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The effects of contract-type mismatch and matching frictions on unemployment duration: Evidence for Portugal

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RESUMO/ABSTRACT

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Keywords: public employment services, job-centers performance, unemployment duration, matching rate, survival analysis

JEL codes: J68, J64, C14

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The effects of contract-type mismatch and matching frictions on unemployment duration: Evidence for Portugal

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Abstract

This paper analyses the impact of matching frictions in the Portuguese labour market on individual unemployment hazard rates and unemployment durations. The coexistence of permanent contracts and temporary contracts in the Portuguese (dual) labour-market is akin to a matching friction, with a contract-type mismatch between jobseekers who have a strong preference for permanent contracts, whereas firms, in turn, prefer to offer temporary contracts. The paper uses a rich micro dataset which allows to compute a time and space varying contract-type mismatch index, over 85 local labour markets, identified by job-centers of the Portuguese Public Employment System. Employing discrete time hazard models and a stock-flow matching mechanism, we find that local labour markets with higher contract-type mismatch rates are characterized by lower hazard rates, especially for job-seekers searching for a permanent contract, and higher exit rates via own means instead of via the job-center. Employing a sub-sample of uncensored spells and regression models, the data show that longer unemployment duration is a price to be paid to hedge against contract mismatch. Improving the desirability of temporary contracts and the information about local contract-type mismatch rates may reduce matching frictions and average unemployment durations due to contract-type mismatch.

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1. Introduction

Since the 1980s and 1990s, the so-called labour market reforms "at the margin", marked by the introduction of temporary (and flexible) contracts, in countries such as Portugal, Spain and Greece, led to the emergence of dual labour markets where good jobs (permanent contracts) and bad jobs (temporary contracts) co-exist, and to labour market performances with high unemployment rates and high unemployment durations. The co-existence of permanent contracts and temporary contracts gives rise to a possible contract-type mismatch, where job-seekers predominantly prefer permanent contracts, whereas firms offer mainly temporary contracts. This contract-type mismatch may be naturally perceived as a matching friction and, consequently, may lead, per se, to longer unemployment duration. Hence, a labour market reform, designed with a primary intention to increase labour market flexibility, may have the unintended effect of leading, via this contract-type mismatch effect, to longer unemployment duration.

Our paper sheds light to this important phenomenon by looking at the Portuguese situation. We investigate the role that matching frictions, due to contract-type mismatch, have in explaining unemployment hazard rates in a dual labour market where good jobs and bad jobs coexist. In particular, we analyse the role that contract-type expectations and labour market mismatch – job-seekers preferring permanent contracts over temporary contracts while firms prefer the opposite – play in increasing unemployment duration.

Since the 1990s labor market analysis has largely used matching functions in search and match frameworks (Mortensen 1987). Matching functions allow researchers to investigate the role of frictions in the labor market in explaining the existence of (frictional) unemployment and labor market effectiveness in matching unemployed workers with available vacancies.

As highlighted by Petrongolo and Pissarides (2001), frictions derive from various sources. For example, they depend on imperfect information about potential trading partners, absence of perfect insurance markets, congestion from large numbers, among other factors. 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 consider 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. Several authors (e.g. van Ours and Ridder 1995; Burgess and Profit 2001) found 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 ages and education groups, indicating the importance of disaggregating 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 arise from other sources, including labour market reform. Reforms "at the margin" – which introduced temporary contracts and were meant to reduce labour market rigidity – may constitute a potential source of matching frictions. The role of temporary contracts in the labour market is manifold. Certain authors (e.g. Ichino et al. 2005) emphasize their role in making it easier for workers to enter in the labour market and, in some cases, for workers to access permanent jobs. However, several studies[3] highlighted possible negative effects from temporary employment with respect to traditional permanent relationships, contributing to rationalize the existence of segmented labour markets divided into primary and secondary sectors and, specifically, a segmentation in good and bad jobs[4]. Permanent jobs (good jobs) feature better working conditions, employment stability and good prospects of career advancements. Temporary jobs (bad jobs), in turn, are associated with lower wages, lower job security and impediments to career advancements (Amuedo-Dorantes 2000). In a dual labour market, where good and bad jobs coexist, it is likely that one will find job-seekers having strong preferences for permanent contracts while firms may offer temporary contracts, since firms may use this contractual form to easily adjust their workforce to business cycle conditions or simply to reduce expected labour costs. Therefore, a labour market characterized by a homogenous supply side, with most unemployed workers searching for a permanent job, and a heterogeneous demand side, where temporary and permanent job offers coexist, may involve a high degree of mismatch, and, hence, high average unemployment duration. In fact, it is likely that individuals looking for a permanent job will tend to first refuse offers if they are for temporary jobs and only after a certain time they will start accepting those temporary job offers if said individuals do not find a suitable permanent job meanwhile.

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[3] For example, Jimeno and Toharia (1993), Dolado, Garcia-Serrano and Jimeno (2002), and Gagliarducci (2005).

[4] See Dolado, Jansen and Jimeno (2007) for a theoretical framework on dual employment protection legislation.

Our paper tests the hypothesis that higher contract-type mismatch leads to higher unemployment duration. To that end, we estimate a matching function using Portuguese data on individual transitions from unemployment to employment or employment to employment. Our empirical strategy consists in estimating individual reemployment probabilities with hazard models, as it allows for more flexible specifications of the matching function when compared to estimates of an aggregate matching function, 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 advantages of using hazard models to estimate matching functions, only a few studies in the literature have done so. For example, Lindeboom, van Ours and Renes (1994) investigated the link between matching functions and hazard models to study the relative effectiveness of 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 (Devine and Kiefer 1991).

We follow the literature and allow two possible approaches in estimating the matching functions: the random matching and the stock-flow matching models [5]. Broersma and van Ours (1999) argue that the estimates of the degree of returns to scale in the matching technology depend 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. Gregg and Petrongolo (2005) 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 technology. In our case, we use data from job-centers and the stock-flow approach is a better representation of the matching mechanism, since the existence of a matchmaker (i.e. the job-center) makes it unlikely that the same job may be re-offered to the same unemployed worker, as allowed by the random matching approach.

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[5] In a random matching set up the unemployed workers randomly 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 must 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.

We use a sample drawn from the IEFP (Instituto do Emprego e Formação Profissional) dataset, the public entity responsible for Portuguese public job placement centers, 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-centers and allows to construct spells of individual unemployment duration and, quite interestingly, to identify the destination contract (if permanent or temporary). In addition, the dataset allows us to construct stocks and flows of unemployed job-seekers and vacancies offered for each month at the job-center level. The dataset also contains information about vacancies, enabling us to determine the number of vacant jobs available for each month at the job-center level. 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 effects of the desired contract on the hazard rates toward multiple destination states and to construct an index[6] of the degree of the heterogeneity found between contracts searched and contracts offered which we use to understand the effects of such contract mismatch on unemployment duration. We estimate a competing risks discrete time hazard model with a log-log specification. We adopt a piece-wise constant baseline hazard where unobserved heterogeneity is assumed to be Gaussian distributed. The heterogeneity between contract-type desired by job-seekers and contract-type offered by firms is approximated by a mismatch index, which we include in the hazard model. The mismatch index is calculated at the job-center level and it thus reflects local labor market aggregate information; consequently, it is a valid regressor. Finally, auxiliary regression models have been adopted to test the stability of declared contract preferences and to investigate the association between unemployment duration and the probability of incurring in contract mismatch.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes contract type preferences. Section 4 introduces our index for contract-type mismatch. Section 5 presents the econometric model. Section 6 discusses the results. Finally, Section 7 concludes.

2. Data

We use an IEFP dataset that provides information on individuals registered at job-centres in (Mainland) Portugal from 1997 to 2002. The IEFP is the agency responsible for running the public employment services, and it is a division of the Ministry of Labour and Solidarity. The IEFP is responsible for job brokering, vocational guidance, administering employment subsidies, vocational training,

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[6] The index varies over time and across job-centers.

apprenticeship training and being registered at a job-center is necessary to collect unemployment benefits (see Addison and Portugal, 2002). The IEFP dataset includes information about job vacancies offered by firms. The original sample containing information on individuals is composed by more than 3 million of observations. To avoid computational problems, we drew a randomized sub-sample equal to 10% of the original sample[7]. The IEFP dataset provides (daily) information about the date of registration at the job-center and the date of placement, making it possible to identify (multiple) spells of unemployment durations. Our duration analysis focuses on unemployment spells starting since 1998 to have at our disposal complete information on all covariates considered. Spells without the date of placement are considered censored. However, individuals may drop out of the job-centers if they fail to present themselves at the job-centers control interviews. We eliminate from our sample spells that terminate in failure to report to the above-mentioned control interviews to avoid misleading identification of censored unemployment durations. 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 monthly rather than a daily basis.

