Dual Labour Markets and Matching Frictions

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ABSTRACT

This paper focuses on friction problems in the matching process arising in a dual labour market where good and bad jobs coexist. Specifically, we investigate the role of strong preferences for permanent contracts, in a labour market where also temporary contracts are offered, in increasing frictional unemployment. We use microdata from Portuguese job centres to estimate a reduced form equation of a matching function applying a competing risks discrete time hazard model that allows for stock-flow matching mechanism. Overall we find that, among unemployed flowing into temporary job, those looking for permanent contracts experience lower hazard rate, i.e. longer unemployment duration due to frictions deriving from contract mismatch. However, the effect tends to disappear controlling for a demand-side variable. Positive effects come from training activities are found, while job centres appear inadequate to favour the match for skilled workers. Policies aimed to reduce matching frictions and to improve labour market effectiveness should take care of that evidence and to increase the desirability of temporary contracts.

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1. Introduction

Since the 1990s labour market analysis largely used matching functions in search and match frameworks (Mortensen, 1987). Matching functions allow the researchers to investigate frictions on the labour market, that play a crucial role to explain the existence of (frictional) unemployment and labour market effectiveness in matching unemployed workers to available vacancies.

Hence, it comes as no surprise that in the recent years there has been a growing if not widespread interest in empirical estimates of matching functions. As highlighted by Petrongolo and Pissarides (2001), frictions derive from various sources. For example, they depend from imperfect information about potential trading partners, absence of perfect insurance markets, slow mobility, congestion from large numbers, and so on. Recently, most contributions devoted to estimating matching functions focused on the role of heterogeneity of job seekers in explaining frictions in the matching process. An important argument put forward by such studies is that failure to take into account the heterogeneity of job seekers may lead to a misspecification of the estimating matching function and, concomitantly, to biased estimates of the estimating parameters and to misleading inferences on search elasticities. van Ours and Ridder (1995), Coles and Smith (1998), Mumford and Smith (1999), Anderson and Burgess (2000) and Burgess and Profit (2001) find evidence of job competition between different skill groups and between employed and unemployed job seekers. Fahr and Sunde (2001) find heterogeneity in matching technologies across members of different age and education groups, indicating the importance to disaggregate the matching function to explain the inner workings of the labour market and to avoid the loss of important information. Hynninen and Lahtonen (2007) find that wider heterogeneity of job seekers in terms of their educational levels increases the importance of frictions in the matching process.

However, matching frictions may also due to other sources. Reforms “at the margin”, that widely were introduced in Europe since the ‘80s[1] to reduce labour market rigidity, constitute a potential source of matching frictions. A large number of studies[2] highlighted possible negative effects from temporary employment with respect to traditional permanent relationships, contributing to rationalize in the economic literature the existence of segmented labour markets divided into primary and secondary sectors and, specifically, a segmentation

[1] In Portugal, temporary jobs were introduced in 1976 and suffered a major revision in 1989.
[2] For example, Jimeno and Toharia, 1993, Bertola and Ichino, 1995; Dolado, Garcia-Serrano and Jimeno, 2002; Cahuc and Postal-Vinay, 2002 and Gagliarducci, 2005.

in good and bad jobs[3]. Permanent job (namely good job) features better working conditions, employment stability and good prospects of career advancement. Temporary job (namely bad job) includes workers that often hold contracts characterized by lower wages, lower job security and impediments to career developments (Amuedo-Dorantes, 2000). In a dual labour market, where good and bad jobs coexist, it is likely to face job seekers having strong preferences for permanent contracts and firms looking for workers to fill their vacancies that prefer to offer, in turn, a temporary contract, since they can use this contractual form to more easily adjust their workforce to business cycle conditions or to reduce expected labour costs. Therefore, a labour market characterized by a quite homogenous supply side, with most unemployed workers searching for a permanent job, and an heterogeneous demand side, where temporary job offers and permanent job offers co-exist, may involve a higher degree of mismatch, and, hence, higher mean unemployment duration. In fact, it is most likely that individuals looking for a permanent job tend to first refuse offers if they are for temporary jobs and only after some time they will accept those temporary job offers in the event that such individuals do not find a suitable permanent job meanwhile.

Our paper tests the hypothesis of higher mismatch probability, hence higher unemployment duration, due to heterogeneity between searched contracts and offered contracts, estimating a matching function using Portuguese data on individual transitions from unemployment to employment.

Before to present our empirical approach, is important to underline that the literature allows two possible approaches in the estimation of matching functions: the random matching models and the stock-flow matching models. Broersma and van Ours (1999) argue that the estimates of the degree of returns to scale in the matching technology depend heavily on the data for active job seekers and posted vacancies used and emphasize the importance of looking at comparable measures for flows and explanatory stocks. Coles and Smith (1998) and Gregg and Petrongolo (2005), among others, argue, in turn, that part of the instability of estimated matching functions derives from problems of misspecification, due to the assumption of random search, rather than a stock-flow matching. As its name suggests, in a random matching set up the unemployed workers randomly routinely select a vacant job from the pool of existing vacancies and apply for it. Under the stock-flow matching technology, at the time an individual becomes unemployed he samples the existing stock of vacancies for a suitable job. If he fails to find a suitable match among the existing stock of vacancies, then he

[3] See Dolado, Jansen and Jimeno (2005) for a theoretical framework on dual employment protection legislation.

has to wait to eventually be matched with the flow of new vacancies and he does not re-apply to the previously searched stock of old vacancies. Stock-flow matching implies that exit rates are higher when individuals first enter the labour market and drop thereafter. This could be due to the fact that the newly-unemployed are able to consider all of the vacancies on offer when they first register at the job center. However, should their search be unsuccessful at this initial stage, the probability of finding a job is reduced in the subsequent periods, since they will only be able to match with the inflow of vacancies (see Coles and Smith, 1998). However, expected negative duration dependence may be also explained in terms of ranking or loss of skills during unemployment. Hazard models allow us to test these predictions[4].

In our case, since we use data from job-centres, stock-flow approach seems better representing matching mechanism, since the existence of a "central matcher" (i.e. the job centre) makes unlikely that the same job place may be re-offered to the same unemployed worker, as allowed by the random matching approach.

Our empirical specification analyses a reduced form equation that estimates the factors affecting the product of the two probabilities, i.e. the probability of receiving a job offer and the probability of accepting it, that constitute the components of the matching process (Petrongolo and Pissarides, 2001). The probability of receiving an offer is determined by individual and job related characteristics and labour market conditions. The probability of accepting the job offer is determined by the individual reservation wage, which, in turn, depends on the expected wage distribution, costs of searching, unemployment benefits, individual and family characteristics, and the distribution of the arrival of new job offers. Estimating individual reemployment probabilities allows for rather more flexible specifications of the matching function when compared to estimates of aggregate matching functions, since hazard models allow for a wide range of distributional forms of unemployment durations. In addition, estimating individual reemployment probabilities allows us to control both for observed and unobserved heterogeneity at the individual level, which are only implicitly considered in an aggregate matching function.

Despite the obvious aforementioned advantages of using hazard models to estimate matching functions, in the literature only a few studies did use hazard models to estimate matching functions. For example, Lindeboom, van Ours and Renes (1994) investigated the link between matching functions and hazard models to study the relative effectiveness of

[4] Positive duration dependence is also possible, for example in presence of unemployment benefits exhaustion.

alternative search channels. Petrongolo (2001) used hazard function specifications to test the empirical relevance of the constant returns to scale hypothesis in the matching technology. Other studies estimated hazard functions to explore the individual determinants of unemployment duration, but they did not investigate the matching technology underlying the matching process (see Devine and Kiefer, 1991, for a review).

We estimate a competing risks discrete time hazard model adopting the complementary log-log specification, that may be seen as the discrete time representation of a continuous time proportional hazard model. Baseline hazard is assumed to be monotonic and unobserved heterogeneity is assumed to be Gaussian distributed.

We use a sample drawn from the IEFP (Instituto do Emprego e Formaçao Profissional) dataset, the public entity responsible for Portuguese public job placement centres, for the period from 1998 to December 2002. This dataset provides information about personal and job related characteristics of all individuals who registered in the Portuguese job centres. Having at our disposal the date of registration and the date of reemployment for each individual, we are able to construct (multiple) spells of individual unemployment durations. The data allow us to identify the destination contract (permanent or temporary) in case the individual leaves unemployment by job offered at job-centres, while the destination contract remains unidentified in case the individual leaves unemployment by own means. In addition, our dataset allows us to construct stocks and flows of unemployed job seekers and vacancies offered for each month at the job-centre level. The dataset also contains information about vacancies, enabling us to determine the number of vacant jobs available for each month at the job centre level. In particular, the IEFP data provide information about the contract type sought by unemployed workers and the contract type offered by firms. Therefore it allows both to control the direct effect of the desired contract on the hazard rates toward multiple destination states and also to construct an index[5] of the degree of the heterogeneity found between contracts searched and contracts offered that we use to understand the effects on unemployment duration.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the econometric specification. Section 4 discusses the relation between unemployment duration and the heterogeneity between contracts searched and contracts offered. Section 5 presents the results. Finally, Section 6 concludes.

[5] The index varies over time and across job centres.

2. Data

The data used are drawn from an IEFP dataset that provides information on individuals registered at job centres in (Mainland) Portugal since 1997 to 2002. The IEFP is the agency responsible for running the public employment services[6], and it is a division of the Ministry of Labour and Solidarity. The IEFP is also responsible for job broking, vocational guidance, administering employment subsidies, vocational training, and apprenticeship training, but it does not administer unemployment benefits (see Addison and Portugal, 2001). However, being registered at a job centre is necessary to collect unemployment benefits. The IEFP dataset also includes information about job vacancies offered by firms, even if employers are not obliged to notify vacancies to the job centres.

The original sample containing information on individuals is composed by more than 3 millions of observations. In order to avoid computational problems, we drew a randomized sub-sample equal to 10% of the original sample[7], and focus only on unemployment spells starting since 1998 in order to have at our disposal complete information on all covariates considered (described below)[8]. The IEFP dataset provides (daily) information about the date of registration at the job centre and the date of placement, making it possible to identify (multiple) spells of unemployment durations for each individual. The IEFP dataset contains a plethora of personal and job related characteristics. Spells without the date of placement are considered censored. However, individuals may drop out of the job centres if they fail to present themselves at the job centres control interviews. We eliminate from our sample spells that terminate in failure to report to the above mentioned control interviews in order to avoid misleading identification of censored unemployment durations. In order to make our results, on the one hand, more readable in economic terms, and, on the other, easily comparable to previous studies found in the literature, unemployment duration is analysed on a monthly basis rather than a daily basis.

