta_4 Child2 + \beta_5 Elderly \\ & + Female\,(\beta_6 Married + \beta_7 Child1 + \beta_8 Child2 + \beta_9 Elderly) \\ & + \beta_{10} Educ + \beta_{11} Age + \beta_{12} NUTS_W + \beta_{13} NAT_W \end{aligned} \tag{4.1}$$

Depending on the model used to estimate variables in equation 4.1, a constant may be explicitly added or be defined implicitly. The interpretation is straightforward; note that coefficients presented in the models of section 3 are taken the exponential and given the proportionality hazard properties, we can interpret the coefficients in the hazard ratio form[27]. For example, if $\beta_2 > 0$ it means that married individuals face a higher risk of unemployment; in the hazard ratio form we have to compute e^{β_2}, where $e^{\beta_2} > 1\ if\ \beta_2 > 0$. In other words, if $\beta_2 = 0{,}18$ then $e^{0{,}18} = 1{,}197$ meaning that married ones are 1,197 times more likely to lose their job or, equivalently, have 19,7% more risk of unemployment than the ones who are not married. Note that for $\beta_1 = 0 => e^0 = 1$, a hazard ratio equal to one means that married and non-married individuals face the same unemployment risk.

[27] From equation 3.3 we have $\frac{\mathrm{h(t|Married=1\,)}}{\mathrm{h(t|Married=0\,)}} = \frac{\mathrm{h_0(t)\ e^{\beta_2 Married}}}{\mathrm{h_0(t)\ e^{\beta_2 Married}}} = \frac{\mathrm{e}^{\beta_2}}{\mathrm{e}^{0}} = \mathrm{e}^{\beta_2}$

Table 1 presents the descriptive statistics and the variables definition considering the sample to be used on the transition from employment to unemployment. There are 119585 individuals in the sample, corresponding to 362,465 observations. About 47.7% are female and 67.2% are married. The average age is 38 years, and individuals aged between 35 and 44 years old represent about 29% of the sample. About 30% have the basic 1 level of education, corresponding to four years of schooling, and 27% have at least a high school diploma. The North region is the one with more observations, accounting for 28.6% followed by Lisbon region with 17.9%. On average, the tenure (time) is 484 weeks (about 9.4 years) with a maximum of 1601 weeks (about 30.7 years).

Table 1 – Descriptive statistics and variable definition: From employment to unemployment

Variable	Definition	Mean
time (weeks)	Time in the current job/occupation (in weeks)	484.61 (414.832)
female	=1 if female	0.477
married	=1 if married	0.672
child1	Number of children younger than 4 years old living in the household	0.158 (0.400)
child2	Number of children aged between 5 and 14 years old, living in the household	0.398 (0.663)
elderly	Number of parents/parents-in-law older than 65 years old living in the household	0.101 (0.409)
NUTS-W	Variation, in percentage points, of the unemployment rate (by gender) from quarter t-1 to quarter t in the individual's NUTS-II workplace	0.057 (0.892)
NAT-W	Difference between the unemployment rate in the individual's NUTS-II workplace (by gender) and the national unemployment rate (by gender), at quarter t-2.	-0.193 (1.903)
Nat. U. Rate	Simple average of total unemployment rate (men and women) in the period 1998 to 2009 (second quarter)	6.1
Nat. U.Rate Male	Simple average of men's unemployment rate in the period 1998 to 2009 (second quarter)	5.2
Nat. U.Rate Female	Simple average of women's unemployment rate in the period 1998 to 2009 (second quarter)	7.2
age		
15 - 24	=1 if the individual is aged between 15 and 24 years old	0.124
25 - 34 (base category)	=1 if the individual is aged between 25 and 34 years old	0.257
35 - 44	=1 if the individual is aged between 35 and 44 years old	0.292
45 - 54	=1 if the individual is aged between 45 and 54 years old	0.234

Table 1 – (Continued)

Variable	Definition	Mean
55+	=1 if the individual is aged between 55 and 64 years old	0.092
educ		
non-educ	=1 if the individual has no educational level	0.040
basic 1 (base category)	=1 if the highest educational level attained is the 1st cycle of basic education (4 years)	0.300
basic 2	=1 if the highest educational level attained is the 2nd cycle of basic education (6 years)	0.209
basic 3	=1 if the highest educational level attained is the 3rd cycle of basic education (9 year)	0.180
high school	=1 if the highest educational level is the secondary education (12 years) or post-secondary non-tertiary education	0.146
college	=1 if the highest educational level is the tertiary education	0.124
workplace (NUTS-II level)		
North	=1 if the individual works in the North region	0.286
Centre	=1 if the individual works in the Centre region	0.137
Lisbon	=1 if the individual works in the Lisbon region	0.179
Alentejo	=1 if the individual works in the Alentejo region	0.105
Algarve	=1 if the individual works in the Algarve region	0.105
Azores	=1 if the individual works in the Azores region	0.097
Madeira	=1 if the individual works in the Madeira region	0.091
Note: Standard deviation in parenthesis		

4.2.2 From unemployment to employment

The model used to estimate the cause-specific hazard of employment is quite similar to the one presented before, with some additional variables. Namely, we add a covariate called *first*, a dummy variable that indicates whether the individual is looking for her first job, which is a relevant variable particularly for the youngest individuals.

As presented in the literature, the job search intensity plays a non-negligible role determining the success of finding a job and leave unemployment status. We add a proxy to job search intensity, the number of active different methods used, in the previous quarter, to find a job (see Riddell and Song, 2011a). We also add the unemployment benefits, to check whether those receiving unemployment assurance in the previous quarter are more prone to remain unemployed. Finally, covariates NUTS-W and NAT-W, from the previous model, where replaced by NUTS-R and NAT-R, respectively. The latter are equal to the former in the way they were computed, with the difference that NUTS-R and NAT-R now use the residence area, rather than the workplace area. Firstly, because we do not have detail about the former workplace area for all unemployed individuals, and secondly, residence area is a better reflection employment prospects for unemployed individuals.

$$
\begin{aligned}
\mathrm{x}\beta = {} & \beta_1 Female + \beta_2 Married + \beta_3 Child1 + \beta_4 Child2 + \beta_5 Elderly \\
& + Female\,(\beta_6 Married + \beta_7 Child1 + \beta_8 Child2 + \beta_9 Elderly) \\
& + \beta_{10} Educ + \beta_{11} Age + \beta_{12} First + \beta_{13} Job\ Search + \beta_{14} Benefits \\
& + \beta_{15} NUTS_{Res} + \beta_{16} NAT_{Res}
\end{aligned}
\tag{4.2}
$$

Formally, the variables in the model are described in the equation 4.2, as before, a constant may be directly added to the model or be assumed implicitly.

Table 2 presents the descriptive statistics for the data to be used in the study on the transition from unemployment to employment. The sample is composed by 16096 individuals, corresponding to a total of 29145 observations. About 54.7% are female and 51.3% are married; the average age is 35 years old. Concerning to education, 29.3% have the basic 1 level while 23.5% have a high school diploma or higher. The region with more observations is the North (33.4%) followed by Lisbon (18.9%). The average duration of unemployment is about one year (i.e. 57 weeks) with a maximum of over 5 years (280 weeks).

We should add that covariates regarding the number of children and elderly living in the household are computed based on the parental relationships and the individuals' age. Due to some error in variables like age and the missing follow-up for some members of the family, these variables were estimated only for families with complete records for all members.