We only consider individuals aged 16 to 60 years old, for whom all information with respect to all the covariates considered is available. This selection leaves us an unbalanced panel composed by 164627 spells and 133234 individuals. We remark that more than 81% of individuals only experiment one spell of unemployment in our samples. This is mainly due to the (1) quite long duration of unemployment spells which characterizes the Portuguese labour market and to the (2) short period analysed in this paper (60 months); both factors concur to explain the high percentage of censored spells in our sample (about 62%).

We consider a plethora of personal and job-related characteristics to control for observed heterogeneity at the individual level. Males and females are analysed separately. Tables 1a and 1b contain descriptive statistics.

<< Table 1a >>

<< Table 1b >>

To be more specific, we control for the following individual characteristics: age, introduced in a non-linear way, marital status, disability status, number of dependent persons in the household and educational level. We also control for job related characteristics. We introduce a variable indicating if the individual is looking

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

for his or her first job, meaning that he or she has no previous work experience, and a dummy indicating if the individual is employed at the outset of the job-search (on-the-job search). We consider a set of dummy variables indicating the motivation of the registration at the job-center. 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; 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, supervision activities and specialists, technicians, administrative workers, service workers, agricultural and fishing workers, blue collars, and individuals without specific occupations (interpreted here as no qualifications). Two variables are introduced to control if the individuals received unemployment or youth benefits or underwent a training period during the registration at the job-center. Year dummies referring to the beginning of the unemployment spell are also considered. Regional dummies are introduced to control for possible specific regional labour markets effects. As anticipated, according to the job-search theory framework, 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-center level. Labour market tightness variables are also introduced and are evaluated monthly at the job-center level. To implement the stock-flow matching mechanism, 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 construct stock values, we use information from the 1997 IEFP dataset, hence at the starting of the period analysed 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 0.075, while it is about 0.47 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.

3. Contract-type preferences

According to the IEFP information 98% of job-seekers are looking for a permanent contract, while just two thirds of vacant jobs offer a permanent relationship. This is indicative of different preferences about contract-type between job-seekers and firms. A first consequence of this dyscrasia is that some job-seekers may accept a contract-type different from the desired one. Table 2 reports the destination contract of the job-seekers according to the declared desired contract. Among individuals looking for a permanent contract just 69% of males effectively find a permanent job, while this percentage decreases to 63% among females. Among individuals looking for a temporary contract 46% of males effectively find a temporary job, while this percentage increases to 57% among females.

<< Table 2 >>

What can explain this different attitude towards permanent/temporary contracts? From a job-seeker perspective, permanent jobs may be preferred to temporary ones as permanent contracts feature better working conditions, employment stability and good prospects of career advancement (e.g. Amuedo-Dorantes 2000). From a firm perspective, temporary contracts mat be preferable because of different reasons. For example, Brencic (2009) highlights that firms may prefer to hire workers by temporary contracts to minimize costs from bad matches. Table 3 reports estimates of a probit model informing us about the determinants of preferences for permanent contract in 1998-2002 IEFP data.

<< Table 3 >>

Another question to be addressed in our analysis concerns the stability of contract preferences. In fact, while the great majority of job-seekers may declare to prefer a permanent contract, they may revise their preferences over time as they learn about labour market conditions (namely contract-type attached to vacant jobs). This is important because the effectiveness of contract mismatch, and hence its effect on matching frictions and unemployment duration, crucially depends on the rigidity of the individual contract preferences. There are at least two types of hypothesis for which rigidity may be questioned: 1) superficiality and 2) preference revision. Under the first case, unemployed workers superficially declare to look for a permanent contract, but they are prone to accept a temporary contract if offered. A second hypothesis is that job-seekers indeed look for a permanent contract, but they are willing to revise their preferences to avoid an unacceptable lengthening of unemployment duration[8]. Obviously, in case one of the previous hypotheses is verified the reliability of the declaration about contract type preferences and,

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[8] The hypothesis of superficiality is an extreme case of the hypothesis of preference revision: the job-seeker revises his/her preference immediately, just when the first contract mismatch takes place.

thus, of the mismatch index to identify contract mismatch and its effect on unemployment duration could be questioned. However, for the sub-sample of job-seekers accepting a job-offer attached to a contract-type different from the declared preferred contract-type, the observed unemployment duration will be included in the support $[t_{min}, t_{max}]$. Specifically, $t = t_{min}$ in case the hypothesis of superficiality is verified, while $t=t_{max}$ in case both the previous hypothesis (superficiality and preference revision) are not verified. Given these premises, we suggest a rigidity index (r) which measures the rigidity of the contract preferences:

$$(1) \quad r = \frac{t - t_{min}}{t_{max} - t_{min}} \quad \text{where } r \in [0, 1] \text{ and } r = \begin{cases} 0 \rightarrow \text{flexibility (superficiality hypothesis)} \\ 1 \rightarrow \text{rigidity} \end{cases}$$

Unfortunately, IEFP data does not provide information to test directly the hypothesis formulated above, nor to measure the rigidity index. The hypothesis of superficiality is tested running a multinomial logit model to uncover if the declared preference for permanent contracts affects the outcomes of the job-search period, i.e. finding a permanent job, finding a temporary job, finding a job by own means, and experiencing a censored spell (our base-category). In case we find evidence of a significant impact of the explanatory variable (job-seekers are looking for a permanent contract) on the probability of finding a permanent job rather than a temporary one, it would be suggestive that the declared contract-type preferences matter in determining the contract-type attached to the job founded. In this case the hypothesis of superficiality is rejected. Conversely, if the preference for permanent contracts does not explain the contract-type of the job accepted, the hypothesis of superficiality is not rejected. Table 4 reports estimates of the multinomial logit model, where in the first column we report alternative outcomes.

<< Table 4 >>

According to multinomial logit estimates, the hypothesis of superficiality is rejected: looking for a permanent contract increases the probability of finding a permanent job and decreases the probability of finding a temporary contract.

The hypothesis of preference revision is tested using quantile regressions. According to ordinary least square estimates, the average impact of looking for a permanent contract (declared at the beginning of the search period) on the log unemployment duration is positive, possibly because of contract mismatch. Nevertheless, it is likely that the positive association is not constant along the job-search period. The hypothesis of preference revision considers this possibility, i.e. job-seekers may revise their preference for

permanent contracts in case of excessive lengthening of the unemployment duration. Empirically this should correspond to a decreasing effect of looking for a permanent contract on unemployment duration as unemployment duration increases. To test this hypothesis, we apply a quantile regression model and evaluate if the positive association between unemployment duration and preferences for permanent contracts decreases with unemployment duration.

<< Table 5 >>

Estimation results presented in Table 5 suggest that: 1) looking for permanent contracts increases unemployment duration (as suggested by the contract-mismatch hypothesis); 2) this positive association is decreasing along the unemployment duration distribution; this supports the hypothesis of preference revision.

