DUAL LABOUR MARKETS AND (LACK OF) ON–THE–JOB TRAINING: PIAAC EVIDENCE FROM SPAIN AND OTHER EUROPEAN COUNTRIES[1]

Antonio Cabrales [a] **, Juan J. Dolado** [b] **& Ricardo Mora** [c]

(a) University College London, (b) European University Institute & (c) Univ. Carlos III de Madrid

This version: September, 2015

ABSTRACT

Using micro data from the *Programme for the International Assessment of Adult Competencies* (PIAAC), we first document how the excessive gap in employment protection between indefinite and temporary workers leads to large differentials against the latter in the intensive and extensive margins of on-the-job training (OTJ). Next, we find that that this OJT gap is positively correlated with gaps in the literacy and numeracy scores achieved by these two types of workers in the PIAAC study. Although we chose Spain as a case study of a dual labour market, we also provide cross-country evidence showing that OJT and scores gaps are quite lower in those European labour markets where dualism is less entrenched than where it is more extended.

Keywords: Dual labour market, On-the-job training, Cognitive skills, Severance pay.

JEL codes: C14, C52, D24, J24.

---

1. We are grateful to Andrea Bassanini, Samuel Bentolila, Roman Fossati, Andrea Ichino, Greg Jolivet, Stepan Jurajda and Helene Turon, as well as participants in the CAGE conference on "Education, Human Capital and Labor Market Outcomes" (Venice), ESSLE 2014 (Ammersee), Marseille (2015) and seminars at Bristol, IMT-Lucca and Padua for useful comments that improved the paper. We also wish to thank Nicolas Escribano for excellent research assistance.
Authors e-mails: uctpcab@live.ucl.ac.uk, juan.dolado@eui.eu and ricmora@eco.uc3m.es .

1. Introduction

This paper looks at whether the gap between the amount of on-the-job training (OJT hereafter) employers provide to permanent workers (those holding an open-ended/indefinite contract, PC) and temporary workers (those holding a fixed-term contract, FTC) is larger in dual labour markets than in less segmented ones. One plausible mechanism leading to this differential in training relies on the larger turnover rate experienced by temporary workers due to the much more lax employment protection legislation (EPL henceforth; in particular dismissal costs) they enjoy relative to permanent workers. Whenever wage rigidity prevents firms neutralizing severance payments (i.e., a transfer from employers to workers), this gap in EPL makes firms more prone to use FTC in sequence and less so to convert these contracts into PC. As a result of the greater job churn of temporary workers, employers do not find it profitable to invest in their on-the-job training (OJT hereafter). Conversely, the higher job stability implied by the much more stringent EPL enjoyed by permanent workers, makes firms more eager to invest in their training-

As a byproduct of exploring the previous channel, we are also interested in documenting whether gaps in OJT due to dual EPL are positively correlated with differences in workers' cognitive skills. To the extent that training at the workplace helps accumulating these skills, dualism in the labour market may not only hinder temporary workers´ specific human capital but may also lead to a negative "value-added" effect (i.e., in addition to the skills achieved through education and other observable characteristics) on their accumulation of general human capital.[2]

Both are issues of considerable importance for policy in Europe, especially in Southern Mediterranean countries which have been so badly hit by the crisis. A well-known example is Spain, often considered as an epitome of a highly segmented labour market (see OECD 2014). For this reason we devote the first part of the paper to carefully illustrate how the mechanism at play works in this country. Yet, because the explored channel is general in nature, in the second part of the paper further empirical evidence is reported on how differences in the degree of EPL dualism affect OJT in a large set of European countries.

Regarding our case study, the rate of temporary work (i.e., the share of employees under temporary contracts) in Spain soared from 15% just before the radical labour market reform of 1984 to 35.4% in the mid-nineties (see, e.g., Dolado et al., 2002 and 2008).[3] Since then, around 90% (94% nowadays) of newly signed contracts each year have been temporary ones (mostly FTC), out of which one quarter last for less than one week and their average duration

---

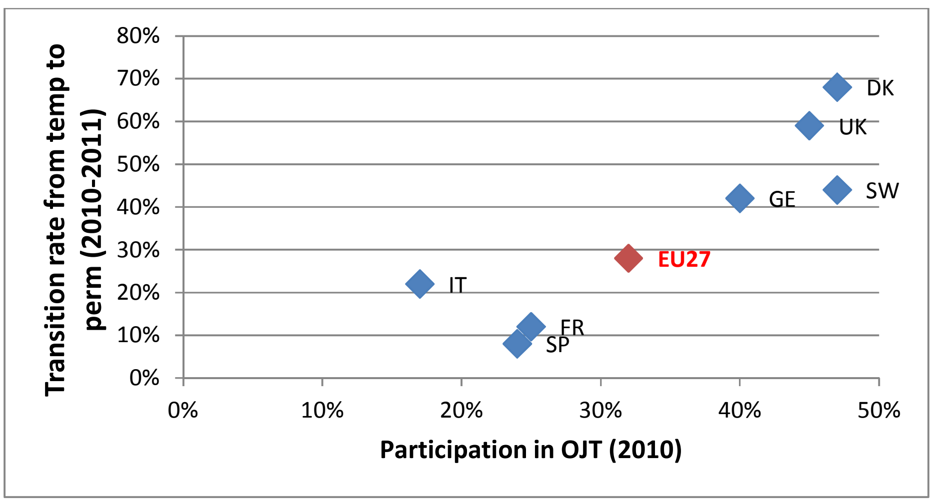
[2] According to Acemoglu and Pischke (1999), when labour market frictions compress the wage structure (for example, through a highly unionized workforce), it might be the case that employer-sponsored training includes financing of investment in human. Thus, OJT might affect not only specific but also general human capital.

[3] The 1984 labour market reform in Spain allowed the indiscriminate use of temporary contracts (with very low termination costs) for any regular productive activity while keeping unchanged the rigid EPL of permanent contracts inherited from industrial relations during the Francoist regime.

hardly reaches around two months. The average temp-to-perm conversion rate has fallen from 12% in the nineties and first half of the 2000s to about 6% in 2012 (see Amuedo-Dorante, 2001 and Güell and Petrongolo, 2007). Following a long sequence of partial labour market reforms after 1984, the rate of temporary work stabilized around 30% at the turn of the new century (see Bentolila et al, 2013). More recently, the mass destruction of temporary jobs during the Great Recession and the sovereign debt crisis has lowered the rate to 25%, which still remains as one of the highest rates in Europe and OECD.

As regards workers´ involvement in OJT schemes, the participation rate in Spain has increased from 10% in the early nineties to 24% in 2010, but still remains at the bottom of the EU, together with Italy. It is 8 percentage points (pp.) below the EU average, and between 20-30 pp. lower than in Scandinavian countries and the UK (see European Commission, 2014). Figure 1 displays the transition rates from temporary to permanent contracts (vertical axis, in percent) in 2011, as a measure of segmentation in labour markets (see Eichorst, 2013), and the fraction of employees participating in OJT schemes (horizontal axis, in percent) in a few EU countries as of 2010. As can be seen, there is evidence that in countries where temporary contracts are a springboard to more stable jobs, participation in OJT schemes tends to be larger.

Figure 1. Temp-to perm transition rates and OJT participation



Note: The sources for transition rates and OJT participation rates are Eichorst (2013) and Fifth European Working Conditions Survey (2010), respectively.

Returning to our argument above, lower OJT attached to FTC might be one of the main reasons for why these contracts are often considered to be *dead ends* in dual labour markets instead of *stepping stones*, as in other labour markets where the EPL gap is smaller or even absent (see Booth et al., 2002 and Autor, 2004). By contrast, stringent EPL for permanent contracts implies that OJT grows for this type of workers. Thus, both features put together imply that a dual labor market structure has *distributional* consequences for OJT. Yet, in principle it is not clear whether we should think of OJT investments as a detrimental or instead even a favorable outcome of dual labor markets. In effect, if training for permanent workers is sufficiently large, then a country with high firing costs and a dual labor-market structure may have greater overall OJT investment than another country with a more unified labor market structure.

However, this is likely to depend on other factors as well. Among them, there are the efficiency of the education system, the industrial specialization of the economy (high value vs. low value-added industries), and the probability that temporary workers obtain permanent contracts at some point in their careers.

The Spanish economy fares rather unsatisfactorily in these three outcomes. Its educational system does not perform well in international comparisons (see Ciccone and Garcia-Fontes, 2000), the economy has been heavily dependent on the real estate and touristic sectors (see Garriga, 2010) and, as already mentioned, the *temp-to-perm* conversion rate is very low. By the same token, given the large turnover, temporary workers may lack the right incentives to improve on their job performance by accumulating better productive capabilities. Hence, since these skills and OJT are important components of multifactor productivity, this mechanism may have played a relevant role in explaining the unsatisfactory development of TFP growth in Spain and other EU countries with highly segmented labour markets (see Bassanini et al., 2009 and Dolado et al., 2013).

To document the role of OJT in the mechanism described above, we use detailed information for Spain and other thirteen European countries drawn from the first wave of the *Survey of Adult Skills*, the main output of the *Programme for the International Assessment of Adult Competencies* (PIAAC, 2013). As will be described below, PIAAC provides a harmonized dataset for a large number of countries on the availability of OJT at individual level (both at the extensive and intensive margins), as well as a wide array of person-level demographics and job characteristics, including type of contract. Further, the availability of PIAAC scores on workers' *literacy* and *numeracy* competencies allows us also to explore whether OJT affects workers' proficiency conditional on predictors of previously acquired skills, including educational attainment or family background.

In order to derive the main testable hypotheses in our empirical approach, we start by laying out a slight modification of the search and matching model for a dual labour market proposed by Berton and Garibaldi (2012, BG hereafter). In such a model, where temporary (fixed-term) and permanent (open-ended) contracts coexist in a long-run equilibrium, firms can increase the productivity of their workers by undertaking costly training in the aftermath of an adverse productivity shift. While BG (2012) assume that temporary workers can be dismissed at will while permanent workers can never be fired, we relax this last assumption by introducing severance pay and the possibility of upgrading temporary contracts to permanent contracts within the same job. We show that for sufficiently low *temp-to-perm* conversion rates, a higher severance pay gap decreases OJT for temporary workers whereas it increases OJT for permanent workers.

