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# ABSTRACT

## Does Informal Learning at Work Differ between Temporary and Permanent Workers? Evidence from 20 OECD Countries*

Several studies have shown that employees with temporary contracts have lower training participation than those with permanent contracts. There is, however, no empirical literature on the difference in informal learning on the job between permanent and temporary workers. In this paper, we analyse this difference across 20 OECD countries using unique data from the recent PIAAC survey. Using a control function model with endogenous switching, we find that workers in temporary jobs engage in informal learning more intensively than their counterparts in permanent employment, although the former are, indeed, less likely to participate in formal training activities. In addition, we find evidence for complementarity between training and informal learning for both temporary and permanent employees. Our findings suggest that temporary employment need not be dead-end jobs. Instead, temporary jobs of high learning content could be a stepping stone towards permanent employment. However, our results also suggest that labour market segmentation in OECD countries occurs *within* temporary employment due to the distinction between jobs with low and high learning opportunities.

JEL Classification: E24, J24, J41

Keywords: temporary contracts, informal learning, training, human capital investments

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## 1. Introduction

The expansion of temporary work has raised serious concerns about undesirable labour market inequality and insecurity in many OECD countries. Various studies have found significant differences in wages as well as in training participation between permanent and temporary employees (e.g. Steijn *et al.*, 2006; O'Connell and Byrne, 2010; Comi and Grasseni, 2012; Cutulli and Guetto, 2013; OECD, 2014; Pfeifer, 2014). However, other studies show that temporary jobs could increase transition probabilities into permanent employment, and reduce subsequent unemployment rates (Booth *et al.*, 2002; Bover *et al.*, 2002; Gagliarducci, 2005; De Graaf-Zijl *et al.*, 2011; Cockx and Picchio, 2012; Jahn and Bentzen, 2012; Jahn and Pozzoli, 2013; Faccini, 2014).

Triggered by this trade-off, policy makers have stressed the importance of finding 'an appropriate balance between flexibility and security' to prevent a part of the labour force being trapped in 'dead-end' jobs (European Commission, 2003). Access to opportunities to develop workers' human capital is considered a crucial issue for many governments to create such a balance. However, little is known about the difference between temporary and permanent workers with respect to the intensity of informal learning on the job, i.e. the learning potential of their jobs (Rosen, 1972). In this paper, we analyse and estimate that difference across 20 OECD countries,[1] taking into account the potential endogeneity of temporary job selection. We estimate an endogenous switching regression model, using one lagged value of the unemployment rate by corresponding country and age group as an exclusion restriction, to provide more precise information about the importance of informal learning in the context of human capital accumulation and the potential career development of temporary employees.

Ideally, temporary work should function as a stepping stone that helps entrants to integrate into the labour market and then make the transition towards better stable employment. More on-the-job investments in human capital are expected to increase temporary workers' chances of finding permanent employment (Autor, 2001; Booth *et al.*, 2002; Gagliarducci, 2005; De Graaf-Zijl *et al.*, 2011; Jahn and Pozzoli, 2013). In view of that, OECD countries have shown a close interest in the securing of skills development at work and recognising informal learning as a rich source for it (OECD, 2010). The European Commission (2007, 2013) has explicitly considered lifelong learning strategies in the context of its so-called *flexicurity* agenda.

Due to a lack of appropriate data, particularly of international comparability, there is hardly any empirical evidence on the difference between temporary and permanent workers with respect to the intensity of human capital investments on the job. The literature on this has, therefore, focused on

[1] Table 1 shows the countries included in our analyses and the distribution of temporary and permanent employment within them.

training participation, although various studies have argued that employees spend much more time on informal learning in the workplace that contributes to the accumulation of human capital as a by-product of work (Arrow, 1962; Mincer, 1974, 1997; Koopmans et.al, 2006; De Grip, 2008). In the workplace, workers informally acquired new skills and competences while performing a combination of tasks, interacting with others, sensing the organisational culture, facing new job-related challenges, conducting trial-and-error experimentation, and observing, reading, or simply executing their job (Koopmans *et al.*, 2006; Billet, 2008; De Grip, 2008; Marsick *et al.*, 2009; Tannenbaum *et al.*, 2010).