4. A heterogeneity index for contract mismatch

The availability of data disaggregated both at the unemployed level and at the job vacancy level is an indispensable condition to the construction of a mismatch index. The IEFP dataset gathers information from 85 job-centers for each month under investigation including the number of job vacancies available; therefore, we can analyse the labour market demand side at an appropriately disaggregated level. To evaluate the effects of contract-type heterogeneity - between permanent contracts searched by unemployed workers and permanent contracts offered by firms - on unemployment duration, we introduce an index (M, Mismatch Index) in the spirit of the Jackman and Roper (1987) mismatch indicator[9]. The mismatch index, measured monthly (m) at the job-centre level (j), is defined as the difference between the ratio of 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:

$$(2) \quad M_{jm} = \frac{U_{jm}^{PC}}{U_{jm}} - \frac{V_{jm}^{PC}}{V_{jm}} \qquad \text{with} \qquad M_{jm} = [-1, +1]$$

M is defined in the support region $[-1, +1]$ with the following particular cases:

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

$$M_{jm} = \begin{cases} -1 & \text{if} \quad U_{jm}^{PC} = 0 \quad \& \quad V_{jm}^{PC} = V_{jm} \\ 0 & \text{if} \quad U_{jm}^{PC} = 0 \quad \& \quad V_{jm}^{PC} = 0 \quad | \quad U_{jm}^{PC} \big/ U_{jm} = V_{jm}^{PC} \big/ V_{jm} \\ +1 & \text{if} \quad V_{jm}^{PC} = 0 \quad \& \quad U_{jm}^{PC} = U_{jm} \end{cases}$$

M takes the value of zero (absence of heterogeneity) in case there are no unemployed workers nor vacant jobs with a preference for a permanent contract, or in case the percentage of unemployed workers looking for a PC is equal to the percentage of vacant jobs offering a PC. *M* takes the values of plus one or minus one in case of full heterogeneity. Hence, higher absolute values of *M* are associated with higher degrees of contract mismatch.

Full positive contract mismatch (i.e. *M* takes value one) indicates that all unemployed workers look for a permanent contract and no permanent contracts are available. On the contrary, full negative contract mismatch, (i.e. *M* takes value minus one) indicates that all unemployed workers look for a temporary contract and no temporary contracts are available.

The average in-sample value of *M* is 0.31, which represents the average value of the difference between unemployed workers looking for a permanent relationship (97.8% of unemployed workers) and the percentage of permanent jobs offered by firms (66.7% vacant jobs). Table 6 and Figure 1 illustrate the distribution of *M* values across job-centers.

<< Table 6 >>

<< Figure 1 >>

A zero value of the index does not imply per se full placement of unemployed workers looking for a permanent contract. The index is an effective instrument to capture contract type heterogeneity, since it is representative of the potential mismatch at the contract level.

5. The econometric model

We employ duration analysis taking into consideration that the start of the job-search process coincides with registration at job-centers. As the dataset has interval-censored data, discrete-time hazard models are estimated (Prentice and Gloecker 1978). According to the hazard-model's framework, the probability that a transition to employment will take place in a given interval $[a_{j-1}, a_j)$ is conditional on the time already spent in unemployment and is estimated as a reduced form equation that considers 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 probability of leaving unemployment can vary over the unemployment spell according to changes in the probability of receiving an offer and the reservation wage: adopting time-varying covariates controls for this variation.

The probability of exiting unemployment in period j reads:

$$(3) \quad h_j \equiv \Pr\left\{T \in [a_{j-1}, a_j) \mid T \geq a_{j-1}\right\}$$

Assuming unit length intervals, the realization j of the discrete random variable T is the recorded spell duration. Discrete-time hazard models require that data are organized into a "sequential binary form." The data form an unbalanced panel of individuals with the individual i contributing $j = 1, 2, \ldots t$ observations, where j indicates the number of periods at risk of the event[10]. Because some individuals transition into employment and possibly back into unemployment, multiple spells $q = 1, 2, \ldots Q$ are observable. In this case, to simplify the analysis, zero temporal correlation across spells is assumed.

Hazard functions are estimated by assuming a complementary log-log specification, that may be seen as the discrete time representation of a continuous time proportional hazard model, with a piecewise constant baseline hazard and Gaussian[11] unobserved heterogeneity[12]. The available data allow to identify the destination contract (PC or TC) only if the individual accepts a job offered at job-center level, 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. The estimated models assume independent competing risks[13], implying that a hazard function for each destination state can be estimated separately by setting to zero the failures on other destinations.

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[10] To be more specific, a binary dependent variable was created. If the individual i's survival time is censored, then the dependent binary variable is always zero; if the individual i's survival time is not censored, then the dependent binary variable has a value of zero in the first j-1 observation and has a value of one in the last observation.

[11] At least for a single spell (or independent spells), Nicoletti and Rondinelli (2010) show that in discrete time hazard models, assuming Gaussian unobserved heterogeneity, misspecifying the error distribution only leads to an equiproportional rescaling of the covariate coefficients.

[12] Estimation results using models without unobserved heterogeneity and/or alternative baseline hazard assumptions are available upon request.

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

Controlling for unobserved heterogeneity may prevent estimation bias arising, for example, from omitted variables or from measurement errors in the observables. If unobserved heterogeneity is ignored, certain problems may arise (Jenkins 2005). For example, the absolute value of the duration dependence parameter in the hazard rate could be under-estimated (spurious duration dependence). The augmented hazard function, for each risk, is given by:

$$(4) \quad h_{iqjd}\left(t_j, X \mid \nu_i\right) = 1 - \exp\left\{-\exp\left[\beta_0 + \beta' X + \gamma_j(t) + u_i\right]\right\}$$

where X is a set of time-varying covariates, including the mismatch index, M, introduced in a non-linear way, β_0 is the intercept, and β is a vector of unknown parameters to be estimated. Finally:

$u_i = \log \nu_i$ is the mixture term, and $\gamma_j(t) = \int_{t_{j-1}}^{t_j} h_0(u)\,du$ is the baseline-hazard.

To estimate this model, the survival and density functions that compose the likelihood function cannot be conditioned on the unobserved effects. Therefore, the likelihood contributions are obtained by integrating the random terms out. The discrete-time likelihood function that incorporates the unobserved heterogeneity term is obtained by summing up the discrete-time likelihood functions of each individual i and spell q given by:

$$(5) \quad L_{iqd}\left(\beta, \gamma, \sigma\right) = \int_{-\infty}^{+\infty}\left[\sum_{j=1}^{t} h_j\left(t, x_{iq} \mid u_{iq}\right)^{y_{iqj}} \left[1 - h_j\left(t, x_{iq} \mid u_{iq}\right)\right]^{1 - y_{iqj}}\right] g_u\left(u_i\right) du_i$$

where y_{iqj} is an indicator that assumes a value of one when the transition takes place in month j (i.e., the spell is uncensored) and a value of zero otherwise, and σ is the vector of unknown parameters in $g_u(u)$.

Our benchmark estimations assume a stock-flow matching mechanism[14] (Petrongolo and Pissarides 2001). Stock-flow matching is more compatible with negative duration dependence than random matching, even if negative duration dependence may also be explained in terms of ranking or loss of skills during unemployment. Positive duration dependence could be explained, for example, because of unemployment benefits exhaustion.

6. Estimation Results

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[14] Random-matching mechanism has been also considered and results are available upon request

6.1 Hazard rates and contract mismatch in local labour markets

Table 7 reports the estimated coefficients from discrete time hazard models for the mismatch index introduced in a non-linear way. These results are obtained under a competing-risk specification, separate for males and females, in which we assume piece-wise constant baseline hazard (see results in Table A1), normally-distributed unobserved heterogeneity and controlling for a plethora of individual and job-related characteristics (see results in Tables A2a and A2b). The predicted hazard rates are reported as a function of the mismatch index in Graph 1[15]. The left-hand-side graph refers to the competing risk analysis and reports the hazard rates against the mismatch index, while the right-hand-side graph illustrates the hazard rate at the job-center level (namely, by summing up hazard rates across individuals finding both a permanent and temporary job) by mismatch index.

<< Table 7 >>

<< Graph 1 >>

Preliminary evidence show that hazard rates are higher for individuals finding a job by own means and that differences by gender are quite negligible. In this context, looking at individuals finding a job by own means, the hazard rates tend to be slightly convex, i.e. higher hazard rates are associated to extreme values of the mismatch index (high contract mismatch), and show a decreasing pattern as the index increases. Convexity could be a consequence of contract mismatch, i.e. where it is stronger, individuals are more likely to accept job offers out of the job-centers (possibly with the aim of reducing their exposure to contract mismatch). The declining pattern of the hazard rates possibly indicates that, in presence of positive contract mismatch (i.e. the percentage of individuals looking for a permanent contract is higher than the percentage of firms offering permanent contracts), finding a job by own means is less likely. This could be a consequence of a higher propensity of individuals looking for a permanent contract to wait for a permanent job-offer in the job-centers.