A note of caution is due before summarizing our main empirical findings. The ideal experiment for testing the main hypotheses of this paper would be one where workers are randomly assigned to FTC and PC (see Autor and Houseman, 2010, for the US), or where comparable labor markets (with the same structure of jobs and workers) are assigned to different regimes of dual EPL (see García-Perez et al., 2014, for Spain). However, such experimental conditions are hard to come by in a cross-country study based on cross-sectional data where the use of selectivity correction procedures based on exclusion restrictions are not easy to defend.

Hence, our approach relies on comparing workers with similar observable characteristics, except type of contract (our treatment). In principle, selection-on-observables assumptions could be considerably less powerful for identifying the causal impacts of contract types on OJT and cognitive skills since firms´ decisions to train different types of workers may depend on unmeasured skills and motivations that cause self-selection both into different jobs and training.[4]

Nonetheless, tempering these caveats, we believe that selection on un-observables is not likely to play a major role in our setup. There are two reasons to think so. First, it is the case that PIAAC contains a wider array of individual and job characteristics than other datasets used in studies about the effects of temporary contracts on labour market outcomes. For example, PIACC includes variables like worker´s motivation, detailed educational achievements and family background which are often considered to be among the standard confounding factors leading to biases in the estimation of causal effects by standard regression analysis.[5] Hence, in our view, the best way to deal with endogeneity with data such as ours is to control for those variables which are likely to be responsible for the aforementioned confounding factors, either in conventional regressions or in using matching techniques to reduce dimensionality. Secondly, as will be argued in the next section, it is also the case that, at least for Spain, a comparison of non-experimental and quasi-experimental estimates of the returns to temporary work does not show major differences. This may possibly reflect that, in a country where more than 90% of entry jobs are temporary, selection issues are not so crucial.

Despite the constraints imposed by the use of cross-sectional data, our interpretation of the main empirical findings obtained from PIAAC is that they are rather supportive of the mechanism stressed above. First, we find a substantially negative and statistically significant relationship between holding a temporary contract and the amount of workplace training. Secondly, we document that the less OJT individuals receive, the worse their literacy and numeracy scores, on top of those predicted by their individual characteristics, and that this effect is primarily due to holding a temporary contract rather than other factors. Foremost, we provide similar evidence for a pool of fourteen European countries for which a novel proxy of dual EPL is constructed. We find that the above-mentioned results are stronger for countries with segmented labour markets than for those with more unified labour markets. Overall, these results turn out to be fairly consistent with the growing empirical evidence about the negative effects of persistent labour market dualism on productivity growth and unemployment (see Blanchard and Landier, 2002, and Bentolila et al., 2012).

The rest of the paper proceeds as follows. Section 2 provides a brief overview of the related literature on this topic. Section 3 develops a simple theoretical model that guides our empirical approach. Section 4 describes the PIAAC database and provides descriptive statistics of the outcome and treatment variables used in the empirical analysis. Section 5 presents the main empirical results for our illustrative case study, Spain. Section 6 reports further cross-country evidence for our set of European countries. Finally, Section 7 draws some brief conclusions. An

[4] For this reason, we refrain throughout the paper from readily admitting a causal interpretation of our results.

[5] See Dearden et al. (2002) for similar arguments in a study of the effects of school quality on students´ labour market outcomes.

Appendix gathers furthers details about the construction of an EPL duality index for these countries.

2. Related Literature Review

From a European cross-country perspective, the closest studies to ours are Arulampanam et al. (2004) and Bassanini et al. (2007) who use panel data from the European Community House Panel (ECHP, waves 1995-2001) to deal with the effects of FTC and PC on OJT. Their focus is mostly on the extensive margin of OJT since ECHP has rather limited information on training duration and intensity.[6] In general they find that temporary workers receive less training but the results are heterogeneous and not too precisely estimated. More recently, a comprehensive empirical analysis based on PIACC has also been undertaken in OECD Employment Outlook (2014), using pooled data for a large set of OECD countries. The main finding is that being on a FTC reduces the probability of receiving employer-sponsored training by 14%. However, their interpretation of this negative effect relies on the fixed-term nature of temporary contracts, which reduces the returns to training, without considering the possibility that, as in Spain, firms may retain workers by upgrading their contracts to PC. [7]

As regards, the relationship between dualism and the incidence of occupational training in Spain, it is worth highlighting the work of Alba-Ramirez (1994) and De la Rica et al. (2008). In both cases, they document that firms invest less in training temporary workers given their high turnover rates. However, they do not examine how the amount of training has varied with the changes observed in the EPL gap. This result is also in line with the findings by Arulampalam et al. (2004) that Spain is one of the countries where being on a fixed-term contract is associated with lower training. In line with this approach, Dolado et al. (2013) present a model where the decisions of employers and workers interact in a dual labour market akin to the Spanish one. Their main result is that, when the EPL gap is large, not only employers find it unprofitable to invest in training temporary workers but also that these workers would respond to the lower and more uncertain promotion prospects by exerting lower effort. This leads to self-fulfilling prophecies where employers do not invest in workers, expecting that they will not exert enough effort, and workers fulfill these expectations by rationally anticipating very low promotion prospects. Using a large panel dataset of manufacturing firms, and focusing on major EPL reforms in Spain, they show that increases (decreases) in the EPL gap lead to lower *temp-to-perm* conversion rates and that the latter imply lower TFP growth at the firm level. Yet, due to lack of information on training and workers' effort in their dataset, they cannot explore the kind of issues we are able to consider here.

In addition, Garda (2013) has recently analyzed the size of wage losses experienced by those workers who have been displaced to other firms as a result of having been subject to a

[6] See Section 2.6 in Bassanini et al. (2007) for a detailed discussion on this issue.

[7] After this draft of the paper was completed, we became aware of a recent paper by Ferreira et al. (2015) which also uses PIAAC data to analyze whether workers under FTC engage more often that workers under PC in *informal* (rather than formal) training activities. Their results will be discussed further below in Section 6.

collective dismissal (ERE) in their previous firm. If firms provide a higher level of specific training to workers under PC than to those under FTC, the loss of this type of human capital will be more significant for the first type of workers than for the second. Therefore, we would expect to find higher wage losses among workers with PC. Using the Social Security records and controlling by job tenure, sector of activity and other covariates, the results confirm that permanent workers subject to EREs suffer higher and more permanent wage cuts than those with FTC.

Lastly, as anticipated in the Introduction, we end this section with a brief discussion on how results derived from non-experimental and quasi-experimental studies compare as regards the effects of temporary work on, say, earnings or employment stability. Most of the literature on the labour market impact of FTC has relied on regression analysis and other non-experimental identification techniques. Yet, to our knowledge, there are only two quasi-experimental studies, one by Autor and Houseman (2010) on temporary-help jobs in the US and another by Garcia-Perez et al. (2014) on FTC in Spain. On the one hand, the first study uses data from a city of Detroit´s welfare-to-work program where workers are randomly assigned to contractors with different placement rates into temporary-help (TH) and direct-hire (DH) jobs. The results in OLS and IV models (using contractor assignments as instrumental variables) differ: while OLS show that TH jobs increase earnings and employment of welfare clients relative to nonparticipants in the program, no statistically significant effects are obtained from IV. It is argued that this difference may arise because OLS captures effects for average clients while IV does so for marginal ones (i.e., those less able to find jobs through family contacts and friends). However, unlike ours, their dataset does not contain information on family background or work experience since labour market entry, which could help control for omitted network effects. On the other hand, Garcia-Perez et al. (2014) uses Social Security records in Spain to assess the long-term impact of FTC deregulation on the two above-mentioned outcomes, following the 1984 EPL reform which facilitated the widespread use of temporary contracts. Focusing on male school dropouts at age 16, they use a cohort regression discontinuity design (RDD) comparing youngsters who entered the labour market just before and right after the reform, under the assumption that differences in entry dates are fairly random. In contrast to Autor and Houseman (2010), the RRD estimates have the same sign and their sizes are in the same ballpark as other studies which use OLS regressions with a large set of controls (see e.g., Amuedo-Dorantes and Serrano-Padial, 2007 and Guell and Petrongolo, 2007) or even as those which use dynamic simulation techniques (Aguirregabíria and Alonso-Borrego).

3. A MODEL OF OJT IN A DUAL LABOUR MARKET

3.1 Preliminaries

In our stylized model, inspired by BG' s (2012) search and matching model of a dual labour market, there is mass one of risk-neutral workers who actively search for a job when unemployed. Workers differ in their (time-invariant) flow utility being unemployed, denoted by z which is not observable to firms and is drawn from a continuous c.d.f. $G(z)$ over the support $[0, \bar{z}]$. Since this idiosyncratic utility of leisure is not observable, workers are identical for firms.

Labour productivity is $y > 0$ and each job is subject to an adverse permanent shock whereby productivity falls to 0 with instantaneous probability μ. Two types of contract exist in the economy: temporary and permanent contracts. In our setup, they differ in that dismissals of permanent workers entail severance pay $F > 0$ (i.e., a transfer from the firm to the worker) whereas $F = 0$ when dismissing temporary workers. Thus, F can be interpreted as the redundancy pay gap between these types of workers.[8] Furthermore, there is a probability α that a temporary contract may be transformed into a permanent one in the same job.[9] Firms can freely decide on to open either temporary or permanent ($i = p,\ t$) vacancies in different submarkets at an identical flow posting cost equal to c. Unemployed workers are freely to move across submarkets but cannot search simultaneously on both. Thus there is direct search. In each submarket, frictions are modeled through standard matching functions $m(u_i, v_i)$, where u_i and v_i denote the measures of vacancies and unemployed workers in submarket i, respectively. From each matching function we can define the corresponding job filling rate $q_i(\theta_i)$ and the job finding rate $h_i(\theta_i) = \theta_i q_i(\theta_i)$ in the *i-th* submarket, where $\theta_i = v_i / u_i$ is the submarket-specific labour market tightness. As is well known, $q_i(\theta_i)$ and $h_i(\theta_i)$ are decreasing and increasing functions of θ_i, respectively and are assumed to satisfy the standard Mortensen-Pissarides conditions when $\theta_i \to 0$ and $\theta_i \to \infty$.