We only consider individuals, aged 16-60, for whom all information with respect to all the covariates considered is available. This selection leaves us an unbalanced panel composed by 3385059 records (time at risk), 149294 spells and 129582 individuals. We remark that

[6] IEFP does not have a placement monopoly, since both temporary work agency and private employment agencies are allowed.

[7] Descriptive statistics of variables contained in the original IEFP dataset and descriptive statistics of our randomized sample are available upon request.

[8] Only since June 1998 was introduced training activity during the registration at the job centres.

more than 86% of individuals only experiment one spell of unemployment in our samples. This is mainly due to the (1) quite long duration of unemployment spells that characterize the Portuguese labour market and to the (2) short period analysed in this paper (60 months). Both of these two factors (1) and (2) concur to explain the high percentage of censored spells in our sample (about 69%).

We consider a number of covariates to control for observed heterogeneity at the individual level. Table 1 contains descriptive statistics.

<< table 1 >>

To be more specific, we control for the following individual or family variables: age, introduced in a non-linear way, gender, educational level, marital status, number of dependent persons in the household, and a dummy indicating if the individual is disabled. We also control for job related characteristics. We introduce a variable indicating if the individual is looking for his or her first job, meaning that he or she has no previous work experience. We also control if the individual is looking for a full time job or for a part time one. We consider a set of dummy variables indicating the motivation of the registration at the job centre. These dummy variables flag if the individual: was formerly a student, finished his or her educational career, finished a training period, was dismissed, resigned and if the individual registered because of the termination of a temporary contract. In this case the base category dummy is constituted by individuals with no previous job experiences. We also control for a set of dummy variables indicating the occupation of the individual, distinguishing between managers, direction activities and specialists, technicians, administrative workers, service workers, agricultural and fishing workers, blue collars, and individuals without occupations (interpreted here as no qualifications). Two variables are introduced to control if the individuals received unemployment benefits or underwent a training period during the registration at the job centre. Year dummies referring to the begin of the unemployment spell are also considered. Regional dummies are introduced to control for possible specific local labour markets effects. As anticipated, the probability of accepting a job offer is related to the expected wage distribution, and, hence, we introduce the mean wage offered by firms, evaluated monthly at the job centre level. Labour market tightness variables are also introduced and are evaluated monthly at the job centre level. To implement the stock-flow matching process, we use stock and flow values of unemployed workers and vacancies in the following way. The IEFP data provide daily information of gross inflows of unemployed workers and vacancies that allow us to construct the monthly magnitude of gross inflows of labour market tightness variables and to reconstruct their stock values. To be more specific, to construct stock values we use information from the 1997 IEFP dataset, hence at the starting of the period analyzed we have at our disposal the accumulated flow values until December 1997. The stock flow approach is implemented using time-varying labour market tightness variables, under the hypothesis that individuals look at the pool of vacancies only in the first round (one month) of their search process, and, afterwards, look at the gross inflow in the following rounds (months) of the search process. Tightness of the labour market expressed in terms of stock values (*V/U*) is about 0.013, while it is about 0.20 if expressed in gross flow terms (*v/u*). These differences are strongly suggestive that mean unemployment duration far exceeds mean vacancy duration, a result in line with other studies in the literature.

The information about the searched contract is introduced to control the effect on the unemployment duration. Specifically, it allows to understand if individuals looking for permanent contracts experience longer unemployment duration than individuals looking for temporary contracts, above all in case they leave unemployment by finding temporary contracts. Finally, as further controls we introduce variables indicating the percentage of permanent contracts searched and offered monthly and at job centres level, to take into account the demand side effect.

3. Econometric Specification

The duration analysis is approached using the standard job search tools, for which the individual in unemployment status starts his/her job search process immediately. Since we dispose of interval censored data, discrete-time hazard models are estimated (Prentice and Gloecker, 1978). According to the hazard models framework, the conditional probability that a transition to employment will take place in a given interval $[a_{j-1}, a_j)$, conditional on the time already spent in it, is estimated as a reduced form equation that resume the product of two probabilities: the probability of receiving a job offer, and the probability of accepting it. The probability of accepting a job offer corresponds to the probability that the wage offer exceeds the reservation wage. The hazard of leaving unemployment can vary over the spell according to changes in the offer probability and to changes in the reservation wage, because of the duration of the time at risk and other exogenous variables that affect hazard rates, i.e. individual and job related characteristics. The hazard of exit in the j_{th} reads:

$$h_j \equiv \Pr\{T \in [a_{j-1}, a_j) \mid T \geq a_{j-1}\} \tag{1}$$

Assuming unit length intervals, the realization j of the discrete random variable T is the recorded spell duration. Discrete-time hazard model requires that data are organized into a "sequential binary form", that is, the data form an unbalanced panel of individuals with the i_{th} individual contributing j = 1, 2, …… t observations, i.e. j indicates the number of period at risk of the event[9]. Since some individuals transit to employment and possibly back in unemployment, multiple spells are observable, q = 1, 2, … Q. In this case, to simplify the analysis, zero temporal correlation across spells is assumed.

The discrete time hazard function assumes a complementary log-log specification, that may be seen as the discrete time representation of a continuous time proportional hazard model. The available data allow to identify the destination contract (PC or TC) only if the individual accepts a vacancy offered at the job-centre, while it remains unidentified if the individual leaves unemployment by own means (OM). It follows that three destination states (d) are possible and competing risks models are estimated. Moreover, to evaluate the effect of the wanted contract (PC or TC) on the matching probabilities, we estimate separately the probability of leaving unemployment according to the declared wanted contract. It follows that we compare the timing of reemployment for unemployed looking for permanent contracts and unemployed looking for temporary contracts. The estimated models assume independent competing risks[10], implying that a hazard function for each destination state can be estimated separately by setting to zero the failures on other destinations. It follows that the hazard function without unobserved heterogeneity, for an unemployed transiting toward the destination state d, reads:

$$h_d(j, X) = 1 - \exp\{-\exp[\beta_d' X + \gamma_d^j]\} \tag{2}$$

[9] Specifically, a binary dependent variable was created. If the individual i's survival time is censored then the dependent binary variable always takes value zero, if the individual i's survival time is not censored then the dependent binary variable takes value zero in the first j-1 observations and value one in the last one.

[10] The assumption holds if specific and alternative conditions are verified (Jenkins, 2005).

where, X is a set of covariates (included time-varying) distinguished according to the wanted contract, and β_d is a vector of unknown parameters, including intercepts, to be estimated for each wanted contract and destination state and, finally, γ_j summarizes the baseline hazard and consists in the log of the difference between the integrated baseline hazard (θ_0) evaluated at the end and the beginning of the interval:

$$\gamma^{j} = \log\left[\int_{a_{j-1}}^{a_j} \theta_0(w)dw\right] \tag{3}$$

The baseline hazard is assumed to follow a monotonic pattern, i.e. the duration dependence specification is assumed to be the log of the time at risk, and may be thought as the discrete-time analogue to the continuous time Weibull model. Specifically, if the duration dependence specification is $\delta\log(j)$, then the hazard rate monotonically increases if $\delta > 0$, monotonically decreases if $\delta < 0$, or is constant if $\delta = 0$. The model is estimated by maximum likelihood, and the partial log-likelihood function for each desired contract and destination is given by:

$$\log L(\beta,\gamma) = \sum_{i=1}^{N}\sum_{q=1}^{Q}\sum_{j=1}^{t}\left[y_{iqj}\log h_{iqj} + \left(1-y_{iqj}\right)\log\left(1-h_{iqj}\right)\right] \tag{4}$$

where y_{ij} is an indicator assuming value one in case the individual transition takes place in the month j (i.e. the spell is uncensored) and zero otherwise. Since the independence assumption was made, the total log-likelihood function simply consists in the sum of the partial log-likelihood function derived for each contract destination.

The model presented above assumes that all differences between individuals were captured by observed explanatory variables. However, as well known, may be relevant to use a model that allow for unobservable individual effects to prevent estimation bias deriving, for example, from omitted variables and/or measurement errors in the observables. If unobserved heterogeneity is important but ignored a number of relevant problems may arise: out of all the over-estimation of the (absolute) value of the duration dependence parameter (the so called spurious duration dependence). Despite of it is well known that the misspecification of the unobserved heterogeneity distribution leads to possible estimation bias (Lancaster, 1990), misspecifying the error distribution, assuming a normal distribution, does not seriously affect the estimation results: it follows that the unobserved heterogeneity is modeled assuming a Gaussian distribution[11]. The hazard function assuming a complementary log-log specification with Gaussian unobserved heterogeneity, may be represented as follows:

$$h_d(j, X) = 1 - \exp\{-\exp[\beta_d' X + \gamma_d^j + \log(\nu_i)]\} \quad (5)$$

where log(v) ≡ u has a Normal distribution with zero mean and finite variance. To estimate the model it is necessary that the survival and density function expressions, that compose the likelihood function, are not conditioned on the unobserved effects. Therefore, the likelihood contributions are obtained by integrating out the random terms. However, on the contrary to the case of the Gamma distribution, in the Gaussian case, since the integral has not a simple closed form solution, it is approximated by the numerical integration that is used to integrate over the distributions of the random effects.

As anticipated, the stock-flow matching mechanism is assumed to drive the matching process. It assumes that job seekers have complete information about the number of available job vacancies and apply to all the ones that they think are likely to be acceptable (see Coles and Smith, 1998; Petrongolo and Pissarides, 2001). The main difference from the random match approach consists in the fact that the unemployed (U) workers sample the entire stock of vacancies (V) during the first period they search. From the second period on, in the event they remain unemployed after the first round of search (here, one month), they only apply for new vacancies, i.e. the gross inflow of vacant jobs (v).