The hazard rate for individuals finding a permanent contract follows an inverted U-shaped trend. To be more specific, the hazard rate is quite low in the presence of strong negative contract mismatch, but it increases for weak negative heterogeneity, reaching a maximum for index values between -0.5 and -0.4, then it decreases, reaching its minimum at full positive contract mismatch. This means that for individuals who find a permanent contract via the job-center, the hazard rate is negatively associated with stronger contract mismatch in the local labour market. With respect to individuals who find a temporary contract via

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[15] Control variables are evaluated at their average values.

the job-center, we find that the hazard rate is close to zero for negative heterogeneity, while it increases for positive contract mismatch. This indicates that in local labour markets characterized by robust positive contract mismatch, we are more likely to observe individuals finding a temporary contract than a permanent contract.

Looking at the total hazard rate at job-centers' level (i.e. summing the hazard rates of individuals finding both a permanent and a temporary job), the resulting trend resembles the one observed for those individuals who find a permanent job via the job-center. This is because the contribution of individuals finding a temporary job is quite negligible. In sum, the right-hand-side graph suggests that at job-centers' level, the hazard rate is higher for intermediate negative values of the mismatch index and lower for extreme values, with the lowest level in corresponding to of full positive contract mismatch. Integrating over these results, the data support the thesis that higher contract mismatch is associated with lower hazard rates.

6.2 Unemployment duration and contract mismatch

In this section we provide further evidence on the association between contract mismatch and unemployment duration looking at the issue from another perspective. The underlying idea is that some job-seekers looking for a permanent contract may refuse temporary contracts job-offers as they wait for a permanent contract job-offer. Empirically, we should find a negative association between probability of contract mismatch and unemployment duration. To look into this issue, we work on a sub-sample of the IEFP data, i.e. we now only consider those job-seekers for whom the exit-contract is observable and the contract mismatch variable may be determined (as a consequence, censored spells and those spells for which job-seekers find a job by own means are eliminated). Fort this data-subset, where contract mismatch is observed (we recall that unemployed individuals report their preferred contract type and vacancies are labelled if for temporary contracts or permanent contracts; finally, the data also records the type of contact of the match whenever a match via the job-center is formed) we estimate a pooled probit model with robust standard errors where the dependent variable takes value one in case of contract mismatch (the job-seeker looks for a permanent contract but finds a temporary job or if the job-seeker looks for a temporary contract but finds a permanent contract), while it takes the value of zero otherwise. Explanatory variables include demographic and job-related characteristics, including the unemployment duration variable expressed in logarithmic terms. As showed in the first line of Table 8 (first row) we find a negative and significant relationship between the probability of mismatch and unemployment duration.

We address possible endogeneity problems of unemployment duration and employ the two-step IV probit approach suggested by Newey (1987), with the following instruments: a variable indicating the month in which the unemployment spell ends and a variable indicating the year in which the unemployment spell begins. All instruments suggest a very strong effect of the instrumented variable (Table 8, third row).

<< Table 8 >>

The validity of these instruments is tested by the Amemiya-Lee-Newey minimum chi-square test under the null hypothesis that the used group of instruments is valid, i.e., they are uncorrelated with the error term in the structural equation. Both for males and females the test does not reject the null hypothesis (Table 9). Then we apply both the Blundell-Smith (1986) and the Wald test of exogeneity under the null hypothesis that the instrumented variable is exogenous (Table 9). The procedure considering for endogeneity confirms the existence of a negative and significant association between the probability of mismatch and unemployment duration (Table 8, second row). On average, job-seekers are prone to accept longer unemployment duration to avoid contract mismatch; it follows that contract mismatch acts as a source of matching frictions in a dual labour market, where permanent and temporary contracts co-exist and job-seekers have strong preferences for permanent contracts.

<< Table 9 >>

7. **Conclusions**

This paper tests the hypothesis that higher labour market mismatch, defined as heterogeneity between contract-type sought by job-seekers and contract-type offered by firms, leads to longer unemployment duration. In this sense, labour market mismatch, as found in a dual labour market where permanent contracts (good jobs) and temporary contracts (bad jobs) co-exist, acts as a matching friction and may lead, per se, to longer unemployment duration. In these circumstances, better information on contract-type availability may lead to more effective job-search strategies at the individual level, who may revisit their expectations in a timely and informed way, avoiding, thus, excessive exposure to long unemployment duration due to this form of matching friction.

Our mismatch index measures the degree of contract-type mismatch between declared preferences of job-seekers and jobs offered by firms at job-center level and assesses the impact of contract-type mismatch on unemployment duration. The reliability and the stability of the declared preferences for a specific contract-type are tested using both multinomial logit and quantile regression models. Our tests suggest that

the individual declared preferences are stable and informative; nevertheless, and as expected, individuals may revise their initial preferences in case such preferences lead to a certain lengthening of the unemployment spell.

Results from a discrete-time competing risk hazard model under a stock-flow matching mechanism suggest a significant impact of contract-type mismatch at job-centers level on individual hazard rates. Among individuals finding a permanent contract the hazard rate is lower for extreme values of the mismatch index, with the hazard rate reaching its lowest level when full positive contract mismatch occurs. In addition, local labour markets characterized by positive values of the mismatch index are associated with a higher incidence of exiting unemployment by accepting a temporary contract, as individuals hedge their position against a low likelihood of finding a permanent contract. Finally, extreme values of the mismatch index, especially negative values, are associated with a higher probability of finding a job by own means, suggesting that in presence of high contract-type mismatch individuals look for a job outside the job-centers.

We focus on the sub-sample of individuals who find a job via the job-center to investigate if experiencing longer unemployment duration may lead individuals to indeed secure their preferred contract type. This could be indicative that individuals are prone to lengthen their unemployment duration if doing so gets them to find their desired contract. Adopting an instrumental variable probit model, we find evidence that longer unemployment duration is associated with a lower incidence of contract mismatch, in the sense that the job-seeker secured a job of his or her declared preferred type. As a result, the existence of contract-type mismatch increases unemployment duration as individuals may rationalize be willing to pay a price in terms of prolonged unemployment, to secure their preferred contract type.

Our work indicates that the Portuguese labour market is characterized by substantial contract-type mismatch: job-seekers have a strong preference for permanent contracts while firms offer both permanent and temporary contracts. Job-seekers may revise their preferences and are also prone to accept temporary jobs, but this contract-type preference revision is not instantaneous: declared desired contracts explains the exit contract-type and individuals with longer unemployment duration experience lower contract mismatch, with extended unemployment duration being the price to pay to avoid exit contract-type mismatch. It follows that contract-type mismatch is akin to a matching friction and is associated with longer average unemployment duration. The underlying motives behind contract-type mismatch may possibly lie in the undesirability of some temporary contracts because of their characteristics, including possible negative

effects on career advancements for some workers on temporary-contracts. Improving temporary workers conditions and their labour market perspective could improve the desirability of temporary contracts, contributing to reduce matching frictions and average unemployment duration because of contract-type mismatch. Workers who are duly informed about actual contract-type mismatch observed at the job-center level may formulate search-strategies which are rational, including search-strategies which may involve revising preferences with respect temporary-contracts. It may also be the case that some workers overestimate their own individual probability of finding a permanent-contract, despite the level of contract-type mismatch observed in their local labour market. This overestimation may be associated with a well-documented cognitive bias (Kahneman, 2015), with individuals systematically overestimating their own ability and relative position with respect the overall distribution. In this sense, better information on contract-type mismatch, coupled with policies which render temporary-contracts more attractive, are likely to increase unemployment exit rates and reduce average unemployment duration.

