# Unemployment duration, technology and skills

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**Abstract**

While technology becomes more present in our daily lives, as well as in our work, the relative demand for skills is shifting. The demand for fast-learning, skilled workers increase in times characterized by technological change. Thus, unskilled people are left with few job opportunities, and might experience higher unemployment rates, as well as longer spells of unemployment. There is also strong evidence that unskilled individuals experience higher hazards of job separation during periods of intense technological change. Therefore, acquiring human capital, and especially technology-specific human capital, is paramount in the new labor market. Using the Portuguese quarterly Labor Force Survey, we estimated econometric duration models. Ours results demonstrate that technology intensity underline the negative relation between skills and unemployment duration.

**Keywords:** Unemployment duration, Technology, Skills, Human capital, Duration models

## 1. Introduction

In the midst of our everyday life, one thing is certain: technological change affects unemployment and the relative demand for skills. It can arise essentially by two different alternatives, from process innovation and product innovation. Process innovation refers to the implementation of a new and improved production, introducing better and cheaper processes. Individuals working repetitive jobs - that can be easily automated - are more susceptible to being displaced. The impact of such innovation can, however, be counterbalanced by various market compensation mechanisms such as new machinery, lower prices, new investments, and lower wages. On the other hand, the introduction of new products through product innovation promotes the creation of entirely new fields of labor, promoting a job-creating effect (Vivarelli, 2014). Workers displaced by technological unemployment can stumble upon difficulties in making use of their skills. This phenomenon might translate into long-term unemployment, where such individuals not only lack the necessary skills in a more skill-demanding labor market, but also cannot accumulate such skills while unemployed. This leads to increased labor market segmentation, where the best jobs are only accessible to high-skilled workers, whereas the low-skilled are excluded from high-tech jobs. Again the latter might experience intermittent short-term low-pay periods of employment with longer periods of unemployment.

The main discussion presented in this work is how technological change affects the way human resources are managed. With the objective of assessing the impact of human capital and technological intensity on unemployment duration, we estimated several continuous-time proportional hazards models with different combinations of variables. We use *Inquérito ao Emprego*, a quasi-longitudinal household survey carried out every three months by sampling, conducted by INE. It includes detailed information on workers, as their educational level and technological intensity of previous firm and job, allowing for mapping in and out of jobs. It is insufficient to study the labor market only by analyzing static variables like rates of employment or unemployment. For the decision making on the labor market it is essential to see the job-to-job flows of individuals, the extent to which they can or cannot rapidly find alternative employment and to which extent different groups of the labor force are more affected than others. Unemployment duration refers to the amount of time that an individual stays unemployed. This time occurs when an individual is looking for the first job, or is between jobs. There are various factors affecting unemployment duration for individuals of the labor force, although it is understandable that if unemployed people could find and accept new jobs quicker, the unemployment rate as well as the unemployment duration would be lower. Our results backup the skill-biased technological change hypothesis where

more-skilled individuals have lower hazards of job separation and that technological change plays a stronger role in the increase of hazard of job separation for less-skilled individuals. Furthermore, the baseline hazard indicates that the accumulation of specific human capital is fundamental in reducing the hazard of job separation in highly technological firms. Individuals with great amounts of human capital have smaller probability of being redundant in a firm and therefore to be displaced (Nickell, 1979). Well-educated individuals have higher levels of firm-specific human capital, as education and firm-specific training are complements (Kiefer, 1985), also they are more likely to receive on-the-job training and to stay in the firm for a longer period of time (Mincer, 1991).

Griliches (1969) provides evidence indicating that capital and skilled labor are relatively more complementary than are capital and unskilled labor. This hypothesis is called capital skill complementarity. Such complementarities were studied in the manufacturing industry in the United States, where companies that used more capital per worker, hired more educated workers and paid higher wages (Katz and Goldin, 1996). The complementarity theory backs up the skill-biased technological change (SBTC) hypothesis, where technological change favors high-skilled workers (Autor et al., 1998). As a result of the rapid growth in the demand for more-skilled workers, wage inequalities started to be an issue (Autor et al., 1998; Bound and Johnson, 1992; Murphy and Katz, 1992). While the share of workers with higher qualifications was rising, the wages of unskilled workers were decreasing and their unemployment rate increasing (Addison and Teixeira, 2001).