Each match signs a long-term contract that sets a wage for the entire employment relationship without ex-post renegotiation. BG (2012) argue that this wage setting is in the spirit of Hall (2005) whereby any wage within the parties' bargaining set at the time of job creation can be supported as an equilibrium. To make the problem interesting we follow these authors in assuming that $w_p = w_t = w$, and $\bar{z} < w < y$, so that all workers participate in the labour market and, to capture no discriminatory rules for workers in different submarkets, wages are set to be the same. Finally the equilibrium of the model is characterized by free-entry conditions in each submarket and by workers' sorting across submarkets.

[8] Our model departs from BG (2012) in that these authors assume that workers under permanent contracts cannot be dismissed when an adverse productivity shock occurs while temporary contracts can be broken by the firm at will. In their model, firms hiring workers under permanent contracts can only rely on quits from existing jobs for downsizing, an assumption that we do not need in our version entailing severance pay. Furthermore, in contrast to Cahuc and Postel-Vinay (2002) and Bentolila et al. (2012), we take the shortcut of assuming the transition probability α is exogenous.

[9] Notice that $\alpha = \beta(1-\mu)$ where β is the *temp-to-perm* conversion rate.

3.2 Asset values

(I) Permanent contracts submarket

Let $U_p(z)$ and $W_p(z)$ denote asset values for an unemployed worker and for an employed worker in submarket of permanent contracts. Likewise, let $J_p(z)$ and V_p be the asset values of a permanent job and vacancy, respectively. The Bellman equations are:

$$rU_p(z) = z + h_p(\theta_p)\left[W_p(z) - U_p(z)\right] \tag{1}$$

$$rW_p(z) = w + \mu\left[U_p(z) + F - W_p(z)\right] \tag{2}$$

$$rJ_p(z) = y - w + \mu\left[V_p - F - J_p(z)\right] \tag{3}$$

$$rV_p = -c + q_p(\theta_p)\left[J_p(z) - V_p\right] \tag{4}$$

where (3) takes into account that a firm dismissing a permanent worker with probability μ has to pay severance pay equal to F. Assuming free entry in this submarket, $V_p = 0$, and using (3) and (4) yields:

$$J_p(z) = \frac{y - w - \mu F}{r + \mu} > 0 \tag{5}$$

$$c = q_p(\theta_p) J_p(z) \tag{6}$$

(II) Temporary contracts submarket

With similar notation for the asset values in this submarket (this time using subscript t), we get the following Bellman equations:

$$rU_t(z) = z + h_t(\theta_t)\left[W_t(z) - U_t(z)\right] \tag{7}$$

$$rW_t(z) = w + \mu\left[U_t(z) - W_t(z)\right] + \alpha\left[W_p(z) - W_t(z)\right] \tag{8}$$

$$rJ_t(z) = y - w + \mu\left[V_t - J_t(z)\right] + \alpha\left[J_p(z) - J_t(z)\right] \tag{9}$$

$$rV_t = -c + q_t(\theta_t)\left[J_t(z) - V_t\right] \tag{10}$$

From (5), (9) and (10), we get:

$$J_t = \frac{y - w + \alpha J_p}{r + \mu + \alpha} = \frac{y - w}{r + \mu + \alpha} + \frac{\alpha(y - w - \mu F)}{r + \mu} \tag{11}$$

$$c = q_t(\theta_t)J_t(z) \tag{12}$$

It can be easily checked that $(r+\mu+\alpha)[J_t(z)-J_p(z)] = \mu F > 0$, and so $J_t(z) > J_p(z)$. The insight for this inequality is that, despite having lower expected duration, it is more profitable for firms to fill a temporary job since they do not need to pay firing costs in the face of adverse productivity shocks. Moreover, since $q_t(\theta_t)J_t(z) = q_p(\theta_t)J_p(z)$ from (6) and (12), from the properties of the matching functions it holds that that $q_t(\theta_t) < q_p(\theta_p)$ and, conversely, $h_t(\theta_t) > h_p(\theta_p)$. The former inequality implies that the job filling rate of a permanent vacancy is larger than that of a temporary vacancy whereas the opposite holds for the job finding rates.

(III) Workers' sorting

As BG (2012) point out, unemployed workers take as given the above-mentioned job finding rates and decide optimally in which submarket to search for a job by comparing $U_p(z)$ to $U_t(z)$. If $U_t(z) > U_p(z)$, they will search in in the submarket of temporary contracts, and vice versa. This leads to the existence of a threshold value for the utility of leisure, z^*, such that $U_t(z^*) = U_p(z^*)$ implying that unemployed workers search in the submarket of permanent contracts for $z > z^*$. Combining (1) with (2) and (7) with (8), yields

$$z^* = w - \frac{h_p(\theta_p)(r+\mu+h_t(\theta_t)) - \alpha(h_t(\theta_t)-h_p(\theta_p))}{(r+\mu)+(h_t(\theta_t)-h_p(\theta_p))}\mu F$$

so that, for a sufficiently small value of α, the coefficient on F is positive and thus an increase in F lowers z^*. For $F = 0$, $z^* = w > \overline{z}$. The intuition is simple: since the wage is the same across the two submarkets, in the absence of severance pay, the fact that the job finding rate is higher for temporary jobs implies that it is better to search for a job in that submarket. By contrast, under severance pay, permanent jobs become more attractive.

3.3 Decisions on Training

Following BG (2012) again, we consider the possibility that firms may be able to return to high productivity $y > 0$ in the aftermath of an adverse shock by paying a lump-sum cost T in the form of training. Then, the Bellman equations for each of the jobs become:

$$rJ_p(z) = y - w + \mu\left[\max\{J_p(z)-T,\ V_p - F\} - J_p(z)\right] \tag{13}$$

$$rJ_t(z) = y - w + \mu\left[\max\{J_t(z)-T,\ V_t\} - J_t(z)\right] + \alpha\left[J_p(z) - J_t(z)\right] \tag{14}$$

Thus, under free entry, a firm with a permanent contract will *undergo* training if $J_p(z) > T - F$, while a firm with a temporary contract will *not undergo* training if $J_t(z) < T$. Given (3) and (11), these conditions translate into the following inequalities:

$$T < T_{upp} = \frac{y - w}{r + \mu} + \frac{rF}{r + \mu}$$

$$T > T_{low} = \frac{(r + \mu)(1 - \alpha) + \alpha}{(r + \mu + \alpha)(r + \mu)}(y - w) - \frac{\alpha \mu F}{r + \mu}$$

where T_{upp} and T_{low} are upper and lower bounds for T, such that $T_{low} < T_{upp}$, and for $T_{low} < T < T_{upp}$ training only takes place in the submarket of permanent contracts.

The novel result in relation to BG (2012) is that while T_{upp} increases with F, T_{low} decreases. Thus, for given T, it is more likely that firms will only provide training to workers under permanent contracts in dual labour markets (where F is large), than in more unified labour markets (where F is smaller). This is the main theoretical prediction to be tested in the empirical section.

4. DATASET AND VARIABLES

The population of interest is defined by those individuals aged 16- 65 who participated in *Survey of Adult Skills* (PIAAC) and had the status of employees in the private sector at the time of the survey. As regards Spain, out of the 6055 individuals who fully responded to the questionnaires, about 2500 individuals were employees.

Our main control variable, *temporary contract*, is a dummy variable that takes value 1 when the contract is a temporary one (defined in PIACC as having a fixed-term contract, temporary employment with an employment agency, or some kind of training contract) and value 0 when the employee holds a permanent contract.

As argued earlier, our empirical approach consists of two sequential stages. First, we focus on testing whether holding a temporary contract is associated with a lower propensity of being involved in training activities provided by the firm. Next, we analyze how the amount of and intensity of training affects the employees' human capital, approximated by *literacy* and *numeracy* skills according to the scores available in the PIAAC database.

To empirically evaluate the validity of these predictions, we consider as training outcomes two proxies of specific human capital accumulation at the workplace. First, we use an indicator variable, D^{OJT}, which takes the value 1 if the worker claims to have attended a training session organized in the workplace or provided by their supervisors or colleagues in the past 12 months, and 0 otherwise. Thus, this variable captures the extensive margin of OJT.[13]

To capture the intensive margin of OJT, we use an additional outcome variable which measures the number of training activities attended by the worker during the past 12 months, denoted as n^{OJT}. It should be noted that, in accordance with the design of the survey, the respondent should count all training tasks that are interrelated as a single activity, even if they have taken place on different days. The essential feature of each activity is that it should be designed "to facilitate the adaptation of personnel to a particular set of new competences"[14]. Therefore, the variable n^{OJT} reflects the intensity of investment in new competencies regardless of their level of difficulty or the time that has been devoted to each one of them.

It is plausible that differences in the training processes within the firm generate differences in workers' promotion opportunities to reach better contracts. However, the extent to which these differences in specific human capital accumulation could lead to differences in general human capital remains an open question. To address this issue, we analyze the effect of OJT activities on the two measurements of general cognitive skills reported in the PIAAC sample, namely, the test scores achieved onliteracy and numeracy. Notice that by including a large range of controls (including educational attainments and parental background) in these last regressions, our interpretation of the latter results would be akin to "value-added" effects, namely the extra skills obtained through OJT on top of those predicted by above-mentioned individual characteristics.

5. Evidence on Spain

5.1 Sample Characteristics and Model Specification

Table 1 presents sample descriptive statistics in Spain of the main outcome variables in the subsequent empirical analysis, i.e., the availability and intensity of formal OTJ activities, the perception on the efficacy of the training process and, finally, the scores in both tests. At first

[13] According to PIAAC, these formal training sessions should be characterized "by planned periods of training, instruction or practical experience, using the normal methods of work." For example, they include "training or instruction courses organized by the directors, managers or colleagues to help the respondent to do their job better or to familiarize them with their new tasks." In particular, the four questions considered to define incidence in formal OJT are: "*Participated in courses conducted through open or distance education?*", "*Attended any organizd sessions for on-the-job training or training by supervisors/co-workers?*", "*Participated in seminars or workshops?*", and "*Participated in courses or private lessons not already reported?*".