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Figure 1. Distribution of the Heterogeneity Index
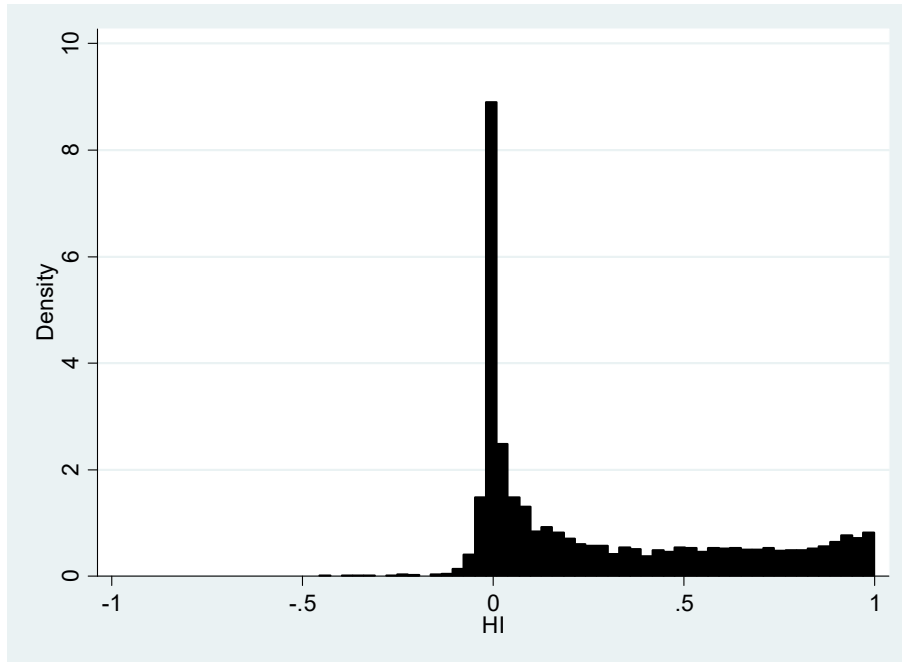
Source: own elaboration on IEFP data

Graph 1. Predicted hazard rates and Mismatch Index

Competing risk analysis by mismatch index	Hazard rates at job-centres level (exit on PC+TC) by mismatch index
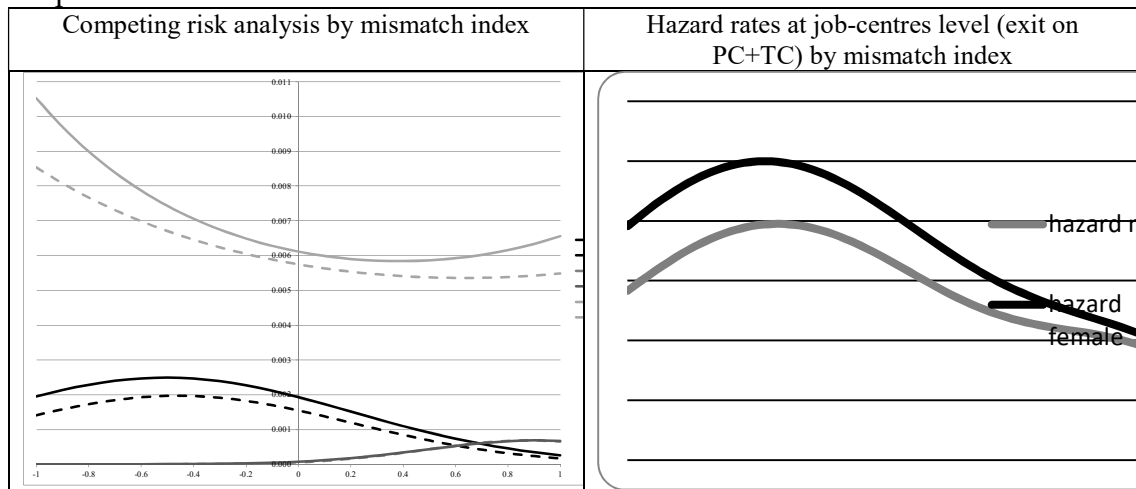
Source: own elaboration on IEFP data

Tables

Table 1a. Descriptive statistics: Male sample

	Male		Censored		PC		TC		OM	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	32.790	12.200	33.553	12.826	28.042	9.857	30.345	10.705	32.833	11.009
Married	0.404	0.491	0.403	0.490	0.303	0.460	0.310	0.463	0.457	0.498
Disabled	0.010	0.101	0.011	0.106	0.010	0.099	0.010	0.099	0.008	0.088
No dependent persons	0.663	0.473	0.675	0.468	0.723	0.447	0.683	0.465	0.606	0.489
1 dependent person	0.152	0.359	0.146	0.354	0.124	0.330	0.139	0.346	0.176	0.381
2 dependent persons	0.118	0.323	0.111	0.314	0.100	0.300	0.111	0.315	0.143	0.350
3 or more dependent persons	0.068	0.251	0.067	0.250	0.052	0.223	0.066	0.249	0.074	0.262
Max 6 year of education	0.453	0.498	0.454	0.498	0.442	0.497	0.453	0.498	0.454	0.498
9 years of education	0.221	0.415	0.221	0.415	0.231	0.421	0.243	0.429	0.212	0.409
11-12 years of education	0.260	0.439	0.252	0.434	0.297	0.457	0.272	0.445	0.266	0.442
More than 12 years of education	0.066	0.249	0.072	0.259	0.031	0.172	0.032	0.176	0.068	0.252
Employed	0.033	0.178	0.034	0.182	0.050	0.218	0.038	0.191	0.022	0.148
First job	0.165	0.371	0.187	0.390	0.232	0.422	0.134	0.341	0.091	0.288
Student	0.065	0.247	0.073	0.260	0.090	0.286	0.065	0.247	0.037	0.189
Ex-student	0.073	0.260	0.084	0.277	0.106	0.308	0.049	0.215	0.038	0.191
End of training period	0.016	0.125	0.015	0.123	0.022	0.146	0.014	0.118	0.016	0.125
Dismissed	0.180	0.385	0.174	0.379	0.179	0.384	0.122	0.327	0.206	0.405
Resigned	0.129	0.335	0.144	0.351	0.117	0.321	0.099	0.299	0.100	0.300
End of temporary contract	0.343	0.475	0.301	0.459	0.276	0.447	0.438	0.496	0.463	0.499
Other motivation	0.175	0.380	0.192	0.394	0.197	0.397	0.203	0.402	0.119	0.324
Manager-Specialist	0.074	0.262	0.084	0.278	0.022	0.147	0.013	0.113	0.075	0.263
Technical	0.112	0.315	0.119	0.324	0.083	0.275	0.066	0.249	0.111	0.314
Administrative	0.132	0.338	0.133	0.340	0.124	0.330	0.139	0.346	0.130	0.336
Services	0.100	0.301	0.097	0.296	0.106	0.308	0.154	0.361	0.099	0.298
Agricultural	0.037	0.188	0.026	0.160	0.015	0.120	0.072	0.258	0.065	0.247
Blue-collar	0.372	0.483	0.366	0.482	0.422	0.494	0.344	0.475	0.377	0.485
Other	0.193	0.394	0.209	0.407	0.210	0.408	0.213	0.410	0.140	0.347
Young benefit	0.044	0.206	0.035	0.183	0.039	0.195	0.045	0.208	0.071	0.257
Unemployment benefit	0.071	0.257	0.077	0.267	0.033	0.179	0.028	0.166	0.074	0.262
Training	0.262	0.794	0.319	0.869	0.146	0.597	0.114	0.537	0.180	0.659
Local wage	53930.8	30445.6	49243.6	32694.4	61027.1	23349.0	66841.7	20567.6	61608.3	24703.3
Norte	0.338	0.473	0.360	0.480	0.371	0.483	0.091	0.288	0.309	0.462
Centro	0.162	0.369	0.150	0.357	0.306	0.461	0.191	0.393	0.141	0.348
Lisbon	0.382	0.486	0.390	0.488	0.281	0.449	0.427	0.495	0.390	0.488
Alentejo	0.063	0.243	0.056	0.231	0.027	0.162	0.058	0.233	0.092	0.289
Algarve	0.054	0.227	0.044	0.204	0.016	0.125	0.233	0.423	0.067	0.251
Log flow unemployment	5.799	0.597	5.839	0.592	5.621	0.614	5.740	0.600	5.766	0.589
Log flow vacancies	4.481	1.018	4.460	1.028	4.546	0.892	4.710	0.953	4.478	1.038
Heterogeneity index	0.303	0.345	0.292	0.340	0.152	0.247	0.630	0.299	0.332	0.355