4. Contract-Type Heterogeneity and Unemployment Duration

The availability of unemployed and job vacancy data at a disaggregate level is an unalterable condition to construct mismatch indexes. Many datasets fail to provide information on job vacancies, making impossible to analyze both labour market side conditions. The IEFP dataset gathers information from 85 job centres for each month under investigation including the number of job vacancies available, therefore potentially we can analyze the labour market demand side at a well-disaggregated level. Specifically, in order to evaluate the effects of (contract type) heterogeneity between permanent contracts searched by

[11] Nicoletti and Rondinelli (2006)

unemployed workers and permanent contracts offered by firms on unemployment duration, we introduce a simple index (*HI,* Heterogeneity Index) measured monthly (*m*) at the job centre level (*j*).

The index that we propose is quite similar to the first Jackman and Roper (1987) mismatch indicator[12], with the difference that we do not consider it at aggregate level and we do not take its absolute value. The latter point is an important issue, since positive heterogeneity may be quite different from negative heterogeneity in the case of contract mismatch. For example, full positive heterogeneity (i.e. the index takes value one) indicates that all unemployed workers look for a permanent contract and no permanent contract is available, possibly implying higher incidence of rejection of contract offered and higher unemployment duration. On the contrary, full negative heterogeneity (i.e. the index takes value minus one) indicates that all unemployed workers look for a temporary contract and no temporary contracts are available. In this case, the probability of refusing the offered contract, i.e. a permanent one, could be lower, and also unemployment duration should be less affected, since the utility deriving from being employed with a permanent contract should be larger than that of being employed with a temporary one. Therefore, in the case of contract type heterogeneity, using the absolute value of the index could lead to the wrong interpretation of the phenomenon.

Analytically, we define the index as the difference between the ratio of the unemployed workers looking for a permanent contract and the pool of unemployed workers, and the ratio of permanent contracts offered by firms and the pool of vacancies:

$$HI_{jm} = \frac{U_{jm}^{PC}}{U_{jm}} - \frac{V_{jm}^{PC}}{V_{jm}} \qquad \text{with} \qquad HI_{jm} = [-1, +1] \tag{6}$$

HI takes the value of zero in the absence of heterogeneity, i.e. the percentage of permanent contracts searched is equal to the percentage of permanent contracts offered. This situation should imply that no frictions in the matching process arise from the possible mismatch associated with contract type searched and contract type offered. *HI* takes the value

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[12] The first indicator proposed by Jackman and Roper (1987) reads: $M = \frac{1}{2}\sum_i |u_i - v_i| \; M \in [0,1]$, where $u_i = U_i \big/ \sum_i U_i$ and $v_i = V_i \big/ \sum_i V_i$ where U_i and V_i are the number of unemployed workers and vacancies in category *i* (where *i* may indicate the sector, skill, region and so on).

of one or minus one in presence of full heterogeneity, i.e. in the extreme case in which all unemployed workers look for a permanent contract and firms only offer temporary contracts, or all unemployed workers look for a temporary contract and firms only offer permanent contracts. This situation should imply a higher degree of mismatch in the labour market, everything else being the same. Hence, increasing values of *HI* should be associated with higher degrees of mismatch. The mean value of the heterogeneity index, as indicated above, is about 0.28, which represents the mean value of the difference between unemployed workers looking for a permanent relationship (about 97%-98% of the total unemployed workers) and the percentage of permanent jobs offered by firms (about 69-70% of total job offers). Table 2 and graph 1 illustrate the distribution of *HI*'s values across job-centres.

<< table 2 >>

<< graph 1 >>

Obviously, our index shows some limitations, since it only takes into account the relative percentages of searched/offered permanent contracts, but it does not consider the absolute values of searched/offered permanent contracts. Consequently, a zero value of the index it is not always indicative of a potential full placement of unemployed workers looking for a permanent contract, and a non-zero value does not always imply a potential non-full placement. However, it remains a rather effective instrument to describe contract type heterogeneity, since it is representative of the potential mismatch at contract level. Moreover, since we can interpret the job-centres role as a matcher role, i.e. job-centres gather the information about searched/offered contract types and make the matches according to the searched/offered contract, the index does not suffer of mismatch due to "job randomly selected" problem[13]. Preliminary evidence of the relationship between unemployment

[13] To clarify the term "job randomly selected" we propose the following example. We consider a job centre in which two unemployed workers are registered (one looking for a permanent contract) and two vacancies (one permanent contract) are available. The matcher (i.e. the job centre) will propose the permanent job offered to the unemployed worker looking for permanent contract, and the temporary job offered to the unemployed worker looking for temporary contract. A "cross offer", i.e. a permanent job offered to the unemployed worker looking for a temporary contract and vice versa, only arises in the presence of over supply of permanent or temporary contracts. Consequently, unemployed workers do not randomly select the offered job, and a refusal of the offered contract would not be imputable to the offered contract type. The absence of a matcher, i.e. the absence of a possible information channel about the nature of the offered contract, could involve contract mismatch due to so called "random selection". Following our example, it could imply that in the first round-search the unemployed

duration and searched/offered contract type heterogeneity is provided by a simple graph analysis (graph 2) by distinguish between males and females. Specifically, we graph the prediction of unemployment duration from the estimation of a fractional polynomial of heterogeneity index and plot the resulting curve. The use of a fractional polynomial rather than of a linear or a quadratic prediction allows us to obtain a more flexible result, since it also admits a not monotonic pattern. According to our hypothesis, we expect a positive shape of the unemployment duration-heterogeneity index curve for non negative values of the index, i.e. unemployment duration should increase as the searched/offered contract type heterogeneity also increases. In fact, a larger positive dyscrasia at searched/offered contract level should imply higher probability of refusing the job offered by unemployed workers hence, in the average, higher unemployment duration.

With regard to negative values of the heterogeneity index, larger negative heterogeneity could imply an unclear effect on unemployment duration. It will depend on the choices of unemployed workers looking for temporary jobs when a permanent contract is offered to them. For clarity, we can consider the two possible extreme cases. In the first one, all individuals looking for temporary jobs strictly prefer a temporary job, and then the unemployment duration-heterogeneity index curve should display a negative shape (the reverse case of positive heterogeneity index). In the second one, all individuals looking for temporary jobs declare to prefer a temporary job only because they believe to increase their reemployment probabilities, but they also accept a permanent job if offered, then the unemployment duration-heterogeneity index curve should display an unclear or a positive shape. In fact, in the last case we could suppose that the acceptance rate of permanent contracts should be higher than the acceptance temporary contract, since the benefits deriving from the first one, could compensate possible other “bad” characteristics of the offered job. In this case we could find a positive shape of the unemployment duration-heterogeneity index curve also for negative values of the heterogeneity index.

Graph 2 shows unemployment duration-heterogeneity index curves of male and female samples. Because of scarce presence of heterogeneity index values lower than -0.7, the male graph does not present predictions for strong negative heterogeneity index values. However,

worker looking for the permanent contract may first come across a temporary contract and this may mean that the probability of mismatch is increased.

when predictions are available, among males we find a positive relationship between predicted unemployment duration and heterogeneity index[14].

<< graph 2 >>

This finding is consistent with our hypothesis of higher mismatch probability, hence larger unemployment duration, in presence of higher positive contract type heterogeneity. Also, the positive shape for negative values of the heterogeneity index, may be explained as suggested above, i.e. unemployed workers looking for a temporary job also accept, and in some cases more rapidly, the offered permanent jobs. We have full information about predicted unemployment duration and heterogeneity index among females. The unemployment duration-heterogeneity index curve for the female sample displays a similar pattern with respect to the male sample. Interestingly, predicted unemployment duration display the lowest values (about five months) for very high negative values of the heterogeneity index, with a strong raise of predicted unemployment duration in correspondence of full negative contract type heterogeneity. It could suggest that, at least a part (probably a residual part), of unemployed workers looking for a temporary jobs have strong preferences for temporary contract, and when only permanent jobs are offered they face very long unemployment duration. On the contrary, as explained above, unemployed workers looking for a temporary jobs as a "second best solution", but ready to accept permanent contracts if it is offered, experience lower predicted unemployment duration, since the acceptance rate for permanent relationships is likely to be greater than the acceptance rate for temporary contracts. Finally, it is also interesting to make a gender comparison at unemployment duration-heterogeneity index curve level. According to graph 2, we firstly find that women experiment larger unemployment duration with respect to males, except that for the highest and positive values of the heterogeneity index. Secondly, and more interestingly, we find evidence that, at least for positive values of the heterogeneity index, the shape of females' curve is flatter than the shape of male's curve. It potentially suggests greater adaptability of women with respect to men, in the acceptance of temporary contracts when they are looking for a permanent job. This evidence is confirmed by table 3, in which we report the destination contract of the unemployed workers. In fact, as explained above, we

[14] We also plot a linear and a quadratic prediction of unemployment duration on the heterogeneity index. In both cases we find a positive shape of the unemployment duration-heterogeneity index curve.

find that 70% of male unemployed workers looking for a permanent contract really are employed with a permanent job, but this percentage goes down to 65% among females.

5. Estimation Results

Tables 3 and 4 present preliminary evidence. Table 3 informs us about the distribution of the spells with respect to their end, distinguishing by the type of searched contract. Inspection of Table 3 reveals that there are no great differences in the numbers of censored spells by type of contract sought after by unemployed workers. Females leaving unemployment who had been looking for a permanent contract seem more likely to find work via job centres (about 46%), with respect to the other sub-groups (about 39%-40%). Finally, and quite interestingly, Table 3 shows that only 70% of male and 65% of female unemployed workers looking for a permanent contract are actually employed in a permanent relationship.

Table 4 reports mean values of unemployment durations distinguishing by type of contract searched and destination states. This preliminary finding is consistent with the hypothesis that individuals looking for a permanent job are likely to first refuse temporary job offers to accept them later on only if they do not find a permanent relationship in the meanwhile.

Tables from 5 to 8 present the estimation results for the adopted stock-flow matching models. The cloglog specification is run many times to take into account, in turn, of unobserved heterogeneity and variables controlling for demand-side variable at job-centres level. A common finding of the estimated models is the quite strong negative duration dependence, even though controlling for unobserved heterogeneity is relevant to prevent over-estimation. Among the possible exit-states, unemployment spells terminating into temporary contracts show the lower duration dependence parameter, indicating that the probability of finding a permanent contract declines faster as the time spent in unemployment increases. Estimated results show that the reemployment probabilities differ quite strongly according to the exit states. Importantly the most of individuals, above all males and married workers, leaves the unemployment state by own means, indicating a potential ineffectiveness of job centres in favouring matching process.