Since individuals continue learning during their working career, the workplace is fundamental for human capital accumulation. On-the-job learning has been considered an investment that contributes to skills acquisition and, consequently, has some positive effect on workers' productivity and wage gains (Mincer 1968; Heckman, 1976; Killingsworth, 1982; Blundell *et al.*, 1999). However, in previous literature a concern has been raised about the quality of jobs and the opportunities for career development associated with temporary work (Arulampalam and Booth, 1998; Booth *et al.*, 2002).

In this paper, we analyse the extent to which the intensity of informal learning on the job differs between temporary and permanent employees. We thereby contribute to the literature in three ways. First, we assess the influence of temporary contracts on individual informal learning intensity on the job across 20 OECD countries. Second, we raise the issue of endogeneity of temporary contracts due to possible selection into such jobs, and account for the binary nature of the endogenous regressor. We estimate a control function (CF) model with endogenous switching, using one lagged value of the unemployment rate by country and age group as an exclusion restriction. Third, we explore whether there is substitution or complementarity between training and informal learning in the workplace for both temporary and permanent employees. For our empirical analyses we use data from the OECD Programme for International Assessment of Adult Competences (PIAAC) study conducted in 2012. This survey contains very detailed information on informal learning at work.

Our results show that workers in temporary jobs engage more intensively in informal learning than their counterparts in permanent contracts do, although the former are, indeed, less likely to participate in formal training activities. In addition, we find complementarity between training and informal learning for both temporary and regular employees. Assuming that workers strongly prefer permanent contracts, we argue that temporary employees engage more intensively in informal workplace learning to increase their chances of upward mobility in the labour market. In line with this hypothesis, our heterogeneous effects analyses show that temporary workers invest more in informal learning earlier in their working career, likely when they have better expectations of transferring to a permanent job.

The remainder of the paper is organised as follows. Section 2 discusses the literature related to our research question. Section 3 describes our empirical strategy and discusses the plausibility of the identifying assumptions. Section 4 presents the dataset, variables, and summary statistics. Section 5 reports the main results and robustness checks. Section 6 assesses the question of complementarity between training and informal learning. Section 7 discusses the main findings and concludes the paper.

## 2. Related Literature

In most OECD countries, laying off workers with permanent contracts is costly and time-consuming. However, the opportunity to employ some workers using temporary contracts allows firms to adjust the size of their labour force more easily. In this situation, employers have fewer incentives to invest in the human capital and long-term retention of those employees. The pursuit of flexible production by firms then has the potential to impose a negative externality on the welfare and skills development of the flex workforce (Arulampalam and Booth, 1998).

According to human capital theory, firms are less inclined to invest in training temporary workers, since the expected period in which they could benefit from these investments is relatively short. Several studies have provided empirical evidence of a negative relation between temporary contracts and training participation in different labour markets (e.g. Atkinson, 1998; Booth and Bryan, 2004; Steijn *et al.*, 2006; O'Connell and Byrne, 2010; Arulampalam *et al.*, 2011; Cutulli and Guetto, 2013). A significant distinction of this negative relation has been introduced by means of the matching approach. Since firms and workers have imperfect information about the quality of the match and firms may use temporary contracts as a mechanism for screening workers, the negative effect of having a temporary contract on training could decrease with the quality of the job match (Jackson, 2012). Similarly, Acemoglu and Pischke (1999) show that employers are encouraged to invest in general training of temporary employees due to labour market imperfections and the often compressed structure of wages in these non-competitive labour markets. Building on this, Autor (2001) tested a model in which firms offer training to induce self-selection and screen high-ability workers, prior to offering a permanent contract. The author shows that firms providing training attract higher-ability workers yet pay them lower wages after training. The key distinction is that, in the human capital model, workers pay ex ante for general training, whereas in Autor's framework training costs and returns are shared ex post by trained workers and training firms. However, if training is transferable between employers with market power in setting wages, Stevens (1994) argues that other firms are very likely to benefit if they can poach the trained employees.

In addition to their participation in formal training activities, workers' human capital development is also affected by informal learning in the workplace. However, because of a lack of adequate data, hardly any empirical studies focus on the relation between informal learning investments and temporary contracts. In the human capital literature, informal learning has mainly been seen as learning-by-doing. Arrow (1962) was one of the first authors to emphasise the importance of learning-by-doing or learning through experience as an automatic by-product of the regular production process. Mincer (1974) claimed that informal learning could constitute the essential part and the major investments in human capital provided by firms. Following Mincer's analysis, many studies have considered years of work experience as a proxy for these unobservable investments in non-formal learning. Killingsworth (1982), for instance, developed a model in which human capital accumulation occurs via both training and learning-by-doing. In this model, the accumulation of training reduces workers' current earnings, while the accumulation of experience does not. By devoting more time to learning-by-doing, workers can raise both current earnings and future productivity.