Table 2 – Descriptive statistics and variable definition: From unemployment to employment

Variable	**Definition**	**Mean**
time (weeks)	Time in unemployment (in weeks)	57.304
		(53.536)
female	=1 if female	0.547
married	=1 if married	0.513
child1	Number of children younger than 4 years old living in the household	0.139
		(0.384)
child2	Number of children aged between 5 and 14 years old, living in the household	0.257
		(0.571)
elderly	Number of parents/parents-in-law older than 65 years	0.117

Table 2 – (Continued)

Variable	Definition	Mean
	old living in the household	(0.389)
first	=1 if the individual is looking for (or in) her the first job	0.166
search	Number of active search methods used by the individual in the previous quarter	1.843
benefits	=1 if in the previous quarter the individual's primary source of income was the public unemployment assurance	0.313
NUTS-R	Variation, in percentage points, of the unemployment rate (by gender) from quarter t-1 to quarter t in the individual's NUTS-II residence	0.075 (0.962)
NAT-R	Difference between the unemployment rate in the individual's NUTS-II residence (by gender) and the national unemployment rate (by gender), at quarter t-2	0.260 (1.930)
Nat. U. Rate	Simple average of total unemployment rate (men and women) in the period 1998 to 2009 (second quarter)	6.1
Nat. U.Rate Male	Simple average of men's unemployment rate in the period 1998 to 2009 (second quarter)	5.2
Nat. U.Rate Female	Simple average of women's unemployment rate in the period 1998 to 2009 (second quarter)	7.2
age		
15 - 24	=1 if the individual is aged between 15 and 24 years old	0.293
25 – 34 (base category)	=1 one if the individual is aged between 25 and 34 years old	0.248
35 - 44	=1 if the individual is aged between 35 and 44 years old	0.184
45 - 54	=1 if the individual is aged between 45 and 54 years old	0.159
55+	=1 if the individual is aged between 55 and 64 years old	0.115
educ		
non-educ	=1 if the individual has no educational	0.050
basic 1 (base category)	=1 if the highest educational level attained is the 1st cycle of basic education (4 years)	0.293
basic 2	=1 if the highest educational level attained is the 2nd cycle of basic education (6 years)	0.217
basic 3	=1 if the highest educational level attained is the 3rd cycle of basic education (9 years)	0.206
high school	=1 one if the highest educational level attained is a high school diploma (12 years) or post-secondary non-tertiary education	0.143

Table 2 – (Continued)

Variable	Definition	Mean
college	=1 if the highest educational level attained is a tertiary education	0.092
residence (NUTS-II level)		
North	=1 if individual works in the North region	0.334
Centre	=1 if individual works in the Centre region	0.101
Lisbon	=1 if individual works in the Lisbon region	0.181
Alentejo	=1 if individual works in the Alentejo region	0.149
Algarve	=1 if individual works in the Algarve region	0.107
Azores	=1 if individual works in the Azores region	0.066
Madeira	=1 if individual works in the Madeira region	0.062

Note: Standard deviation in parenthesis

5 Results and discussion

In this section, we present the results for cause-specific hazard (single risk). Section 5.1 refers to the transition from employment to unemployment model, whereas in Section 5.2 we present the estimation results for the unemployment to employment model.

We also estimate the cumulative incidence function, CIF, (competing risks) that yield similar results as those found in this section; the results can be found in appendix C.

5.1 From employment to unemployment

Table 3 presents the estimation results for the cause-specific hazard of unemployment (single risk), for three alternative models (Cox PH, PCE and Weibull PH), that yielded quite similar estimates for all models.

All models were estimated considering stratification by economic activity[28] using the Stata® command *strata*, except the PCE model where the stratification was made by adding a dummy variable for each economic activity (omitted from the output). In the PCE model, model 2, we try different time intervals, and use the Akaike Information Criterion to choose the optimal time intervals. Our final choice was intervals of 52 weeks up to week 520 (ten intervals), 260 weeks intervals onwards up week 1560 (30 years), and a final interval for more than 30 years. In the Weibull PH model estimation, model 3, we omitted the ancillary estimators for each stratum, for a matter of space and readability. Also note that robust standard errors were used, allowing for intragroup correlation within the household (family), i.e., the observations are considered independent across households but correlated within the household. For those aged between 45 and 54 a time interaction was added by the mean of two dummies, one for those working form less than 1300 weeks (25 years) and other for those working for more than 25 years. The purpose of these interactions is to guarantee that proportional hazard rate was not violated, as preliminary estimations suggested.

The results show that single women have a higher risk of job loss comparing to men (5.3% in Cox model), although the estimators are not significant at 10% for all models. Regarding to marital status, the difference between married men and married women is given by:

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[28] See appendix B for mode detail about the stratification.

$$ln[h(t|\, female = 1, married = 1) - h(t|\, female = 0, married = 1)]$$
$$= (\beta_1 + \beta_2 + \beta_6) - (\beta_1 * 0 + \beta_2 + \beta_6 * 0) = \beta_1 + \beta_6$$

The estimated result for Cox model is 1.2067 with Wald statistic of 7.23, significant at a 1% level. Comparing married men with single ones, the former have lower risk of unemployment: 17.5% in the Cox model and 19.2% in the Weibull PH model. Married women do not significantly differ from single women (10% level).

Our results suggest that the family structure plays an important role to the transition to unemployment, and affects men and women differently. A joint test for covariates child1, chil2 and elderly show that they are statistically relevant at 1% in Cox and Weibull PH models in the likelihood-ratio test[29],[30]:

Table 3 – Cause-specific hazard of unemployment estimation results[31]

VARIABLES	(1) Cox	(2) PCE[32]	(3) Weibull PH[33]
female	1.053	1.068	1.061
	(0.0633)	(0.0636)	(0.0630)
married	0.825***	0.849**	0.808***
	(0.0576)	(0.0587)	(0.0562)
child1	0.969	0.958	0.952
	(0.0750)	(0.0736)	(0.0733)
child2	0.863***	0.859***	0.846***
	(0.0485)	(0.0478)	(0.0479)
elderly	1.161**	1.157**	1.119**
	(0.0677)	(0.0665)	(0.0634)
female*married	1.146	1.131	1.158*
	(0.0967)	(0.0942)	(0.0969)
female*chil1	1.313***	1.319***	1.315***
	(0.123)	(0.123)	(0.122)
female*chil2	1.144**	1.145**	1.174**
	(0.0773)	(0.0768)	(0.0800)
female*elderly	0.933	0.923	0.920
	(0.0845)	(0.0829)	(0.0817)
Education			

29 $LR\ \chi^2(6) = 29.56$ (p<0.01) for Cox model, and $LR\ \chi^2(6) = 26.26$ (p<0.01) for Weibull PH model.

30 In order to perform the test, we have to estimate the models without robust standard errors.

31 The results are presented in the form of hazard ratio, where values above 1 mean a higher hazard and values below 1 indicate a lower hazard of transition.

32 The model specification also included variables such as the time dummies and the stratum dummies, which results have not been reported for simplicity reasons.

33 The model specification also included the stratum parameters, which results have not been reported for simplicity reasons.