<< graphs 3 - 4>>

However, this result is strongly affected by educational and professional level: while low educated and low skilled workers are more likely to leave unemployment by working positions offered at job-centre level, high educated and skilled workers are more likely to find a job by own initiative. It is a confirmation that the most of vacancies registered at job-centres are poor in terms of skill contents.

The competing risks analysis is also relevant to isolate the effect of the wished contract on the unemployment duration according to the exit contract. The main hypothesis of this paper is that in a labour market where individuals have strong preferences for permanent contracts, since temporary contracts are bad in terms of wages, career development, job conditions and so on, but temporary contracts are substantial in terms of job offered by firms, unemployment duration may be higher and frictional unemployment may increase. It follows because individuals looking for permanent contracts possibly, at the first rounds of search, refuse the temporary contract offers and continue the search of permanent contracts. However, as the time spent in unemployment increases, individuals may revise their wishes (for example by reducing the reservation wage) and the probability of accepting a temporary contract offer increases. Empirically we should observe that individuals leaving unemployment by temporary contracts with preference for permanent employment experience longer unemployment duration than individuals leaving unemployment by temporary contracts with preference for temporary employment. The descriptive analysis presented above confirmed this hypothesis, even though the t-test is significant only at 10%. Econometric analysis brought further evidence to this finding: both controlling and not controlling for unobserved heterogeneity the hazard rate of individuals that exit on temporary contracts but preferring permanent contracts is lower than the hazard rate of individuals that exit on temporary contracts but preferring temporary contracts (tables 5 and 6). The estimated coefficient is significant at 10% and the effect is quite small (about 12%). This finding tends to loss significance by introducing a demand-side control in the estimated hazard function (tables 7 and 8). Specifically, we add two variables indicating the percentage of vacancies offering permanent contracts at monthly and job centre level, and the percentage of unemployed looking for permanent contracts at monthly and job centre level to take into account the effect from competition for permanent jobs. In particular the information about the type of vacancies offered allow us to approximate the effect due to the job-offers month by month. Also, the results may indicate that the preference for permanent contracts is quickly adapted to the labour market conditions, in terms of percentage of temporary contracts offered, wage offered as well as the relative costs of search activities. However, in this frame the decomposition of the full-sample into sub-groups may be relevant, since demographic and social characteristics may address different behaviour in matching process. Preliminary evidence, that we do not show for brevity, anticipate that variables as age or gender may drive different behaviour in terms of searched/offered contract mismatch, rapidity of revision about own wishes, and channels of exit from unemployment status.

The main advantage of the micro-econometric approach to the matching function estimation, is that it allows to better understand the sources underlying the matching process. A first evidence, as anticipated above, is that adult, married and male workers are more likely to leave unemployment by own means rather than by vacancies offered at job centres level. More important is the effect from educational and professional level. While low skilled and low professional workers largely leave unemployment by job-centres, skilled and high professional leaves unemployment prevalently by own means, as a consequence of the type of jobs offered at job-centres level. This finding highlights the ineffectiveness of job centres to gather heterogeneous job positions in terms of demanded education and profession, and scarce recourse of firms offering skilled jobs to job-centres. Skilled workers also experience higher probability of transiting toward permanent employment rather than temporary employment. Temporary contracts are more likely be reached by unmarried and females. Having dependent persons reduce the probability of leaving unemployment by own means while favours the transitions by job-centres. In general, the disability reduce the probability of finding a job, indicating that job-placement services and the targeted policies to favour employability of disabled people remain inadequate, even though the disabled people leaving unemployment by own means are rather small part. Having previous job experiences increase reemployment probabilities, and the effect is strong overall for individuals leaving unemployment by own means, while it is less important for individuals transiting toward permanent employment. Contrarily to theoretical predictions, receiving benefits increase the hazard rates. Receiving training also increase the reemployment probabilities above all among individuals leaving unemployment by job-centres, i.e. the low skilled workers. The wage offered monthly and at job centres level introduced to control the demand-side effect display a positive sign for transition toward temporary employment, possibly indicating the existence of an adaptation process from searched to accepted contracts. Less clear are the estimated coefficients with respect to the transitions toward permanent contracts and transitions by own means. Regional dummies describe an heterogeneous situation of the Portuguese labour market: in the region “Centre” the job-centres appear to be rather effective if compared with other regions, while transitions toward temporary contracts are less likely in the region “Norte” and more likely in the regions “Alentejo” and “Algarve”, with respect to the reference region “Lisboa”. Year dummies are often significant. Labour market tightness variables present the expected signs in all specifications. We find that an increase in the value of the logarithm of the stock-flow of unemployed workers reduces reemployment probabilities, most likely owing to congestion problems, while an increase in the value of the logarithm of the gross stock-flow of vacancies increases reemployment probabilities, as implied by thick market externalities. Tightness variables allow us to test the hypothesis of constant return to scale. The hypothesis seems to be refused, anticipating the existence of increasing returns to scale and the possibility of multiple unemployment equilibrium in the Portuguese labour market.

<< tables 5-8 >>

6. Conclusions

This paper tests the hypothesis of higher mismatch probability in a segmented labour market populated by unemployed workers having strong preferences for permanent contracts and firms offering both permanent and temporary contracts. Specifically, estimating a matching function using data on individual transitions from unemployment to employment, we investigate if higher level of searched/offered contract heterogeneity increases frictions in the matching process lengthening, hence, unemployment durations. We estimate a reduced form matching function using competing risks cloglog model by taking into account for Gaussian unobserved heterogeneity, applied to a sample of Portuguese unemployed workers, drawn from an IEFP dataset. The stock-flow matching processes is accommodated by considering monthly information at job centres-level about unemployed seeking for a job and vacancies offered by firms.

Preliminary evidences are provided plotting the prediction of unemployment duration from estimation of a fractional polynomial of a specific monthly heterogeneity index introduced to measure the searched/offered contract type dyscrasia at job centres level. Graph analysis is consistent with the hypothesis of higher mismatch probability in presence of higher positive contract type heterogeneity (i.e. prevalence of temporary contracts offered).

Moreover it also seems to suggest that unemployed workers looking for a temporary job also accept, and in some cases more rapidly, the offered permanent jobs, except in the rare cases in which temporary contracts are strongly preferred. Finally, women are found to experience longer unemployment durations, an exception being in situations in which the contracts on offer are predominantly for temporary jobs. In such cases, women appear to be more adaptable than men, demonstrating a greater willingness to accept temporary contracts as a stop-gap measure, without renouncing the desire for permanent employment

Econometric results show the existence of negative duration dependence and significant unobserved heterogeneity. Importantly the most of individuals, above all males and married workers, leaves the unemployment state by own means, indicating a potential ineffectiveness of job centres in favouring matching process. In this frame, empirical evidence prove that looking for permanent contracts reduces the hazard rate, lengthening the unemployment duration and contributing to increase the frictional unemployment. The evidence tend to loss significance by controlling for demand-side variables, anticipating that the wished contract has a limited effect on unemployment duration possibly as a consequence of quick adaptation to the labour market conditions, including the types of contract offered. However further investigation should be addressed to better understand the role of demographic and social characteristics, as age, gender, education. In this sense, specific sub-groups may be characterized by different behaviour in the matching process, also according to the relevance of the mismatch between searched/offered contracts. Importantly, results provide evidence that job-centres are ineffective to favour the reemployment of skilled workers, that experiment the highest hazard rate by leaving unemployment by own-means rather than accepting the low-skill jobs offered by firm at job centres level. Disabled people experience lower reemployment probabilities than not disabled people, indicating the ineffectiveness of targeted policies aimed to favour their employability. Previous job experiences and training decrease unemployment duration, as well as receiving benefits and higher wage offered at job centres level. Heterogeneity at regional level and evidence of increasing returns to scale are found.

Further investigation are necessary to better understand the role of labour market duality on frictional unemployment, since it possibly acts differently among the segments composing the labour force, according to demographic and social characteristics. However, our paper bears some policy suggestions. In order to reduce frictions in the matching process, and hence to reduce the time to (re)employment, the evidence support the notion that providing training does shorten unemployment durations. Having some job experience matters a great deal to find a job. With respect to the contract heterogeneity observed in regional labour markets which may give rise to increased frictions in the matching process two measures should be implemented. On the one hand, better information on the real conditions of the labour market in terms of the probability of finding a permanent contract could be suggested. On the other hand, and more interestingly, measures capable of increasing the perceived desirability of temporary jobs by unemployed workers could reduce the extent of the contract searched–offered mismatch. In this sense, policies which aim to reduce the gap between permanent and temporary contracts in terms of wage, job security and accumulation of human capital, could bring about the strongly positive effect on reemployment probabilities that we document here.

