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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 prefer 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 86 local labour markets (job-centers of the Portuguese Public Employment System) and five years. 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 and longer unemployment duration. Improving the desirability of temporary contracts and information about local contract-type mismatch rates may reduce matching frictions and average unemployment duration.

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Unemployment duration; matching frictions; dual labour markets; survival analysis; stock-flow matching functions

1. Introduction

Certain European labor markets have experienced, over the last decades, a dual structure, where temporary contracts make up a significant share of overall employment relationships and coexist with permanent contracts, under stringent differences (see Bentolila, Dolado, & Jimeno, 2020 for a recent survey). This is especially true in Spain, Portugal, the Netherlands, France, Italy, Germany, and Greece (Bentolila et al., 2020). The prevalence and persistence of dual-labour markets across Europe have motivated studies on the performance of said labor markets and their political economy aspects; early analyses include Saint-Paul (1996, 2000), Dolado, Garcia-Serrano, and Jimeno (2002) and Boeri (2011), whereas Bentolila, Cahuc, Dolado, and LeBarbanchon (2012), Cahuc, Charlot, and Malherbet (2016), Dolado (2017), Bentolila et al., 2020) provide more recent reviews of theoretical and empirical insights on European dual-labour markets and offer evidence that dual-labor markets may lead to higher unemployment duration rates. Most interestingly, the co-existence of permanent contracts and temporary contracts gives rise to a possible contract-type mismatch, as jobseekers predominantly prefer permanent contracts, whereas firms offer mainly temporary contracts.

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This contract-type mismatch may be perceived as a matching friction (in the spirit of Mortensen & Pissarides, 1994 and Pissarides 2000) 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 at the margin via higher incidence of fixed-term contracts (FTC), may have the unintended effect of leading, via this contract-type mismatch effect, to longer unemployment duration.

Our paper sheds light to this important yet overlooked phenomenon by looking at the Portuguese (dual) labor market, which has the second highest share of FTC among all EU countries (see Bentolila et al., 2020 for a recent pan-EU perspective; Blanchard, 2007; Blanchard & Portugal, 2017; Carneiro, Portugal, & Varejão, 2014; Centeno & Novo, 2012, 2014; Fonseca, Lima, & Pereira, 2018 for studies on the Portuguese dual-labour market, albeit with different data sources and purposes than this study). We investigate the role that matching frictions due to contract-type mismatch have in explaining unemployment hazard rates in a dual-labor market where good jobs and bad jobs coexist using a previously unexplored and, most importantly, rich micro dataset, which allows us to contribute in a novel way to the empirical literature on matching frictions and unemployment duration.

Since the 1990s labor market analysis has largely used matching functions in search and match frameworks (see Mortensen, 1987; Mortensen & Pissarides, 1994 for seminal works; Petrongolo & Pissarides, 2001 for an early survey; Petrongolo, 2001; Gregg & Petrongolo, 2005, Petrongolo; Coles & Coles, 2008; Petrongolo & Pissarides, 2008; Ebrahimy & Shimer, 2010; Christiano, Eichenbaum, & Trabandt, 2021 for more recent applications of matching frameworks). Matching functions allow researchers to investigate the role of frictions in the labour market, including how said frictions lead to unemployment duration and impact the labor market effectiveness in matching jobseekers with available vacancies.

As highlighted by Petrongolo and Pissarides (2001), matching 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 jobseekers in explaining frictions in the matching process. An important argument put forward by such studies is that failure to consider the heterogeneity of jobseekers 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., Burgess & Profit, 2001; van Ours & Ridder, 1995) found evidence of job competition between different skill groups and between employed and unemployed jobseekers. Fahr and Sunde (2001) found 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) found that wider heterogeneity of jobseekers in terms of their educational levels increases the importance of frictions in the matching process. More recently, Lange and Papageorgiou (2020) explored how jobseekers' search behaviour heterogeneity impacts matching function specification and search elasticities biases.

However, matching frictions may also arise from other sources, including labour market reforms. The so-called "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, Mealli, & Nannicini, 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 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.[2] 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 (Bentolila et al., 2020). In a dual-labour market, where good and bad jobs coexist, it is likely that one will find jobseekers having strong preferences for permanent contracts, while firms may offer temporary contracts, since firms may use this contractual form to adjust their workforce to business cycle conditions in a more cost-effective way or simply to reduce expected labour costs. Therefore, a labour market characterized by a homogenous supply side, with most jobseekers searching for a permanent job, and a heterogeneous demand side, where temporary and permanent job offers coexist, may involve a high degree of (contract-type) 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 these offers are for temporary jobs and only after a certain time they will start accepting those temporary job offers if these individuals do not find a suitable permanent job meanwhile.

Our paper tests the hypothesis that higher contract-type mismatch is associated with higher unemployment duration by leveraging on the space-and-time variation of contract-type mismatch across Portugal over time. To that end, we estimate a matching function using Portuguese rich micro 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 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.

We follow the literature and allow two possible approaches to estimate the matching functions: the random matching and the stock-flow matching models.[3] 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 jobseekers and posted vacancies used and emphasize the importance of looking at comparable measures for flows and explanatory stocks. Gregg and

[2]For example, see Dolado et al. (2002).See also Dolado, Jansen, and Jimeno (2007) and Bentolila et al. (2020) for a theoretical framework on dual employment protection legislation.

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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. Ebrahimy and Shimer (2010) calibrate a stock-flow matching model to replicate the cyclical volatility behaviour of key labour market metrics.

In our case, we use data from job-centers and consequently 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 less likely that the same job offer is re-offered to the same jobseeker, as allowed by the random matching approach.[4]

We use a dataset from the IEFP (Instituto do Emprego e Formação Profissional), the public entity responsible for all Portuguese public job placement centers, for the period from 1998 to 2002. As documented in Bentolila et al. (2020) authoritative review of European dual-labour markets, the share of FTC in Portugal has hovered around 20% since 1998 until 2017 (Bentolila et al., 2020, (Figure 1) and during this period Portugal has always experienced the second largest share of FTC in Europe (after Spain). In addition, and as documented by Blanchard and Portugal (2017), the coexistence of a large share of FTC and permanent contracts in Portugal has been accompanied by striking and perennial differences in the respective levels of employment protection legislation; in this sense, the period under analysis is fundamentally equivalent to the current-day period (in the sense that the labour market objectively presents a dual-tier structure, where “good” and “bad” jobs co-exist). Consequently, and in other words, the