Table 3 – (Continued)

VARIABLES	(1) Cox	(2) PCE[32]	(3) Weibull PH[33]
non-educated	0.961	0.975	1.012
	(0.0920)	(0.0917)	(0.0948)
basic2	0.951	0.935	0.917
	(0.0524)	(0.0510)	(0.0496)
basic3	0.932	0.913	0.891*
	(0.0563)	(0.0547)	(0.0528)
high school	0.832***	0.813***	0.794***
	(0.0563)	(0.0542)	(0.0524)
college	0.745***	0.744***	0.755***
	(0.0649)	(0.0635)	(0.0638)
Age			
15-24	1.137**	1.081	1.251***
	(0.0635)	(0.0600)	(0.0696)
35-44	1.083	1.067	0.956
	(0.0607)	(0.0589)	(0.0522)
45-54, working <25 yr	1.092	1.061	0.931
	(0.0768)	(0.0745)	(0.0644)
45-54, working >25 yr	0.496*	0.424**	0.289***
	(0.206)	(0.184)	(0.0974)
55+	1.155	1.118	0.916
	(0.105)	(0.102)	(0.0812)
NUTS	1.297***	1.306***	1.320***
	(0.0251)	(0.0254)	(0.0261)
NAT	1.106***	1.111***	1.120***
	(0.0107)	(0.0106)	(0.0107)
constant		0.003157***	0.0245***
		(0.0002426)	(0.00295)
p			0.570***
PH test	13.90		
Log pseudo-likelihood	-19199.06	-9381.49	-9844.45
AIC	38440.12	18856.97	19778.90
Wald χ^2	415.45***	4424.58***	719.77***
Observations[34]	291476	328381	291476
Failures	3011	3011	3011

Robust SE in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[34] The number of observation are different (higher) than the number of observations presented in descriptive statistic tables in section 4, because the time interactions was computed using the Stata® command *stplit*. When we use this command to split time at 52 weeks, for example, it duplicates the observations that where measured at $t = 52\ weeks$, for one of these observations the status covariate is left missing. This happen so the interval is inclusive or exclusive at $t = 52\ weeks$, in our example. Despite this "transformation" in data, the results are not affected, is just the way Stata® handle this operations. Additionally, the PCE models are the one with more observations, because it required us to *stplit* time in more cut points.

For men, an additional child younger than four years has no relevant effect on transition to unemployment, but for women it increases the unemployment risk by over 30% (compared to women with no young children), in all models. Living in a household with children aged between 5 and 14 years old reduces the risk of unemployment by nearly 15%, but an additional child (aged between 5 to 14 years) increases the females' risk of unemployment by nearly 20%[35]. An extra elderly person in the household increases the unemployment hazard for men by about 16% (more precisely, 16.1% in Cox model and 15.7% in PCE model); no significant gender difference was found.

Such gender difference regarding small children was expected, given the traditional roles of both genders in society. Small children require care competing in time and attention with parents' jobs; given the traditional role of women raising children, it came as no surprise that women have higher chances of losing their jobs. Our estimates are in accordance with Lauer (2003), who found evidence that children younger than six years increase the female risk of unemployment, but not its male counterpart. The author also found evidence that being married in France reduce the unemployment risk for both male and female, while in Germany marriage increases the risk for women, but it lowers the risk for men.

All age dummy variables are jointly significant for Cox model[36] (marginally) and Weibull PH model[37], but not for PCE model[38]. In general younger workers face higher risk of unemployment as opposed to older workers. As age is indirectly related with job experience and human capital accumulation, within a company, we expect younger employees to have less experience than older co-workers. Buhai, Portela, and Teulings (2014) found evidence, for Portugal and the Netherlands, of the existence of a LIFO (Last In First Out) rule, implying that employers tend to dismiss worker with shorter tenure, favouring the ones who work in the company for longer a period of time.

The unemployment rate variables, NUTS and NAT, are both statistically significant at 1% level. An increase of one percentage point in the workplace area unemployment rate, comparing to the previous quarter, increases the risk of unemployment between 29.7% (Cox model) and 32.0% (Weibull PH model). When we compare the local unemployment rate with the national unem-

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[35] $(1.053 * 1.144 = 1.2046;\ p < 0.05)$

[36] Wald statistic 10.94 (p<0.10)

[37] Wald statistic 34.75 (p<0.01)

[38] Wald statistic 8.29 (p>0.10)

ployment rate, NAT, an additional percentage point in the difference between the former and the previous is associated with a higher risk of unemployment, ranging between 10.6% (Cox model) and 12.0% (Weibull PH model). These results are not surprising as an increase in unemployment rates reflects the worsening of the economic activity and a reduction in workforce by employers.

In general, the higher the education level is associated with a lower the risk of unemployment. When compared to the basic1 level, only a high school diploma or a college degree reduces the risk of unemployment. Workers holding a high school diploma have 83.2% (Cox model) of the unemployment hazard of the ones with a basic1 level (or, in different way, 16.8% less hazard), whereas the effect for college degree vary between 24.5% (Weibull PH model) and 25.5% (Cox model), compared to basic1 level. For all, models the college degree offers a better protection against unemployment than the high school, however, the difference between college and high school graduation is not statistically significant[39].

When an employer has to reduce hers workforce, we expect her to dismiss the workers with lower productivity trying to keep the best workers. As pointed in session 2, some authors show that education has a positive impact on individuals' productivity, while others think that education is used by individuals to signal their higher productivity. The fact that higher levels of education are associated with lower risk of job loss may reflect the higher productivity of higher schooled workers.

5.2 From unemployment to employment

The estimated results for the cause-specific hazard (single risk) of employment among those who are unemployed are presented in Table 4. The intervals in the PCE model were chosen by using the use the Akaike Information: intervals of 26 weeks (six months) up to 104 weeks (two years) of unemployment (four intervals of six months in the first two years), 52-weeks intervals from week 104 to week 208 (four years) and a final interval for more than 208 weeks in unemployment. As before, we use robust standard errors in respect to household. In order to fulfil the proportional hazard assumption, variables such as married, individuals aged between 45 to 54, individuals aged between 55 to 64, the evolution of unemployment in the residence area, and benefits were interacted with time. The time interaction distinguishes those who were unemployment for less or more than one years (52 weeks), with the exception of the benefits for which we distinguish three

[39] Being $H0\colon High\,School = College$ we cannot reject the null hypotheses for all models at a 10% significance level [Cox model, Wald statistic 1.67 (p>0.1); PCE model, Wald statistic 1.08 (p>0.1); and Weibull PH model, Wald statistic 0.37 (p>0.1)].

periods (the period up to one year, between one year up to one and half year, and more than one and half years - 78 weeks).

In general, the estimated coefficients are similar across all models that give strength to our findings. The results suggest that married men without job for less than one year have higher chances of returning to employment, with the estimates varying between 22.8% (PCE model) and 48.1% (Weibull PH model). For men who are married and unemployed for more than one year the estimation results are not so close. In the Cox model the estimate is 37.7% statistically significant at 1%, whereas in the Weibull model it is 0.6%, although it is not statistically different from zero. On the other hand, married women have lower chances of finding a new job, when compared to married men: nearly 30% less employment opportunities in all models if unemployed for less than one year. Married women, unemployed for more than one year, have a hazard about 50% lower compared to married men[40]

The family structure variables (child1, child2 and elderly) are jointly significant at 1%[41]. The estimated coefficient for elderly is negative, but not statistically significant at 5% level, and no difference had been found between men and women. These results suggest that men are not affected by having children of both age groups, whilst for women an additional child reduces the re-employment probability by about 29%. The lower employment hazard for women with young children, may be explained in two ways. On one hand, young children may compete with the task of job searching, as previously stated, lower job search intensity leads to lower job opportunities. At the same time, women may be willing to dedicate more time to their child(ren) and sacrifice job opportunities that do not offer flexitime. On the other hand, employer may be reluctant to hiring women with young children, expecting low punctuality and attendance due the traditional role of child care, usually attributed to women.