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Table 1. Descriptive Statistics

	Mean	Std. Dev.
Age	32.662	11.735
Male	0.398	0.490
Married	0.452	0.498
No dependent persons	0.603	0.489
1 dependent person	0.195	0.396
2 dependent person	0.139	0.346
3 or more dependent person	0.062	0.242
Disabled	0.006	0.079
Education less than 9 years	0.499	0.500
Education 9 years	0.191	0.393
Education 11-12 years	0.222	0.416
Education more than 12 years	0.088	0.283
Look for the first job	0.196	0.397
Look for a full-time	0.990	0.098
Student	0.072	0.258
Ex-student	0.091	0.287
End of training period	0.017	0.131
Dismissed	0.179	0.383
Resigned	0.120	0.325
End of temporary job	0.357	0.479
Other reasons	0.164	0.370
Manager-specialist	0.084	0.278
Technicians	0.074	0.262
Administrative	0.169	0.375
Services	0.206	0.404
Agricultural	0.044	0.206
Blue-collars	0.217	0.412
No profession	0.205	0.404
Benefit	0.294	0.455
Training	0.461	0.498
Wage offered	41551.1	96970.6
Norte	0.345	0.475
Centro	0.166	0.372
Lisboa	0.359	0.480
Alentejo	0.077	0.266
Algarve	0.054	0.226
Year 1998	0.223	0.416
Year 1999	0.205	0.404
Year 2000	0.184	0.388
Log stock-flow unemployment	0.178	0.382
Log stock-flow vacancies	0.210	0.407
% PC vacancies	0.696	0.339
% PC unemployed	0.977	0.056
Log stock-flow unemployment	8.773	0.965
Log stock-flow vacancies	4.573	0.763
Look for a PC	0.977	0.151

Source: our elaboration on IEFP data

Table 2. Heterogeneity Index by Job Centre

		Males					Females				
Region	Job-Centre	Obs	Mean	S.d.	Min	Max	Obs	Mean	S.d.	Min	Max
Norte	Viana do Castelo	737	0.373	0.221	0.016	0.658	1,102	0.369	0.226	-0.010	0.658
	Braga	1,089	0.065	0.138	-0.071	0.621	1,886	0.052	0.122	-0.088	0.621
	Fafe	446	-0.006	0.033	-0.100	0.075	650	0.001	0.025	-0.100	0.075
	Guimareas	990	0.007	0.040	-0.100	0.141	1,294	0.015	0.028	-0.053	0.141
	Vila Nova de Famaliçao	643	0.132	0.126	-0.027	0.500	934	0.141	0.130	-0.025	0.500
	Amarante	678	0.078	0.107	-0.125	0.440	1,138	0.093	0.111	-0.182	0.440
	Matosinhos	1,113	-0.008	0.031	-0.111	0.056	1,379	0.002	0.017	-0.062	0.056
	Penafiel	794	-0.012	0.031	-0.143	0.041	1,300	-0.003	0.012	-0.067	0.041
	Porto	1,263	0.422	0.198	-0.056	0.870	1,537	0.440	0.198	-0.066	0.870
	Pòvao do Varzim/Vila do Conde	797	0.003	0.037	-0.167	0.087	1,170	0.003	0.031	-0.073	0.087
	Santo Tirso	563	-0.005	0.045	-0.182	0.169	933	-0.023	0.043	-0.136	0.064
	Vila Nova de Gaia	1,984	0.011	0.030	-0.088	0.096	2,735	0.009	0.030	-0.058	0.096
	Vila Real	591	0.301	0.257	-0.245	0.880	837	0.314	0.249	-0.071	0.880
	Chaves	491	-0.004	0.033	-0.167	0.063	778	-0.004	0.031	-0.200	0.063
	Bragança	369	0.010	0.018	0.000	0.068	543	0.005	0.032	-0.167	0.068
	Macedo de Cavaleiros	214	0.072	0.090	-0.200	0.333	307	0.055	0.104	-0.500	0.333
	Mirandela	236	0.051	0.122	-0.333	0.429	376	0.062	0.109	-0.333	0.444
	Torre de Moncorvo	97	0.035	0.064	0.000	0.250	176	0.024	0.049	0.000	0.250
	Felguiras	279	-0.003	0.023	-0.143	0.020	408	-0.001	0.019	-0.167	0.020
	Porto Ocidental	289	-0.010	0.053	-0.333	0.040	459	-0.003	0.024	-0.200	0.040
	Basto	610	0.402	0.399	-0.042	1.000	747	0.435	0.410	-0.063	1.000
	Lamego	502	0.311	0.152	0.000	0.750	743	0.327	0.163	0.000	0.750
	S.Joao da Madeira	920	0.003	0.022	-0.111	0.048	1,635	0.001	0.022	-0.077	0.048
	Arcas de Valvedez	214	0.308	0.150	0.037	0.808	300	0.301	0.169	0.037	0.808
	Barcelos	514	0.003	0.029	-0.187	0.107	763	0.008	0.021	-0.054	0.107
	Maia	646	0.093	0.168	0.000	0.673	1,001	0.082	0.163	-0.045	0.673
	Valongo	525	0.015	0.053	-0.113	0.297	854	0.025	0.052	-0.143	0.297
	Gondomar	947	0.085	0.168	-0.105	0.721	1,233	0.082	0.162	-0.052	0.804
	Valença	264	0.014	0.037	-0.125	0.113	398	0.016	0.029	0.000	0.113
Centro	Aveiro	980	0.194	0.159	0.010	0.555	1,666	0.204	0.161	0.037	0.545
	Agueda	427	0.043	0.064	-0.194	0.231	887	0.035	0.053	-0.086	0.231
	Coimbra	1,091	0.354	0.201	0.023	0.807	1,663	0.381	0.200	0.054	0.807
	Figueirada Foz	750	0.558	0.118	0.258	0.733	1,064	0.553	0.120	0.308	0.763
	Lousa	171	-0.128	0.287	-0.687	0.800	343	-0.090	0.202	-0.962	0.333
	Leiria	642	0.098	0.070	-0.010	0.269	1,332	0.106	0.069	0.000	0.249
	Marinha Grande	218	0.152	0.128	-0.200	0.429	399	0.158	0.110	-0.058	0.429
	S.Pedro do Sul	247	-0.004	0.047	-0.200	0.125	531	0.000	0.028	-0.091	0.125
	Viseu	889	-0.006	0.051	-0.158	0.094	1,279	0.000	0.043	-0.113	0.094
	Guarda	480	-0.006	0.039	-0.167	0.080	654	-0.016	0.053	-0.200	0.080
	Castelo Branco	393	0.273	0.141	-0.086	0.625	719	0.283	0.122	0.045	0.625
	Covilha	591	0.011	0.032	-0.063	0.112	756	0.010	0.032	-0.056	0.112
	Arganil	254	0.176	0.087	-0.198	0.407	428	0.175	0.080	0.000	0.407
	Figueiro dos Vinhos	166	0.151	0.142	-0.360	0.482	316	0.191	0.109	0.023	0.482
	Tondela	348	0.646	0.133	0.159	0.900	526	0.658	0.127	0.230	1.000
	Seia	319	0.006	0.036	-0.143	0.071	437	0.010	0.021	-0.069	0.071
	Serta	187	0.046	0.057	-0.104	0.289	313	0.047	0.060	-0.143	0.289
	Pinhel	132	0.189	0.152	-0.206	0.492	250	0.207	0.154	0.000	0.649

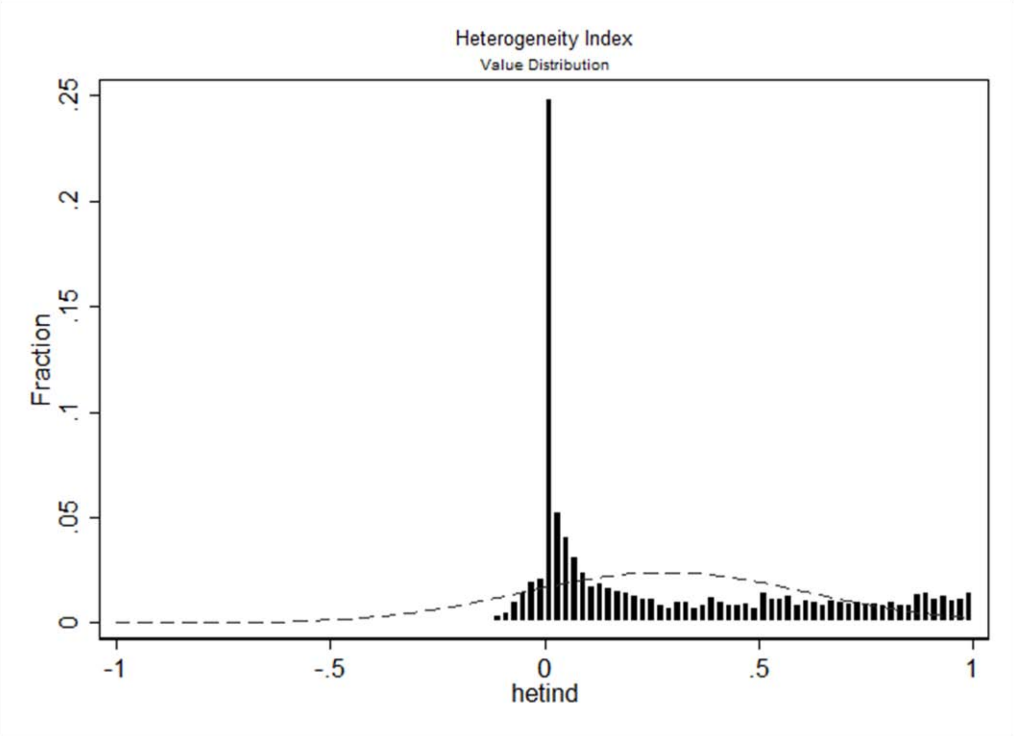
cont…

Table 2. Heterogeneity Index by Job Centre (…cont)