[14] PIAAC also provides a subjective measurement that reflects to some degree the intensity with which the worker acquires new skills in the job. In the survey, workers are asked to indicate, approximately, the frequency with which their job involves learning new skills. Besides the problem of interpretation often encountered with such subjective statements, this variable does not have enough variation to be really informative: over 90% of respondents reply that their job involves learning new skills "at least once a month." For these reasons, we have decided to discard it in this study.

sight, the results of Table 1 seem fairly consistent with the basic predictions of the model. Temporary workers undertake less training activities than permanent workers. This finding is robust both at the *extensive margin* (i.e., using D^{OJT} as a measure of the availability of training) and the *intensive margin* (i.e., using n^{OJT} as a measure of the intensity of training). Finally, both literacy and numeracy scores are significantly lower among temporary workers.

Table 1. Descriptive Statistics (PIAAC, Spain)

Panel A	**No. Obs.**	**Pop. 16- 65 years[a]**	**Employed[a]**	**Employees[a]**	
PIAAC sample	6055				
Sample with ages between 16 and 65 years old	5954				
Type of workers	3060	53.18			
Self-employed	547	9.41	17.69		
Employee	2513	43.77	82.31		
Temporary	589	9.71	18.26	22.18	
Panel B	Training and abilities by type of contract[a]		Difference (abs and %)	Stand. Dev.[b]	P-value
	Permanent	**Temporary**			
Percentage of employees with training activities	48.43	31.81	16.62 (52.25)	2.35	0.000
Average number of activities	2.85	2.23	0.62 (22.32)	0.29	0.053
Index of literacy[c]	262.68	255.63	7.05 (2.76)	2.10	0.001
Index of numeracy [c]	260.94	246.81	14.13 (5.73)	2.00	0.000
	$D^{OJT}=1$	$D^{OJT}=0$			
Index of reading literacy [c]	268.89	254.69	14.20 (5.58)	1.51	0.000
Index of numeracy [c]	268.09	249.44	18.65 (7.48)	1.49	0.000

Notes: A worker has a temporary contract when he/she has a fixed-term contract, a temporary job with a temporary work agency or any type of training contract. D^{OJT} takes the value 1 when the worker claims to have attended training activities in the last 12 months, and 0 in the opposite case. The indices of *literacy* and *numeracy* are measurements attributed from the responses to exercises which are part of the survey. *Literacy* measures the ability to understand and use texts (written or in a digital format) in different contexts, while *numeracy* measures the use, application, interpretation and communication of mathematical information and ideas.
[a] Percentages of population estimated using weights of the whole sample as weightings.
[b] Using the replication method JK1.
[c] Using the attributed value 5.

However, as pointed out in the Introduction, it is important to stress that the negative relationship reported in Table 1 between temporary contracts and OJT activities does not necessarily imply causality, since both the type of contract and training activities could be jointly affected by other variables. For example, consider a worker with a high level of motivation to perform well in the job. Then, precisely because of this feature, this individual could influence his/her employer to obtain a permanent contract and freely choose to participate intensively in OJT activities. In that case, a positive correlation between having a permanent contract and participation in training activities would be observed but the intense process of accumulating specific human capital would be the result of the high motivation of the individual, not of holding a permanent contract. To avoid such confounding issues in our analysis, it is essential to control for a vast array of potential factors which simultaneously affect the respective outcome variables (i.e., predetermined variables both related to training activities as well as the skills competence variables) and the treatment variable (in our case, the type of contract).

To do so we start by presenting in the next section the estimates obtained from several econometric models which include two types of controls. First, we use individuals' basic characteristics such as age, gender, educational attainment, marital status, children, immigrant status, and parental educational background. In addition, we will also control for a potentially key variable which often is not available in other datasets but which PIAAC reports. This is the degree of worker's motivation, measured by a dummy variable, denoted as *motivation*, which takes the value 1 when the individual claims to feel identified "to a great extent" or "to a very great extent" with learning new skills, with working out difficult tasks, with relating new things to what they already know, and with seeking more information when they do not understand something". Secondly, in some specifications we also control for occupational dummies (as measured by the ISCO08 classification to two digits), industry dummies (as measured by the one-digit classification from the fourth ISIC revision) as well as having a part-time job.

In addition to standard regression models, we take a second approach which involves controlling for selection in observables using propensity score matching techniques (PSM). In our setup, PSM involves matching each individual holding a temporary contract with one or more individuals who hold permanent contracts but who would be similar to a temporary worker in all other observable characteristics. In this way, we effectively create matched "treatment" and "control" samples of employees under temporary and permanent contracts who are "statistical twins" in every other observable respect (Rosenbaum and Rubin, 1983). If matching is sufficiently good, differences in mean outcomes (e.g., OJT availability and intensity, cognitive scores) may be used as estimates of the causal effect of holding a temporary contract.

5.2 DUAL EPL AND OJT GAPS

Table 2 reports marginal effects of the covariates in a *probit* model explaining the probability of receiving training at the workplace ($D^{OJT} = 1$) as a function of our variable of interest, *temporary contract*, plus a wide array of controls. In column [1], we present the results in the case when type of contract is the only covariate in this model. In column [2], job tenure, worker's age and its square (as a proxy for potential experience, given the higher educational level reached), gender (female = 1) and educational level (with a low level as the reference category) are included as additional covariates. In column [3], the previous group of controls is extended by also including dummy variables of the parents' educational level, marital status, immigrant status and the degree of motivation of the worker. In column [4], dummy variables of sector/industry and occupation are also added. Finally in column [5], which constitutes the more general specification of the *probit* model, the literacy and numeracy scores contained in PIAAC are also included as additional proxies of unobserved ability before training.[16] For convenience, this ordering by columns, from the most restrictive specification to the most general, is kept for the rest of Tables in this section. It is also important to note that the

[16] In spite of the fact that these scores are measured at the time of the survey and that, as shown below, they are endogenous (since they are affected by OJT which itself depends on holding a temporary contract), we use them in column [5] to check that the results reported in columns [2] to [4] are fairly robust to the inclusion of scores.

number of observations in the different specifications varies slightly because some controls are not available for all individuals analyzed in the larger samples.

Table 2. Probit Model (Marginal Effects). Dep. variable: D^{OJT}

	[1]	[2]	[3]	[4]	[5]
Temporary contract	**-0.1636*** **	**-0.0923*** **	**-0.0795*** **	**-0.0774*** **	**-0.0732*** **
	(0.0223)	**(0.0265)**	**(0.0284)**	**(0.0306)**	**(0.0302)**
Job tenure	---	**0.0053*** **	**0.0049*** **	**0.0035** **	**0.0037** **
		(0.0014)	(0.0015)	(0.0016)	(0.0015)
Age	---	**0.0132***	**0.0179** **	**0.0150***	**0.01460***
		(0.0071)	(0.0084)	(0.0088)	(0.0088)
(*Age*) ^{2} / 100	---	**-0.0002** **	**-0.0002** **	**-0.0002** **	**-0.0002** **
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	---	**-0.0359***	**-0.0376***	-0.0117	-0.0098
		(0.0205)	(0.0219)	(0.0270)	(0.0268)
Middle educational level	---	**0.1279*** **	**0.1359*** **	**0.0947*** **	**0.0899*** **
		(0.0286)	(0.0305)	(0.0329)	(0.0315)
High educational level	---	**0.2731*** **	**0.2550*** **	**0.1578*** **	**0.1479*** **
		(0.0227)	(0.0258)	(0.0328)	(0.0330)
Educational level of parents	No	No	Yes	Yes	Yes
Civil status, children	No	No	Yes	Yes	Yes
Immigrant	No	No	Yes	Yes	Yes
Motivation	No	No	Yes	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes	Yes
Literacy/Numeracy scores	No	No	No	No	Yes
					Yes
No. obs.	2503	2501	2258	2226	2243
Pseudo R-sq.	0.015	0.065	0.074	0.102	0.104
Prob. obs.	0.4371	0.4374	0.4353	0.4424	0.4424

Note: The marginal effects of the dichotomous variables are calculated as the change of the estimation of the probability when the variable changes from 0 to 1. *Temporary contract* variable is an indicator variable which takes the value 0 when the individual has a permanent contract and 1 when he/she has a temporary contract. *Job tenure* measures the duration of the current job. *Middle educational level* is a dichotomous variable which takes value 1 when an individual has vocational training at an intermediate level, the baccalaureate, or old higher baccalaureates and pre-university courses. *High educational level* takes a value of 1 when the individual has a tertiary education degree. The variables about the educational level of the parents are dichotomous variables for the three levels of education. *Civil status* reflects whether the individual is married, *Children* reflects whether they have children, and *immigrant* reflects whether the individual was born in this country. The *motivation* variable takes the value 1 when the individual claims to feel "greatly" or "very greatly" identified with the learning of new skills, working out difficult tasks, relating new things to what they already know, and looking for information when they don't understand something. In column [4]., the variables of *occupation* are obtained from the ISCO08 to two digits while the variables of *sector* are obtained with the one-digit classification from the fourth ISIC revision. In column [5], Literacy and Numeracy scores are obtained from PIAAC. Levels of significance: * p<0.10, ** p<0.05, *** p<0.01

The main finding in Table 2 is that, in line with our main prediction, the estimated coefficient on the *temporary contract* dummy variable is negative and highly statistically significant in all specifications. Furthermore, the estimates suggest that the marginal effect is quantitatively very relevant. In the absence of further controls (column [1]) , having a temporary contract is associated with a reduction in the probability of receiving OJT of 16.4 percentage points (pp.), where the baseline probability of receiving OTJ among permanent workers is 43.7%. By progressively adding further covariates, the estimated marginal effect is halved, falling to about 8-9 percentage points, a result which is fairly robust across columns [2] to [5].[20] Therefore, from this evidence one can infer that the detrimental effect of contractual instability on the specific training received in the workplace is substantial. For example, the marginal effects reported in the most extended specifications (columns [4]and [5]) imply that, for the typical worker with a permanent contract, switching to a temporary contract reduces the probability of receiving training at the workplace by between 17% and 18% (= -0.077/.437).