Table 4 – Cause-specific hazard of employment estimation results[42]

VARIABLES	(4) Cox PH	(5) PCE[43]	(6) Weibull PH
female	0.984	0.979	0.978
	(0.0529)	(0.0516)	(0.0561)
married, jobless <12 m	1.255***	1.228**	1.481***

[40] Wald Statistic 35.76 (p<0.01)

[41] Likelihood-ratio test: $LR\ \chi^2(6) = 78.48$ (p<0.01) for Cox model and $LR\ \chi^2(6) = 41.09$ (p<0.01) for Weibull PH model

[42] See footnote 31

[43] The model specification also included the time dummies, which results have not been reported for simplicity reasons.

Table 4 - (Continued)

VARIABLES	(4) Cox PH	(5) PCE[43]	(6) Weibull PH
	(0.107)	(0.104)	(0.130)
married, jobless >12 m	1.377***	1.369***	1.006
	(0.154)	(0.153)	(0.112)
child1	1.064	1.052	1.039
	(0.0959)	(0.0919)	(0.0929)
child2	0.988	0.986	0.981
	(0.0615)	(0.0600)	(0.0624)
elderly	0.876*	0.877*	0.842**
	(0.0629)	(0.0629)	(0.0647)
female*married, jobless <12 m	0.717***	0.736***	0.734***
	(0.0702)	(0.0712)	(0.0736)
female*married, jobless >12 m	0.511***	0.513***	0.484***
	(0.0638)	(0.0638)	(0.0631)
female*chil1	0.721***	0.728***	0.723***
	(0.0771)	(0.0760)	(0.0773)
female*chil2	0.987	0.981	1.003
	(0.0754)	(0.0737)	(0.0779)
female*elderly	0.965	0.961	0.971
	(0.0972)	(0.0965)	(0.104)
Education			
non-educated	1.151	1.149	1.209*
	(0.127)	(0.125)	(0.137)
basic2	1.018	1.018	1.011
	(0.0623)	(0.0618)	(0.0645)
basic3	1.092	1.083	1.082
	(0.0684)	(0.0672)	(0.0708)
high school	1.131*	1.115	1.150*
	(0.0776)	(0.0755)	(0.0825)
college	1.627***	1.591***	1.720***
	(0.124)	(0.120)	(0.136)
Age			
15-24	1.263***	1.226***	1.375***
	(0.0668)	(0.0638)	(0.0759)
35-44	0.804***	0.805***	0.782***
	(0.0497)	(0.0491)	(0.0499)
45-54, jobless <12 m	0.548***	0.545***	0.565***
	(0.0485)	(0.0476)	(0.0508)
45-54, jobless >12 m	0.331***	0.327***	0.284***
	(0.0411)	(0.0407)	(0.0355)
55+, jobless <12 m	0.293***	0.298***	0.306***
	(0.0376)	(0.0382)	(0.0402)
55+, jobless >12 m	0.0856***	0.0847***	0.0716***
	(0.0177)	(0.0175)	(0.0148)

Table 4 – (Continued)

VARIABLES	(4) Cox PH	(5) PCE[43]	(6) Weibull PH
first	0.526***	0.536***	0.487***
	(0.0294)	(0.0296)	(0.0291)
search, jobless <12 m	1.048**	1.055***	1.174***
	(0.0191)	(0.0187)	(0.0192)
search, jobless >12 m	1.123***	1.121***	0.848***
	(0.0327)	(0.0328)	(0.0254)
unemploy benefits, jobless <12 m	0.538***	0.553***	0.566***
	(0.0324)	(0.0327)	(0.0345)
unemploy benefits, jobless <18 m	0.567***	0.566***	0.771**
	(0. 0774)	(0.0772)	(0.0981)
unemploy benefits, jobless >18 m	1.234*	1.236*	0.994
	(0.141)	(0.141)	(0.108)
NUTS_RES, jobless <12 m	0.812***	0.785***	0.789***
	(0.0172)	(0.0169)	(0.0182)
NUTS_RES, jobless >12 m	0.769***	0.770***	0.780***
	(0.0297)	(0.0295)	(0.0267)
NAT_RES	1.022**	1.019*	1.021*
	(0.0106)	(0.0104)	(0.0110)
constant		0.00905***	0.00100***
		(0.000733)	(0.000109)
p			1.534***
PH test	38.01		
Log pseudo-likelihood	-26020.83	-6804.48	-6607.58
AIC	52103.67	13684.96	13281.16
Wald χ^2	1037.60***	1275.84***	1516.68***
Observations[44]	34540	36,723	34540
Failures	3272	3272	3272

Robust SE in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In general, holding a college degree improves the chances of finding a new job. The educational level with higher hazard of finding a job is the tertiary education, the estimates vary from 59.1% (in PCE model) to 72.0% (in Weibull PH model), both statistically significant at 1%. Individuals who finish high school have better chances of finding a new job (13.1% in Cox model; 11.5% in PCE model, and 15.5% in Weibull PH model, but the estimators are marginally significant at best for Cox and Weibull models). No difference had been found between those with a high school

[44] See footnote 34

diploma and individuals who just attend the third cycle of the basic education. These results are in accordance with previous studies (Kettunen, 1997; Núñez & Livanos, 2009; Riddell & Song, 2011b). The positive effect of education on individuals' re-employment probability may be explained by the crowding-out theory and the existence of a positive effect of education in individuals' productivity. At the same time, more educated individuals may have higher unemployment costs associated to the investment in education, making them to put more effort in job hunting (Bloemen, 2005; Weber & Mahringer, 2007).

Age also play an important role explaining the transition from unemployment to employment, all age dummy variables are jointly significant in Cox[45], PCE[46] and Weibull[47] models. Individuals aged from 15 to 24 years old have between 22.6% (PCE model) and 37.5% (Weibull PH model) higher chances of finding a job than the ones aged between 25 to 34 years old. Unemployed with more than 55 years old, who lost their jobs for less than one year, have about 70% less chances of finding a job, compared to the ones aged between 25 to 34 years old. The chances are even lower, about 90% if the individuals are unemployed for more than one year. This difference, observed for individuals with more than 55 years old, if unemployed for less or more than one year is statistically significant at 1%[48]. These result may have different possible explanations. First, younger individuals may have a lower reservation wage or may be willing to accept a lower salary given their lower job experience. Second, employers may be looking for future employer to make carrier inside the company, hence the preference for younger individuals with higher prospect of job/carrier progression. Third, younger individuals may be more motivated to search for a job, than older individuals who are near the retirement age.

The higher probability of re-employment observed for individuals in the younger age groups may indicate the preference of employers for individuals that are more dynamic, creative, more prone to adapt and learn (The Pedagogy for Employability Group, 2012). When companies are looking for future employees to make long-term carriers that require training and a high learning curve in the company, younger applicants may be a wise choice. Older applicants, although more experienced, may be less permeable to the company's philosophy or environment as opposed to younger applicants who are more malleable by employers.