However, simply accumulating years of experience does not mean that a person will learn from them (Quinones *et al.*, 1995; Tesluk and Jacobs, 1998), and not everyone is inherently good at learning from experience (Maurer and Weiss, 2010). Moreover, jobs differ widely in their learning content potential and opportunities (Rosen, 1972). The quality of learning experiences at work depends on the degree to which the kind of job and workplace offer people opportunities to undertake challenging tasks, interact with others, and organise their work (Billet, 2008; De Grip, 2008; Cedefop, 2011).[2]

A more recent framework by Destré *et al.*, (2008) states that workers can learn both by themselves and from others. This model provides a closed-form solution that revises Mincer and Jovanovic's (1981) treatment of tenure in the human capital earnings function by relating earnings to individuals' job-specific learning potential. In such a setting, a worker's human capital increases with both training and tenure and converges towards the firm's job-specific knowledge, which is no longer fixed, since workers are continuously learning by themselves and from each other. Some of the most emphasised implications of this study are that the supply of informal learning could be interpreted as tied to workers' contracts and that both the direct and indirect costs of investments in formal training are expected to be higher than investments in informal learning. Therefore, workers might invest more time on the latter than on formal training activities, even though formal and informal human capital investments are likely to be complementary (Nelen and De Grip, 2009).

Research on the stepping stone effects of temporary employment has particularly argued that on-the-job skills development is probably the main mechanism through which temporary contracts offer a

[2] Informal workplace learning has mostly been studied in fields such as human resource development, management, and organisation studies. This literature has primarily focused on the nature of individual and collective learning through everyday activity in the workplace; what organisational factors can influence particular learning styles at work and learning capability; and how to support and reward learning within firms (Straka, 2000; Svensson *et al.*, 2004; Billet, 2008; Keogh, 2009; Marsick *et al.*, 2009; Cedefop, 2011).

path into permanent jobs.[3] These studies argue that transition odds likely increase with the improvement of human capital, work experience, and general labour skills while being on assignment (Abraham, 1990; Autor, 2001; Booth *et al.*, 2002; Gagliarducci, 2005; Dekker, 2007; De Graaf-Zijl *et al.*, 2011; Cockx and Picchio, 2012; Jahn and Pozzoli, 2013; Jahn and Rosholm, 2014). It is often claimed that temporary work can provide opportunities to gain experience and acquire human capital, to deepen the attachment to the labour market and to search more effectively for permanent jobs.

Thus, from the worker's perspective, taking on a temporary job with a high learning potential instead of staying unemployed can be a good strategy to maximise lifetime income (Sicherman and Galor, 1990). Booth *et al.* (2002) and Berton *et al.* (2011), for instance, found that having a temporary contract at the beginning of the working career does not have a negative effect on workers' wage profiles. Those who start in flex jobs and move to permanent employment fully catch up to those who start in permanent jobs. Nonetheless, if temporary jobs are recurrent, the stepping stone effect decreases, training participation is lower, and age earnings profiles are flatter. In that case, temporary positions could be seen as dead-end jobs.[4] All this suggests that temporary contracts are more effective in paving the way to stable employment if combined with human capital development (Dekker, 2007).

## 3. Empirical Strategy

Our primary regression equation of interest is

$$\mathrm{IL}_i = \mathbf{x}_i\boldsymbol{\beta} + \delta\mathrm{T}_i + \mu_i \qquad (1)$$

where IL is a continuous variable, the on-the-job informal learning intensity of worker *i*, X is a vector of covariates composed by worker and firm characteristics along with a set of country dummies, and T is a binary indicator of the type of contract (T = 1 for employees on temporary contracts and T = 0 for employees on permanent contracts). All the variables are described in the next section. For this model, the difference in informal learning between workers with temporary and permanent contracts is measured by the estimate of $\delta$.