Source: own elaboration on IEFP data

Table 1b. Descriptive statistics: Female sample

	Female		Censored		PC		TC		OM	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	31.662	11.058	32.118	11.407	28.177	9.395	32.550	11.173	31.589	10.446
Married	0.486	0.500	0.478	0.500	0.449	0.497	0.526	0.499	0.510	0.500
Disabled	0.004	0.064	0.004	0.067	0.004	0.064	0.005	0.068	0.003	0.056
No dependent persons	0.552	0.497	0.571	0.495	0.564	0.496	0.441	0.497	0.523	0.499
1 dependent person	0.234	0.423	0.218	0.413	0.234	0.423	0.280	0.449	0.263	0.440
2 dependent persons	0.156	0.363	0.151	0.358	0.148	0.355	0.200	0.400	0.164	0.370
3 or more dependent persons	0.058	0.234	0.060	0.238	0.054	0.227	0.079	0.269	0.050	0.218
Max 6 year of education	0.450	0.497	0.453	0.498	0.437	0.496	0.492	0.500	0.436	0.496
9 years of education	0.188	0.391	0.188	0.391	0.203	0.402	0.191	0.393	0.181	0.385
11-12 years of education	0.267	0.442	0.261	0.439	0.308	0.462	0.233	0.423	0.275	0.447
More than 12 years of education	0.096	0.294	0.098	0.297	0.052	0.223	0.084	0.278	0.108	0.310
Employed	0.037	0.189	0.040	0.196	0.050	0.219	0.029	0.168	0.027	0.163
First job	0.188	0.390	0.218	0.413	0.234	0.423	0.122	0.327	0.109	0.312
Student	0.067	0.251	0.076	0.264	0.086	0.280	0.059	0.235	0.042	0.200
Ex-student	0.083	0.276	0.098	0.297	0.106	0.308	0.047	0.211	0.044	0.205
End of training period	0.024	0.153	0.020	0.141	0.024	0.152	0.019	0.136	0.035	0.184
Dismissed	0.157	0.364	0.156	0.363	0.170	0.376	0.116	0.320	0.164	0.370
Resigned	0.098	0.298	0.111	0.315	0.100	0.301	0.067	0.250	0.071	0.257
End of temporary contract	0.354	0.478	0.295	0.456	0.293	0.455	0.519	0.500	0.489	0.500
Other motivation	0.195	0.396	0.222	0.416	0.204	0.403	0.164	0.371	0.129	0.336
Manager-Specialist	0.083	0.276	0.097	0.295	0.023	0.150	0.014	0.119	0.086	0.281
Technical	0.044	0.205	0.048	0.213	0.028	0.166	0.015	0.123	0.046	0.210
Administrative	0.201	0.401	0.202	0.402	0.213	0.410	0.160	0.366	0.204	0.403
Services	0.277	0.448	0.278	0.448	0.321	0.467	0.284	0.451	0.256	0.437
Agricultural	0.055	0.229	0.027	0.163	0.024	0.154	0.155	0.362	0.117	0.321
Blue-collar	0.114	0.317	0.115	0.319	0.166	0.372	0.080	0.271	0.099	0.298
Other	0.217	0.412	0.244	0.430	0.221	0.415	0.174	0.379	0.155	0.362
Young benefit	0.051	0.220	0.038	0.192	0.044	0.204	0.065	0.246	0.083	0.277
Unemployment benefit	0.088	0.283	0.093	0.290	0.046	0.208	0.045	0.207	0.102	0.302
Training	0.309	0.828	0.380	0.907	0.236	0.730	0.156	0.591	0.188	0.654
Local wage	55389.3	29411.7	51139.1	31799.5	62399.4	21939.3	65461.7	19000.9	61405.2	24956.5
Norte	0.318	0.466	0.360	0.480	0.357	0.479	0.078	0.268	0.248	0.432
Centro	0.167	0.373	0.161	0.367	0.297	0.457	0.147	0.355	0.142	0.349
Lisbon	0.364	0.481	0.364	0.481	0.286	0.452	0.364	0.481	0.394	0.489
Alentejo	0.089	0.284	0.070	0.256	0.043	0.202	0.180	0.385	0.132	0.339
Algarve	0.062	0.241	0.045	0.207	0.017	0.128	0.231	0.421	0.084	0.278
Log flow unemployment	5.754	0.608	5.806	0.600	5.623	0.584	5.621	0.628	5.701	0.615
Log flow vacancies	4.452	1.048	4.449	1.033	4.547	0.908	4.505	1.029	4.413	1.131
Heterogeneity index	0.314	0.349	0.290	0.340	0.165	0.256	0.619	0.314	0.363	0.361

Source: own elaboration on IEFP data

Table 2. Desired and destination contracts

MALE							
Looking for a PC				Looking for a TC			
61403				1368			
97.82%				2.18%			
Censored	Uncensored			Censored	Uncensored		
38885	22518			936	432		
63.33%	36.67%			68.42%	31.58%		
	Own means	Employment-center			Own means	Employment-center	
	15032	7486			288	144	
	66.76%	33.24%			66.67%	33.33%	
		PC	TC			PC	TC
		5166	2320			78	66
		69.01%	30.99%			54.17%	45.83%
FEMALE							
Looking for a PC				Looking for a TC			
95975				2185			
97.77%				2.23%			
Censored	Uncensored			Censored	Uncensored		
59088	36887			1396	789		
61.57%	38.43%			63.89%	36.11%		
	Own means	Employment-center			Own means	Employment-center	
	23398	13489			541	248	
	63.43%	36.57%			68.57%	31.43%	
		PC	TC			PC	TC
		8507	4982			107	141
		63.07%	36.93%			43.15%	56.85%

Source: own elaboration on IEFP data

Table 3. Determinants of looking for a Permanent contract

	Male			Female		
	Coef.	s.e.		Coef.	s.e.	
Age	0.017	0.008	**	0.022	0.007	***
Age square	0.000	0.000		0.000	0.000	***
Married	-0.030	0.037		0.051	0.024	**
Disabled	-0.118	0.107		-0.257	0.116	**
1 dependent person	0.058	0.043		0.050	0.028	*
2 dependent persons	0.061	0.051		0.028	0.034	
3 or more dependent persons	-0.113	0.056	**	0.043	0.049	
9 years of education	-0.029	0.032		-0.003	0.027	
11-12 years of education	-0.073	0.031	**	-0.009	0.025	
More than 12 years of education	-0.047	0.053		0.019	0.036	
Employed	-0.050	0.068		0.105	0.055	*
First job	0.125	0.075	*	0.080	0.055	
Student	-0.364	0.079	***	-0.257	0.060	***
Ex-student	-0.098	0.081		0.010	0.061	
End of training period	-0.131	0.098		0.068	0.075	
Dismissed	0.181	0.049	***	0.163	0.038	***
Resigned	-0.024	0.045		0.033	0.038	
End of temporary contract	-0.035	0.037		-0.033	0.029	
Manager-Specialist	0.103	0.055	*	-0.004	0.040	
Technical	-0.034	0.043		0.065	0.049	
Administrative	0.036	0.042		0.070	0.032	**
Services	0.070	0.047		0.024	0.028	
Agricultural	-0.187	0.068	***	0.047	0.054	
Blue-collar	0.090	0.035	***	0.013	0.039	
Young benefit	0.287	0.073	***	0.092	0.045	**
Unemployment benefit	0.423	0.058	***	0.268	0.037	***
Training	-0.021	0.016		-0.008	0.012	
Local wage	0.000	0.000		0.000	0.000	***
Norte	0.683	0.035	***	0.726	0.029	***
Centro	0.305	0.036	***	0.398	0.030	***
Alentejo	0.464	0.069	***	0.400	0.047	***
Algarve	0.422	0.063	***	0.444	0.045	***
Log flow unemployment	-0.183	0.025	***	-0.182	0.020	***
Log flow vacancies	0.012	0.010		0.013	0.008	*
Year 1998	0.390	0.080	***	0.650	0.066	***
Year 1999	0.375	0.083	***	0.585	0.068	***
Year 2000	0.360	0.088	***	0.627	0.072	***
Year 2001	0.070	0.092		0.337	0.076	***
Constant	2.245	0.207	***	2.093	0.166	***