[45] Wald statistic=292.99 ($p<0.01$)

[46] Wald statistic=286.74 ($p<0.01$)

[47] Wald statistic=342.65 ($p<0.01$)

[48] Wald statistic=29.21 ($p<0.01$)

Individuals entering the labour market for the first time, i.e. looking their first job, struggle more to find a new job compared to those with more experience. The estimates for the PCE model suggest that inexperienced applicant have 46.4% less chances of finding a job than other applicant who had a past job experience (in the Weibull PH model is 51.3%). Workers with past job experience may require less initial training given the what they have learned in past job experiences, although there is no information on whether the past experience is relevant for the new job. In any case, the result is in line with Addison and Portugal (2002), using the Portuguese labour force survey for the period from 1992 to 1996. They also found evidence that inexperience applicants have lower chances of leaving unemployment. From the employer point of view, job experience may signal what to expect from the potential worker in terms of training and knowledge in the execution of specific tasks. At the same time, it is expected that an experienced worker have a higher learning curve, representing lower direct and indirect costs for the employer.

The job search effort can help improving the chances of finding a new job; the number of different methods to find a job can be used as a proxy. Among individuals who are unemployed for less than a year, those who use more job search methods have more chances of leaving the unemployment status. An additional job search method increases the employment hazard by 4.8% (Cox model), if the individual is unemployed for less than one year, and by 12.3% (Cox model), if unemployed for more than one year, and the difference between these two effects is statistically significant at 5%[49]. This mean that long term unemployed can improve their chances of leave unemployment and minimize the lower employability chances associated to the long term unemployment, by intensifying job search. The positive effect of search intensity in re-employment prospect is supported by Bloemen[50] (2005) and McVicar[51] (2008) who found a positive effect of job search intensity and re-employment. However, the Weibull model give a different insight, suggesting a negative effect for those unemployed for more than one year of about 15.2%. Such contradictory results may be related with the fact that the search variable measures the number of active job search methods, providing no information about the quality of each method (some method combinations may be more effective than others).

[49] Wald statistic 4.53 ($p<0.05$)

[50] Bloemen (2005) used a composite variable to measure the search intensity, which included among other indicators the number of applications sent.

[51] McVicar (2008) found evidence that public policies that force an active and direct approach in job search lead to higher escape rates from unemployment.

Those for whom unemployment benefits is their primary income source have lower chances of finding a new job; it is about 55% less if the individual is unemployed for less than 78 weeks. No difference was found between the period of less than 52 weeks and 52 to 78 weeks, except for the Weibull PH model. Addison and Portugal (2008) and Portugal (2008), using Portuguese data, also conclude that receiving unemployment benefits reduce the hazard of finding a job for about 50%. This results suggest that unemployment benefits may reduce the urgency to find a new job, a postpone effect, but on the other hand, they allow the individuals to have time to find a better job (matching) and do not force them to accept the first job opportunity. However, when the individual is unemployed for more than 78 weeks, the effect of unemployment benefits became positive (23.4% in Cox model; and 23.6% in PCE model) or non-different from zero (in the Weibull PH model). Although, the low significance, the estimates (for more than 78 weeks in unemployment) suggest that individuals who are close to benefits exhaustion search harder for new jobs. David, Chetty and Weber (2007), using Austrian data, found evidence of a spike in scape rates (from unemployment) when unemployment benefits are exhausted.

The estimation results for unemployment rates covariates show unexpected results. The coefficient of NUTS_RES is negative and statistically significant in all models, with no difference found between unemployed for more or less than one year. As expected, an increase in the unemployment rate suggests that companies are reducing their workforce and, therefore, hiring less. Considering the relative position of the residence area unemployment rate compared to the national unemployment rate, it was expected that a relative higher unemployment rate in residence area would reduce the chances of finding a new job, but the results lean in a different path, with slightly positive and marginally significant estimates (Cox model: 2.2%; PCE model: 1.9%; and Weibull PH model: 2.1%). This result although weak is intriguing and may reflect the possibility of mobility, i.e., those who live in regions with high unemployment rates may start looking for jobs in areas with more favourable labour markets.

In addition to the cause-specific hazards, we also estimate the CIF for the employment and unemployment; see Table 9 and Table 10 in appendix C. The results support those obtained for the cause-specific hazards. Education has a positive and significant impact on labour market transitions. Individuals with a high school diploma or college graduates have higher protection against unemployment and those with tertiary education who lost their job have higher chances of finding a new job.

5.3 Discussion

Our results show that education has a positive effect on labour market transitions. Individuals with a high school diploma or higher have higher security on work, in the sense that they face a lower risk of unemployment. Such lower risk of unemployment may be a result of individuals' higher productivity and hence the preference of the employers for such workers. Regarding the effect of the education level among those who lost their job or those who are looking for their first job, only having a college degree increases the chances of leaving unemployment. This may be a result of the crowding-out effect or a shift in the preferences or needs of the employer for more qualified workers.

In addition to the estimation results presented in the previous sections, we also try to address the problem of unobserved heterogeneity[52,53], by estimating two alternative models that control for it: gamma distribution frailty under a Weibull PH and PCE models. Regarding the transition from unemployment to employment we successfully test for the presence of unobserved heterogeneity at individual[54] and family[55] level with a stronger effect at the family level. A potential source of unobserved heterogeneity is the individual and family wealth. The family network may help smoothing the financial distress raised by the job loss, or even may be a source of job opportunities. Finally, it is possible that some individuals may have a job in the so-called underground economy, which alleviate their income restrictions and allow them to search for a job for a longer period of time. Unfortunately, we did not obtained results for the model with unobserved heterogeneity for employed individuals given the lack of convergence due non-concave function; further research can be made to address this issue.

Despite the robustness of our estimates under different models specifications further investigation can still be done to gain more insight into the role of education on labour market transitions.

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[52] For more detail about unobserved heterogeneity, also known as frailty models, see Cleves et al. (2010) and Hosmer, Lemeshow, and May (2008).

[53] Unobserved heterogeneity estimated using the options *shared* and *forceshared* in Stata®. Option *shared*, alone, is not allowed in the presence of delay entry (also known as left truncations), when the set on risk occur before the individual starts to be followed in LFS. To overcome this limitation, we use option *forceshared* developed by Gerard van den Berg and Bettina Drepper, which allow the estimation of unobserved heterogeneity in the presence of delay entry under the assumption that unobserved heterogeneity distribution is independent of covariates and truncation points (van den Berg and Drepper, 2011). Given the sample selection of LFS, discussed in section 4, the truncation points are random whereby we think it is safe to assume the independence between the unobserved heterogeneity and truncation points.

[54] The estimated variance ($\hat{\theta}$) at individual level was: $\hat{\theta}_{individual} = 0.993$ in Weibull PH model and $\hat{\theta}_{individual} = 0.260$ in PCE model, both statistically significant at 1% level in likelihood ratio test.

[55] The estimated variance ($\hat{\theta}$) at family level was: $\hat{\theta}_{family} = 1.271$ in Weibull PH model and $\hat{\theta}_{family} = 0.623$ in PCE model, both statistically significant at 1% level in likelihood ratio test.

Our results account for the level of education, but do not account for the quality of education or the field of study. The data on the quality of education was not available. Information on the field of study started to be collected in 2004, and as such only few observations were available to perform the analysis. Additionally, when modelling the transition from unemployment to employment we do not take in account the income (and wealth) of the individual or of the household, to control for budget constraints. We believe that income restrictions play an important role in defining the individual job search intensity and the type of job offers she is willing to accept given her financial status, as the estimation results for unemployment benefits seems to suggest.