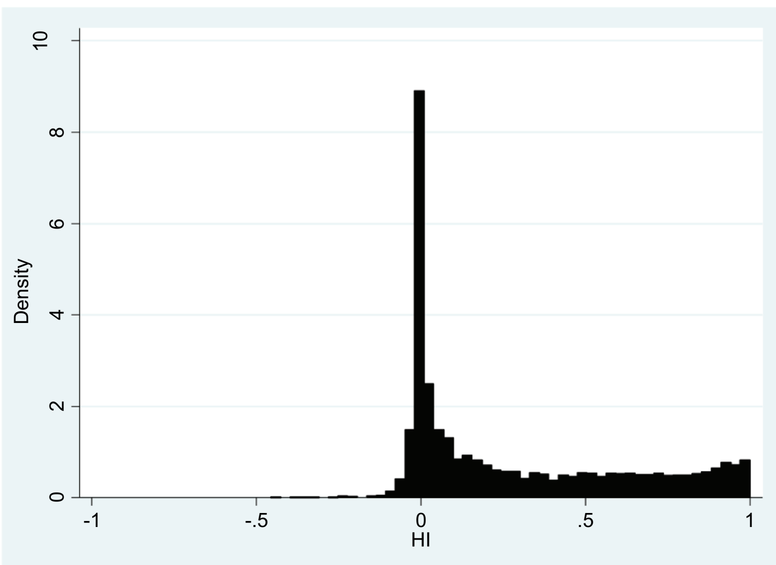

Figure 1. Distribution of the Heterogeneity Index. Source: own elaboration on IEFP data.

period for which these (previously) unexplored data was obtained is akin to the nowadays

[3]...

period in a structural sense, as Portugal remains a country with a dual-labour market in the recognized sense in the literature, which supports the timeliness and current relevance of the dataset used.

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 jobseekers 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 jobseekers and the contract type offered by firms. Therefore, it allows to control the direct effects of the desired contract on the hazard rates toward multiple destination states and to construct a time and space varying index of the degree of the heterogeneity found between contracts searched by jobseekers and contracts offered by firms which we use to understand the relationship between such contract-type mismatch and unemployment duration. We estimate a competing risk discrete time hazard model with a (multinomial) logit model for its flexibility and breadth of robustness checks allowed. The heterogeneity between contract-type desired by jobseekers and contract-type offered by firms is approximated by a contract-type mismatch index, which we include in the hazard model in a flexible way as a categorical value. The mismatch index is calculated monthly at the job-center level, and it thus reflects local labor market aggregate information, and we leverage the space and time variation of the contract-type mismatch to assess how it is associated with unemployment duration.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes the contract-type mismatch index. Section 4 presents the econometric model. Section 5 presents the econometric results, including robustness checks. Finally, Section 6 concludes.

2. Data

We use an IEFP dataset that provides information on individuals registered at jobcentres 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, apprenticeship training and being registered at a job-center is necessary to collect unemployment benefits, which explains the widespread usage of their job-centers across the Portuguese territory and across the span of the different socio-economic and demographic characteristics of jobseekers (see Addison and Portugal 2002 for further details; see Teixeira & Nunes, 2009; Santos, 2010 for studies on IEFP data from an ALMP efficacy perspective). Coelho (2003) investigates unemployment duration and vacancy duration using hazard models with the IEFP dataset but does not consider contract-type mismatch (and its space-time variation). Hence, and to the best of our knowledge, the IEFP dataset was never used to investigate contract-type mismatch, or estimate matching models via hazard models, or, for that matter, to study the implications of the Portuguese dual-labour market structure. 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. 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 Jan. 1998 until Dec. 2002 with 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 the spells that terminate in failure to report to the above-mentioned control interviews to avoid misleading identification of censored unemployment durations (which are less than 1% of total spells, in any case, an immaterial quantum). To make our results easily comparable to studies in the literature, we analyse unemployment duration on a monthly rather than a daily basis.

We only consider individuals aged 16–60 years old, for whom all information with respect to all the covariates considered is available. This selection leaves us an unbalanced panel composed by 164,627 spells and 133,234 individuals. We remark that more than 81% of individuals only experience 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 (see Blanchard & Portugal, 2001, 2017 for in depth documentations of this perennial and salient feature of the Portuguese labour market) and to the (2) period analysed in this paper (60 months); both factors also 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. Table 1 contains descriptive statistics (for sample used in estimations, and Table A5 reports full sample descriptive statistics).

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 for his or her first job, meaning that he or she has no previous work experience, and a dummy variable indicating if the individual is employed at the onset of the job-search (on-the-job search).[5] 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 experience. We control for the occupation of the individual, through a set of dummy variables to distinguish between managers, supervision activities and specialists, technicians, administrative workers, service workers,

[4]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.

Table 1. Descriptive statistics.

	Males						Females					
	All		Permanent contract		Temporary contract		All		Permanent contract		Temporary contract	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Age	32.79	12.20	28.30	10.06	30.58	10.84	31.66	11.06	28.36	9.49	32.75	11.23
Age squared	1224.02	906.81	901.88	683.23	1052.84	771.41	1124.78	799.82	894.21	626.65	1198.91	812.83
Married	0.40	0.49	0.31	0.46	0.31	0.46	0.49	0.50	0.45	0.50	0.53	0.50
Disabled	0.01	0.10	0.01	0.10	0.01	0.10	0.00	0.06	0.00	0.06	0.00	0.07
No dependent persons	0.66	0.47	0.72	0.45	0.68	0.47	0.55	0.50	0.56	0.50	0.44	0.50
1 dependent person	0.15	0.36	0.13	0.33	0.14	0.35	0.23	0.42	0.23	0.42	0.28	0.45
2 dependent persons	0.12	0.32	0.10	0.30	0.11	0.32	0.16	0.36	0.15	0.36	0.20	0.40
3 or more dependent persons	0.07	0.25	0.05	0.23	0.07	0.25	0.06	0.23	0.06	0.23	0.08	0.27
Max 6 years of education	0.45	0.50	0.44	0.50	0.45	0.50	0.45	0.50	0.44	0.50	0.49	0.50
9 years of education	0.22	0.41	0.23	0.42	0.24	0.43	0.19	0.39	0.20	0.40	0.19	0.39
11–12 years of education	0.26	0.44	0.29	0.46	0.27	0.44	0.27	0.44	0.31	0.46	0.23	0.42
More than 12 years of education	0.07	0.25	0.03	0.17	0.03	0.18	0.10	0.29	0.05	0.22	0.08	0.28
Employed	0.03	0.18	0.05	0.22	0.04	0.19	0.04	0.19	0.05	0.22	0.03	0.17
First job	0.17	0.37	0.23	0.42	0.13	0.34	0.19	0.39	0.23	0.42	0.12	0.32
Student	0.07	0.25	0.09	0.28	0.06	0.24	0.07	0.25	0.08	0.28	0.06	0.23
Ex-student	0.07	0.26	0.10	0.31	0.05	0.21	0.08	0.28	0.10	0.30	0.05	0.21
End of training period	0.02	0.13	0.02	0.15	0.01	0.12	0.02	0.15	0.02	0.15	0.02	0.13
Dismissed	0.18	0.38	0.18	0.38	0.12	0.33	0.16	0.36	0.17	0.38	0.12	0.32
Resigned	0.13	0.34	0.12	0.32	0.10	0.30	0.10	0.30	0.10	0.30	0.07	0.25
End of temporary contract	0.34	0.47	0.28	0.45	0.44	0.50	0.35	0.48	0.29	0.46	0.52	0.50
Other motivation	0.18	0.38	0.20	0.40	0.20	0.40	0.20	0.40	0.20	0.40	0.16	0.37
Manager-Specialist	0.07	0.26	0.02	0.15	0.01	0.11	0.08	0.28	0.02	0.15	0.01	0.12
Technical	0.11	0.32	0.08	0.28	0.07	0.25	0.04	0.20	0.03	0.17	0.02	0.12
Administrative	0.13	0.34	0.12	0.33	0.14	0.35	0.20	0.40	0.21	0.41	0.16	0.37
Services	0.10	0.30	0.10	0.31	0.15	0.36	0.28	0.45	0.32	0.47	0.28	0.45
Agricultural	0.04	0.19	0.01	0.12	0.07	0.26	0.06	0.23	0.02	0.15	0.15	0.36
Blue-collar	0.37	0.48	0.42	0.49	0.34	0.47	0.11	0.32	0.17	0.37	0.08	0.28
Other	0.19	0.39	0.21	0.41	0.21	0.41	0.22	0.41	0.22	0.42	0.17	0.38
Young benefit	0.04	0.21	0.04	0.20	0.05	0.21	0.05	0.22	0.05	0.21	0.07	0.25
Unemployment benefit	0.07	0.26	0.04	0.19	0.04	0.19	0.09	0.28	0.05	0.22	0.05	0.23
Training	0.26	0.79	0.15	0.61	0.12	0.56	0.31	0.83	0.24	0.74	0.17	0.61
Local wage	53,930.8	30,445.6	60,209.3	24,247.5	66,324.8	21,271.6	55,389.3	29,411.7	61,509.6	22,989.3	64,678.5	20,188.7
Norte	0.34	0.47	0.37	0.48	0.09	0.29	0.32	0.47	0.36	0.48	0.08	0.27