Source: own elaboration on IEFP data

Table 4: Multinomial logit model: testing the hypothesis of superficiality

Outcomes	Male						Female					
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Permanent	0.497	0.119	***	0.378	0.120	***	0.643	0.101	***	0.521	0.101	***
Temporary	-0.172	0.129		-0.333	0.131	**	-0.189	0.090	**	-0.361	0.091	***
Own means	0.233	0.068	***	0.146	0.069	**	0.014	0.051		-0.054	0.052	
Year dummies	No			Yes			No			Yes		

Source: own elaboration on IEFP data

Table 5: Quantile regression: testing the hypothesis of preference revision

	Male			Female		
	Coef.	Std. Err.		Coef.	Std. Err.	
OLS estimates	0.120	0.031	***	0.164	0.024	***
First quintile	0.288	0.087	***	0.288	0.118	**
First quartile	0.223	0.083	***	0.223	0.105	**
Median	0.154	0.050	***	0.143	0.036	***
Third quartile	0.150	0.043	***	0.182	0.043	***
Fourth quintile	0.103	0.035	***	0.130	0.023	***

Source: own elaboration on IEFP data

Table 6. Mismatch index by employment-center

Region	Job-centre	Mean	Std. Dev.	Min	Max	Region	Job-centre	Mean	Std. Dev.	Min	Max
Norte	Viana do Castelo	0.421	0.254	-0.008	0.791	Lisboa	Caldas da Rainha	0.156	0.141	-0.059	0.661
	Braga	0.064	0.151	-0.046	0.780		Abrentes	0.089	0.143	-0.024	0.977
	Fafe	0.005	0.040	-0.034	0.209		Santarem	0.422	0.247	-0.041	0.910
	Guimaraes	0.016	0.040	-0.026	0.189		Tomar	0.506	0.168	0.179	0.990
	Vila Nova de Famaliçao	0.145	0.172	-0.007	0.827		Torres Novas	0.138	0.150	-0.015	0.972
	Amarante	0.099	0.128	-0.052	0.458		Amadora	0.641	0.449	-0.010	1.000
	Matosinhos	0.000	0.026	-0.069	0.087		Cascais	0.556	0.393	-0.033	0.968
	Penafiel	-0.003	0.023	-0.054	0.152		Conde Redondo	0.343	0.198	-0.044	0.731
	Porto	0.421	0.224	-0.032	0.804		Picoas	0.431	0.319	-0.099	0.952
	Povao do Varzim/Vila do Conde	0.013	0.063	-0.032	0.442		Loures	0.488	0.262	-0.017	0.992
	Santo Tirso	-0.011	0.024	-0.077	0.068		Moscavide	0.091	0.141	-0.052	0.538
	Vila Nova de Gaia	0.016	0.048	-0.026	0.291		Torres Vedras	0.034	0.073	-0.030	0.398
	Vila Real	0.377	0.253	-0.069	0.923		Vila Franca de Xira	-0.011	0.067	-0.230	0.257
	Chaves	0.012	0.084	-0.034	0.556		Almada	0.611	0.162	-0.015	0.982
	Bragança	0.006	0.029	-0.021	0.164		Barreiro	0.147	0.265	-0.119	0.885
	Macedo de Cavaleiros	0.124	0.183	-0.048	0.720		Montijo	0.045	0.128	-0.157	0.403
	Mirandela	0.065	0.124	-0.051	0.616		Setubal	0.832	0.120	0.258	0.986
	Torre de Moncorvo	0.029	0.069	-0.043	0.345		Salvaterra de Magos	0.678	0.249	-0.028	0.971
	Felguiras	-0.005	0.010	-0.035	0.019		Alcobaça	0.114	0.100	-0.020	0.424
	Porto Ocidental	-0.005	0.012	-0.045	0.025		Sintra	0.546	0.229	-0.455	0.784
	Basto	0.458	0.410	-0.027	1.000		Alcantara	0.018	0.052	-0.053	0.192
	Lamego	0.297	0.185	0.000	0.819		Benfica	0.781	0.175	-0.014	0.994
	S. Joao de Madeira	0.004	0.023	-0.028	0.158		Seixal	0.576	0.158	-0.102	0.889
	Arcas de Valvedez	0.337	0.206	0.000	0.857	Alentejo	Alacer do Sal	0.785	0.247	-0.050	1.000
	Barcelos	0.011	0.047	-0.030	0.304		Sines	0.260	0.285	-0.036	0.794
	Maia	0.073	0.181	-0.018	0.979		Elvas	0.582	0.244	0.049	0.978
	Valongo	0.043	0.119	-0.022	0.662		Portalegra	0.505	0.292	-0.021	0.961
	Gondomar	0.077	0.152	-0.056	0.789		Estremoz	0.644	0.256	0.052	0.989
	Valença	0.019	0.063	-0.015	0.432		Evora	0.338	0.209	-0.005	0.812
Centro	Aveiro	0.229	0.195	-0.008	0.992		Beja	0.787	0.245	0.000	1.000
	Agueda	0.055	0.075	-0.037	0.326		Ourique	0.053	0.156	-0.036	0.817
	Coimbra	0.400	0.233	-0.016	0.970		Ponte de Sor	0.601	0.330	-0.054	1.000
	Figueirada Foz	0.595	0.159	-0.020	0.984		Montemor o Novo	0.458	0.290	-0.018	1.000
	Lousa	-0.031	0.246	-0.449	0.668		Moura	0.811	0.275	-0.011	1.000
	Leiria	0.134	0.112	-0.041	0.370	Algarve	Faro	0.874	0.142	0.218	1.000
	Marinha Grande	0.198	0.141	-0.029	0.517		Portimao	0.883	0.152	-0.032	0.989
	S. Pedro do Sul	0.003	0.018	-0.022	0.080		Vila Real de Santo Antonio	0.864	0.117	0.476	0.992
	Viseu	0.003	0.059	-0.090	0.275		Loule	0.870	0.147	0.000	0.960
	Guarda	-0.005	0.029	-0.065	0.099		Lagos	0.617	0.223	-0.011	0.993
	Castelo Branco	0.450	0.237	-0.005	0.882						
	Covilha	0.015	0.050	-0.028	0.207						
	Arganil	0.167	0.093	-0.014	0.493						
	Figueiro dos Vinhos	0.185	0.144	-0.048	0.629						
	Tondela	0.674	0.173	-0.006	1.000						
	Seia	0.022	0.061	-0.036	0.280						
	Serta	0.074	0.095	-0.018	0.422						
	Pinhel	0.271	0.235	0.000	0.803						

Source: own elaboration on IEFP data

Tables 7. Hazard rates and contract mismatch in local labour markets

		Permanent Contract			Temporary Contract			Own Mean		
		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
MALES	Heterogeneity index	-1.049	0.176	***	5.700	0.295	***	-0.222	0.098	**
	Heterogeneity index square	-1.141	0.242	***	-3.248	0.282	***	0.175	0.111	
FEMALES	Heterogeneity index	-1.011	0.135	***	4.878	0.207	***	-0.239	0.079	***
	Heterogeneity index square	-1.000	0.182	***	-2.661	0.196	***	0.309	0.088	***

Source: own elaboration on IEFP data

Table 8. Probability of mismatch and unemployment duration

	MALES				FEMALES			
Pooled probit	Coef.	r.s.e.		mfx	Coef.	r.s.e.		mfx
	-0.071	0.020	***	-0.024	-0.060	0.016	***	-0.022
IV Probit model	Coef.	s.e.		mfx	Coef.	s.e.		mfx
	-0.116	0.023	***		-0.093	0.018	***	
Instruments:								
Ending month of the spell	0.085	0.001	***		0.081	0.001	***	
Starting year of the spell	-0.087	0.001	***		-0.078	0.001	***	

Source: own elaboration on IEFP data

Table 9. Over-identification and exogeneity tests

OVERIDENTIFICATION TEST				
Null hypothesis: instruments are uncorrelated with the error term in the structural equation				
	MALES		FEMALES	
	Chi2	P-value > Chi2	Chi2	P-value > Chi2
Amemiya-Lee-Newey minimum Chi2 test	0.46	0.497	1.02	0.313
EXOGENEITY TESTS				
Null hypothesis: the specified endogenous regressor may be treated as exogenous				
	MALES		FEMALES	
	Chi2	P-value > Chi2	Chi2	P-value > Chi2
Smith-Blundell test	17.69	0.000	15.72	0.000
Wald test	17.70	0.000	15.74	0.000