Future research can be done in in this topic, which will extend the conclusions of the present research. First, we can add some control variables for budget restrictions of the household, which we believe is an important driver of search intensity. Second, the issue of unobserved heterogeneity should be better addressed. Third, the research should be extended to the period after the second quarter of 2009, to allow for evaluating whether the Portuguese sovereign debt crisis changed the way the labour market transitions are determined by the education level of the individuals. This would allow for the distinction between the two periods, that is, it would make it possible to distinguish between before and after the crisis. Fourth, we may extend the analysis to other countries in order to introduce a comparative perspective, especially within the European countries. Such research would allow investigating the presence of differences among countries and it would shed some light on the design of future employment policies at the European level.

6 Conclusion

In the recent past we have experienced an increase in educational levels of the population driven by youth, while at the same time we have experienced an increase in the unemployment rates, especially the among younger adults. This apparent contradiction justified our interest in accessing the role of education in the labour market transitions. Namely, we aim at understanding whether education protects individuals against unemployment, and whether it eases the transition from unemployment to employment.

In order to evaluate the role of education in the labour market transitions we use the Portuguese's LFS from 1998 to 2009 (second quarter), a very rich panel dataset (each household is followed for six quarters, after which it is replaced by a new household). To take advantage of the panel structure of the data, we applied duration analysis techniques in continuous time, namely, the Cox PH, the PCE and Weibull PH models were estimated to access how the educational level of the individual affects the hazard of unemployment and the chances of finding a job among the unemployed.

After controlling for individual characteristics (like gender, civil status, education and unemployment rate) and household characteristics (such as the number of children and elderly), our findings suggest that education, at higher levels, have an impact in labour market transitions. Starting with the risk of unemployment, we found evidence that those with a high school diploma or higher, have a lower hazard of job loss, although no difference was found between secondary education and tertiary education degrees. This suggests that individuals with more education (with some degree of differentiation and specialization) are preferred by employers, which may suggest that they are more productive or more difficult to replace, compared to unskilled workers.

Regarding those who lost their job or are looking for the first job opportunity, our results show that only the college degree is associated with higher chances of finding a job. This may be due to the presence of the crowding-out effect, with employers preferring (or needing) more qualified employers. We also found that individuals without past job experience have lower chances of leaving unemployment, which signals the preference for experienced workers and the need of employment programs design targeting this group of unemployed, mainly youths.

The combined results may help to explain the long term unemployment among low-educated adults; they are the first to be dismissed and when it happens they have lower chances of finding a new job due to their lower educational level. Apart from education, older unemployed individuals also have lower chances of leaving unemployment, and the longer the unemployment duration the lower their chances of returning to work.

Finally, although, the younger individuals face higher unemployment rates, despite the higher levels of education compared to older generations, the investment in education still is a wise decision. Those with higher levels of education have higher security in job, with lower risk of unemployment, and those who are unemployed with a college degree have the highest chances of finding a new job.

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Appendix

A. Data preparation

Regarding employment duration, some observations show some unusual values for the age at which the individual started working in the current job or occupation or become unemployed. To deal with this issue, some observations were dropped. Table 5 presents the conditions considered to drop observations dropout based on the age (divided in five age groups). Table 6 presents the conditions that apply to the highest educational level attained and Table 7 presents the conditions related to the job occupation category and age. These rules aim at representing the evolution and changes in the minimum mandatory educational level, as well as changes in labour market, namely the minimum legal age for entering the labour market. An observation was eliminated if it satisfied at least one condition.

Table 5 – Outliers conditions based on age, from authors

Age group	Dropped if age at which the subject started working in the current job or occupation is:	Dropped if age at which the individual become jobless is:
15-24	<15	<15
25-34	<15	<15
35-44	<14	<15
45-54	<13	<16
55+	<12	<16

Table 6 – Outliers conditions based on Education, from authors

Education	Dropped if age at which the subject started working in the current job or occupation is:	Dropped if age at which the individual become jobless is:
No Educ	<12	<15
Basic 1	<12	<15
Basic 2	<14	<15
Basic 3	<15	<15
High School	<17	<17
Post-Secondary	<17	<19
Higher Education	<18	<20

Table 7 – Outliers condition based on job's occupation description, from authors

<table>
<tr><td rowspan="2"></td><td colspan="5">Dropped if age at which the subject started working in the current job or occupation is:</td></tr>
<tr><td colspan="5">Age</td></tr>
<tr><td>Occupation</td><td>15-24</td><td>25-34</td><td>35-44</td><td>45-54</td><td>55+</td></tr>
<tr><td>Unskilled workers</td><td rowspan="5"><15</td><td rowspan="6"><15</td><td rowspan="4"><14</td><td rowspan="4"><12</td><td rowspan="4"><12</td></tr>
<tr><td>Machine operators and assemblers</td></tr>
<tr><td>Craft and related workers</td></tr>
<tr><td>Farmers and skilled agricultural and fishery workers</td></tr>
<tr><td>Personal services and sales</td><td rowspan="2"><16</td><td rowspan="2"><16</td><td rowspan="2"><14</td></tr>
<tr><td>Administrative staff and similar</td><td><18</td></tr>
<tr><td>Technicians and associate professionals</td><td rowspan="3"><20</td><td rowspan="3"><20</td><td><20</td><td><18</td><td><18</td></tr>
<tr><td>Specialist of scientific and intellectual professions</td><td><21</td><td><21</td><td><21</td></tr>
<tr><td>Senior officials of government, senior officials of companies</td><td><18</td><td><18</td><td><18</td></tr>
</table>

B. Stratified models by economic activity

As said before, a stratified analysis can be useful when we want to control for a covariate that we know that affect the final outcome, but its effect is not of main interest for the analysis. Additionally, stratified duration models can also be used to solve the violation of proportional hazard assumption (Singer and Willett, 2003).

In our case, the non-stratified Cox model for the transition from employment to unemployment violates the proportional hazard assumption, hence the decision of stratify our analysis by economic activity.

Table 8 – Sectors of Economic Activity.

A	Agriculture and Foresting
B	Fishing
C	Mining and Quarrying
D	Manufacturing
E	Production and distribution of electricity, gas and water
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Accommodation and food service activities
I	Transporting, storage and communication
J	Financial and insurance activities
K	Real estate activities and business services
L	Public administration and defence; compulsory social security
M	Education
N	Human health and social work activities
O	Other services activities
P	Activities of households as employers of domestic personnel
Q	Activities of extraterritorial organisations and bodies

Sectors B, C, E and Q where excluded from the sample, because they had very few observations to perform the stratified analysis. The stratified model, excluding sector B, C, E and Q, shows the proportional hazard properties based on Schoenfeld residuals. Nevertheless, and as suggested by Cleves et al. (2010), we have tested the proportionality hazard assumption for each stratum.

We consider the sector has proportional hazard properties if the global Schoenfeld residuals, where the null hypothesis assume proportionality, was not rejected at a 10% significance level. One sector prove to fail the proportional hazard assumption: sector M – "Education" [statistics 57.21 ($p<0.01$)]. These sector whose employees are mainly government workers, faced several changes in the period of analysis, particularly entry conditions and career progression, what may explain the violation of proportional hazard.

C. Cumulative Incidence Functions (competing risks)

In this appendix we present the estimation of the cumulative incidence function of unemployment (Table 9) and of employment (Table 10).

There are three possible states, being (i) employed; (ii) unemployed; and (iii) inactive. When estimating the CIF of unemployment of those who are employed, the competing risk is to become inactive. When estimating the CIF of employment of those who are unemployment, the competing risk is to become inactive, as well.