However, the binary indicator $T_i$ cannot be treated as exogenous since it is potentially based on individual self-selection or selection by employers. Unobservable worker characteristics such as ability and motivation (Loh, 1994; Mincer, 1997; Autor, 2001; Booth *et al.*, 2002; Givord and Wilner, 2015) as well as time preferences and risk aversion (Weiss, 1986; Mincer, 1997; Belzil and Leonardi,

[3] Besides, temporary employees can increase learning investments for signalling reasons, because employers can use temporary contracts to investigate the match and screen workers' ability.

[4] Usually workers with less favoured labour positions (youths, women, and the low educated) fall into this segment of temporary dead-end jobs.

2007; Berton and Garibaldi, 2012) may affect both the temporary job and investment in informal learning decisions, resulting in biased estimates when using least squares. For instance, if the typical individual selected into temporary contracts has relatively lower ability or lower motivation, then the OLS estimate of δ will underestimate the treatment effect. We might expect the bias to also be negative if most temporary employees are workers who tend to have stronger time preferences for the present (or a higher discount rate) or have below-average risk aversion. If we feel these hypotheses are correct, then we would argue that δ underestimates the influence of temporary contracts on on-the-job informal learning intensity.

We account for the endogeneity of temporary job selection by estimating an endogenous switching regression model of informal learning intensity where workers face two regimes, temporary and permanent employment (with only one regime observed). Following Heckman (1978), Heckman and Vytlacil (1999) and Heckman *et al.* (2001), the more general model is the following. The potential informal learning outcomes $(\mathrm{IL}_0, \mathrm{IL}_1)$ of the treatment $\mathrm{T} = (0, 1)$ are assumed to depend linearly upon observable variables X and unobservables $\mu_i$, as in equation (1). The decision process for the temporary contract indicator is posed as a nonlinear function of observables $z$ and unobservables $\upsilon$, and linked to the observed outcome $\mathrm{IL}_i$ through the latent variable $\mathrm{T}^*$:

$$\mathrm{T}_i^* = \boldsymbol{z}_i\gamma - \upsilon_i \quad (2)$$

$$\mathrm{T}_i = \begin{cases} 1, & \text{if } \mathrm{T}_i^* > 0 \\ 0, & \text{if } \mathrm{T}_i^* \leq 0 \end{cases}$$

$$\mathrm{Prob}(T_i = 1|\boldsymbol{z}_i) = \Phi(\boldsymbol{z}_i\boldsymbol{\gamma})$$
$$\mathrm{Prob}(T_i = 0|\boldsymbol{z}_i) = 1 - \Phi(\boldsymbol{z}_i\boldsymbol{\gamma})$$

Consistent with our previous conjecture, the conditional independence assumption does not hold in these kinds of models. Instead, $\mu_i$ and $\upsilon_i$ are allowed to be correlated by a coefficient $\rho$ and assumed to be jointly normally distributed $(\mu_i, v_i) \sim N(0, \Sigma)$ (Maddala, 1983; Wooldridge, 2010; Greene, 2012). Under these assumptions, the bias caused by the correlation of the regressor T with omitted variables is addressed by the non-zero expectation of the error term $\mu_i$ in equation (1), as follows:

$$\mathrm{E}(\mathrm{IL}_i|\, T_i = 1, \mathbf{x}_i, \mathbf{z}_i) = \mathbf{x}_i\boldsymbol{\beta} + \delta + \rho\sigma_\mu \left[\frac{\phi(-\boldsymbol{z}_i\boldsymbol{\gamma})}{\Phi(-\boldsymbol{z}_i\boldsymbol{\gamma})}\right]$$

$$\mathrm{E}(\mathrm{IL}_i|\, T_i = 0, \mathbf{x}_i, \mathbf{z}_i) = \mathbf{x}_i\boldsymbol{\beta} + \rho\sigma_\mu \left[\frac{-\phi(-\boldsymbol{z}_i\boldsymbol{\gamma})}{1 - \Phi(-\boldsymbol{z}_i\boldsymbol{\gamma})}\right] \quad (3)$$

Then, the expected difference in informal learning intensity between temporary and permanent employees is

$$\mathrm{E}(\mathrm{IL}_i|\, T_i = 1, \mathbf{x}_i, \mathbf{z}_i) - \mathrm{E}(\mathrm{IL}_i|\, T_i = 0, \mathbf{x}_i, \mathbf{z}_i) = \delta + \rho\sigma_\mu \left[\frac{\phi_i}{\Phi_i(1-\Phi_i)}\right] \qquad (4)$$

where $\phi$ and $\Phi$ are the standardised normal density and distribution functions respectively.