Source: own elaboration on IEFP data

Appendix

Table A1 Estimation of duration dependence parameters (stock-flow matching)

	Duration	Permanent Contract			Temporary Contract			Own Mean		
		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
MALES	1-3 months	1.225	0.055	***	1.316	0.086	***	0.621	0.034	***
	4-6 months	0.886	0.057	***	1.114	0.088	***	0.875	0.033	***
	7-9 months	0.421	0.064	***	0.716	0.096	***	0.504	0.035	***
	10-12 months	0.237	0.069	***	0.357	0.109	***	0.229	0.039	***
	13-18 months	base-category								
	19-24 months	-0.359	0.075	***	-0.146	0.117		-0.424	0.045	***
	25-36 months	-0.844	0.078	***	-0.663	0.128	***	-0.705	0.046	***
	over 36 months	-1.257	0.104	***	-1.041	0.181	***	-1.176	0.065	***
FEMALES	1-3 months	0.766	0.042	***	0.657	0.057	***	0.369	0.028	***
	4-6 months	0.710	0.042	***	0.765	0.055	***	0.653	0.026	***
	7-9 months	0.246	0.047	***	0.544	0.059	***	0.406	0.028	***
	10-12 months	-0.015	0.052		0.003	0.072		0.132	0.031	***
	13-18 months	base-category								
	19-24 months	-0.288	0.053	***	-0.333	0.075	***	-0.230	0.034	***
	25-36 months	-0.650	0.054	***	-0.713	0.079	***	-0.464	0.035	***
	over 36 months	-1.004	0.073	***	-1.124	0.113	***	-0.859	0.050	***

Source: own elaboration on IEFP data

Table A2a. Estimation of covariates (stock-flow matching): male sample

	Permanent Contract			Temporary Contract			Own Mean		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Age	0.003	0.011		0.009	0.016		0.062	0.007	***
Age square	-0.001	0.000	***	0.000	0.000	**	-0.001	0.000	***
Married	-0.009	0.053		-0.140	0.076	*	0.327	0.030	***
Disabled	-0.336	0.160	**	-0.375	0.249		-0.295	0.109	***
1 dependent person	0.012	0.059		0.068	0.085		0.035	0.032	
2 dependent persons	0.057	0.066		0.160	0.096	*	0.051	0.036	
3 or more dependent persons	-0.068	0.082		0.161	0.114		-0.097	0.045	**
9 years of education	0.059	0.040		0.016	0.061		-0.044	0.026	*
11-12 years of education	0.013	0.042		-0.104	0.062	*	-0.052	0.026	**
More than 12 years of education	-0.331	0.094	***	-0.352	0.137	***	-0.111	0.044	**
Employed	0.164	0.082	**	0.030	0.134		-0.176	0.067	***
First job	-0.054	0.090		-0.309	0.158	*	-0.320	0.073	***
Student	0.147	0.096		-0.070	0.173		-0.101	0.082	
Ex-student	0.265	0.094	***	0.079	0.177		-0.012	0.081	
End of training period	0.227	0.122	*	0.137	0.212		0.563	0.085	***
Dismissed	0.159	0.055	***	-0.039	0.088		0.625	0.036	***
Resigned	0.129	0.061	**	-0.023	0.094		0.240	0.041	***
End of temporary contract	0.063	0.050		0.149	0.070	**	0.786	0.032	***
Manager-Specialist	-1.455	0.112	***	-1.824	0.195	***	0.450	0.047	***
Technical	-0.570	0.064	***	-0.796	0.105	***	0.289	0.040	***
Administrative	-0.413	0.057	***	-0.252	0.085	***	0.243	0.038	***
Services	-0.261	0.059	***	-0.157	0.084	*	0.089	0.041	**
Agricultural	-0.733	0.132	***	0.585	0.115	***	0.826	0.052	***
Blue-collar	-0.034	0.042		-0.214	0.068	***	0.202	0.031	***
Young benefit	-0.013	0.082		-0.060	0.117		0.428	0.040	***
Unemployment benefit	-0.230	0.088	***	-0.511	0.141	***	0.213	0.040	***
Training	-0.293	0.026	***	-0.348	0.045	***	-0.284	0.014	***
Local wage	0.000	0.000		0.000	0.000		0.000	0.000	
Norte	0.021	0.042		-0.594	0.088	***	-0.165	0.026	***
Centro	0.612	0.045	***	0.321	0.073	***	-0.179	0.033	***
Alentejo	-0.477	0.102	***	-0.756	0.117	***	0.389	0.043	***
Algarve	-0.073	0.133		0.452	0.087	***	0.154	0.050	***
Log flow unemployment	-0.371	0.023	***	-0.399	0.044	***	-0.081	0.017	***
Log flow vacancies	0.209	0.020	***	0.208	0.031	***	0.122	0.011	***
Constant	-4.258	0.242	***	-7.479	0.412	***	-6.228	0.167	***

Source: own elaboration on IEFP data

Table A2b. Estimation of covariates (stock-flow matching): female sample

	Permanent Contract			Temporary Contract			Own Mean		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Age	-0.020	0.010	**	-0.027	0.013	**	0.025	0.006	***
Age square	0.000	0.000	**	0.000	0.000		-0.001	0.000	***
Married	-0.064	0.033	*	-0.071	0.045		0.044	0.021	**
Disabled	-0.156	0.199		0.047	0.267		-0.143	0.141	
1 dependent person	0.063	0.037	*	0.218	0.051	***	0.025	0.024	
2 dependent persons	0.093	0.045	**	0.246	0.060	***	-0.047	0.029	*
3 or more dependent persons	0.054	0.063		0.312	0.080	***	-0.269	0.043	***
9 years of education	0.028	0.034		-0.087	0.048	*	-0.060	0.023	***
11-12 years of education	0.041	0.032		-0.032	0.049		-0.013	0.021	
More than 12 years of education	-0.072	0.060		-0.061	0.074		0.014	0.031	
Employed	0.225	0.065	***	-0.006	0.105		-0.189	0.051	***
First job	-0.004	0.063		-0.406	0.111	***	-0.315	0.049	***
Student	0.125	0.071	*	0.389	0.124	***	-0.211	0.058	***
Ex-student	0.334	0.068	***	0.466	0.125	***	-0.231	0.057	***
End of training period	0.161	0.086	*	0.014	0.129		0.794	0.049	***
Dismissed	0.258	0.044	***	0.173	0.066	***	0.495	0.030	***
Resigned	0.205	0.051	***	0.098	0.078		0.098	0.036	***
End of temporary contract	0.222	0.040	***	0.319	0.053	***	0.671	0.026	***
Manager-Specialist	-1.568	0.087	***	-2.009	0.139	***	0.438	0.038	***
Technical	-0.608	0.080	***	-1.234	0.135	***	0.394	0.044	***
Administrative	-0.193	0.041	***	-0.441	0.060	***	0.250	0.028	***
Services	-0.069	0.036	*	-0.308	0.049	***	0.061	0.025	**
Agricultural	0.023	0.088		0.815	0.075	***	1.114	0.041	***
Blue-collar	0.395	0.042	***	-0.152	0.071	**	0.161	0.032	***
Young benefit	0.016	0.062		0.102	0.072		0.471	0.031	***
Unemployment benefit	-0.211	0.062	***	-0.343	0.086	***	0.255	0.030	***
Training	-0.273	0.017	***	-0.416	0.029	***	-0.357	0.012	***
Local wage	0.000	0.000	**	0.000	0.000	**	0.000	0.000	***
Norte	-0.077	0.034	**	-0.723	0.069	***	-0.263	0.023	***
Centro	0.526	0.036	***	0.114	0.058	**	-0.187	0.027	***
Alentejo	-0.285	0.069	***	-0.180	0.070	***	0.150	0.035	***
Algarve	-0.233	0.103	**	0.549	0.066	***	0.279	0.040	***
Log flow unemployment	-0.295	0.018	***	-0.486	0.030	***	-0.069	0.014	***
Log flow vacancies	0.178	0.014	***	0.254	0.022	***	0.121	0.008	***
Constant	-4.270	0.202	***	-6.274	0.301	***	-5.282	0.142	***

Source: own elaboration on IEFP data