When we estimate the cause-specific of unemployment, we stratified the model by economic activity to guarantee that PH assumption was jot rejected. The CIF estimation does not allow the stratification, to solve the violation of PH assumption we had to use a different model specification using time interactions. Nevertheless, we exclude those working in educational economic activity; see the discussion in appendix B.

Table 9 – Cumulative Incidence Function of Unemployment[56]

	(7)	(8)
VARIABLES	Cox	CIF
female	1.010	0.994
	(0.0587)	(0.0579)
married, working <10 yr	0.828***	0.853**
	(0.0594)	(0.0613)
married, working >10 yr	0.997	1.005
	(0.166)	(0.167)
child1	0.963	0.961
	(0.0741)	(0.0739)
child2	0.862***	0.859***
	(0.0480)	(0.0479)
elderly	1.160**	1.155**
	(0.0674)	(0.0674)
female*married, working <10 yr	1.196**	1.149
	(0.103)	(0.0995)
female*married, working >10 yr	0.798	0.801
	(0.120)	(0.121)
female*chil1	1.319***	1.327***

[56] See footnote 31

Table 9 - (Continued)

VARIABLES	(7) Cox	(8) CIF
	(0.123)	(0.124)
female*chil2	1.133*	1.131*
	(0.0759)	(0.0759)
female*elderly	0.924	0.940
	(0.0836)	(0.0854)
Education		
non-educated	1.079	1.032
	(0.100)	(0.0968)
basic2	0.908*	0.926
	(0.0497)	(0.0508)
basic3	0.856***	0.875**
	(0.0501)	(0.0514)
high school, working <15 yr	0.754***	0.770***
	(0.0490)	(0.0503)
high school, working >15 yr	0.347***	0.352***
	(0.126)	(0.128)
college, working <15 yr	0.626***	0.659***
	(0.0514)	(0.0542)
college, working >15 yr	0.281**	0.287**
	(0.143)	(0.146)
Age		
15-24	1.136**	1.080
	(0.0633)	(0.0607)
35-44	1.050	1.052
	(0.0586)	(0.0587)
45-54, working <10 yr	1.052	1.046
	(0.0758)	(0.0758)
45-54, working >10 yr	0.803	0.801
	(0.120)	(0.120)
55+	1.112	1.056
	(0.0998)	(0.0952)
NUTS	1.309***	1.294***
	(0.0257)	(0.0255)
NAT	1.119***	1.114***
	(0.0108)	(0.0107)
PH test	18.03	
Log pseudo-likelihood	-26194.165	-26372.551
AIC	52438.39	52795.1
Wald χ^2	504.24***	437.10***
Observations	305,296	305296
Failures	3039	3039

Robust SE in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In addition to CIF estimation we also estimate the Cox model using the same model specification for a better comparison of results. As previous Cox model in Table 3, the new Cox model estimation, point us to a positive effect of education in the protection of job loss. Those with a high school diploma or a college degree have lower hazards of lost their job, especially if they are in that job or occupation for more than 780 weeks (15 years). An individual working for less than 15 years with a high school degree have 24.6% ($p<0.01$) less hazard of job loss compared to a basic1 level, whereas a college graduate have 37.4% less ($p<0.01$) being this difference statistically significant at 5% (Wald statistic 4.89).

As expected, as the tenure increase, an individual gain more experienced in her job tasks at the same time that is expected to her to growth in her carrier. From the point of view of the employer, if the employer has to lay off some of the workforce it starts by those who are less costly (whether for the contract termination payments, the investment in training or by the direct cost of replacement). Buhai, Portela, and Teulings (2014) found evidence that employer use a LIFO rule to dismiss employees, our finding seem to support their findings.

Table 10 – Cumulative Incidence Function of Employment[57]

	(4)	(9)
VARIABLES	Cox	CIF
female	0.984	0.979
	(0.0529)	(0.0529)
married, jobless <12 m	1.255***	1.117
	(0.107)	(0.0960)
married, jobless >12 m	1.377***	1.891***
	(0.154)	(0.233)
child1	1.064	1.051
	(0.0959)	(0.0985)
child2	0.988	0.996
	(0.0615)	(0.0626)
elderly	0.876*	0.888*
	(0.0629)	(0.0641)
female*married, jobless <12 m	0.717***	0.690***
	(0.0702)	(0.0688)
female*married, jobless >12 m	0.511***	0.499***
	(0.0638)	(0.0654)
female*chil1	0.721***	0.759**
	(0.0771)	(0.0832)
female*chil2	0.987	0.949

[57] See footnote 31

Table 10 – (Continued)

VARIABLES	(4) Cox	(9) CIF
	(0.0754)	(0.0736)
female*elderly	0.965	0.989
	(0.0972)	(0.0993)
Education		
non-educated	1.151	1.052
	(0.127)	(0.116)
basic2	1.018	1.032
	(0.0623)	(0.0635)
basic3	1.092	1.071
	(0.0684)	(0.0682)
high school	1.131*	1.100
	(0.0776)	(0.0764)
college	1.627***	1.596***
	(0.124)	(0.125)
Age		
15-24	1.263***	1.121**
	(0.0668)	(0.0609)
35-44	0.804***	0.862**
	(0.0497)	(0.0545)
45-54, jobless <12 m	0.548***	0.550***
	(0.0485)	(0.0492)
45-54, jobless >12 m	0.331***	0.397***
	(0.0411)	(0.0522)
55+, jobless <12 m	0.293***	0.287***
	(0.0376)	(0.0368)
55+, jobless >12 m	0.0856***	0.0913***
	(0.0177)	(0.0196)
first	0.526***	0.544***
	(0.0294)	(0.0305)
search, jobless <12 m	1.048**	0.996
	(0.0191)	(0.0186)
search, jobless >12 m	1.123***	1.417***
	(0.0327)	(0.0332)
unemploy benefits, jobless <12 m	0.538***	0.555***
	(0.0324)	(0.0335)
unemploy benefits, jobless <18 m	0.567***	0.546***
	(0.0774)	(0.0751)
unemploy benefits, jobless >18 m	1.234*	1.374**
	(0.141)	(0.170)
NUTS_RES, jobless <12 m	0.812***	0.833***
	(0.0172)	(0.0179)
NUTS_RES, jobless >12 m	0.769***	0.811***
	(0.0297)	(0.0358)

Table 10 - (Continued)

VARIABLES	(4) Cox	(9) CIF
NAT_RES	1.022**	1.027**
	(0.0106)	(0.0108)
PH test	38.01	
Log pseudo-likelihood	-26020.83	-26894.951
AIC	52103.67	53851.9
Wald χ^2	1037.60***	1167.73***
Observations	34,540	34,540
Failures	3272	3272

Robust SE in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In Table 10 we present the cumulative incidence function of employment and the Cox model from cause-specific hazard presented before for comparison purposes. In general de estimates from CIF model greatly confirm the estimation from cause-specific hazard. Concerning to education, only tertiary education prove to have a statistic effect, those with a college degree have 59.6% higher chances of find a new job. The marginal effect of high school in Cox model was not confirmed in CIF estimation.

The major differences refer to marital status and the number of job search methods. The results for marital status in CIF model, show that married men unemployed for less than 12 months are not statistical different than non-married ones, compared to the positive effect found in Cox model. However, long-term unemployed married men have 89.1% (p<0.01) higher chances of find a new job comparing to non-married man, this results is greater than the 37.7% (p<0.01) found in Cox model. In relation to job search methods, the CIF estimation suggest that an additional search methods has no effect for short-term unemployed and a much positive effect for long-term unemployed, 41.7% (p<0.01). This suggest that, although the longer the jobless status the harder the chances of finding a new job, long-term unemployed may reverse the odds if they invest more in the job hunting by hiding the job search methods. Nonetheless, we should remember that, as stated before, this covariate does not give insight about the quality and good use of the search methods used.