The model is identified through exclusion restrictions: first, the nonlinearity of the selection equation and thus the correlation between $\mu_i$ and $\upsilon_i$ and, second, by including variables in $\boldsymbol{z}$ that satisfy the constraints $\mathrm{Cov}(z, \mu_i) = 0$ and $\gamma \neq 0$. To take into account selection into temporary employment based on observable and unobservable characteristics, we need a selection instrument that directly affects the incidence of temporary contracts but which is not related to potential confounders. We use as an instrument the unemployment rate of the year preceding the interview date by the individual's corresponding country, gender, and age group. We establish the admissibility of this instrument in Sections 4 and 5.

CF estimators are the most used in the framework of endogenous switching regression models. Simple two-step procedures first estimate the model of endogenous regressors as a function of instruments, as in the first stage of 2SLS but through nonlinearities, and then use the generalised errors from this model as an additional regressor in the main model. Maximum likelihood (ML) methods simultaneously fit the continuous equation (1)-(3) and the binary equation (2) of the model to yield consistent and efficient estimates of the average treatment effect (ATE) and consistent standard errors. Given the assumptions with respect to the distribution and correlation of the disturbance terms $\mu_i$ and $\upsilon_i$, the logarithmic likelihood function[5] for the system of (1–2) provided by Maddala (1983):

$$\ln \mathrm{IL}_i \begin{cases} \ln\Phi\left\{\dfrac{\mathbf{z}_i\gamma + (\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta} - \delta)\,{}^{\rho}/_{\sigma}}{\sqrt{1-\rho^2}}\right. - \dfrac{1}{2}\left(\dfrac{(\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta} - \delta}{\sigma}\right)^2 - \ln\left(\sqrt{2\pi}\sigma\right) & \mathrm{T}_i = 1 \\ \ln\Phi\left\{\dfrac{-\mathbf{z}_i\gamma + (\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta})\,{}^{\rho}/_{\sigma}}{\sqrt{1-\rho^2}}\right. - \dfrac{1}{2}\left(\dfrac{(\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right)^2 - \ln\left(\sqrt{2\pi}\sigma\right) & \mathrm{T}_i = 0 \end{cases} \qquad (5)$$

Furthermore, by also allowing $\beta_0 \neq \beta_1$ and $\sigma_0^2 \neq \sigma_1^2$, where $\sigma^2$ represents the variance of $\mu_i$ in $\Sigma$, we obtain the full endogenous switching regression model in which the impact of the independent variables varies across regimes (Maddala, 1983; Wooldridge, 2010). Then the model (1) becomes

$$\mathrm{IL}_i = \mathbf{x}_i\boldsymbol{\beta}_0 + \delta\mathrm{T}_i + \mathrm{T}_i(\mathbf{x}_i - \bar{\mathbf{x}})\psi + \mu_0 + \mathrm{T}_i(\mu_1 - \mu_0) \qquad (6)$$

[5] It is fit by the Stata command *etregress*. Standard errors are approximated through the delta method.

This model is very restrictive, because the treatment may create interaction effects with observed or unobserved personal characteristics (Maddala, 1983). This way of expressing the outcome model emphasises our primary interest in $\delta$, although $\delta + (\mathbf{x}_i - \bar{\mathbf{x}})\psi$ is of interest for studying how the ATE changes as a function of observables, that is, to estimate nonconstant treatment effects and average effects on the treated (ATT, Wooldridge, 2010). If $(\mu_i, v_i) \sim N(0, \Sigma)$, we obtain an identical representation to the endogenous switching regression model previously described, also estimated by (5).

This CF approach derived in the context of endogenous switching regression models adds more structure to explicitly account for the binary nature of the endogenous regressor. If the nonlinear model approximates the conditional expected function of the treatment variable better than the linear model, the resulting linear estimates will be more efficient than those using a linear first stage (Newey, 1990; Angriest and Pischke, 2009; Wooldridge, 2010). This approach has further advantages. A continuous selection instrument is appropriate for use for a binary endogenous regressor (Imbens and Wooldridge, 2009). This method distinguishes between excluded and included variables in outcome and treatment assignment equations and take advantage of exclusion restrictions to use the relevant information available to obtain identification (Heckman and Navarro-Lozano, 2004). Finally, it can be applied to estimate unconditional ATE and/or ATT, thus allowing estimation of heterogeneous treatment effects (Angrist and Pischke, 2009; Wooldridge, 2010).