Technological change is of particular interest since it has great impact on technological unemployment and labor market segmentation. Our results regarding unemployment duration are specially relevant in a context where innovation displaces low-skilled individuals, increasing their probability of suffering long-term unemployment or of being offered short-term employment jobs. Long-term unemployment refers to people who have been unemployed for 12 months or more, and shows the proportion of these long-term unemployed among all unemployed. The data provided by OECD on long-term unemployment from 2017 shows an alarming situation for Europe, representing around 42% of the total unemployment. Where Greece records the highest rate with a total of 72.8%, and higher than 50% for Slovak Republic and Italy (58.8%), Bulgaria (55.7%), and Belgium and Portugal (50%).

We will discuss the literature in the section that follows. Section 3 presents the data set and main variables used. We present the applied methodology in Section 4, followed by the section with the estimation and discussion of the results. Finally, section 5 includes the conclusions to this work.

## 2. Technology and skills

The relationship between technology and employment has long been debated. Though the general consensus in the literature agrees that innovation has a positive relationship with employment, the discussion is far from over (Vivarelli, 2014).

The effects of process innovation are balanced by the effects of product innovation. While, process innovation has a labor-saving effect, by increasing labor productivity, process innovation creates new business opportunities boosting labor demand. In a study of the manufacturing industry in Italy, (Vivarelli et al., 1996) identifies a decrease in employment associated with innovation, driven for the most part by process innovation. Contrasting, in industries in industries characterized by higher occurrence of product innovation it is observed an increase in employment. This two possible outcomes from innovation have been accompanying the overall skill composition change of the labor market. The usage of new technologies generally requires more skills and education (Doms and Troske, 1997), giving advantage to high-skilled workers in the implementation of new technologies.

The study about technology skill complementarity provided by Griliches (1969), has led to the formulation of the skill-biased (or unskilled labor saving) technological change (SBTC) hypothesis, where technological change is considered to favor skilled workers (Katz and Autor, 1999; Acemoglu and Autor, 2010; Berman et al., 1998). SBTC is a shift in the production that changes the relative demand for skills (Castro Silva and Lima, 2017), favoring skilled over unskilled workers (Violante, 2000), where capital reallocates from slow to fast learning workers (Caselli, 1999). The increase in the share of well-educated workers in employment came to prove that skilled workers are in a more favorable position in the labor market than unskilled workers (Addison and Teixeira, 2001).

In 1990, the demand for medium-skilled workers decreased when compared with the demand for high and low-skilled people. With this phenomenon there was a raising in the polarization of the labor markets all over the world: in the United States (Autor et al., 2006; Autor and Dorn, 2013), in Europe (Goos et al., 2009; Spitz-Oener, 2006) and in the United Kingdom (Goos and Manning, 2007). (Goos et al., 2014) explained the job polarization effect through routine-biased technological change (RBTC) and task offshoring, since SBTC cannot support the recent situation facing job polarization. RBTC means that technological change is biased

against labor in routine tasks. RBTC and task offshoring combined provoke a decrease in the demand for middle-skilled workers (Autor et al., 2003, 2006; Goos and Manning, 2007; Autor and Dorn, 2013). Autor et al. (2003, 2006) analyzed job polarization by studying the effects of computers in the relative demand for skills. Their model predicts that labor intensive firms performing routine tasks, will invest more in computer capital, as their price decreases. Therefore, substituting low-skilled labor by computer capital.Autor et al. (2003, 2006) suggest assigning more abstract tasks to high-skilled workers, routine tasks to middle-skilled and manual tasks to the low-skilled.

Human capital and the level of training can much influence the duration of the unemployment spell. In technology intensive industries, highly educated displaced workers tend to have higher post-displacement employment rates and a better chance at being re-employed at a full-time job Farber (2003). On the other hand, low-skilled people have a low complementarity with capital and are less productive when working in high-technological environments.

Authors such as Nickell (1979), Ashenfelter and Ham (1979), Lancaster and Nickell (1980), and Kiefer (1985) studied the implication of human capital investments and education applied to unemployment duration, by using the years of schooling as a descriptive variable. Another factor influencing unemployment duration is technological change. Aaronson and Housinger (1999) analyzed the effects of new technology on the re-employment of displaced workers while, Friedberg (2003) focused on an older population of workers.

Typically highly educated individuals earn more and spend more hours at work during their lives (Ashenfelter and Ham, 1979). A person that has a great amount of human capital has a smaller probability of being redundant in a firm (Nickell, 1979). Well-educated individuals have higher levels of firm-specific human capital, since education and firm-specific training are complements (Kiefer, 1985), they are also more likely to receive on-the-job training and to stay in the firm for a longer period of time (Mincer, 1991). Therefore, there is an obvious relation between the probability of an individual entering unemployment and the level of schooling (Azariadis, 1976). Nickell (1979) and Kiefer (1985) suggest that there is a negative relation between education and unemployment duration. Schooling up to 12 years can reduce the expected length of unemployment by more than 4%, and qualifications above that level can reduce up to 12% (Nickell, 1979). As job oportunities rise with the amount of years spent on education (Kettunen, 1997). On the other hand, Ashenfelter and Ham (1979) found no evidences of the impact of the level of education relative to the duration of unemployment, but concluded that work experience can reduce the duration of unemployment spells.