(*Continued*)

Table 1. (Continued).

	Males						Females					
	All		Permanent contract		Temporary contract		All		Permanent contract		Temporary contract	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Centro	0.16	0.37	0.30	0.46	0.19	0.39	0.17	0.37	0.29	0.46	0.15	0.36
Lisboa	0.38	0.49	0.28	0.45	0.43	0.50	0.36	0.48	0.29	0.45	0.36	0.48
Alentejo	0.06	0.24	0.03	0.16	0.06	0.23	0.09	0.28	0.04	0.20	0.18	0.39
Algarve	0.05	0.23	0.02	0.12	0.23	0.42	0.06	0.24	0.02	0.13	0.23	0.42
Log-flow unemployment	5.80	0.60	5.62	0.62	5.74	0.60	5.75	0.61	5.63	0.59	5.62	0.63
Log-flow vacancies	4.48	1.02	4.54	0.90	4.70	0.96	4.45	1.05	4.54	0.91	4.50	1.03
Mismatch index (average)	0.30	0.34	0.15	0.25	0.63	0.30	0.31	0.35	0.17	0.26	0.62	0.32
(0.5, 1]	30.97		12.33		69.14		32.05		13.36		67.52	
(0.3, 0.5]	9.60		7.93		13.50		9.82		7.84		12.02	
(0.1, 0.3]	12.56		14.68		8.64		12.73		16.25		9.92	
(−0.1, 0.1]	46.25		64.30		8.44		44.75		61.90		10.26	
(−0.3, −0.1]	0.52		0.62		0.25		0.53		0.48		0.19	
[−0.46, −0.3)	0.10		0.15		0.04		0.12		0.17		0.09	
Unemployment duration (average)	18.66	14.37	11.16	10.58	10.39	10.17	18.45	14.15	11.73	10.64	10.88	10.31
# Spells	60,656		5,361		2,430		94,249		8,835		5,323	

agricultural and fishing workers, blue collars, and individuals without specific occupations (interpreted here as no qualifications). Three variables are introduced to control if the individual 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 suggest that mean unemployment duration exceeds mean vacancy duration, a result in line with the literature (see Christiano et al., 2021).

According to the IEFP information 98% of jobseekers are looking for a permanent contract at the onset of their job search,[6] while two-thirds of vacant jobs offer a permanent relationship. A first consequence of this dyscrasia is that some jobseekers may accept a contract-type different from the desired one. Table 2 reports the destination contract of the jobseekers who find a job via the job-center services per declared desired contract-type; for those individuals, in particular, for the ones looking for a permanent contract and do find a job via the job-centre, 69% of males effectively find a permanent job, while this percentage decreases to 63% among females. Among individuals looking for a temporary contract and do find a job via the jobcentre, 46% of males effectively find a temporary job, while this percentage increases to 57% among females.

3. A heterogeneity index for contract-type mismatch

The availability of data disaggregated both at the jobseeker level and at the job vacancy level is an indispensable condition to the construction of a contract-type mismatch index. The IEFP dataset gathers information from 85 job-centers for each month under

[5]It should be noted that only 3% of registered individuals (the jobseekers) are employed and given the very small order of importance of this quantum, the empirical work henceforth presented does not decompose the sample per employment status (yet controls for employment status). In addition, when presenting the results, we refer to the unemployment duration interchangeably with spell spent waiting for employment or re-employment.

Table 2. Desired and destination contracts.

Males								Females							
Looking for a PC				Looking for a TC				Looking for a PC				Looking for a TC			
59,351				1305				92,178				2071			
97.85%				2.15%				97.80%				2.20%			
Censored	Uncensored			Censored	Uncensored			Censored	Uncensored			Censored	Uncensored		
36,697	22,384			878	427			55,617	36,561			1296	775		
62.29%	37.71%			67.28%	32.72%			60.34%	39.66%			62.58%	37.42%		
	Own means	Employment-center			Own means	Employment-center			Own means	Employment-center			Own means	Employment-center	
	14,738	7646			282	145			22,656	13,905			522	253	
	65.84%	34.16%			66.04%	33.96%			61.97%	38.03%			67.35%	32.65%	
		PC	TC			PC	TC			PC	TC			PC	TC
		5283	2363			78	67			8728	5177			107	146
		69.09%	30.91%			53.79%	46.21%			62.77%	37.23%			42.29%	57.71%

Source: Own elaboration on IEFP data

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 jobseekers 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.[7] The mismatch index, measured monthly (m) at the job-centre level (j), is defined as the difference between the ratio of jobseekers looking for a permanent contract and the pool of jobseekers, and the ratio of permanent contracts offered by firms and the pool of vacancies:

$$M_{jm} = \frac{U_{jm}^{PC}}{U_{jm}} - \frac{V_{jm}^{PC}}{V_{jm}} \quad with\ M_{jm} = \ [-1, \ +1] \tag{1}$$

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

$$M_{jm} = \begin{cases} -1 & \text{if} \quad U_{jm}^{PC} = 0 \quad \& \quad V_{jm}^{PC} = V_{jm} \\ 0 & \text{if} \quad U_{jm}^{PC} = 0 \quad \& \quad V_{jm}^{PC} = 0 \quad |U_{jm}^{PC} \Big/ U_{jm} = V_{jm}^{PC} \Big/ V_{jm} \\ +1 & \text{if} \quad V_{jm}^{PC} = 0 \quad \& \quad U_{jm}^{PC} = U_{jm} \end{cases} \tag{2}$$

M takes the value of zero (lowest mismatch) in case there are no jobseekers nor vacant jobs with a preference for a permanent contract, or in case the percentage of jobseekers looking for a PC is equal to the percentage of vacant jobs offering a PC. Full positive contract-type mismatch (i.e., M takes value one) indicates that all jobseekers look for a permanent contract and no permanent contracts are available. On the contrary, full negative contract-type mismatch, (i.e., M takes value minus one) indicates that all jobseekers workers look for a temporary contract and no temporary contracts are available. Hence, higher absolute values of M indicate higher mismatch.