		Males					Females				
Region	Job-Centre	Obs	Mean	S.d.	Min	Max	Obs	Mean	S.d.	Min	Max
	Caldas da Rainha	644	0.116	0.116	-0.083	0.582	1,021	0.108	0.119	-0.147	0.582
	Abrentes	372	0.077	0.058	-0.167	0.190	569	0.063	0.073	-0.165	0.223
	Santarem	728	0.356	0.204	0.004	0.870	1,525	0.367	0.201	0.038	0.870
	Tomar	319	0.501	0.148	-0.114	0.800	668	0.488	0.137	0.183	0.800
	Torres Novas	556	0.111	0.081	-0.021	0.370	951	0.109	0.079	0.012	0.370
	Amadora	1,564	0.573	0.456	-0.029	1.000	1,981	0.581	0.455	-0.026	1.000
	Cascais	1,722	0.516	0.409	-0.079	0.986	2,053	0.531	0.417	-0.071	0.995
	Conde Redondo	932	0.343	0.200	-0.043	0.729	927	0.351	0.200	-0.042	0.729
	Picoas	893	0.426	0.328	-0.192	0.955	1,013	0.421	0.312	-0.208	0.953
	Loures	1,060	0.455	0.245	0.068	0.993	1,367	0.459	0.249	0.035	0.993
	Moscavide	878	0.044	0.106	-0.154	0.398	966	0.038	0.097	-0.143	0.398
Lisboa	Torres Vedras	711	0.025	0.052	-0.106	0.248	1,413	0.024	0.049	-0.071	0.248
	Vila Franca de Xira	1,097	-0.034	0.078	-0.338	0.068	1,596	-0.022	0.056	-0.231	0.068
	Almada	1,063	0.613	0.136	0.270	0.849	1,398	0.599	0.146	0.195	0.882
	Barreiro	1,217	0.147	0.289	-0.231	0.909	1,638	0.145	0.266	-0.139	0.939
	Montijo	380	0.006	0.120	-0.250	0.340	607	0.022	0.119	-0.231	0.340
	Setubal	1,204	0.820	0.099	0.491	1.000	1,719	0.814	0.101	0.433	0.989
	Salvaterra de Magos	510	0.698	0.221	0.179	0.965	1,489	0.690	0.222	0.179	0.965
	Alcobaça	402	0.080	0.092	-0.096	0.380	654	0.084	0.084	-0.097	0.380
	Sintra	1,336	0.510	0.209	-0.102	0.821	1,968	0.525	0.207	-0.198	0.795
	Alcantara	539	0.001	0.062	-0.200	0.131	625	0.010	0.044	-0.131	0.105
	Benfica	861	0.773	0.156	0.203	1.000	974	0.776	0.155	0.332	1.000
	Seixal	1,030	0.555	0.119	0.223	0.753	1,540	0.559	0.109	-0.080	0.797
	Alacer do Sal	152	0.752	0.257	-0.042	1.000	425	0.748	0.257	-1.000	1.000
	Sines	523	0.106	0.142	-0.200	0.556	937	0.099	0.140	-0.100	0.556
	Elvas	316	0.486	0.176	0.111	0.917	512	0.463	0.171	0.111	0.917
	Portalegre	356	0.416	0.273	-0.100	0.870	538	0.445	0.278	-0.063	0.870
	Estremoz	302	0.504	0.211	0.143	1.000	811	0.469	0.195	0.143	0.889
Alentejo	Evora	583	0.177	0.127	-0.134	0.526	1,114	0.171	0.127	-0.022	0.524
	Beja	520	0.730	0.228	-0.069	1.000	971	0.738	0.232	0.022	1.000
	Ourique	105	0.008	0.140	-0.333	0.333	200	0.020	0.073	-0.067	0.333
	Ponte de Sor	179	0.435	0.324	-0.250	1.000	428	0.429	0.265	-0.125	1.000
	Montemor o Novo	167	0.338	0.216	0.000	1.000	468	0.318	0.207	0.000	1.000
	Moura	306	0.776	0.294	0.000	1.000	490	0.786	0.276	0.000	1.000
	Faro	721	0.839	0.139	0.422	1.000	1,017	0.849	0.125	0.422	1.000
	Portimao	751	0.873	0.110	0.485	0.989	1,381	0.878	0.107	0.592	0.983
Algarve	Vila Real de Santo Antonio	315	0.851	0.098	0.609	0.981	663	0.851	0.092	0.609	1.000
	Loule	630	0.851	0.091	0.481	0.983	1,111	0.863	0.078	0.496	0.989
	Lagos	269	0.514	0.201	-0.059	0.939	537	0.532	0.199	0.025	0.939

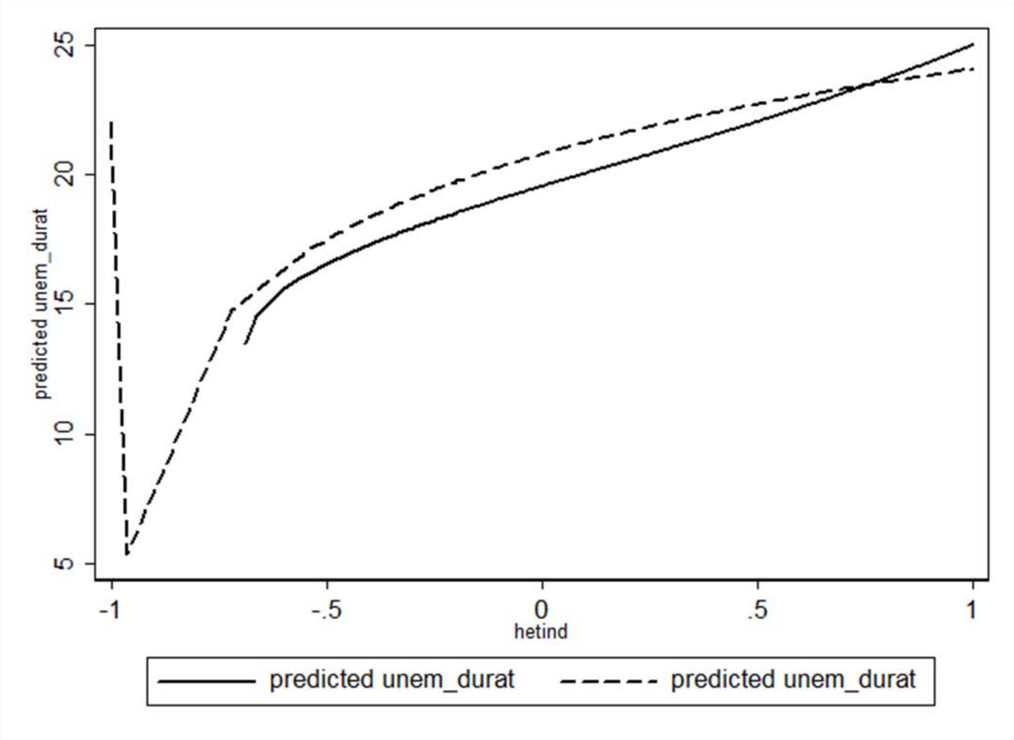
Source: our elaboration on IEFP data

Graph 1. Heterogeneity Index Distribution



Source: our elaboration on IEFP data

Graph 2. Predicted Unemployment Duration-Heterogeneity Index Curves



Source: our elaboration on IEFP data
Males: continuous line, Females: dashed line

Table 3. Spells by Searched Contract

Looking for PC				Looking for TC			
145831				3463			
97.68%				2.32%			
Censored	Uncensored			Censored	Uncensored		
100091	45740			2479	984		
68.63%	31.37%			71.59%	28.41%		
	By Own Mean	By CTE			By Own Mean	By CTE	
	25960	19780			615	369	
	56.76%	43.24%			62.50%	37.50%	
		Exit PC	Exit TC			Exit PC	Exit TC
		13203	6577			190	179
		66.75%	33.25%			51.49%	48.51%

Source: our elaboration on IEFP data

Table 4. Mean Unemployment Duration

	Look for a TC		Look for a PC		
	Mean	s.d.	Mean	s.d.	
Censored	24.31	17.81	28.86	18.29	***
Exit on PC	7.87	10.29	10.29	11.43	***
Exit on TC	8.43	9.41	9.99	10.80	*
Exit by OM	8.67	9.86	8.72	9.56	

Source: our elaboration on IEFP data

Table 5. Estimation results: model 1

	Exit on PC			Exit on TC			Exit by OM		
	b	s.e.		b	s.e.		b	s.e.	
Age	0.021	0.006	***	0.049	0.008	***	0.052	0.004	***
Age square	-0.001	0.000	***	-0.001	0.000	***	-0.001	0.000	***
Male	-0.037	0.020	*	-0.156	0.029	***	0.128	0.014	***
Married	-0.025	0.024		-0.144	0.031	***	0.217	0.016	***
1 dependent person	0.075	0.027	***	0.055	0.035		-0.052	0.018	***
2 dependent person	0.076	0.032	**	0.059	0.041		-0.102	0.021	***
3 or more dependent person	0.044	0.043		-0.089	0.056		-0.350	0.030	***
Disabled	-0.278	0.115	**	-0.102	0.154		-0.733	0.119	***
Education 9 years	-0.035	0.024		0.034	0.033		-0.012	0.018	
Education 11-12 years	-0.078	0.025	***	-0.062	0.037	*	0.037	0.018	**
Education more than 12 years	-0.258	0.046	***	-0.139	0.055	**	0.057	0.023	**
Look for the first job	0.049	0.046		-0.244	0.080	***	-0.184	0.049	***
Look for a full-time	0.325	0.112	***	0.209	0.156		0.178	0.079	**
Student	0.027	0.050		0.272	0.088	***	0.111	0.054	**
Ex-student	0.198	0.048	***	0.215	0.091	**	0.180	0.052	***
End of training period	0.222	0.062	***	0.022	0.097		0.018	0.067	
Dismissed	0.127	0.031	***	0.087	0.048	*	0.766	0.025	***
Resigned	0.090	0.035	**	0.010	0.053		0.287	0.031	***
End of temporary job	0.084	0.029	***	0.254	0.039	***	1.011	0.023	***
Manager-specialist	-1.348	0.061	***	-1.852	0.105	***	0.666	0.027	***
Technicians	-0.499	0.045	***	-0.786	0.069	***	0.456	0.027	***
Administrative	-0.178	0.031	***	-0.406	0.043	***	0.242	0.023	***
Services	-0.087	0.027	***	-0.248	0.035	***	0.090	0.022	***
Agricultural	-0.071	0.060		0.910	0.045	***	1.055	0.027	***
Blue-collars	0.174	0.026	***	-0.269	0.041	***	0.275	0.021	***
Benefit	0.190	0.061	***	0.281	0.068	***	0.256	0.036	***
Training	0.858	0.019	***	0.776	0.027	***	0.402	0.014	***
Wage offered	0.000	0.000	***	0.000	0.000	***	0.000	0.000	***
Norte	0.363	0.023	***	-1.179	0.045	***	-0.171	0.016	***
Centro	0.642	0.024	***	-0.176	0.037	***	-0.519	0.021	***
Alentejo	-0.129	0.052	**	0.527	0.054	***	0.276	0.027	***
Algarve	-1.068	0.069	***	1.014	0.036	***	-0.184	0.027	***
Year 1998	-0.423	0.038	***	-0.448	0.052	***	-0.267	0.024	***
Year 1999	0.095	0.026	***	0.039	0.034		-0.050	0.019	***
Year 2001	0.032	0.026		-0.408	0.037	***	-0.114	0.019	***
Year 2002	-0.130	0.026	***	-0.503	0.037	***	-0.140	0.018	***
Log stock-flow unemployment	-0.120	0.009	***	-0.075	0.013	***	-0.158	0.006	***
Log stock-flow vacancies	0.266	0.016	***	0.429	0.022	***	0.282	0.011	***
Log t	-0.807	0.010	***	-0.707	0.015	***	-0.817	0.007	***
Look for a PC	0.289	0.074	***	-0.130	0.077	*	-0.039	0.041	
Constant	-5.048	0.187	***	-6.558	0.259	***	-5.091	0.131	***
Log likelihood	-78372.879			-42668.687			-139420.68		
LR chi2	17065.08			12073.27			31121.13		
Observations	3378628								
Failures	13297			6751			26523		