In times characterized by technological change, the average unemployment duration will probably rise (Wolff, 2005). Not only skill matters, but also the age of the displaced workers. Older people will consider whether to upgrade a skill, after all they have a reduced time horizon (Friedberg, 2003). Aaronson and Housinger (1999) studies show that with the increase of technology intensity, it is less likely for a person to find a new job after being displaced. Such situation is aggravated when the people in question are older and low-skilled. The length of unemployment will be higher for older workers and workers with low levels of education, as the average weeks of unemployment rise proportionally with age (Wolff, 2005). In her study, Friedberg (2003) analyzes the relationship between computer usage and retirement. Estimating that computer use lowers the likelihood of retirement. Meaning that skilled workers stay in the labor market for longer times, filling vacancies that could be occupied by more younger unemployed individuals. Older and poorly educated workers remain unemployed for longer periods of time, times which are characterized by low human capital investments, leading to long-term unemployment.

In conclusion, the extant literature expresses that high-skilled workers have lower separation rates in more technology-intensive industries, since human capital requirements are more demanding in those industries. The complementarities between technology and skills also favor high-skilled workers. Low-skilled workers are not as productive when in advanced technological environments and cannot escape from this low-productivity situation once they receive less on-the-job training leading to higher unemployment duration.

### 2.1. Other variables affecting unemployment duration

Other variables such as gender and marital status may affect the unemployment duration. Nickell (1979) found that unmarried men and men without children have longer expected duration of unemployment. There is no strong position regarging gender in the extant literature. Ciucă and Matei (2011) found no relevant difference between men and women, just a lightly higher hazard for men. Hernæs and Strøm (1996) finds that the exit probability is higher for women than men, and attributes that to the lower reservation wage of women. In this case, women would accept jobs with lower wages than men. Tansel and Tasci (2010) compared the unemployment duration for men and women in Turkey, and concluded that the hazard was substan-

tially lower for women. Bowers and Harkess (1979) studied the impact of gender in the British labor market, and concluded that there was a rise in the rate of entry of men to the unemployment register and a fall in the expected duration of an entry. For women there was a rise in expected duration but no fall in entry rates. A study from Finland by Ollikainen (2003) states that women aged 16 to 19 years old experience shorter durations compared to men when exiting to employment, but longer durations when exiting to economic inactivity. Women have higher hazard of re-employment between 16 and 29 and men have higher hazards when aged between 20 and 39 years.

Haile (2004) found that previous jobs and labor market history had importance on the re-employment hazard. Workers who had unskilled manual jobs experience longer periods of unemployment compared with those who had high-technological jobs or managerial positions. Those who worked in small and medium sized firms have 28% higher hazards, thus experiencing shorter periods of unemployment, when compared with those working in large firms.

The length of unemployment can be also be affected by unemployment insurance (UI) (Burda and Sachs, 1988; Meyer, 1990, 1995; Katz and Meyer, 1990; Bover et al., 2002). When Mortensen (1970) included unemployment benefits into the job search analysis, came to a conclusion that individuals would accept a job offer if the benefit of it was larger than the reservation wage. The amount of the unemployment benefit sets the price at which an unemployed individual is willing to work. The higher the unemployment benefit, the weaker is the incentive to accept a job offer (Hernæs and Strøm, 1996). Katz and Meyer (1990) and Burda and Sachs (1988) give evidence that countries with generous unemployment benefits have higher unemployment rates, as well as, substantially longer periods of unemployment spells. The impact of benefit levels on the conditional probability of getting a job in any given moment is significant for the first 20 weeks (Nickell, 1979). Bover et al. (2002) concludes that the hazard rate for recipients is double the rate of workers without benefits, when the largest effects occur for a three month period of unemployment. Therefore, unemployment insurance reduces the hazard of leaving unemployment.

There is a duration dependence associated with the job-finding process. There is a negative relationship between unemployment duration and the likelihood of finding a job, i.e. long-term unemployment affects negatively the re-employment chances of an individual (Steiner, 1990). The probability of an unemployed individual finding a job declines steadily after the first six months of a spell (Nickell, 1979). Long periods of unemployment are usually times characterized by low training and even loss of human capital, and may be seen by employers as a signal of reduced productivity. On the other hand, may occur positive duration dependence as the result of the long-term unemployed being less selective when it comes to accepting jobs (Hernæs and Strøm, 1996).