However, this approach, while likely more efficient than a direct IV approach, is less robust. Consistency of the CF estimator hinges on the bivariate normality assumption of $\mu_i$ and $\upsilon_i$; thus the probit equation be correctly specified to predict effectively which observations are selected into treatment. The better the prediction, the more precise the estimates will be. Successful use of the CF method usually requires that at least one selection variable in $\boldsymbol{z}$ is not included in $\mathbf{x}$ (Heckman, 1978; Heckman and Vytlacil, 2005; Wooldridge, 2010).

Since the benefit of increased precision of estimation might be at the cost of a greater chance of misspecification error, we perform various robustness checks of our CF estimations. One important robustness check is based on Wooldridge's (2003, 2010) robust approach. The author demonstrates that, under weaker distributional and functional assumptions, an alternative IV estimator can be consistently applied to estimate the homogeneous and heterogeneous effects of a discrete endogenous variable. The alternative is to use the probit fitted values for each $\mathrm{T}_i$ as valid generated IVs in a simple 2SLS procedure. Then, the first-stage estimation does not need to be correctly specified, as it is in the CF approach. This method is more efficient than direct 2SLS methods and fully robust to misspecification of the probit model, yet it is less efficient than the CF estimator if the additional assumptions needed for CF consistency hold (Wooldridge 2003, 2010).

## 4. Data and Descriptive Statistics

### *4.1 Data and Sample*

We use data from the OECD PIAAC survey, conducted in 2012 in 24 industrialised countries and based on a representative sample of the population of OECD participant countries.[6] This is a unique dataset that measures the incidence of training as well as the intensity of on-the-job informal learning. The latter measure, which is not available in any other large-scale dataset, is based on a conceptual framework that takes into account three pathways of learning, namely, learning-by-doing, learning from others, and learning by keeping up-to-date with new products or services.

We restrict the sample to include full-time[7] employed males[8] – excluding self-employed and armed forces employees– aged 17 to 65, not participating in any formal education programme, and who have an employment contract that is not an apprenticeship. The sample consists of 25,366 observations balanced[9] throughout 20 OECD countries[10], with 88.2 percent permanent contracts and 11.8 percent temporary contracts. The distribution of permanent and temporary contracts in the sample coincides with the population distribution according to the OECD statistics published for 2012 (see Table 1).

*[Insert Table 1 about here]*

### *4.2 Variables*

#### *4.2.1 Outcome Variables*

First, on-the-job informal learning intensity is a standardised index[11] derived from the following questions; all measured on a five-point Likert scale:[12]

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[6] See the OECD (2014b) for further details about data validation.

[7] We consider full-time employees those who reported a minimum of 35 working hours a week.

[8] We focus on males due to the higher probability of working career interruptions among women. This makes temporary jobs differ in significance between men and women, since women may prefer career flexibility throughout a significant portion of their working lives (Booth *et al.*, 2002).

[9] In Canada the sample consisted of some 5,044 cases, from which we took a random sample of 23.1 percent, resulting in 1,165 cases, to reduce possible bias due to oversampling of Canadian respondents.

[10] Four countries were excluded from our sample: Australia, Cyprus, the Russian Federation and the United States. Australian data were not available due to confidentiality reasons. OECD statistics for Cyprus were not available. Data from the Russian Federation were preliminary and considered by the OECD (2014b) to not be representative of the population, since Moscow was excluded from the survey. Last, the particular characteristics of the US labour market led to a loss of 58 percent of observations due to employees who stated not having any contract at all. In that case, only 387 non-random observations would have remained in our sample, of which 31.3 percent presumably corresponded to temporary jobs, a percentage very different from the OECD statistic, which estimates only 4.2 percent temporary employment in the United States. Therefore, our main variable of interest would capture something different in the United States, not comparable to other countries. As shown by the ILO (2010) and the OECD (2006), due to very low employment protection legislation (EPL), the distinction between temporary and permanent employment is of much less significance in the United States.