Source: our elaboration on IEFP data

Table 6. Estimation results: model 2

	Exit on PC			Exit on TC			Exit by OM		
	b	s.e.		b	s.e.		b	s.e.	
Age	0.020	0.009	**	0.049	0.008	***	0.054	0.005	***
Age square	-0.001	0.000	***	-0.001	0.000	***	-0.001	0.000	***
Male	-0.028	0.027		-0.156	0.029	***	0.148	0.015	***
Married	-0.045	0.034		-0.144	0.031	***	0.246	0.019	***
1 dependent person	0.112	0.038	***	0.055	0.035		-0.065	0.020	***
2 dependent person	0.100	0.044	**	0.059	0.041		-0.114	0.024	***
3 or more dependent person	0.066	0.058		-0.089	0.056		-0.393	0.034	***
Disabled	-0.373	0.151	**	-0.102	0.154		-0.791	0.127	***
Education 9 years	-0.054	0.033	*	0.034	0.033		-0.012	0.020	
Education 11-12 years	-0.095	0.035	***	-0.062	0.037	*	0.046	0.020	**
Education more than 12 years	-0.326	0.060	***	-0.139	0.055	**	0.055	0.026	**
Look for the first job	0.079	0.062		-0.244	0.080	***	-0.200	0.052	***
Look for a full-time	0.460	0.146	***	0.209	0.156		0.198	0.086	**
Student	0.003	0.069		0.272	0.088	***	0.101	0.058	*
Ex-student	0.235	0.066	***	0.215	0.091	**	0.179	0.056	***
End of training period	0.268	0.085	***	0.022	0.097		0.004	0.072	
Dismissed	0.120	0.043	***	0.087	0.048	*	0.838	0.029	***
Resigned	0.123	0.048	**	0.010	0.053		0.307	0.033	***
End of temporary job	0.064	0.038	*	0.254	0.039	***	1.119	0.027	***
Manager-specialist	-1.772	0.078	***	-1.852	0.105	***	0.757	0.031	***
Technicians	-0.692	0.061	***	-0.786	0.069	***	0.515	0.031	***
Administrative	-0.267	0.042	***	-0.406	0.043	***	0.261	0.026	***
Services	-0.112	0.037	***	-0.248	0.035	***	0.095	0.024	***
Agricultural	-0.107	0.079		0.910	0.045	***	1.220	0.034	***
Blue-collars	0.243	0.036	***	-0.269	0.041	***	0.308	0.023	***
Benefit	0.300	0.088	***	0.281	0.068	***	0.305	0.042	***
Training	1.262	0.028	***	0.776	0.027	***	0.454	0.016	***
Wage offered	0.000	0.000	***	0.000	0.000	***	0.000	0.000	***
Norte	0.455	0.032	***	-1.179	0.045	***	-0.197	0.018	***
Centro	0.852	0.034	***	-0.176	0.037	***	-0.578	0.024	***
Alentejo	-0.233	0.067	***	0.527	0.054	***	0.321	0.031	***
Algarve	-1.383	0.086	***	1.014	0.036	***	-0.187	0.031	***
Year 1998	-0.550	0.046	***	-0.448	0.052	***	-0.267	0.026	***
Year 1999	0.046	0.030		0.039	0.034		-0.054	0.019	***
Year 2001	0.011	0.029		-0.408	0.037	***	-0.124	0.019	***
Year 2002	-0.172	0.030	***	-0.503	0.037	***	-0.158	0.019	***
Log stock-flow unemployment	-0.121	0.010	***	-0.075	0.013	***	-0.158	0.007	***
Log stock-flow vacancies	0.328	0.019	***	0.429	0.022	***	0.305	0.012	***
Log t	-0.581	0.016	***	-0.707	0.015	***	-0.731	0.011	***
Look for a PC	0.370	0.095	***	-0.130	0.077	*	-0.042	0.047	
Constant	-7.027	0.250	***	-6.558	0.259	***	-5.714	0.151	***
Sigma u	1.877	0.039	***	0.001	.		0.893	0.038	***
LR test	537.2			0.0			180.4		
rho	0.682	0.009	***	0.000	.		0.326	0.019	***
Log likelihood	-78104.3			-42668.7			-139330.5		
Wald chi2	11054.4			11909.4			24586.4		

Source: our elaboration on IEFP data

Table 7. Estimation results: model 3

	Exit on PC			Exit on TC			Exit by OM		
	b	s.e.		b	s.e.		b	s.e.	
Age	0.025	0.006	***	0.045	0.008	***	0.052	0.004	***
Age square	-0.001	0.000	***	-0.001	0.000	***	-0.001	0.000	***
Male	-0.032	0.020		-0.164	0.029	***	0.127	0.014	***
Married	-0.042	0.025	*	-0.130	0.031	***	0.217	0.016	***
1 dependent person	0.074	0.028	***	0.059	0.035	*	-0.052	0.018	***
2 dependent person	0.061	0.032	*	0.085	0.041	**	-0.100	0.021	***
3 or more dependent person	0.031	0.043		-0.068	0.056		-0.348	0.030	***
Disabled	-0.261	0.115	**	-0.135	0.154		-0.732	0.119	***
Education 9 years	-0.027	0.024		0.022	0.033		-0.013	0.018	
Education 11-12 years	-0.068	0.025	***	-0.069	0.037	*	0.036	0.018	**
Education more than 12 years	-0.255	0.046	***	-0.149	0.055	***	0.058	0.023	***
Look for the first job	0.028	0.045		-0.229	0.080	***	-0.184	0.049	***
Look for a full-time	0.359	0.112	***	0.175	0.156		0.177	0.079	**
Student	0.042	0.050		0.280	0.089	***	0.110	0.054	**
Ex-student	0.185	0.048	***	0.285	0.091	***	0.180	0.052	***
End of training period	0.188	0.062	***	0.080	0.098		0.020	0.067	
Dismissed	0.106	0.031	***	0.131	0.048	***	0.766	0.026	***
Resigned	0.060	0.035	*	0.076	0.053		0.287	0.031	***
End of temporary job	0.077	0.029	***	0.279	0.039	***	1.011	0.023	***
Manager-specialist	-1.316	0.061	***	-1.932	0.105	***	0.665	0.027	***
Technicians	-0.503	0.045	***	-0.826	0.069	***	0.456	0.027	***
Administrative	-0.176	0.031	***	-0.440	0.043	***	0.243	0.023	***
Services	-0.086	0.027	***	-0.266	0.035	***	0.089	0.022	***
Agricultural	-0.020	0.060		0.838	0.046	***	1.055	0.027	***
Blue-collars	0.159	0.026	***	-0.284	0.041	***	0.276	0.021	***
Benefit	0.181	0.061	***	0.291	0.068	***	0.256	0.036	***
Training	0.816	0.019	***	0.835	0.027	***	0.403	0.014	***
Wage offered	0.000	0.000		0.000	0.000	**	0.000	0.000	***
Norte	-0.046	0.024	*	-0.323	0.050	***	-0.160	0.017	***
Centro	0.410	0.025	***	0.391	0.041	***	-0.512	0.022	***
Alentejo	-0.062	0.051		0.432	0.056	***	0.278	0.028	***
Algarve	-0.112	0.075		0.293	0.039	***	-0.206	0.029	***
Year 1998	-0.456	0.039	***	-0.340	0.051	***	-0.265	0.024	***
Year 1999	0.051	0.026	*	0.106	0.034	***	-0.048	0.019	***
Year 2001	-0.118	0.026	***	0.003	0.038		-0.108	0.019	***
Year 2002	-0.254	0.026	***	-0.172	0.038	***	-0.134	0.019	***
% PC vacancies	1.868	0.045	***	-2.304	0.048	***	-0.038	0.023	*
% PC unemployed	0.530	0.199	***	0.486	0.226	**	0.023	0.116	
Log stock-flow unemployment	-0.110	0.009	***	-0.091	0.013	***	-0.158	0.006	***
Log stock-flow vacancies	0.276	0.016	***	0.351	0.023	***	0.283	0.011	***
Log t	-0.793	0.010	***	-0.727	0.015	***	-0.817	0.007	***
Look for a PC	0.062	0.075		0.062	0.078		-0.036	0.042	
Constant	-6.825	0.263	***	-5.781	0.335	***	-5.095	0.169	***
Log likelihood	-77155.9			-41360.1			-139240.3		
LR chi2	19199.6			14586.3			31085.2		
Observations	3378628								
Failures	13297			6751			26523		