## 3. Data

For the unemployment duration study we use the *Inquérito ao Emprego* (Labor Force Survey) with a quasi-longitudinal capacity. This survey is conducted by the Portuguese Institute of Statistics with the purpose of recording the job-to-job flows of individuals in the labor force. Every household has a unique identification number (ID) and is interviewed every three months for a maximum of 6 consecutive quarters. The survey consists of various questions about employment and unemployment as well as personal characteristics. From all the questions included in the survey, the ones of our interest are: gender, age, education level, technology intensity of previous job and firm and unemployment duration. We use data from the years 2011 to 2013, with a total of 479 326 observations from 134 956 individuals. In this data set we have multiple observations per ID.

### 3.1. The sample

For this study we consider individuals who are at least 15 years old and not older that 64 years [1]. From the original data set we also excluded individuals that for every observation were either employed or inactive, and those who were only employed and inactive. Since we have information about the start date of unemployment, we are able to account for every unemployed individual, not only those that become unemployed during the time of observation. From the start date of unemployment and the entries' date of each observation we are able to obtain the unemployment spell duration, measured in quarters. In the sample, it is recorded a maximum unemployment spell duration of 11 quarters.

To be considered unemployed one must not be working, but available to and must be either searching for a job or engaged in some kind of job-seeking activity. Is waiting to be called back to a job from which was temporarily laid off, or is waiting to report to a new job within 30 days. A person can become unemployed by various reasons, although we treat every unemployed the same way no matter the reason for it.

As with any survey there is always inaccuracy associated with responses. We noticed some inconsistent and contradictory responses when related to

[1] The official age of retirement in Portugal was 66 years in 2011. However the mean age of retirement was 64.

dates. Some individuals stated that the start date of unemployment was after the interview date or would give different dates when we know they did not find a job. The decision was to eliminate the individuals with contradictory answers.

After applying these restrictions as well as removing invalid observations, the final sample is left with a total of 25,336 observations corresponding to 11,806. individuals.

To classify firms regarding the manufacturing technology intensity, we use the Eurostat's version with NACE Revision 2 codes for 2-digit level, according to the OECD's definition. We divided into four categories – High-technology (including medium-high-technology), Low-technology (including medium-low-technology), Knowledge-intensive services (KIS), and Less knowledge-intensive services (LKIS). Jobs are classified into two categories of technological presence — Technological and Non-technological.

### 3.2. Covariates and descriptive statistics

Table 3.2 shows the descriptive statistics of the main covariates present in our study. We have fixed covariates and dynamic covariates. The fixed covariates correspond to unchangeable personal characteristics such as gender and country of origin. From the dynamic group we have covariates that can change with the passage of time — age, marital status, residency location, education, technological/knowledge intensity of previous job and firm.

Regarding gender, 55% of our sample are men. Over 40% of the sampled individuals are married and, 89% were born in Portugal. About 41% of the unemployed were fired from their previous job, and 39% of the unemployed in our sample receive unemployment insurance. The residency location is im- portant for our study regarding the availability of more technological firms and job positions. There is more people living in North (26%) and Lisbon (19%) than other areas of Portugal. However, there is more people applying for the same job in more populated areas, thus increasing the competition be- tween candidates. By analyzing education we conclude our sample is fairly uneducated in line with the Portuguese pop- ulation: 66% of people have basic education, while 22% hold a high school diploma, and only 12% have superior education. Consequently, more people work in non-knowledge-based jobs. More than 80% of the unemployed previously worked in services compared to 18% that worked in the manufacturing industry. Portugal has a higher share of service focused companies as opposed to companies in the manufacturing sector, but it might be possible that manufacturing companies have greater necessity for workers (keeping workers for longer periods of time). Only 5% worked in high- and medium-high-tech firms. However, it is to note that the number of people working in less knowledge-intensive services is similar to the number in knowledge-intensive services.

Finally, about 29% of our sample experienced failure (re-employment) until the end of the observation time, corresponding to 3,395 individuals. In the following study we will analyze the differences between those who were re-employed and those who remain unemployed.