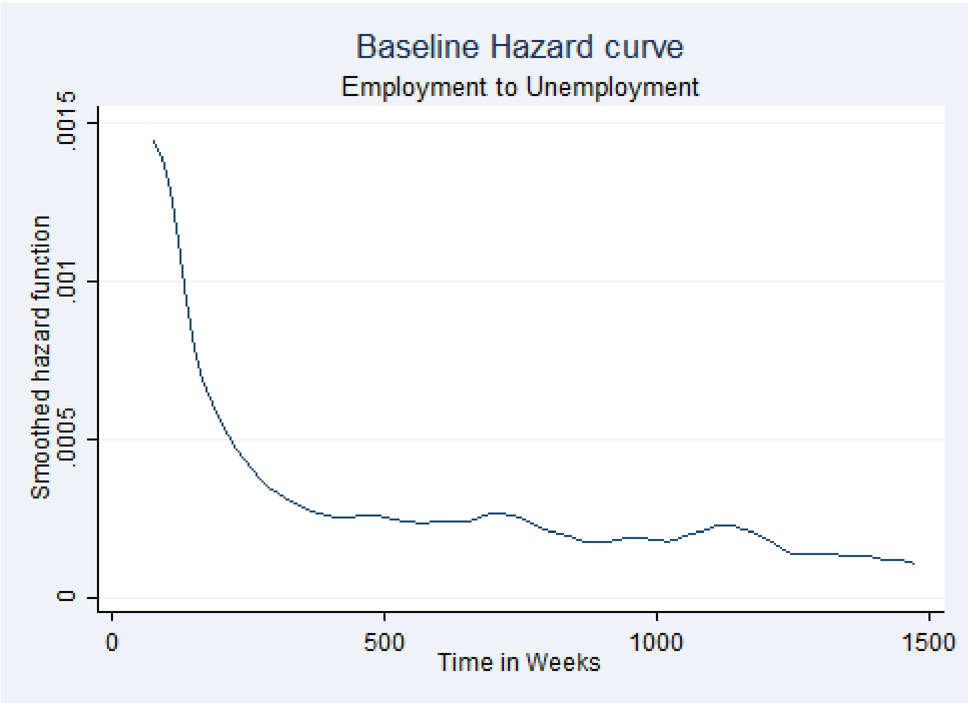
D. Baseline Hazard Function Plot

Although the estimation of Cox PH model do not yield a direct estimate of the baseline hazard function, we can use Stata® *stcurve* command to graph a kernel smooth graphic of the estimated baseline hazard function setting all covariates at their base (or zero) values. This is useful to gain insight about the true nature of the baseline hazard function without imposing any distribution.

Figure 1 presents the estimated baseline hazard curve of unemployment, the curve show a clear downward trend in hazard as time goes by, the longer an individual stays in a company the less likely is that she leaves (because she is sacked or is looking for new employment opportunities). In the initial months (years) the hazard of unemployment is very high, after the fifth or eighth year the hazard curve slop is less pronounce. The initial higher hazard is expected; usually new employees start working under a probation period and/or with a fixed-term employment contract before if become a permanent employment contract. We expect employers to use the initial months (years) of contract to distinguish workers' productivity, keeping the most productive ones and sacking, or not renewing the employment contract, to the less productive ones. Additionally, the longer the tenure in a company the higher are the contract termination payments and benefits that the employer has to pay to sack an employee

This is in accordance with human capital theory, when a given employee starts working she has

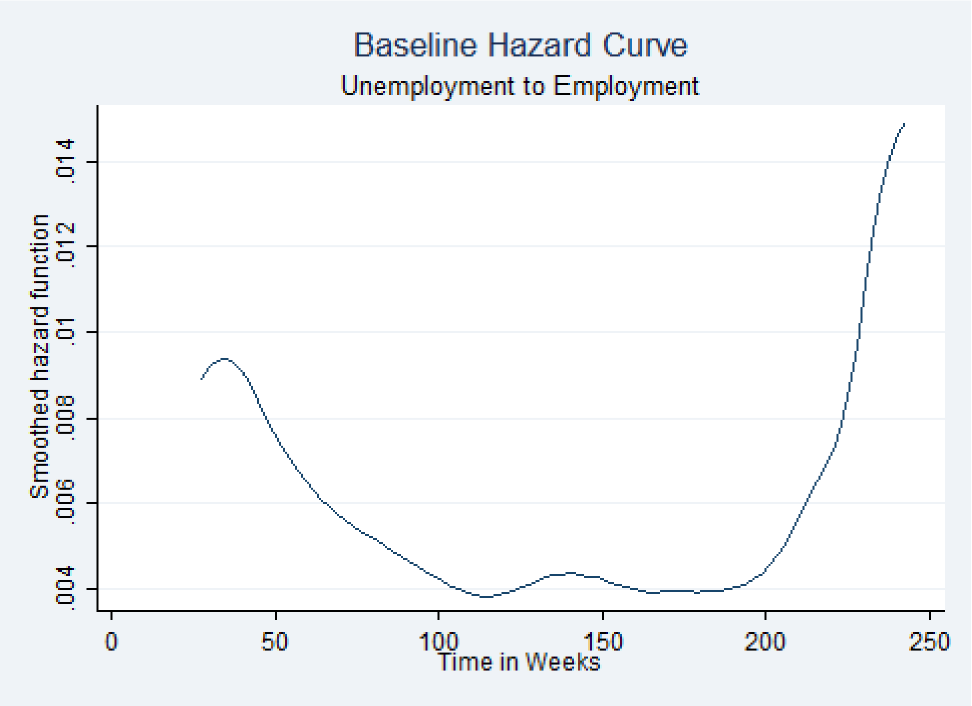
Figure 1 – Estimated baseline hazard curve of unemployment from Cox model (model 7)



not (or has a lower stock of) specific human capital to that work. As the time goes by, her knowledge about her's work duties increase, in other words, hers work specific human capital increases. This increase in specific knowledge can be seen as an investment by the company, if the worker leaves the company, it losses all the training that was invested in her. Buhai, Portela, and Teulings (2014) found evidence that employers use a LIFO (Last In, First Out) rule to dismiss employees, our finding seem to support this concept.

Figure 2 refers to the baseline hazard curve of employment with a U-shape, descending in the first two years, where from the second to the fourth year the hazard rate is almost plain before starting raising rapidly again. This pattern may be explain by an income effect, those who are have higher cost associated to the unemployment condition try harder to find a job and leave the unemployment, where we can include the one looking for the first job, those without unemployment benefits and the one with previous high income jobs (once unemployed their income is reduced increasing the cost of unemployment).

Figure 2 – Estimated baseline hazard curve of employment from Cox model (model 4)



On the other hand, those who are receiving unemployment benefits and the gap between previous job income and the unemployment benefits is not great have lower cost associated to unemployment status. Due their lower unemployment cost they may search less hard to find a job and do not feel compelled to accept the first job offer. However once the unemployment benefits is over their unemployment cost increase dramatically. David et al. (2007) found evidence of a spike in scape rate (from unemployment) when the unemployment benefits end, which also explain the steeper hazard after the fourth year.