The average in-sample value of M is 0.31, which represents the average value of the difference between jobseekers looking for a permanent relationship (97.8% of jobseekers) and the percentage of permanent jobs offered by firms (66.7% vacant jobs). Table 3 and Figure 1 illustrate the distribution of M values across job-centers.

As expected, positive contract-type mismatch is prevalent in the data, with negative contract-type mismatch seldomly occurring. In addition, the distribution of M across job-centers justifies a flexible empirical approach in the sense that the estimating strategy allows for asymmetric effects between positive (M greater than zero) and negative (M smaller than zero) contract-type mismatch on (re)employment probabilities.

4. The econometric model

We employ hazard models 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. According to the hazard model analysis, 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 searching and is

[6]The question about contract-preference is asked only at the onset of the registration at the job-center and the recorded answer does not change over the unemployment/job-search as it is never asked again.

Table 3. 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

estimated as a reduced form equation that considers the product of two probabilities: the probability of the individual receiving a job offer and the probability of the individual accepting it. The probability of the individual accepting a job offer corresponds to the probability that the wage offer received exceeds his or her reservation wage. Thus, the probability of the individual leaving unemployment (or his or her current employment into the new job in case the individual is employed) can vary over the unemployment spell (or on-the-job search spell if employed) 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 from the current state into a new job in period j reads:

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

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.[8] Because some individuals transition into employment and possibly back into unemployment, multiple spells $q = 1, 2, \ldots$ Q are observable.

We estimate the hazard functions by assuming a flexible discrete-time logistic hazard model as our benchmark model. We also employ a discrete-time multinomial logit hazard model to relax the assumption of independent competing risks (considering correlated random effects). The contract-type mismatch index is included in a categorical form to allow for flexible and asymmetric effects on unemployment duration from positive versus negative contract-type mismatch. For robustness, we compare results for the hazard model for two-competing outcomes and for three-competing outcomes. To be specific, we note that 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 thus competing risks models are estimated and we consider both cases of independent competing risks and non-independent competing risks, for robustness and completeness sake of the analysis. We control for unobserved heterogeneity to prevent estimation bias arising from omitted variables or from measurement errors in the observables.

The augmented hazard function, for each risk, is given by:

$$h(t|x, u) = \frac{exp(\gamma(t) + x\beta + u)}{1 + exp(\gamma(t) + x\beta + u)} \tag{4}$$

[7](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 jobseekers and vacancies in category i (where i may indicate the sector, skill level, region and so on).

where x is a set of time-fixed and time-varying covariates, including the mismatch index, M, introduced according to a categorical specification,[9] β is a vector of unknown parameters to be estimated, while u is a term capturing the role of unobserved characteristics, such as motivation, ability and job-search effort.

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:

$$\mathrm{logL}(\beta, \gamma, \sigma) = \int_{-\infty}^{+\infty} \left[\sum_{q=1}^{Q} \sum_{i=1}^{n} \sum_{j=1}^{t} y_{qij} \mathrm{log} h_{qij} + \left(1 - y_{qij}\right) log\left(1 - h_{qij}\right) \right] g_u(u_i) du_i \qquad (5)$$

where y_{qij} 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 (see Petrongolo & Pissarides, 2001 for an early survey). 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.

5. Estimation results

5.1. Hazard rates and contract mismatch in local labour markets

Table 4 reports the estimated coefficients from discrete time hazard models with 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 a piece-wise constant baseline hazard, normally distributed unobserved heterogeneity and control for a plethora of individual and job-related characteristics (see results in Table A1 in Appendix). The results support the presence of duration dependence, in a statistically meaningful way, for both samples, males and females, and regardless of if job seekers state they prefer permanent or temporary contracts; it should be noted that these results are in line with is observed in the literature. When we look at the effects of the individual and job-related characteristics (Table A1 in Appendix), several noteworthy results surface, albeit all in line with the literature, once more. Having a disability lowers the hazard rate, an effect which is particularly relevant for males searching for permanent contracts. Interestingly, being employed at the onset of registration at the job-center increases the hazard rate, ceteris paribus, a result especially acute in a statistical sense for females looking for a permanent

[8]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.

Table 4. Hazard model (benchmark specification): Duration dependence, mismatch index and local labour market parameters.

	Males						Females					
	Permanent contract			Temporary contract			Permanent contract			Temporary contract		
	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
Unemployment duration												
1–3 months	1.396	0.055	***	1.513	0.087	***	0.882	0.043	***	0.868	0.058	***
4–6 months	1.010	0.057	***	1.260	0.088	***	0.800	0.042	***	0.922	0.056	***
7–9 months	0.490	0.064	***	0.791	0.097	***	0.296	0.047	***	0.630	0.060	***
10–12 months	0.272	0.069	***	0.394	0.109	***	0.007	0.053		0.041	0.072	
13–18 months	base-category											
19–24 months	−0.381	0.075	***	−0.172	0.117		−0.308	0.053	***	−0.372	0.075	***
25–36 months	−0.875	0.079	***	−0.714	0.128	***	−0.678	0.054	***	−0.781	0.079	***
over 36 months	−1.272	0.104	***	−1.090	0.181	***	−1.004	0.073	***	−1.184	0.113	***
Mismatch index												
(0.5, 1]	base-category											
(0.3, 0.5]	0.694	0.072	***	−0.470	0.072	***	0.653	0.055	***	−0.478	0.051	***
(0.1, 0.3]	1.031	0.063	***	−1.163	0.083	***	1.006	0.048	***	−0.979	0.056	***
(−0.1, 0.1]	1.319	0.055	***	−2.390	0.092	***	1.242	0.043	***	−2.217	0.065	***
(−0.3, −0.1]	1.185	0.188	***	−1.690	0.456	***	1.176	0.139	***	−1.229	0.268	***
(−0.3, −0.46]	−0.203	0.724		−1.604	1.023		1.199	0.269	***	−1.621	0.724	**
Local labour markets												
Log flow unemployment	−0.380	0.023	***	−0.383	0.044	***	−0.306	0.018	***	−0.525	0.030	***
Log flow vacancies	0.208	0.020	***	0.228	0.032	***	0.184	0.015	***	0.296	0.023	***
$\sigma^2_{Tc} \to \sigma^2_{Tc}\sigma^2_{Tc}\sigma^2_{PC}$	0.937	0.085					1.222	0.075				
	1.483	0.145					1.643	0.108				
Log-likelihood	−28,003.3			−13,404.9			−47,043.5			−27,195.6		
Observations	1,095,030						1,728,678					