As for the other controls, it is worth pointing out that a higher educational level increases the probability of receiving OJT and also that this probability also increases with age up to a threshold of about 30 years due to the concave shape of the quadratic polynomial for this variable. Furthermore, although statistically less significant than the above-mentioned estimates, there is evidence about women having a lower probability of receiving OJT, although this gender effect disappears as the number of controls in columns [3] and [4] is extended. In this regard it should be pointed out that, as mentioned earlier, another variable (not reported in Table 2) which has been included in all the specifications is whether the individual has a part-time job (where the reference category is full-time work). Its inclusion did not change any of the previous results, either in this Table or in any of those shown further below, but it did cancel out the above-mentioned gender effect. This is probably due to the high incidence of part-time working schemes among female employees, making it impossible to identify whether the relevant covariate is gender or working part time. Finally, though not reported to save space, the coefficients on immigrant status and motivation proved to be significant in columns [3] to [5], with negative and positive signs, respectively.

We next report in Table 3 the results from estimating the coefficients of a count data model based on the *Negative Binomial* distribution (which is used after rejecting the equality of mean and variance implied by the more restrictive *Poisson* distribution), in order to detect the discrete nature of the dependent variable, namely, the number of training activities which the worker has attended over the past 12 months, n^{OJT}.

As can be inspected, the results for *temporary contract* are similar to those in Table 2, in the sense that the coefficient on this covariate systematically exhibits a negative sign, indicating again that holding a temporary contract reduces the number of OJT activities. However, unlike what happened in the *probit* model for D^{OJT}, the estimated coefficient on this variable is only statistically significant at the 10 percent level when all the controls are included. This may be due to the small number of individuals who report this information (around 1000), representing less than half the sample size used in the *probit* model.

[20] We also included an interaction term between *Temporary contract* and being younger than 30 years old. In this case the marginal effects are -0.1191 (0.0463) for younger workers and -0.0504 (0.0346) for older ones. However, a chi-square test cannot reject the null hypothesis that these marginal effects are the same (p-value=0.213).

Table 3. Negative Binomial Model (Coefficients). Dep. variable: n^{OJT}

	[1]	[2]	[3]	[4]	[5]
Temporary contract	**-0.1999*****	**-0.1666****	**-0.1445****	**-0.1399***	**-0.1197***
	(0.0512)	**(0.0614)**	**(0.0684)**	**(0.0709)**	**(0.0701)**
Job tenure	---	**0.0076***	0.0052	0.0049	0.0045
		(0.0039)	(0.0041)	(0.0043)	(0.0044)
Age	---	-0.0152	**-0.0417***	-0.0109	-0.0223
		(0.0193)	(0.0231)	(0.0236)	(0.0241)
$(Age)^2 / 100$	---	0.0066	0.00401	0.0043	0.0041
		(0.0239)	(0.0277)	(0.0281)	(0.0279)
Female	---	-0.0144	-0.0367	**-0.1367****	**-0.1158***
		(0.0543)	(0.0576)	(0.0657)	(0.0651)
Middle educational level	---	0.0574	-0.014	-0.0645	-0.0612
		(0.0846)	(0.0900)	(0.0923)	(0.0899)
High educational level	---	**0.2234*****	0.0954	0.0942	0.0899
		(0.0688)	(0.0769)	(0.0906)	(0.0912)
Educational level of parents	No	No	Yes	Yes	Yes
Civil status, children	No	No	Yes	Yes	Yes
Immigrant	No	No	Yes	Yes	Yes
Motivation	No	No	Yes	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes	Yes
Literacy/Numeracy scores	No	No	No	No	Yes
Dispersion Coefficient	-0.8518***	-0.8766***	-0.8999***	-1.1637***	-1.2357***
	(0.0689)	(0.0695)	(0.0736)	(0.0823)	(0.0807)
No. obs.	1092	1092	981	974	974
Pseudo R-squared	0.001	0.005	0.015	0.056	0.058

Note: The variable n^{OJT} measures the number of training activities which the worker has attended in the last 12 months. See the note in Table 2 for the definition of the controls. Levels of significance: * p<0.10, ** p<0.05, *** p<0.01

A brief summary of the main findings reported so far indicates that holding a temporary contract exhibits a negative relationship with training availability and intensity. Moreover, the finding that the estimated relationship is more robust to model specification when the dependent variable is D^{OJT} may be due to its smaller measurement error relative to the other outcome variable.

5.3 OJT and Test Score Gaps

In view of these results, the next step is to check how the availability or the intensity of OJT activities is related to the individual's test scores in the PIAAC *literacy* and *numeracy* tests. To do so, we present the results derived from estimating a linear regression model by OLS, where the outcome variables are the test scores and the covariates of interest are the two margins of OJT discussed above. Note that in both models the *temporary contract* treatment variable is excluded from the set of controls in order to test whether the effect of this variable on the test scores is mainly due to the amount of OJT workers receive at the workplace, and not to any other channels associated to holding such contracts.

Tables 4 and 5 present the estimated coefficients in a regression where the dependent variable is *literacy* and *numeracy*, respectively. Columns [1] and [2] in both Tables differ in that D^{OJT} is used as a covariate in the first column while n^{OJT} is used in the second column. As can be inspected, the results indicate that both variables exhibit a positive relationship with PIAAC test scores, though its statistical significance in the case of *literacy* is low in the last two columns of Table 5 where more general specifications are considered. By contrast, this estimated coefficient tends to be larger and statistically more significant when the relationship between D^{OJT} and *numeracy* is examined in Table 5. Hence, from the comparison of the estimates in these two Tables with the raw differences reported in Table 1 between the PIAAC test scores achieved by employees with and without OJT (14.2 pp. in *literacy* and 18.6 pp. in numeracy), we get that, *ceteris paribus*, the availability of such specific training activities accounts for 15 % (2 pp.) and 28% (5 pp.) of the raw test score gaps in *literacy* and *numeracy*, respectively.

Table 4. Ordinary Least Squares (Coefficients). Dep. variable*: Literacy* test scores.

	[1]	[2]	[3]	[4]
D^{OJT}	**3.5467****	---	**2.0723**	**1.2566**
	(1.5939)		**(1.6009)**	**(1.6095)**
n^{OJT}	---	**0.5380****	---	---
		(0.2557)		
Job tenure	**0.2672****	**0.3766****	0.1667	0.0734
	(0.1059)	(0.1727)	(0.1085)	(0.1119)
Age	**2.6996*****	**2.6412*****	**3.4779*****	**3.6443*****
	(0.5096)	(0.8166)	(0.5709)	(0.5850)
$(Age)^2 / 100$	**-4.2135*****	**-4.1243*****	**-4.9442*****	**-5.1794*****
	(0.6347)	(1.0341)	(0.6886)	(0.7046)
Female	**-9.2612*****	**-7.8979*****	**-7.4145*****	**-9.7869*****
	(1.5476)	(2.3168)	(1.5449)	(1.9085)
Middle educational level	**24.1234*****	**24.1112*****	**21.7160*****	**17.6391*****
	(2.2114)	(3.6625)	(2.2112)	(2.3179)
High educational level	**45.3710*****	**45.8212*****	**36.8107*****	**24.6992*****
	(1.8098)	(2.8883)	(1.9208)	(2.2671)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2807	1162	2536	2475
R-sq.	0.250	0.219	0.295	0.327

Note: Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Table 5. Ordinary Least Squares (Coefficients). Dep. variable: *Numeracy* scores.

	[1]	[2]	[3]	[4]
D^{OJT}	**7.4523*****	---	**5.7716*****	**3.7712****
	(1.6198)		**(1.6325)**	**(1.6500)**
n^{OJT}	---	1.3888	---	---
		(1.2555)		
Job tenure	**0.3878*****	**0.3854****	**0.2628****	0.1511
	(0.1055)	(0.1728)	(0.1094)	(0.1135)
Age	**2.5632*****	**3.1910*****	**3.1082*****	**3.2456*****
	(0.5295)	(0.8415)	(0.5917)	(0.6103)
$(Age)^2 / 100$	**-4.1618*****	**-4.8786*****	**-4.6634*****	**-4.8173*****
	(0.6566)	(1.0565)	(0.7117)	(0.7327)
Female	**-16.9921*****	**-14.6935*****	**-16.3784*****	**-16.4630*****
	(1.5759)	(2.3156)	(1.5976)	(1.9500)
Middle educational level	**25.9530*****	**27.3051*****	**23.1693*****	**18.6021*****
	(2.2359)	(3.6899)	(2.2672)	(2.4043)
High educational level	**48.1732*****	**48.5652*****	**39.9913*****	**27.4181*****
	(1.8621)	(3.0138)	(1.9874)	(2.3328)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2807	1162	2536	2475
R-sq.	0.288	0.247	0.322	0.35

Note: See the notes of Tables 1 and 2 for definitions of the variables.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Therefore, our evidence suggests that the availability of training at the workplace and, to a lesser extent, the intensity of this training is associated with a significant improvement of workers' cognitive skills. In order to check whether this correlation is mainly due to holding a temporary contract, this covariate is now included in the previous specifications, in addition to the two training variables. The main result that we find (not reported in the Tables for sake of brevity) is that the coefficient on *temporary contract* is never significant and the estimated coefficients on D^{OJT} and n^{OJT} hardly experience any significant changes.[21] Thus, we conclude that OJT plays an important role in explaining the relationship between type of contracts and PIAAC scores.

Next, Table 6 (dependent variable: *literacy*) and Table 7 (dependent variable: *numeracy*) report the estimated coefficients obtained from the reduced forms of the previous models in which the training variables are now replaced by the *temporary contract* covariate, to which the remaining array of controls are gradually added. The idea of these reduced forms is that, if the

[21] For example, the estimated coefficient on D^{OJT} in most extended specification is 3.465 (s.e.: 1.692) whereas that on *temporary contract* is -0.065 (s.e.: 0.113).

mechanism we explore is valid, we should expect that, *ceteris paribus*, being a temporary worker has a negative effect on the scores mainly through the reduction of the amount of OJT they undertake, and not so much through other alternative channels. The results are supportive since the coefficients on *temporary contract* in all specifications are always negative and statistically significant, albeit only at the 10 percent level in columns [3] and [4].