Table 1: Descriptive statistics

| | Mean | Std. Dev. |
|---|---|---|
| Unemployment duration (quarters) | 4.98 | 3.29 |
| Short-term unemployment | 0.54 | 0.49 |
| Long-term unemployment | 0.46 | 0.49 |
| Age (years) | 37.99 | 12.46 |
| Age: 15-24 | 0.17 | 0.37 |
| Age: 25-34 | 0.25 | 0.25 |
| Age: 35-44 | 0.24 | 0.43 |
| Age: 45-54 | 0.22 | 0.41 |
| Age: 55-64 | 0.12 | 0.33 |
| Female | 0.45 | 0.50 |
| Married | 0.43 | 0.50 |
| Born in Portugal | 0.89 | 0.32 |
| Unemployment insurance | 0.39 | 0.49 |
| Residency location | | |
| North | 0.26 | 0.44 |
| Algarve | 0.14 | 0.34 |
| Center | 0.12 | 0.33 |
| Lisbon | 0.19 | 0.39 |
| Alentejo | 0.12 | 0.32 |
| Madeira | 0.08 | 0.28 |
| Azores | 0.10 | 0.30 |
| Reason for separation | | |
| Collective/individual dismissal | 0.43 | 0.49 |
| Temporary job | 0.36 | 0.48 |
| Other | 0.21 | 0.40 |
| Education | | |
| Basic | 0.66 | 0.47 |
| High-school | 0.22 | 0.41 |
| College | 0.12 | 0.33 |
| Technology/knowledge intensity of previous sector | | |
| Low-tech manufacturing | 0.13 | 0.34 |
| High-tech manufacturing | 0.05 | 0.22 |
| Less knowledge-intensive services | 0.42 | 0.49 |
| Knowledge-intensive services | 0.40 | 0.49 |
| Knowledge intensity of previous job position | | |
| Knowledge-based | 0.40 | 0.49 |
| Non-knowledge-based | 0.60 | 0.49 |
| Number of observations | | 25,336 |
| Number of individuals | | 11,806 |
| Number of failures | | 3,395 |
| Proportion of failures (%) | | 28.76 |

Statistics computed using only the last observation of each individual.

## 4. Methodology

Survival analysis uses two quantitative terms; the survival function ($S(t)$) and the hazard function ($h(t)$). We will be using continuous-time proportional hazard models. This choice is justified given the ease of implementation and interpretation of

continuous models. Let $T$ be a non-negative continuous random variable representing the duration of a specific state, i.e. the time elapsed until the occurrence of the event of interest (spell length), with a cumulative distribution function defined as follows:

$$F(t) = Pr(T < t) \tag{1}$$

The hazard function allows to estimate the instantaneous probability of an individual getting re-employed at an instant $t$, given that he remained unemployed until $t$ (Portugal and Addison, 2008). The following function can specify the probability of distribution duration. Assuming the probability density function $f(t)$ and cumulative distribution function $F(t)$ of $T$, the hazard function is given by Equation 2.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \triangle t \mid T > t)}{\triangle t} \tag{2}$$

Where $S(t)$ is the survivor function. Note that $h(t)$ gives the conditional density of $T$ given $T > t$. The hazard function is often modelled using an exponential or Weibull distribution Kiefer (1988)). The exponential distribution is widely used in duration analysis. This model is simple to use and analyze, but its main assumption is that there is no duration dependence. According to Kiefer (1988) the most appropriate specification for this kind of studies is the Weibull model. The Weibull is a two parameter hazard function that assumes a monotonic baseline hazard.

The most frequently used model in this case is the proportional hazards model. The Cox proportional hazard model also known as Cox regression model proposed by Cox (1972) is a very popular method for survival analysis because of its simplicity and straightforward interpretation (Arellano, 2008). The model is mentioned as a semi-parametric method since no particular form of the distribution is assumed for the survival time; it is based on the assumption of proportional hazards. The result derives from the combination of the proportional hazard assumption with several other insights and assumptions and a partial likelihood (PL) method of estimation (Jenkins, 2005).

The hazard model used to analyze the durations of the unemployment spells is the Cox partial likelihood proportional hazards model. The hazard is assumed to be of the form:

$$\lambda(t; \mathbf{z}) = \exp(\beta' \mathbf{z})\ \lambda_0(t) \tag{3}$$

where $\mathbf{z}$ contains time-varying covariates describing the unemployed individuals, $\beta$ is a $p \times 1$ vector of regression coefficients representing the effect of the covariates on survival, and $lambda_0(t)$ is the baseline hazard function for an individual for whom is associated a vector $\mathbf{z} = 0$, which is allowed to be non-parametric (if the covariates are measured as deviations from means, the baseline hazard may be interpreted as the hazard for the mean individual). A problem encountered in hazard rate analysis of unemployment is unobserved heterogeneity, especially because individuals with poor unobserved qualities are of a larger proportion of unemployed at longer durations. Meyer (1990) and others suggests that if the hazard rate is allowed to be non-parametric, explicitly modeling unobserved heterogeneity changes the coefficients suffer just little deviation.