Source: Own elaboration on IEFP data

contract. The status of the jobseekers (beyond employment) regarding why they are registering at the job-center do have statistical significance as regressors for both samples. It is also interesting to note that having received unemployment benefits immediately prior to registering at the job-center decreases the hazard rate in a statistical sense for both males and senses and for both types of sought after contracts; this result is particularly interesting given the fact that unemployment duration is already controlled for, in addition to the vast plethora of individual and job-related characteristics, suggesting that there is something particular regarding either these individuals or how they are perceived by the prospective employers (tentatively, a form of stigma). The same can be said regarding having received training; in this sense, the data do not support that the training received increases per se the subsequently experienced hazard rate. It is also interesting to note that the local-labour market variables, monthly gross inflows of unemployment and monthly gross inflows of vacancies, have the usual effects, with unemployment inflows decreasing the hazard rates and vacancies inflows increasing the hazard rates, both with statistically meaningful effects, for both males and females, regardless of if the jobseekers prefer permanent or temporary contracts.

The predicted hazard rates are reported as a function of unemployment duration in Figure 2.[10] For both males and females, the data show negative duration dependence with hazard rates dropping with unemployment duration, a result in line with

[9]In order to account for non-linear/asymmetric effects of mismatch index on hazard rates, the continuous-type indicator is used in a categorical form in the empirical specification.

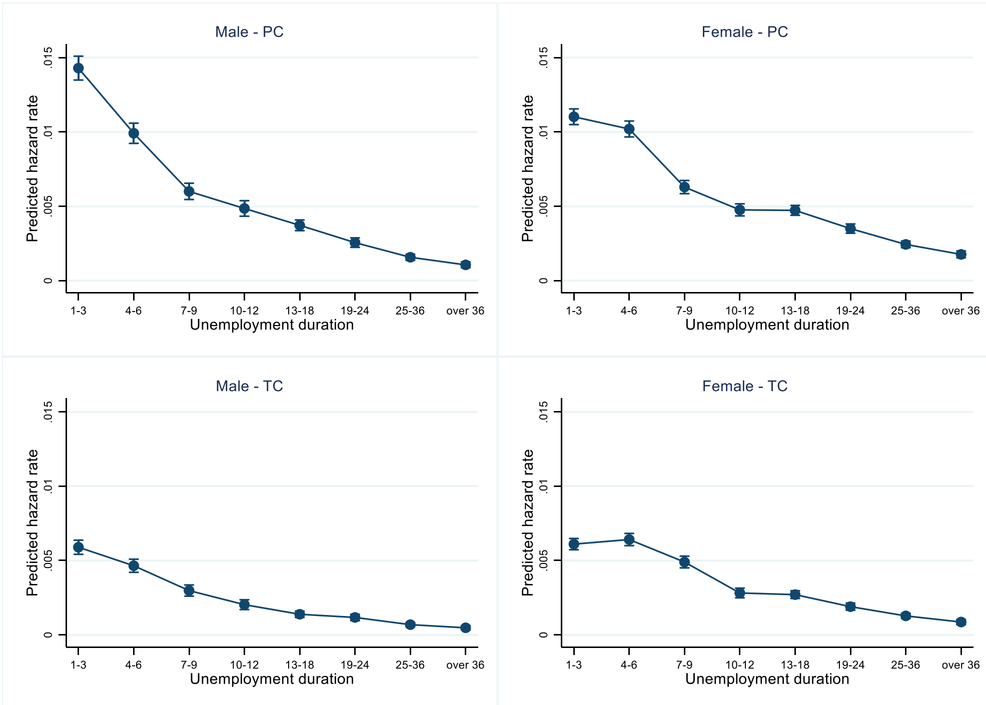

Figure 2. Predicted hazard rate by unemployment spell duration. Source: own elaboration on IEFP data.

the literature. Quite interestingly, the drop in the hazard rates is particularly pronounced for jobseekers who seek permanent contracts, despite their gender. Figure 3, in turn, reports the predicted hazard rates for different levels of the mismatch index.[11] It is remarkable to note that for jobseekers who seek permanent contracts the hazard rates are highest when heterogeneity or contract-type mismatch is lowest or close to zero; this result is valid for both males and females. It is also noteworthy to notice the drop in the hazard rates as the contract-type mismatch index increases in absolute value. Integrating over all these results, the data support an association between higher contract-type mismatch and lower hazard rates.

5.2. Robustness checks

In this section, we provide certain robustness checks. First, we employ a discrete-time multinomial logit hazard model to relax the assumption of independent competing risks by allowing for correlated random effects (Table A2). The analysis shows that random effects are positively correlated in a statistically significant way. Once accounting for this circumstance, the magnitude of the coefficients associated with the baseline hazard declines up to 15%, indicating that the negative duration dependence weakened. The

[9]In order to account for non-linear/asymmetric effects of mismatch index on hazard rates, the continuous-type indicator is used in a categorical form in the empirical specification.
[10]Control variables are evaluated at their average values.

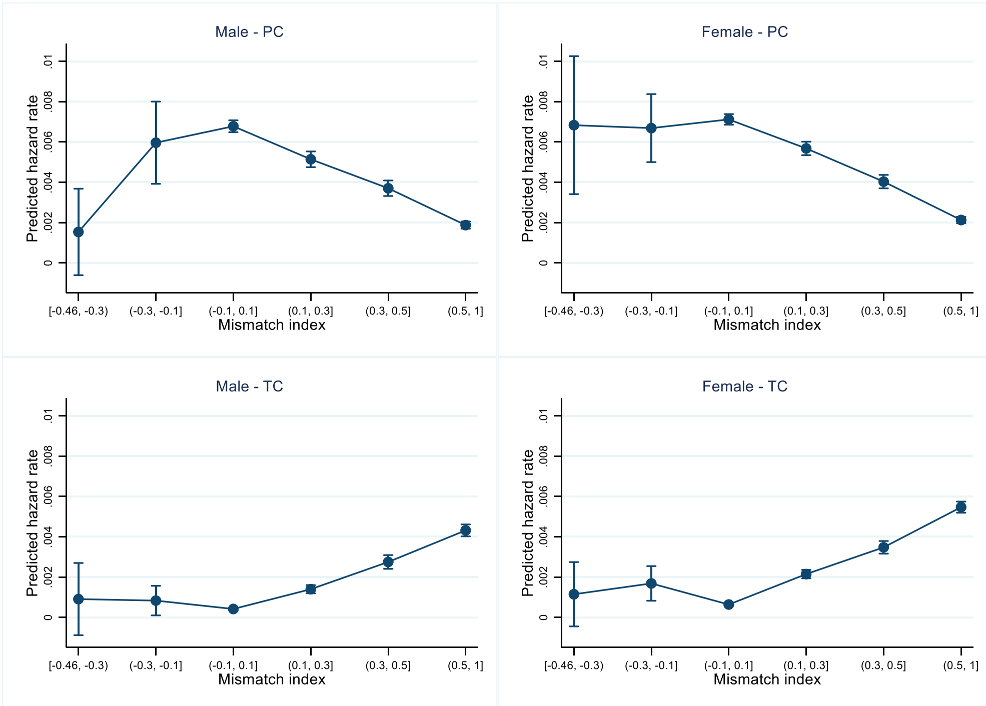

Figure 3. Predicted hazard rate by Mismatch index. Source: own elaboration on IEFP data.

coefficients associated with the contract-type mismatch index and with the local labor market variables also declined, even though in a quite negligible way. In sum, these results suggest that while accounting for correlated competing risks may be conceptually important, the essence of our findings remains unchanged.