Table 6. Ordinary Least Squares (Reduced Form). Dep. variable: *Literacy* test scores

	[1]	[2]	[3]	[4]
Temporary contract	**-6.5503*** **	**-5.0915*** **	**-4.9321** **	**-4.0831* **
	(2.2086)	**(2.1914)**	**(2.3618)**	**(2.2537)**
Job tenure	---	**0.2758** **	**0.1982* **	0.0748
		(0.1174)	(0.1204)	(0.1236)
Age	---	**3.2708*** **	**3.6018*** **	**3.5278*** **
		(0.5666)	(0.6226)	(0.6257)
(*Age*) ^{2} / 100	---	**-0.0479*** **	**-0.0511*** **	**-0.0505*** **
		(0.0070)	(0.0075)	(0.0075)
Female	---	**-8.3752*** **	**-7.2715*** **	**-9.6194*** **
		(1.6260)	(1.6280)	(1.9786)
Middle educational level	---	**22.3422*** **	**21.6332*** **	**17.4162*** **
		(2.3669)	(2.3380)	(2.4210)
High educational level	---	**42.0032*** **	**37.3696*** **	**24.7004*** **
		(2.8883)	(1.9208)	(2.2671)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2513	2447	2266	2244
R-sq.	0.003	0.262	0.291	0.321

Note: See the notes of Tables 1 and 2 for definitions of the variables.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Table 7. Ordinary Least Squares (Reduced Form). Dep. variable: *Numeracy test* scores.

	[1]	[2]	[3]	[4]
Temporary contract	**-12.5522*** **	**-4.5196** **	**-3.8685***	**-3.5884***
	(2.2851)	**(2.2124)**	**(2.2375)**	**(2.2010)**
Job tenure	---	**0.3751*** **	**0.2631** **	0.1115
		(0.1190)	(0.1217)	(0.1253)
Age	---	**3.2379*** **	**3.4562*** **	**3.4258*** **
		(0.5779)	(0.6392)	(0.6438)
$(Age)^2/100$	---	**-0.0486*** **	**-0.0509*** **	**-0.0503*** **
		(0.0071)	(0.0077)	(0.0077)
Female	---	**-15.8232*** **	**-15.6563*** **	**-15.7823*** **
		(1.6537)	(1.6757)	(2.0082)
Middle educational level	---	**23.6664*** **	**22.8811*** **	**18.3916*** **
		(2.3976)	(2.3863)	(2.4894)
High educational level	---	**44.2566*** **	**40.2667*** **	**27.2830*** **
		(2.0353)	(2.0713)	(2.3874)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2513	2447	2266	2244
R-sq.	0.012	0.289	0.313	0.345

Note: See the notes of Tables 1 and 2 for definitions of the variables. Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Finally, Table 8 reports further results on the effects of the extensive margin of OJT on PIAAC scores, this time using a restricted control group. Following the strategy proposed by Leuven and Oosterbeek (2008), which is used in OECD (2014), this new control group for workers who received OJT includes those employees who had the possibility to undertake employer-sponsored training activities but ended up not doing so for exceptional and unexpected events.[22] Specifically, PIAAC contains two questions that can be used for this purpose. First, all workers are asked whether during the prior 12 months there were any learning activities they wanted to attend but did not. Those answering affirmatively are then asked to indicate the reasons why they could not attend OJT. We use as control group those who declare that they could not attend because either "the course or programme was offered at an inconvenient time or place" or "something unexpected came up that prevented [them] from taking education or training". The treatment and control groups contain 1237 and 216 individuals, respectively. As can be observed, the estimates are qualitatively similar to those reported earlier in specification [4] of Tables 4 and 5, although they turn out to be smaller in size and statistically insignificant in the case of literacy test scores.

.

[22] We are grateful to Andrea Bassanini for pointing out to us that this procedure had been used in an Annex containing further material for chapter 4 of the OECD Employment Outlook (2014).

Table 8. Ordinary Least Squares. Restricted sample. Dep. variables: *Numeracy & Literacy* test scores

	Numeracy	*Literacy*
D^{OJT}	**2.341****	1.121
	(1.213)	(1.219)
No. obs.	1453	1453
R-sq.	0.331	0.372

Note: Both specifications include those workers who did receive on the job training over the last 12 months as treatment group and those who were offered training but did not take it, either because of unexpected reasons or because the place and time of the course/ program were inconvenient, as control group. Additional covariates are the same as in specification [4] in Tables 5 and 6. Levels of significance: * p<0.10, ** p<0.05, *** p<0.01

5.4 Propensity score matching

We next present estimates of the relationship between holding a temporary contract and OJT availability and *numeracy* test scores using a PSM estimation method. For illustrative purposes, the reported results are restricted to these two outcome variables because they are the ones where the estimates presented above exhibit higher statistical significance. We use the nearest neighbour matching procedure which is available in the *teffects* Stata 11 command, because it computes more accurate standard errors than those computed by bootstrapping in other popular PSM estimation commands, as is the case of *psmatch2* (see Abadie and Imbens, 2011). After imposing the common support condition, we report two estimates of interest that are provided by this command: the average treatment effect (ATE) and the average treatment effect on the treated (ATT).

To assess the quality of the matching, Table 9 presents the differences between the mean values of a subset of the covariates (occupational and industry dummies are not reported to save space) which are used to match the treatment (temporary contract, TC) and control (permanent contract, PC) groups.

Table 9. Quality of matching procedure. Treatment: *Temporary contract*

Covariates	**Treated**	**Control**	**% bias**	***p*-value**
Tenure	3.6482	3.6825	-0.9	0.145
Age	34.914	34.389	1.5	0.424
Age2	13.348	13.083	2.1	0.597
Female	0.5335	0.5493	-1.3	0.126
Deduc2	0.2178	0.2071	2.6	0.662
Deduc3	0.3214	0.2978	7.9	0.223
Deduc4	0.0071	0.0059	4.6	0.469
Married	0.5214	0.5032	3.9	0.542
Children	0.4464	0.4257	4.3	0.485
Immigrant	0.2071	0.2136	-3.0	0.244
Motivation	0.4534	0.4732	-4.1	0.313
Df_ed2	0.1517	0.1375	1.0	0.497
Df_ed3	0.1142	0.1071	2.3	0.704
Dm_ed2	0.1182	0.1092	8.2	0.417
Dm_ed3	0.0696	0.0864	-6.7	0.195

Note: Calculations performed with the *teffects* module in Stata 11. Statistics for the remaining controls considered in column (4) of Tables 2 and 8 have been omitted for brevity but are available upon request.

Overall, the estimates in Table 9 confirm that our treatment and comparisons, though initially different, appear to be rather similar after the matching, with no significant statistical differences in the means of the reported values and only two significant ones among the 42 background variables used in PSM. They correspond to two of the (omitted) occupational and industry dummies.

Finally, Table 10 displays the ATE (column 2) and ATT (column 3) estimates of the relationship between *temporary contract* and OJT availability (D^{OJT}) and *numeracy* test scores using PSM estimation. For convenience we also append in column 1 the estimate of the marginal effect of temporary contract on D^{OJT} appearing in Table 2, as well as the OLS estimate of the coefficient on such variable in the regression model for the *numeracy* score in Table 8. As can be observed, the PSM estimates are very similar to those presented before. Despite being slightly less significant than the probit/OLS ones, they point out to an unambiguously negative effect of holding a temporary contract on both outcome variables. In fact the ATE estimates are higher than the ATT and probit/OLS estimates, suggesting that to the extent that *temporary contract* has a causal effect on these two outcomes, that effect would be somewhat higher for individuals less likely to work under such a contract.

Table 10. Treatment effects (Temporary contract, training availability and *Numeracy* test score)

	[1] **Probit/OLS**	**[2]** **PSM:ATE**	**[3]** **PSM: ATT**
D^{OJT}	**-0.0765*****	**-0.1035*****	**-0.0699****
	(0.0293)	(0.0334)	(0.0323)
Numeracy score	**-3.5884***	**-5.9952****	**-4.1304***
	(2.2010)	(2.5925)	(2.6002)

Note: Column 1 reports the probit marginal effects presented in in Table 2 whereas columns 2 and 3 show ATE and ATT-PSM estimates including all the covariates in the most extensive specification as controls. We impose the common support condition using the *teffects* Stata command which implements nearest-neighbour matching on an estimated propensity score. The standard errors implemented in *teffects psmatch* are those derived by Abadie and Imbens (2012). Levels of significance:* p<0.10, ** p<0.05, *** p<0.01

Overall the results presented in this section are consistent with the basic prediction of our model. Temporary workers are significantly less likely to engage in OJT activities at the workplace that workers under permanent contracts, even after controlling for a wide array of individual and job characteristics which include workers' motivation. By contrast, temporary workers do not seem to differ from permanent workers in their perceptions regarding the appropriateness of their training with respect to the skills requirements in their current jobs. Finally, both the scores on literacy and numeracy skills are significantly lower for workers who receive less training. Moreover, among those who receive OJT, the scores are lower for those who receive less training.

6. European Cross-Country Evidence

To provide further evidence on the general validity of the mechanism discussed above, we devote this section to report results for other European countries participating in PIAAC. In particular, we consider pooled data (around 41,000 and 18,000 observations regarding the OJT extensive and intensive margins, respectively) for 14 countries (including Spain), out of the 24 countries that participated in PIAAC.[23] The choice of specific countries is dictated by the availability in their datasets of the same covariates that were used before for the analysis of our case study.

6.1 Dual *vs*. unified labour makets

Our empirical strategy here adapts the one used for Spain to this cross-country study. For example, we run *Probit* and Negative Binomial regressions of OJT on the temporary contract dummy, a proxy of the EPL gap and the interaction between the two, in addition to the remaining covariates mentioned earlier. This would allow for a direct assessment of the link between EPL gaps and the impact of temporary work on OJT across countries. Notice that the interpretation of the interaction effect would even remain meaningful in presence of confounding unobserved factors that could bias the country-specific effects as long as the bias is not related to the EPL gaps (i.e., under the assumption that the bias is the same in all countries). In addition the statistical significance of the interaction term would allow for a direct assessment of the relevance between EPL gaps and the effects of holding a temporary contract on OJT.