### 4.1. Hypotheses

The hypotheses considered in this work are the following:

1. Older individuals have lower hazards of re-employment.
2. Men have higher hazards of re-employment.
3. Unemployment insurance recipients have lower hazards of re-employment.
4. More educated individuals have higher hazards of re-employment.
5. Individuals that worked in technology/knowledge intensive firms have higher hazards of re-employment.
6. Individuals that performed knowledge-based jobs have higher hazards of re-employment.

## 5. Results

We now present the results of the unemployment duration analysis. All models control for year, quarter and residency location, beyond those we can see in Table 5 (age, gender, marital status, country of origin, unemployment insurance, reason for separation and education). The coefficients are presented in hazard ratios (exponential of the coefficients). We estimated four models to analyze the impact of the different covariates. Every model has a total of observation 24,221 (not every unemployed individual provided information on the reason for unemployment) and 3,326 exits to employment. Our study portrays the Portuguese population. After including the sampling weights in our models the population for which we are controlling for is composed by 7,080,283 individuals.

### 5.1. Explanatory Variables

The age group estimations show that the older the individual is, the worse are his/her prospects of exiting unemployment and thus, the longer the unem-

Table 2: Estimation results for the Cox model

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Age: 25-34 | 0.909 | 0.896* | 0.885* | 0.879* |
| | (0.060) | (0.059) | (0.058) | (0.058) |
| Age: 35-44 | 0.733*** | 0.718*** | 0.705*** | 0.698*** |
| | (0.052) | (0.051) | (0.050) | (0.050) |
| Age: 45-54 | 0.630*** | 0.616*** | 0.606*** | 0.599*** |
| | (0.049) | (0.048) | (0.047) | (0.047) |
| Age: 55-64 | 0.410*** | 0.399*** | 0.397*** | 0.391*** |
| | (0.041) | (0.040) | (0.040) | (0.039) |
| Female | 0.953 | 0.987 | 0.981 | 1.002 |
| | (0.043) | (0.046) | (0.044) | (0.047) |
| Married | 1.219*** | 1.215*** | 1.222*** | 1.219*** |
| | (0.063) | (0.063) | (0.063) | (0.063) |
| Born in Portugal | 1.171** | 1.172** | 1.169** | 1.171** |
| | (0.086) | (0.086) | (0.086) | (0.086) |
| Unemployment insurance | 0.907* | 0.904* | 0.907* | 0.906* |
| | (0.047) | (0.047) | (0.047) | (0.047) |
| Reason for separation: Temporary job | 1.363*** | 1.371*** | 1.328*** | 1.335*** |
| | (0.067) | (0.072) | (0.070) | (0.070) |
| Reason for separation: Other | 1.291** | 1.137** | 1.139** | 1.136** |
| | (0.071) | (0.067) | (0.067) | (0.067) |
| Education: High-school | 1.092* | 1.086 | 1.079 | 1.074 |
| | (0.057) | (0.057) | (0.057) | (0.057) |
| Education: College | 1.291*** | 1.225*** | 1.212*** | 1.172** |
| | (0.086) | (0.087) | (0.082) | (0.084) |
| Previous job: Knowledge-based | | 1.124** | | 1.088* |
| | | (0.054) | | (0.056) |
| Previous sector: Less-knowledge intensive service | | | 1.068 | 1.098 |
| | | | (0.076) | (0.080) |
| Previous sector: Knowledge intensive service | | | 1.298*** | 1.298*** |
| | | | (0.094) | (0.094) |
| Previous sector: High-tech manufacturing | | | 1.188* | 1.219** |
| | | | (0.118) | (0.0123) |
| Observations | 24,221 | 24,221 | 24,221 | 24,221 |
| Failures | 3,326 | 3,326 | 3,326 | 3,326 |

Hazard ratios, and standard errors (in brackets). All models are estimated with sampling weights and control for year, quarter and regional effects. The base level of each categorical variable is omitted (age: 15-24; reason for separation: fired collectively or individually; education: basic; previous sector: low-tech manufacturing; previous job: non-knowledge-based) — * significant at 10%; ** significant at 5%; *** significant at 1%

ployment spell will be. The age group more sensitive to exits to active labor market is the age group between the ages of 15-24. The results show that the hazard decreases with age: the age group 25-34 when compared to the age group 15-24 is not significant but the age group 35-44 has a 30.2% smaller hazard of re-employment (results from Model 4). The oldest age group results show that people with more than 55 years are unlikely to exit unemployment and to get re-employed.