Second, we exploit the presence of multiple spells (corresponding to about 20% of the observations) to improve the identification of unobserved heterogeneity. We relax the assumption that spells of the same individuals are uncorrelated by running a three-level discrete-time logistic hazard model. This allows for random effects at the individual level and random effects at the spell nested in individual level. Results reported in Table A3 show that it doesn't emerge any clear correlation at spells level. However, once this aspect is accounted for, the variability of unobserved heterogeneity is slightly altered. In addition, we note a slight reduction in the negative duration dependence for both males and females and for both outcomes (permanent and temporary contracts). Quite interestingly, changes in the role of the contract-type mismatch index and of local labor market indicators for estimated hazard rates are negligible.

Finally, we run a supplementary analysis to test whether and how our benchmark results change once jobseekers who find a job by own means are included in the sample. Results are reported in Tables A4a and A4b (males and female, respectively) and indicate (compared to the benchmark case) a slight decline in the duration dependence parameters for both permanent and temporary outcomes and for both males and females. Incidentally, duration dependence is even smaller for individuals who find a job by own means. Quite interestingly, when looking at the characteristics of the local labour market we find that they play a relatively negligible role for this pool of individuals. The coefficients associated to the contract-type mismatch index are often not statistically significant and small in magnitude. Prima facie, this result suggests that the degree of contract-type mismatch between jobseekers and firms preferences is less relevant for individuals who exit unemployment (or current employment) by own means. Similar evidence emerged when looking at coefficients associated with log-flow unemployment and log-flow vacancies.

6. Conclusions

This paper tests the hypothesis that higher labour market mismatch, defined as heterogeneity between contract-type sought by jobseekers and contract-type offered by firms, is associated with 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 job 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 contract-type preferences of jobseekers and jobs offered by firms at the job-center level and assesses the impact of contract-type mismatch on unemployment duration by leveraging on the variation found across space and time (over 5 years) in Portugal on contract-type mismatch at the job-center level (86 of them) while using in a novel way a rich set of individual data for jobseekers and vacancies.

Results from a flexible discrete-time competing risk hazard (multinomial) logit model under a stock-flow matching mechanism suggest a significant association of contract-type mismatch at job-centers level on individual hazard rates. Among individuals finding a permanent contract the hazard rate is highest in the absence of contract-type mismatch and lower for extreme values of the mismatch index, with the hazard rate reaching its lowest level when full positive contract-type mismatch occurs. In addition, local labour markets characterized by positive values of the contract-type mismatch index are associated with a higher incidence of exiting unemployment by accepting a temporary contract, as individuals may 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 the presence of high contract-type mismatch individuals look for a job outside the job-centers.

Our work indicates that the Portuguese labour market is characterized by substantial contract-type mismatch: jobseekers prefer permanent contracts while firms offer both permanent and temporary contracts but mostly temporary contracts. 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 perspectives could improve the desirability of temporary contracts, contributing to reduce matching frictions and average unemployment duration owing to 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, 2011), 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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Table A1. Hazard model (benchmark specification): other covariates.

	Males						Females					
	Permanent contract			Temporary contract			Permanent contract			Temporary contract		
	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
Age	0.017	0.011		0.025	0.017		−0.012	0.010		−0.015	0.013	
Age squared	−0.001	0.000	***	−0.001	0.000	***	0.000	0.000	***	0.000	0.000	
Married	0.055	0.054		−0.063	0.077		−0.059	0.034	*	−0.050	0.045	
Disabled	−0.358	0.163	**	−0.388	0.252		−0.182	0.202		0.043	0.263	
1 dependent person	0.017	0.060		0.080	0.086		0.072	0.038	*	0.227	0.050	***
2 dependent persons	0.069	0.067		0.173	0.097	*	0.080	0.046	*	0.220	0.060	***
3 or more dependent persons	−0.091	0.083		0.130	0.115		0.029	0.065		0.231	0.079	***
9 years of education	0.063	0.042		0.000	0.062		0.025	0.036		−0.063	0.049	
11–12 years of education	0.029	0.043		−0.107	0.066		0.062	0.034	*	−0.005	0.050	
More than 12 years of education	−0.363	0.096	***	−0.362	0.139	***	−0.061	0.062		−0.031	0.074	
Employed	0.154	0.084	*	0.020	0.136		0.214	0.067	***	0.042	0.106	
First job	−0.086	0.094		−0.320	0.160	**	−0.062	0.065		−0.444	0.112	***
Student	0.118	0.099		−0.079	0.176		0.110	0.074		0.412	0.126	***
Ex-student	0.258	0.098	***	0.063	0.179		0.314	0.071	***	0.472	0.127	***
End of training period	0.345	0.127	***	0.236	0.219		0.346	0.090	***	0.170	0.133	
Dismissed	0.254	0.056	***	0.087	0.090		0.326	0.046	***	0.280	0.067	***
Resigned	0.139	0.063	**	0.007	0.096		0.203	0.053	***	0.112	0.079	
End of temporary contract	0.183	0.052	***	0.302	0.071	***	0.312	0.042	***	0.480	0.054	***
Manager-Specialist	−1.410	0.113	***	−1.785	0.196	***	−1.537	0.089	***	−1.984	0.139	***
Technical	−0.536	0.065	***	−0.741	0.107	***	−0.584	0.082	***	−1.207	0.134	***
Administrative	−0.378	0.058	***	−0.206	0.087	**	−0.142	0.043	***	−0.398	0.060	***
Services	−0.256	0.060	***	−0.134	0.086		−0.051	0.037		−0.307	0.049	***
Agricultural	−0.582	0.135	***	0.715	0.118	***	0.269	0.091	***	1.155	0.076	***
Blue-collar	−0.006	0.043		−0.190	0.068	***	0.437	0.044	***	−0.144	0.071	**
Young benefit	0.131	0.085		0.150	0.122		0.161	0.064	**	0.288	0.076	***
Unemployment benefit	−0.161	0.090	*	−0.405	0.142	***	−0.138	0.063	**	−0.216	0.087	**
Training	−0.311	0.026	***	−0.378	0.046	***	−0.306	0.018	***	−0.469	0.030	***
Local wage	0.000	0.000		0.000	0.000		0.000	0.000	***	0.000	0.000	
Norte	0.024	0.043		−0.674	0.088	***	−0.093	0.035	***	−0.802	0.068	***
Centro	0.626	0.046	***	0.215	0.074	***	0.524	0.037	***	−0.045	0.057	
Alentejo	−0.457	0.103	***	−0.592	0.117	***	−0.276	0.070	***	−0.139	0.070	**
Algarve	−0.414	0.129	***	0.612	0.086	***	−0.507	0.101	***	0.628	0.064	***
Constant	−5.870	0.254	**	−5.728	0.420	***	−5.646	0.212	***	−4.371	0.301	***

Source: Own elaboration on IEFP data

Table A2. Hazard model with correlated unobserved heterogeneity: duration dependence, mismatch index and local labour market parameters.