To construct a country-level proxy of dual EPL, we use information drawn from the OECD EPL Database (update 2013, item 7: "Compensation following unfair dismissal") for PC and OECD (2014, Table 4.4, Column 4: "Severance pay at end date") for FTC. Through both pieces of information, we compute the gap in 2012 between the mandated severance pay (in terms of monthly wages) of an unfair dismissal of a permanent worker with *four* years of tenure and the total compensation pay (also in terms of monthly wages) associated to hiring four temporary workers in sequence with a one-year contract each which is not renewed at its end date.[24] The choice of four years relies on the existence of limits in some countries to use temporary contracts beyond that duration.[25] Whenever costs of dismissals are the same for both contracts, the corresponding EPL gap is set equal to zero. Table A1 in the Appendix reports some further details on our measure of the gaps. As can be seen, gaps range from about three monthly wages in Spain to zero in Ireland, UK and Russia.

The first two columns in Table 11 show the estimated marginal effects/coefficients on the *temporary contract* dummy and its interaction with EPL in the *Probit* and Negative Binomial models explaining OJT availability (D^{OJT}) and OJT intensity (n^{OJT}) for our pooled datasets. Likewise, for completeness, the last two columns report the coefficients on the two margins of

[23] Our sample of European countries includes Belgium, Czech Republic, Denmark, France, Ireland, Italy, Netherlands, Norway, Poland, Slovak Republic, Spain, Sweden, United Kingdom and Russian Federation. Other countries, like Austria, Finland or Germany, are excluded because important covariates, like age, parental education or occupation, are missing in their datasets.

[24] For example, in 2012, the dismissal costs of an unfair dismissal of a permanent worker in our illustrative country (Spain) were 33 days of wages per year of service (d.w.y.s.), so that after 5 years the total amount received by the worker would be 132 d.w.y.s. (=4x33). Each temporary worker was entitled to compensation of 10 d.w.y.s. for the non-renewal of her contract, so that the cost of the alternative strategy of hiring four temporary workers in sequence amounts to 40 d.w.y.s. (=4x10). Thus the EPL gap is 92 d.w.y.s. (=132-40) or about 3.1 monthly wages

[25] Yet, the gap would be proportional for any other job tenure of the dismissed worker (usually up to a cap between 20 and 30 years of tenure). So, for example, if the aforementioned hiring strategy were for 8 years instead of 4 years, the gap would double.

training in OLS regressions, and their interactions with the EPL gaps, in OLS regressions with the *Literacy* and *Numeracy* test scores as dependent variables. In all instances, the estimated models include country dummies while the remaining set of covariates is the one used in the most extensive specifications presented in Tables 2 to 6 for Spain.

Table 11. Estimated effects of Dual EPL on OJT and PIAAC test scores (pooled sample)

Dep. Variable/ Covariates	**OJT (ext. margin)**	**OJT (int. margin)**	***Literacy* test scores**	***Numeracy* test scores**
Temp. contract	**-0.0293******	**-0.0151******	--	--
	(0.0103)	(0.0265)		
Temp. contract*EPL gap	**-0.0151******	**-0.0389******	--	--
	(0.0060)	(0.0147)		
OJT (ext. margin)	--	--	**0.7562******	**2.156******
			(0.2167)	(0.328)
OJT (ext. marg.)*EPL gap	--	--	**0.1793******	**0.503******
			(0.0753)	(0.0696)
OJT (int. margin)	--	--	0.1944	0.3363
			(0.1273)	(0.2389)
OJT (int. marg.)*EPL gap	--	--	0.0345	0.1127
			(0.0676)	(0.0883)
No. obs.	41167	18838	41167	41167
Pseudo R-sq/ R-sq	0.092	0.029	0.321	0.308

Note: The first two columns gather results from the estimation of *probit* and NB models, where the last two columns correspond to OLS estimation of models for each of the test scores. The remaining covariates are those included in the last columns of Tables 2 to 6, in addition to country dummies. The Pseudo-R2 applies to the probit model. Levels of significance:* p<0.10, ** p<0.05, *** p<0.01.

As can be inspected in the first two columns, the estimated coefficients on the interaction terms are negative and highly significant, indicating that training gaps increase in countries where EPL gaps are large. For example, the gap in the extensive margin of OJT for the UK, one of the countries with unified employment protection (EPL gap=0), is 2.93pp. whereas it jumps to 7.6pp. (=0.0293+0.0151*3.1) in Spain, the epitome of a dual labour market (EPL gap=3.1). Similar results hold for the intensive margin. As regards the link of test score gaps with OJT gaps, the last two columns show that differentials in the extensive margin of OJT, rather than in the intensive margin, are strongly correlated with gaps in cognitive skills. Furthermore, the interaction term between the extensive margin and the EPL gap is positive and highly significant, indicating that if the training mechanism impinges on the tests score gaps this effect is bound to be stronger in dual than in more unified labour markets.

Table 12. Test Score Gaps by Type of Contract (Workers older than 30 years of age)

A. *Literacy* test scores		
	Spain	**UK**
Temp.contract	**-10.56*** **	**-14.83*** **
	(2.85)	(2.36)
Constant	**261.00*** **	**280.88*** **
	(1.18)	(0.82)
No. obs.	1990	3503
B. *Numeracy* test scores		
	Spain	**UK**
Temp.contract	**-12.23*** **	**-17.58*** **
	(2.92)	(2.61)
Constant	**258.90*** **	**273.88*** **
	(1.21)	(0.91)
No. obs.	1990	3503

Note: OLS estimates. No other covariates. Levels of significance:* p<0.10, ** p<0.05, *** p<0.01.

Finally, we end up by providing some suggestive evidence about selection into temporary contracts. It has been argued earlier than these contracts are likely to be *dead ends* in countries with dual labour markets whereas they are *stepping stone*s in countries with more unified labour markets. Our presumption is that adult and older workers, say above 30, under temporary contracts are likely to be negatively selected in the latter countries, since their chances of reaching a permanent contract earlier are high. In contrast, the opposite selection is likely to take place in the former countries, since the probability of working under a temporary contract at 30-35 years of age is still substantial (about 40% against 90% at entry age in Spain). Thus, we should expect that workers above 30 would perform relatively worse in PIAAC, say, in UK than in Spain.

Table 12 reports raw gaps in *Literacy* and *Numeracy* tests cores between *temps* and *perms* above 30 in those two countries. As can be seen, the gaps in the UK are particularly larger than in Spain. Thus, we conclude that, in terms of OJT and proficiency, what really matters is not having a temporary contract per se, but rather holding a very precarious one because of the strong duality in employment protection.

6.2 Formal *vs*. informal training

As mentioned earlier (see footnote 9) Ferreira et al. (2015) have recently used PIAAC data to test for differences in the intensive margin of formal and informal OJT between temporary and permanent workers. To do so they use pooled data for 20 OECD countries. Whereas their results for formal training do not differ much from ours, namely, workers under FTC receive less OJT, the opposite happens with informal learning. Their finding suggests that, on average, temporary employment need not be dead-end jobs since temporary workers would rationally invest on this kind of learning to improve their transition to more stable employment. Their definition of informal learning incidence is based on three questions from PIAAC. [26] They use a dummy variable for informal learning incidence that takes the value zero when none of the three questions were answered, and one otherwise. Since this dummy is equal to one in 95% of observations, we construct another dummy ever based on a more restrictive definition of informal learning which requires learning to have taken place at least once a month during the last 12 months. As before, we estimate a probit model where the probability of engaging in informal learning is explained by the TC dummy, its interaction with the index of labour market dualism regressed is incidence and a wide array of covariates corresponding to the specification in column [5] of Table 2 .

Table 13 reports the results for this model. As can be observed, they are similar to those shown in Table 11 for formal OJT in that workers under FTC experience less informal learning than workers under PC. However, in contrast to formal OJT, this effect is less negative in more dual labor markets (recall that the average of our duality measure is 1.23). Although these results differ from the ones reported by Ferreira et al. (2015), where it is claimed that FTC are positively correlated with informal learning, they point out that temporary workers in dual

[26] The three questions are: *"How often do you learn new work-related things from co-workers or supervisors?"*, *"How often does your job involve learning-by-doing from the tasks you perform?"*, and *"How often does your job involve keeping up-to-date with new products or services?"*.

labour markets may substitute for the lack of formal OJT by investing more on informal learning. [27]

Table 13. Probit model. (Marginal effects). Dep. Variable: Informal Learning

	[5]
Temporary contract	**-0.0635*** **
	(0.0106)
Temporary contract * EPL gap	**0.0239*** **
	(0.0064)
Job Tenure	0.0004
	(0.0003)
Age	**0.0079*** **
	(0.0018)
(*Age*) ^{2} / 100	**-0.0047** **
	(0.0021)
Female	**0.0318*** **
	(0.0060)
Middle educational level	**-0.0511*** **
	(0.0096)
High educational level	**-0.0947*** **
	(0.0107)
Country Dummies	Yes
Educational level of parents	Yes
Civil status, children, immigrant status, motivation	Yes
Dummies by Sector and Occupation	Yes
Literacy/Numeracy scores	Yes
No. obs.	40490
Pseudo R-sq.	0.078
Prob. obs.	0.5345

Note: The reported results correspond the estimates of the marginal effects of a Probit model as in column [5] of Table 2, and Table 11. The intensive margin of informal learning is defined as replying to at least one of the questions "(*How often do you learn new work-related things from co-workers or supervisors?", "How often does your job involve learning-by-doing from the tasks you perform?*", and *"How often does your job involve keeping up-to-date with new products or services?*") at least once a month during the last 12 months. Levels of significance:* p<0.10, ** p<0.05, *** p<0.01.

[27] To account for potential endogeneity of temporary job selection, Ferreira et al. (2015) use lagged unemployment rates by country, gender and age group. We also tried this IV and found very similar, though less precise, results to those reported in Table 13 (available upon request).

7. Conclusions

We began this paper by observing that the gap in OJT between permanent and temporary workers tends to be larger in labour markets where the transition to job stability is low, because of their dual EPL structure. On the basis of this observation, our goal here has been to analyze how the gap in severance pay between these types of workers may have affected the extensive and intensive margins of OJT that they receive at the workplace.

To address this issue, we first illustrate, by means of a simple search and matching model, the mechanism linking both gaps. In a context where firms and workers sort into permanent and temporary contracts and where, for non-discriminatory reasons, wages are the same in booth submarkets, a high EPL gap leads to a high OJT gap because differences in expected job durations between these types of workers exceed differences when the EPL gap is low. In addition, we argue that the underinvestment in training that temporary workers experience may have negative consequences over the skills competences that they acquire beyond the education system.