The variable gender is not significant in any of the models, not allowing us to take a position and be certain regarding the results obtained. In Models 1, 2 and 3, men have a slight advantage when compared to women. Women have less hazard of re-employment. However, by adding the covariates of *previous job* (Model 2) or *previous sector* (Model 3) the difference between genders decreases, and by adding *previous job* and *previous sector* together (Model 4) women becomes more prone to getting re-employed. However, the percentage is minimal and the estimates are not significant. The trend towards equality between genders means that the Portuguese population is well balanced when it comes

to the number of men and women working in technological and knowledge-based jobs.

The results show that married individuals have greater hazards of re-employment when compared to non-married individuals. The *married* covariate is significant across all models and vary marginally between them. In Model 1, married individuals have 21.9% more chance of re-employment, in Model 2 21.5%, in Model 3 22.2% and in Model 4 21.9%. The advantage between married and non-married individuals can be related to having to provide for others and having the need to have a job. Married people would have urgency to find a job, and would accept a job offer more quickly.

Similarly to the previous analyzed covariate, the estimates of the hazard ratios for *born in Portugal* remains fairly unchanged across the different models. The covariate *born in Portugal* is significant at 5% in all models, and individuals that are born in Portugal have in average 17.1% more chances of being re-employed than people that were born outside of Portugal. These results show that companies prefer to hire people from their own country, for reasons such as language.

The position about unemployment insurance is unanimous regarding the effects on unemployment duration. Unemployment insurance lowers the chances of re-employment. This covariate is significant at 10% for all models and hold approximately the same value. Recipients of unemployment benefits have less 9.3% to 9.6% chances of getting re-employed, according to our estimates.

We also control for the covariate *reason* in every model, where individuals are compared to those who were fired collectively or individually from their previous job. Individuals displaced by temporary jobs have 33.5% more chances at leaving unemployment (Model 4). This may be related with the fact that they already knew that that job would end in a near future. Giving them an advantage in the job seeking activity, where people can anticipate the displacement by searching for jobs earlier. Individuals displaced by *other* reasons have 13.6% more hazard of re-employment.

Education is one of the most discussed factors for unemployment duration. The extant literature points to a positive relationship between the level of education and the hazard of re-employment. The significance of education, as well as the values of the hazard ratios, decrease by adding more covariates to the model. In Model 1, where we control for education alone, high-school is significant at 10% but is not significant for the remaining models, suggesting that there is no considerable difference between high-school and basic education in terms of re-employment once we account for previous job experience we do find a significance difference to education in all models. The decrease in the significance might result from the correlation with the variables previous job and previous sector, not allowing us to distinguish the true covariate that is affecting the exit of unemployment and the duration of unemployment. This is the reason why, in Model 1 we control solely for education. People with high-school education have 9.2% higher hazards of exiting unemployment, and people with higher education have an advantage of more 29.1%. This means that having university qualifications does increase the exit rate and shortens the duration of unemployment spells. Hence, validating Hypothesis 4 of our analysis.

We now examine whether previous employment affects the exit rate in the current spell. This may occur because of differentiation against people with unemployment histories, and because of deterioration of human capital and work habits, resulting in lower exit rates to employment. The estimations from the covariate *previous job* are significant at the 5% level in Model 2 and at 10% in Model 4. In Model 4 the significance decreases further with the addition of *previous sector*, where the following sequence occurs: highly educated people perform knowledge-based tasks in high-tech manufacturing or in knowledge intensive services. The covariates *education*, *previous job* and *previous sector* are highly correlated. Thus, there is an effect from not accumulating human capital on the job, as well as a separate negative impact from being unemployed. People performing knowledge-based tasks in Model 1 have 12.4%, and in Model 4 have 8.8% more chances of re-employment.

In Model 3, we analyze the impact of *previous sector*. We conclude that the difference between individuals in low-tech manufacturing and less-knowledge intensive services in not significant with this combination of variables. However, people in less-knowledge intensive services have 6.8% more hazard. We observe more significance as well as a higher difference in hazard ratio in the group of people performing knowledge intensive services, with 29.8% more hazard of re-employment. High-tech manufacturing is significant at the 10% level and provides 18.8% more chances in the exit of unemployment. In Model 4 we observe an increase in the hazard ratios of less-knowledge intensive services and high-tech manufacturing, just by adding the covariate *previous job*. This increase may be related with the collinearity between *previous job* and *previous sector*. In the latter model, we observe that people in less-knowledge intensive services have 9.8% more hazard and people in high-tech manufacturing have 21.9% more hazard of re-employment.