	Males						Females					
	Permanent contract			Temporary contract			Permanent contract			Temporary contract		
	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
Unemployment duration												
1–3 months	1.152	0.056	***	1.188	0.089	***	0.668	0.043	***	0.533	0.059	***
4–6 months	0.846	0.057	***	1.047	0.089	***	0.653	0.042	***	0.692	0.056	***
7–9 months	0.398	0.064	***	0.676	0.097	***	0.215	0.047	***	0.501	0.060	***
10–12 months	0.225	0.069	***	0.335	0.109	***	−0.031	0.053		−0.022	0.072	
13–18 months	base-category											
19–24 months	−0.347	0.075	***	−0.124	0.117		−0.270	0.053	***	−0.305	0.075	***
25–36 months	−0.815	0.079	***	−0.628	0.128	***	−0.611	0.055	***	−0.667	0.079	***
over 36 months	−1.212	0.104	***	−0.990	0.181	***	−0.941	0.073	***	−1.058	0.113	***
Mismatch index												
(0.5, 1]	base-category											
(0.3, 0.5]	0.681	0.071	***	−0.487	0.071	***	0.653	0.055	***	−0.466	0.051	***
(0.1, 0.3]	1.011	0.062	***	−1.149	0.083	***	1.000	0.048	***	−0.945	0.057	***
(−0.1, 0.1]	1.282	0.055	***	−2.386	0.091	***	1.227	0.043	***	−2.190	0.065	***
(−0.3, −0.1]	1.124	0.187	***	−1.724	0.455	***	1.180	0.138	***	−1.137	0.268	***
(−0.3, −0.46]	−0.182	0.722		−1.562	1.019		1.237	0.268	***	−1.438	0.723	**
Local labour markets												
Log flow unemployment	−0.378	0.023	***	−0.379	0.044	***	−0.296	0.018	***	−0.465	0.030	***
Log flow vacancies	0.200	0.020	***	0.219	0.032	***	0.171	0.014	***	0.268	0.022	***
σ^2_{PC}	1.037	0.093					1.346	0.082				
	1.870	0.166					2.265	0.128				
$cov\left(\sigma^2_{PC}, \sigma^2_{TC}\right)$	1.372	0.127					1.441	0.095				
Log-likelihood	−122,309.9						−200,836.1					
Observations	1,095,030						1,728,678					

Source: Own elaboration on IEFP data

Appendix

Table A3. Hazard model with nested unobserved heterogeneity: duration dependence, mismatch index and local labour market parameters.

	Males						Females					
	Permanent contract			Temporary contract			Permanent contract			Temporary contract		
Spell duration	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
1–3 months	1.221	0.055	***	1.319	0.086	***	0.762	0.042	***	0.666	0.057	***
4–6 months	0.882	0.057	***	1.116	0.088	***	0.706	0.042	***	0.769	0.056	***
7–9 months	0.418	0.064	***	0.716	0.096	***	0.243	0.047	***	0.549	0.059	***
10–12 months	0.235	0.069	***	0.357	0.109	***	−0.017	0.052		0.007	0.072	
13–18 months	base-category											
19–24 months	−0.358	0.075	***	−0.146	0.117		−0.286	0.053	***	−0.333	0.075	***
25–36 months	−0.838	0.079	***	−0.670	0.128	***	−0.643	0.054	***	−0.723	0.079	***
over 36 months	−1.249	0.104	***	−1.056	0.181	***	−0.992	0.073	***	−1.148	0.113	***
Mismatch index												
(0.5, 1]	base-category											
(0.3, 0.5]	0.678	0.071	***	−0.486	0.071	***	0.649	0.055	***	−0.467	0.051	***
(0.1, 0.3]	1.014	0.062	***	−1.167	0.083	***	1.006	0.048	***	−0.948	0.056	***
(−0.1, 0.1]	1.295	0.055	***	−2.394	0.091	***	1.233	0.043	***	−2.190	0.065	***
(−0.3, −0.1]	1.133	0.186	***	−1.685	0.455	***	1.174	0.138	***	−1.163	0.268	***
(−0.3, −0.46]	−0.185	0.721		−1.590	1.020		1.223	0.267	***	−1.555	0.724	**
Local labour markets												
Log flow unemployment	−0.378	0.023	***	−0.383	0.044	***	−0.298	0.018	***	−0.477	0.030	***
Log flow vacancies	0.199	0.020	***	0.221	0.032	***	0.170	0.014	***	0.271	0.022	***
σ^2_{Pc} [individuals]	0.849	0.082					1.093	0.069				
σ^2_{Pc} [spells]	0.000	0.000					0.000	0.000				
σ^2_{Tc} [individuals]	1.493	0.139					1.886	0.113				
σ^2_{Tc} [spells]	0.000	0.000					0.000	0.000				
Log-likelihood	−29,008.16			−13,975.15			−48,657.073			−28,585.07		
Observations	1,231,895						1,959,714					

Source: Own elaboration on IEFP data

Table A4a. Hazard model (including OM outcome): duration dependence, mismatch index and local labour market parameters.