The cross-sectional database provided by PIAAC is used to explore these issues. Specifically, the availability of several different OJT measures, as well as workers' test scores on *literacy* and *numeracy* , allows us to check, firstly, the direct relation between the type of contract held by workers and the amount of OJT they receive and, secondly, whether the gap in training is correlated with the gap in cognitive skills.

We present econometric results for several outcome variables: two measures of training activities (availability and intensity), and another two measures of cognitive skills. For each econometric model (including propensity score matching estimation and a quasi-experimental design), we report results using different specifications. In our broader specification we consider (in addition to the *temporary contract* indicator) a wide set of person-level demographics, including proxy variables of the workers' family background, ability, motivation, and job characteristics.

Using Spanish data as an illustrative case study of the mechanism at hand, our main empirical findings support in general the existence of a positive relationship between labour market dualism and the training gap at the workplace, as well as a positive relationship between the amount/intensity of OJT activities and workers' cognitive skills. Furthermore, the previous results seem to hold for a wider set of European countries which differ in their degree of labour market dualism. In general, we find that in those countries where the EPL gap is large, the gap in training and in cognitive skills is also large. This could explain why temporary contracts become *dead ends* in dual labour markets whereas they play the role of *stepping stones* towards more stable jobs in more unified labour markets.

Although admittedly the cross-sectional nature of PIAAC makes it difficult to derive neat causal statements from such results, we argue however that the evidence presented here suggests that the proposed mechanism may have played a relevant role in explaining the previous facts.

REFERENCES

Abadie, A., and G. W. Imbens (2008): "On the Failure of the Bootstrap for Matching Estimators. *Econometrica* 76: 1537--1557.

Abadie, A., and G. W. Imbens (2012): " Matching on the Estimated Propensity Score". Harvard University and NBER. http://www.hks.harvard.edu/fs/aabadie/pscore.pdf.

Acemoglu, D. and J-S. Pischke (1999): "The Structure of Wages and Investment in General Training", *Journal of Political Economy*, 107, 539-572.

Alba-Ramirez, A. (1994): "Formal Training, Temporary Contracts, Productivity and Wages in Spain," *Oxford Bulletin of Economics and Statistics*, 56(2), 151--170.

Amuedo-Dorantes, C. (2001): "From "temp-to-perm": Promoting Permanent Employment in Spain," *International Journal of Manpower*, 22(7), 625--647.

Amuedo-Dorantes, C. and R. Serrano-Padial (2007): "Wage Growth Implications of Fixed-term Employment: An Analysis by Contract Duration and Job Mobility", *Labour Economics*, 2007, 14(5), 829-847.

Arulampalam, W., Booth, a. and M. Bryan (2004): "Training in Europe," *Journal of the European Economic Association*, 2, 346—360.

Autor, D. (2004) (2004): "Why Do Temporary Help Firms Provide Free General Skills?, *Quarterly Journal of Economics,* 116, 1409-1448.

Autor, D. and S. Houseman (2010): "Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from Work First", *American Economic Journal: Applied Economics*, 2, 96-128.

Bassanini, A., Booth, A., Brunello, G., De Paola, M. and E. Leuven (2007): "Training in the Workplace", in G. Brunello, P. Garibaldi and E. Wasmer (*eds.*), *Education and Training in Europe*, Oxford University Press.

Bassanini, A., L. Nunziata, and D. Venn (2009): "Job Protection Legislation and Productivity Growth in OECD Countries," *Economic Policy*, 24, 349-402.

Bentolila, S., Dolado, J. and J. F. Jimeno (2008): Two-tier Employment Protection Reforms: The Spanish Experience" *CES-Ifo-DICE, Journal for International Comparisons* (2008), 6, 49-56.

Bentolila, S., P. Cahuc, J. Dolado, and T. Le Barbanchon (2012): "Two-Tier Labour Markets in a Deep Recession: France vs. Spain," *The Economic Journal*, 122, 155-187.

Berton, F. and P. Garibaldi (2012): "Workers and Firms Soring into Temporary Jobs," *The Economic Journal*, 122, 125-154.

Blanchard, O. and A. Landier (2002): ""The Perverse Effects of Partial Labor Market Reform: Fixed Duration Contracts in France", *The Economic Journal*, 112, 214-244.

Boeri, T., Garibaldi, P. and E. Moen (2013): "The Economics of Severance Pay," IZA DP No. 7455.

Booth, A., Francesconi, M. and J. Frank (2002): "Temporary Jobs: Stepping Stones or Dead Ends?" *The Economic Journal,* 112, F189-F213.

Cahuc, P. and F. Postel-Vinay (2002): Temporary Jobs, Employment Protection and Labor Market Performance," *Labour Economics*, 9, 63-91.

Ciccone, A. and W. Garcia-Fontes (2008): "The Quality of the Catalan and Spanish Education Systems: A Perspective from PISA", Universitat Pompeu Fabra, mimeo.

De la Rica, S., J. Dolado, and V. Llorens (2008): "Ceilings or Floors? Gender Wage Gaps by Education in Spain," *Journal of Population Economics*, 21, 751-776.

Dearden, L., Ferri, J. and C. Meghir (2002): "2002. "The Effect Of School Quality On Educational Attainment And Wages," *The Review of Economics and Statistics*, 84, 1-20.

Dolado, J., C. Garcia-Serrano, and J. F. Jimeno (2002): Drawing Lessons From The Boom Of Temporary Jobs In Spain," *The Economic Journal*, 112(721), 270--295.

Dolado, J., Ortigueira, S. and R. Stucchi (2013): " Does Dual Employment Protection affect TFP? Evidence from Spanish Manufacturing Firms", mimeo, Universidad Carlos III de Madrid.

Eichhorst, W (2013): "The Unequal Distribution of Labor Market Risks: Permanent vs. Temporary Employment", IZA, http://www.iza.org/conference_files/EULaMaFuEm_2013/eichhorst_w2291.pdf

European Commision (2014): EU Skills Panorama. Brussels.

Ferreira, M., de Grip, A. and R. van der Velden (2015): "Does , Informal Learning at Work Differ between Temporary and Permanent Workers Evidence from 20 OECD countries", IZA DP 9322.

Fifth European Working Conditions Survey (2010). http://www.eurofound.europa.eu/surveys/ewcs/2010/

Garriga, C. (2010):."The Role of Construction in the Housing Boom and Bust in Spain., in S. Bentolila, M. Boldrin, J. Dolado and J. Diaz-Gimenez (*eds*.) , *The Crisis of the Spanish Economy*, Marcial Pons, 2010.

García Perez J.I, Marinescu, I. and J. Vall-Castello (2014): "Can Fixed-Term Contracts Put Low Skilled Youth on a Better Career Path? Evidence from Spain," FEDEA Working Paper 2014-08.

Garda, P. (2013): "Wage Losses after Displacement in Spain: The Role of Specific Human Capital," mimeo, Universitat Pompeu Fabra.

Güell, M. and B. Petrongolo (2007): "How Binding are Legal Limits? Transitions from Temporary to Permanent Work in Spain," *Labour Economics*, 14, 153--183.

Hall, R. (2005): " Employment Fluctuations with Equilibrium Wage Stickiness., *The American Economic Review*, 95, ,50-65.

Leuven, E. and H. Oosterbeek (2008): "An Alternative Approach to Estimate the Wage Returns to Work-related Training. *Journal of Applied Econometrics,* 23, 423-434.

OECD (2013): "Employment Protection Legislation, 2012-2013," OECD EPL database

OECD (2014): *Employment Outlook*. Chapter 4: Non Regular Employment, Job Security and the Labour Market Divide. Paris

Rosembaum, P. and D.B. Rubin (1983): "The Central role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41—55.

World Bank (2013): "Employing Workers Data", Doing Business Indicators.

Appendix (Construction of EPL gaps)

The construction of the EPL gap for each country in our sample is based on the following two pieces of information. On the one hand, OECD (2013) provides a detailed account of EPL rules for PC in OECD countries during 2012-2013. There are 21 items for each country summarizing severance pay, notice periods, rules for fair/unfair and for personal/collective dismissals, etc.; these items serve as inputs in the design of the well-known EPL categorical indicators which have been widely used in the literature (see, e.g., Boeri et al, 2013, for a nice overview). In particular, we choose item 7 where OECD provides a representative/average calculation in terms of monthly wages of "compensation following unfair dismissal of a worker under a PC with 20 years of tenure". Following our benchmark comparison of the redundancy costs for a firm which lays off a workers with a PC after 4 years of tenure against hiring four workers in sequence under one-year long FTC, the corresponding figure in item 7 is divided by 5. Column [1] in Table A1 gathers the severance pay for PC in each country. On the other hand, regarding EPL for FTC, we use information from OECD (2014, Table 4.4) where there are detailed descriptions of difficulty of dismissals, severance and notice period, procedural inconveniences, etc. Specifically we choose the item "notice and severance at end date of contract, expressed in monthly wages per year of service and multiplied it by 4. In some cases there is no compensation ("none") or it is the same as for FTC ("same"). Column [2] in Table A1 gathers this FTC non-renewal compensation cost. Finally, column [3] reports the EPL gap. If we were interest in the EPL gap at tenure $d \neq 4$ then the figures reported in column [3] should be multiplied by $d/4$.

Table A1 EPL gaps

	[1]	[2]	[3]
Belgium	2.07	None	**2.07**
Czech Rep.	1.20	None	**1.20**
Denmark	1.32	None	**1.32**
France	5.00	4.8	**0.20**
Ireland	2.14	Same	**0**
Italy	4.2	2.8	**1.40**
Netherlands	1.40	None	**1.40**
Norway	2.40	None	**2.40**
Poland	0.60	None	**0.60**
Russian Fed.	1.20	Same	**0**
Slovak. Rep.	2.40	None	**2.40**
Spain	4.40	1.33	**3.07**
Sweden	6.40	4.00	**2.40**
UK	1.10	Same	**0**

Note: [1] EPL for PC, [1] EPL for FTC, [3] EPL gap.