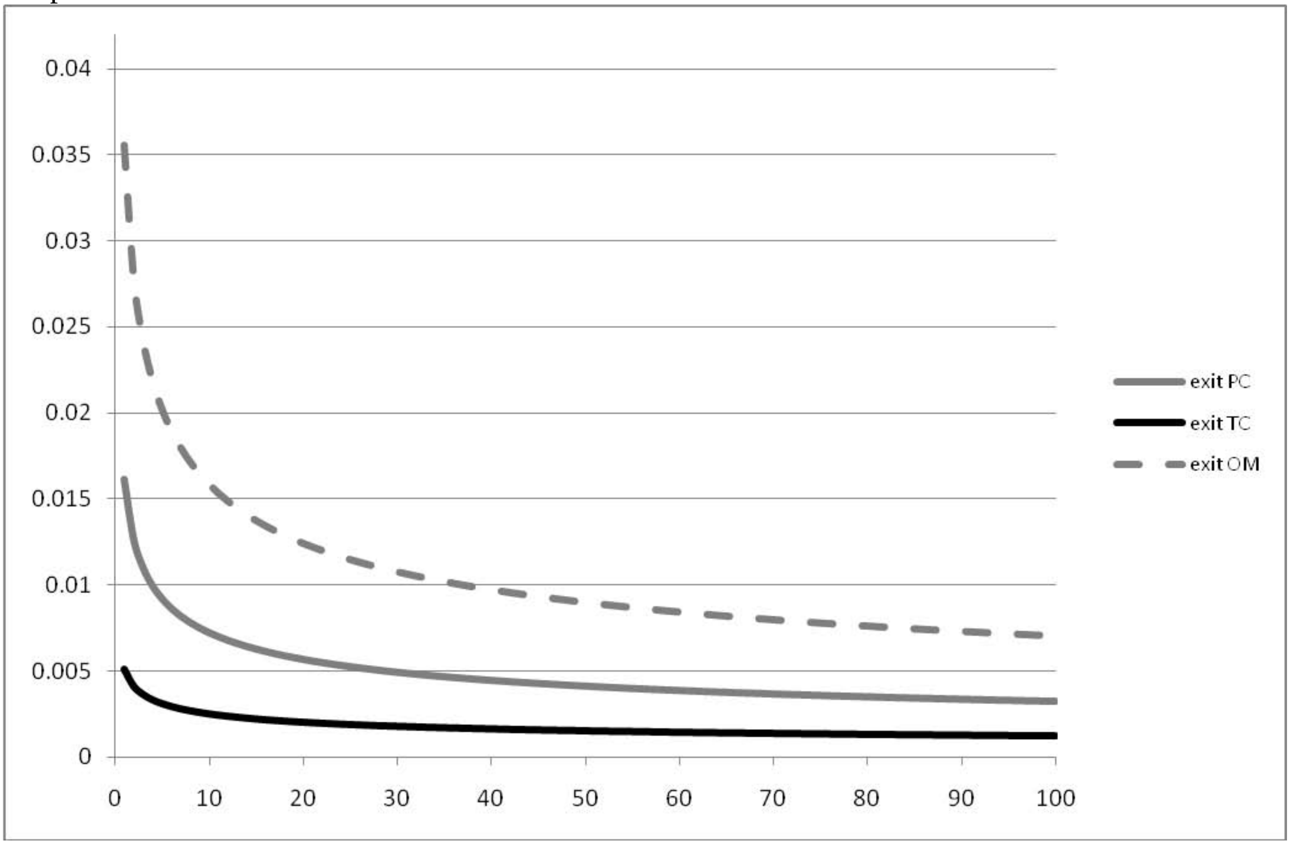
Source: our elaboration on IEFP data

Table 8. Estimation results: model 4

	Exit on PC			Exit on TC			Exit by OM		
	b	s.e.		b	s.e.		b	s.e.	
Age	0.025	0.008	***	0.055	0.011	***	0.062	0.006	***
Age square	-0.001	0.000	***	-0.001	0.000	***	-0.001	0.000	***
Male	-0.017	0.024		-0.134	0.037	***	0.185	0.018	***
Married	-0.039	0.029		-0.166	0.042	***	0.263	0.022	***
1 dependent person	0.079	0.033	**	0.057	0.047		-0.071	0.024	***
2 dependent person	0.046	0.039		0.082	0.054		-0.119	0.028	***
3 or more dependent person	0.009	0.051		-0.166	0.074	**	-0.410	0.039	***
Disabled	-0.359	0.135	***	-0.457	0.208	**	-0.870	0.139	***
Education 9 years	-0.040	0.029		0.029	0.043		-0.009	0.023	
Education 11-12 years	-0.083	0.030	***	-0.070	0.047		0.038	0.023	*
Education more than 12 years	-0.296	0.052	***	-0.149	0.071	**	-0.020	0.031	
Look for the first job	0.058	0.054		-0.253	0.097	***	-0.217	0.057	***
Look for a full-time	0.383	0.127	***	0.196	0.186		0.170	0.095	*
Student	0.069	0.060		0.300	0.107	***	0.083	0.063	
Ex-student	0.273	0.057	***	0.353	0.109	***	0.192	0.061	***
End of training period	0.272	0.073	***	0.221	0.120	*	0.012	0.078	
Dismissed	0.094	0.037	***	0.089	0.057		0.899	0.031	***
Resigned	0.044	0.041		0.054	0.064		0.357	0.036	***
End of temporary job	0.032	0.034		0.181	0.048	***	1.114	0.028	***
Manager-specialist	-1.476	0.068	***	-2.169	0.119	***	0.866	0.035	***
Technicians	-0.574	0.053	***	-0.959	0.083	***	0.575	0.036	***
Administrative	-0.216	0.036	***	-0.485	0.055	***	0.291	0.030	***
Services	-0.110	0.032	***	-0.286	0.046	***	0.101	0.028	***
Agricultural	-0.002	0.071		1.089	0.068	***	1.138	0.041	***
Blue-collars	0.208	0.031	***	-0.270	0.052	***	0.344	0.027	***
Benefit	0.154	0.073	**	0.230	0.087	****	0.214	0.047	***
Training	0.987	0.023	***	1.061	0.033	***	0.489	0.017	***
Wage offered	0.000	0.000	**	0.000	0.000	***	0.000	0.000	***
Norte	-0.010	0.029		-0.377	0.057	***	-0.186	0.022	***
Centro	0.507	0.030	***	0.330	0.050	***	-0.591	0.027	***
Alentejo	-0.064	0.059		0.456	0.071	***	0.396	0.037	***
Algarve	-0.136	0.082	*	0.460	0.054	***	-0.164	0.039	***
Year 1998	-0.413	0.041	***	-0.181	0.056	***	-0.126	0.027	***
Year 1999	0.067	0.028	**	0.208	0.036	***	0.018	0.020	
Year 2001	-0.168	0.027	***	-0.035	0.040		-0.171	0.020	***
Year 2002	-0.346	0.028	***	-0.312	0.041	***	-0.252	0.021	***
% PC vacancies	1.965	0.050	***	-2.584	0.057	***	-0.021	0.028	
% PC unemployed	0.517	0.209	**	0.333	0.250		-0.006	0.130	
Log stock-flow unemployment	-0.092	0.009	***	-0.051	0.013	***	-0.158	0.007	***
Log stock-flow vacancies	0.315	0.017	***	0.479	0.026	***	0.346	0.013	***
Log t	-0.670	0.012	***	-0.515	0.018	***	-0.583	0.010	***
Look for a PC	0.096	0.087		0.072	0.099		-0.086	0.055	
Constant	-8.067	0.294	***	-7.976	0.398	***	-6.507	0.204	***
Sigma u	1.262	0.029	***	1.646	0.035	***	1.330	0.020	***
LR test	1061.0			1772.9			3856.9		
rho	0.492	0.011	***	0.622	0.010	***	0.518	0.007	***
Log likelihood	-76625.4			-40473.7			-137311.8		
Wald chi2	14502.3			9420.9			16444.0		

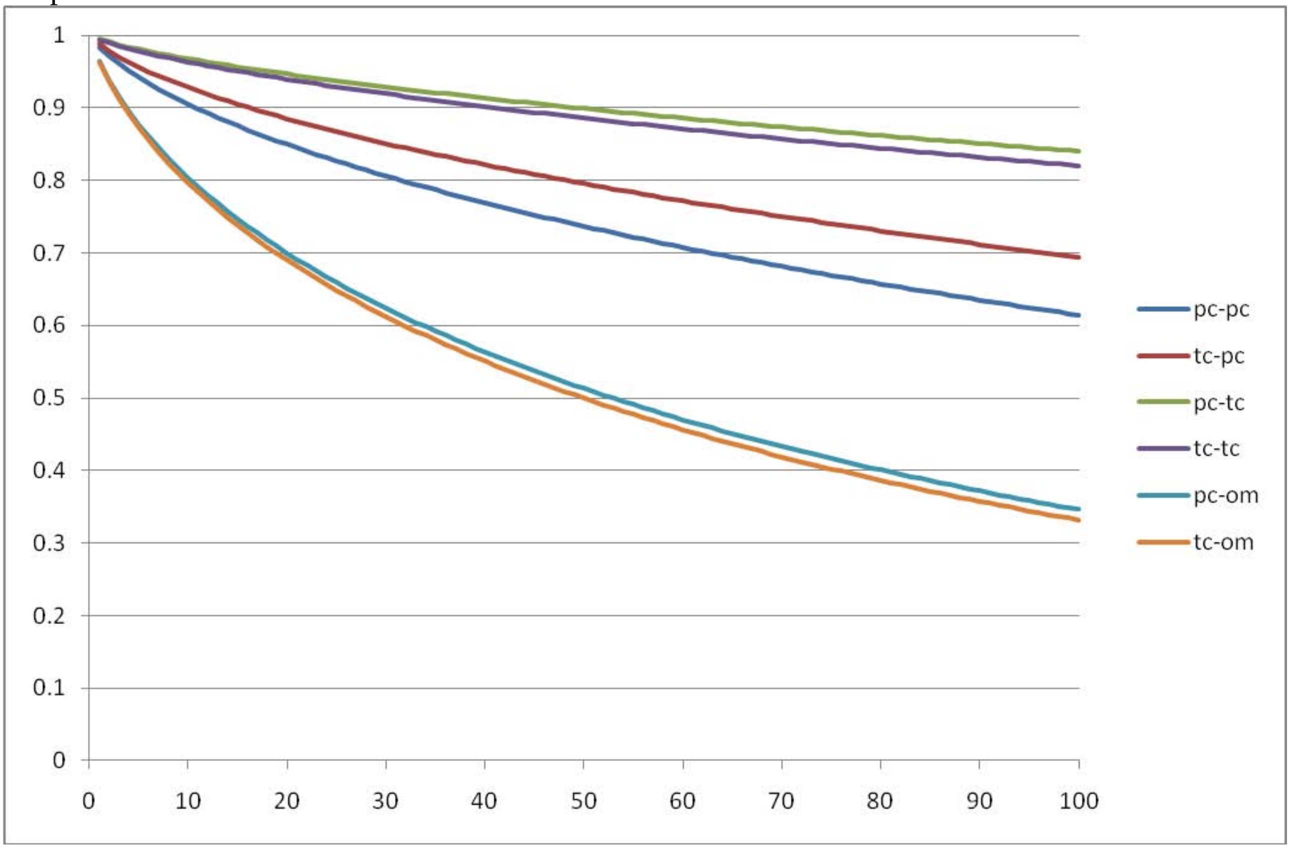
Source: our elaboration on IEFP data

Graph 3. Hazard rates



Source: our elaboration on IEFP data

Graph 4. Survival functions



Source: our elaboration on IEFP data