	Males								
	Permanent contract			Temporary contract			Own means		
	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
Unemployment duration									
1–3 months	1.221	0.055	***	1.319	0.086	***	0.620	0.035	***
4–6 months	0.882	0.057	***	1.116	0.088	***	0.875	0.033	***
7–9 months	0.418	0.064	***	0.716	0.096	***	0.503	0.035	***
10–12 months	0.235	0.069	***	0.357	0.109	***	0.229	0.039	***
13–18 months				base-category					
19–24 months	−0.358	0.075	***	−0.146	0.117		−0.424	0.045	***
25–36 months	−0.838	0.079	***	−0.670	0.128	***	−0.704	0.046	***
over 36 months	−1.249	0.104	***	−1.056	0.181	***	−1.175	0.065	***
Mismatch index									
(0.5, 1]				base-category					
(0.3, 0.5]	0.678	0.071	***	−0.486	0.071	***	−0.017	0.034	
(0.1, 0.3]	1.014	0.062	***	−1.167	0.083	***	0.025	0.031	
(−0.1, 0.1]	1.295	0.055	***	−2.394	0.091	***	0.062	0.026	**
(−0.3, −0.1]	1.133	0.186	***	−1.685	0.455	***	0.057	0.119	
(−0.3, −0.46]	−0.185	0.721		−1.590	1.020		0.445	0.292	
Local labour markets									
Log flow unemployment	−0.378	0.023	***	−0.383	0.044	***	−0.081	0.017	***
Log flow vacancies	0.199	0.020	***	0.221	0.032	***	0.121	0.011	***
σ^2_{PC}	0.849	0.082							
σ^2_{TC}	1.493	0.139							
σ^2_{OM}	0.820	0.043							
Log-likelihood	−29,008.2			−13,975.1			−72,269.4		
Observations				1,231,895					

Source: Own elaboration on IEFP data

Table A4b. Hazard model (including OM outcome): duration dependence, heterogeneity index and local labour market parameters.

	Females								
	Permanent contract			Temporary contract			Own means		
	Coeff.	s.e.		Coeff.	s.e.		Coeff.	s.e.	
Unemployment duration									
1–3 months	0.762	0.042	***	0.666	0.057	***	0.369	0.028	***
4–6 months	0.706	0.042	***	0.769	0.056	***	0.653	0.026	***
7–9 months	0.243	0.047	***	0.549	0.059	***	0.406	0.028	***
10–12 months	−0.017	0.052		0.007	0.072		0.132	0.031	***
13–18 months				base-category					
19–24 months	−0.286	0.053	***	−0.333	0.075	***	−0.230	0.034	***
25–36 months	−0.643	0.054	***	−0.723	0.079	***	−0.463	0.035	***
over 36 months	−0.992	0.073	***	−1.148	0.113	***	−0.858	0.050	***
Mismatch index									
(0.5, 1]				base-category					
(0.3, 0.5]	0.649	0.055	***	−0.467	0.051	***	−0.103	0.027	***
(0.1, 0.3]	1.006	0.048	***	−0.948	0.056	***	−0.068	0.025	***
(−0.1, 0.1]	1.233	0.043	***	−2.190	0.065	***	−0.021	0.022	
(−0.3, −0.1]	1.174	0.138	***	−1.163	0.268	***	0.134	0.088	
(−0.3, −0.46]	1.223	0.267	***	−1.555	0.724	**	0.392	0.211	*
Local labour markets									
Log flow unemployment	−0.298	0.018	***	−0.477	0.030	***	−0.070	0.014	***
Log flow vacancies	0.170	0.014	***	0.271	0.022	***	0.121	0.008	***
σ^2_{PC}	1.093	0.069							
σ^2_{TC}	1.886	0.113							
σ^2_{OM}	1.044	0.037							
Log-likelihood	−48,657.073			−28,585.074			−112,053.290		
Observations				1,959,714					

Source: Own elaboration on IEFP data

Table A5. Full sample descriptive statistics.

	Males				Females			
	10% sample		Full sample		10% sample		Full sample	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Age	32.790	12.200	32.807	12.259	31.662	11.06	31.650	11.026
Age squared	1224.02	906.81	1226.56	911.62	1124.78	799.82	1123.30	796.53
Married	0.404	0.491	0.405	0.491	0.486	0.50	0.485	0.500
Disabled	0.010	0.101	0.010	0.100	0.004	0.06	0.004	0.063
No dependent persons	0.663	0.473	0.663	0.473	0.552	0.50	0.554	0.497
1 dependent person	0.152	0.359	0.151	0.358	0.234	0.42	0.232	0.422
2 dependent persons	0.118	0.323	0.118	0.322	0.156	0.36	0.157	0.364
3 or more dependent persons	0.068	0.251	0.068	0.252	0.058	0.23	0.057	0.233
Max 6 years of education	0.453	0.498	0.448	0.497	0.450	0.50	0.451	0.498
9 years of education	0.221	0.415	0.222	0.415	0.188	0.39	0.190	0.392
11–12 years of education	0.260	0.439	0.263	0.440	0.267	0.44	0.264	0.441
More than 12 years of education	0.066	0.249	0.067	0.251	0.096	0.29	0.095	0.293
Employed	0.033	0.178	0.032	0.177	0.037	0.19	0.037	0.189
First job	0.165	0.371	0.163	0.370	0.188	0.39	0.188	0.391
Student	0.065	0.247	0.064	0.245	0.067	0.25	0.068	0.252
Ex-student	0.073	0.260	0.075	0.263	0.083	0.28	0.083	0.275
End of training period	0.016	0.125	0.015	0.122	0.024	0.15	0.024	0.152
Dismissed	0.180	0.385	0.183	0.387	0.157	0.36	0.157	0.364
Resigned	0.129	0.335	0.129	0.335	0.098	0.30	0.099	0.298
End of temporary contract	0.343	0.475	0.343	0.475	0.354	0.48	0.354	0.478
Other motivation	0.190	0.380	0.188	0.375	0.215	0.40	0.214	0.390
Manager-Specialist	0.074	0.262	0.074	0.261	0.083	0.28	0.083	0.276
Technical	0.112	0.315	0.112	0.316	0.044	0.20	0.046	0.209
Administrative	0.132	0.338	0.129	0.335	0.201	0.40	0.198	0.399
Services	0.100	0.301	0.101	0.302	0.277	0.45	0.277	0.448
Agricultural	0.037	0.188	0.037	0.188	0.055	0.23	0.055	0.227
Blue-collar	0.372	0.483	0.372	0.483	0.114	0.32	0.115	0.318
Other	0.193	0.394	0.191	0.393	0.217	0.41	0.216	0.411
Young benefit	0.044	0.206	0.044	0.205	0.051	0.22	0.051	0.220
Unemployment benefit	0.071	0.257	0.070	0.255	0.088	0.28	0.087	0.281
Training	0.262	0.794	0.267	0.803	0.309	0.83	0.310	0.830
Local wage	53,930.84	30,445.60	54,007.95	30,408.16	55,389.32	29,411.66	55,470.29	29,385.30
Norte	0.338	0.473	0.340	0.474	0.318	0.47	0.318	0.466
Centro	0.162	0.369	0.161	0.368	0.167	0.37	0.169	0.374
Lisboa	0.382	0.486	0.382	0.486	0.364	0.48	0.362	0.481
Alentejo	0.063	0.243	0.063	0.243	0.089	0.28	0.089	0.284
Algarve	0.054	0.227	0.054	0.226	0.062	0.24	0.062	0.241
Log-flow unemployment	5.799	0.597	5.799	0.593	5.754	0.61	5.756	0.610
Log-flow vacancies	4.481	1.018	4.481	1.016	4.452	1.05	4.451	1.051
Heterogeneity index (average)	0.303	0.345	0.304	0.345	0.314	0.35	0.314	0.349
# Spells	60,656		603,536		94,249		943,098	

Source: Own elaboration on IEFP data