5.2. Baseline Hazard

The construction of the baseline hazard form Model 4 (Figure 5.1) allows us to see the duration dependence in unemployment. By looking at the baseline hazards for exiting unemployment we see that there is negative duration dependence (the likelihood of staying unemployed decreases with time) up to a peak at the at the analysis time between 10-13 quarters. However, after reaching the peak, the hazard rates appear to decline sharply. It was not expected to have the highest hazard in the interval between 10 quarters (2.5 years) and 13 quarters (3.25 years). The baseline hazard function follows and inverted U-shape — increasing hazard in the beginning as individuals use those initial periods for job searching or recipient of unemployment insurance fall out of the benefit program, followed up by deceasing chances of exit that translate into long-term unemployment. A typical discovery when negative duration dependence is observed is that it is not possible to distinguish whether longer duration spells result in lower exit rates, or whether there is unobserved heterogeneity leading to low exit rates, remaining in unemployment for longer. The information contemplated in inquiries, such as the LFS, is often times insufficient to clearly understand the true effects of unemployment duration.

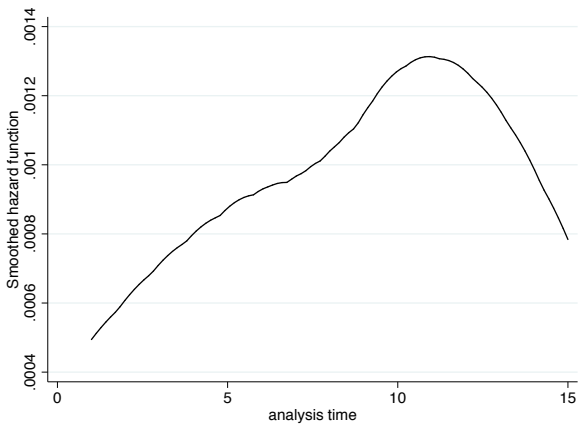


Figure 1: Cox proportional hazard regression

## 6. Conclusions

The present work analyzed the determinants of unemployment duration in Portugal between the years 2011 and 2013, by using a data-set surveyed every quarter — Inquérito ao Emprego. The aim of this study was to, first, find which determinants affected unemployment duration and, second, to estimate the impact of each covariate, by focusing on technology and skills. We analyzed nine determinants (age, gender, marital status, country of origin, unemployment insurance, reason for separation, education, knowledge intensity of previous job and technology/knowledge intensity of previous sector) of unemployment duration.

The results of the preceding analysis show that there is no simple explanation for unemployment duration, and that it cannot be explained solely by traditional supply-demand arguments. An individual re-employment probability is affected by many variables, variables which can be unobserved. Among the many determinants, we have personal characteristics, previous labor market experiences, economic trends. There is also a strong state dependence in the unemployment process. The results of the es- timates were in line with the extant literature. In Hypothesis 1 and 2 we tested the effect of age and gender, respectively. We found a negative relationship between age and unemployment duration, i.e. the probability of re-employment decreases with age, and found that the difference between sexes is not significant in Portugal, but men have slightly higher hazards than women. Our estimates also confirm Hypothesis 3. Unemployment insurance recipients spend in average more time unemployed.

Regarding Hypotheses 4, 5 and 6, we find that education, knowledge intensity of previous job and technology/knowledge intensity of previous firm are related. We find education to be one of the most de- cisive determinants for the duration of unemployment. People with more years of schooling and higher levels of education have higher hazard of re-employment. The difference between people with basic and high-school education is not so significant. By analyzing previous labor market experiences (knowledge intensity of previous job and technology/knowledge intensity of previous firm) we can understand the impact of technological change. In times of great technological change, the relative demand for skills change, people working in high-tech and knowledge-based positions are better in terms of employment opportunities. These individuals stay employed for longer periods of time, and unemployed for shorter periods of time. While unemployment individuals working in low-tech manufacturing and less knowledge-intensive services have higher rates of displacement due to the technological progress and automation of manual tasks. These individuals are characterized by low levels of human capital, hence prolonging their unemployment duration by lower complementarity than capital and skilled and more educated labor. The results also point to a negative duration dependence for exit of unemployment, after a maximum peak of 10-13 quarters, where more time spent in unemployment causes a decrease in the probability of re-employment, as suggested by the "scarring" theory of unemployment.

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