[11] This index was derived by PIAAC using the generalised partial credit model estimated by weighted likelihood estimation. Its validity was assessed based on cross-country comparability, scale reliability and scale correlations. For further details, see the OECD (2014b). The index cannot be estimated for 554 respondents in our sample who reported never to all three questions; therefore, the lowest value of the index by country was

a) *How often do you learn new work-related things from co-workers or supervisors?*

b) *How often does your job involve learning-by-doing from the tasks you perform?*

c) *How often does your job involve keeping up-to-date with new products or services?*

This variable takes the lowest value if all three questions were answered 'never' and the highest if answered 'every day'. To facilitate the interpretation of results, the variable was standardised. In addition, a dummy variable for on-the-job informal learning incidence was derived that takes the value zero when the previous questions were all answered never and one otherwise.

Second, training incidence is a dummy variable of participation in job-related training during the previous 12 months. It is based on the following questions: *During the last 12 months, have you*

*a) Participated in courses conducted through open or distance education?*

*b) Attended any organised sessions for on-the-job training or training by supervisors/co-workers?*

*c) Participated in seminars or workshops?*

*d) Participated in courses or private lessons not already reported?*

This variable takes the value one if the individual participated in any of the training activities mentioned and the current/last training activity was reported to be mainly job-related and zero otherwise.[13]

*4.2.2 Explanatory Variable*

Temporary contract[14] is a dummy variable that takes the value one for temporary contracts and zero for permanent contracts. Temporary contracts in our sample include fixed-term positions (90.5 percent) and agency work (9.5 percent).[15]

*4.2.3 Control Variables*

The questionnaire contains detailed information about individual, current job, and firm characteristics. As suggested by the evidence found in the empirical human capital literature, we control for age, educational level (years of education proxied by the highest level of education obtained), educational

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imputed to those observations. The findings are robust to different constructions of the index; for example, very similar results are obtained by using the standardised principal component factor of the three statements.

[12] The response rate to these questions was about 98 percent, with the following answer options: 1) never, 2) less than once a month, 3) less than once a week but at least once a month, 4) at least once a week but not every day, and 5) every day.

[13] The response rate to these questions was about 90 percent.

[14] According to OECD concepts, permanent workers are, generally, persons whose main job is of indefinite duration. A job may be regarded as temporary if it is understood by both the employer and the employee that the duration of the job is limited.

[15] The variable is derived from the question what kind of employment contract do you have? The answer options are: 1) an indefinite contract, 2) a fixed term contract, 3) a temporary employment agency contract, 4) an apprenticeship or other training scheme, and 5) no contract.

mismatch (dummies for overeducation and undereducation),[16] firm tenure, actual weekly working hours (top coded at 60), elaborate learning[17]; and firm size (five categories), occupation (nine ISCO one-digit categories), industry (ten ISIC one-digit categories), and country dummies.

*4.2.4 Selection instrument variable*

We use the annual male unemployment rate by country and five-year age groups for 2011 as a selection instrument in our estimations. We collected these data from the OECD Statistics website and matched them to the individuals in our sample by country and age.

The unemployment rate likely represents a suitable instrument for the individual probability of having a temporary contract, which is uncorrelated with the error term $\mu_i$. First, unemployment measures have been shown to be correlated with the subsequent incidence of temporary employment (Wasmer, 1999; Holmlund and Storrie, 2002; Virtanen *et al.*, 2005; Kahn, 2010).[18] The average likelihood that workers will be employed in temporary jobs increases when the unemployment rate is relatively high. This is expected, since temporary jobs have been promoted as a mechanism to improve the labour market integration of the unemployed (Gagliarducci, 2005; Gebel, 2013) and because a higher unemployment rate often means a risk for the active working population and job seekers that reduces the chance of finding more stable employment (European Commission, 2010). When economic prospects are tight, workers anticipate that opportunities in the labour market will be scarce; therefore, they have a higher probability of accepting temporary contracts (Abraham, 1990; Holmlund and Storrie, 2002; Givord and Wilner, 2015). From a demand-side point of view, employers add greater value to the use of temporary contracts as a low-cost short-run buffer or as a probationary period when there is excess

[16] These dummies are derived from the following question: Thinking about whether this qualification is necessary for doing your job satisfactorily, which of the following statements would be most true? Answer options: 1) This level is necessary, 2) a lower level would be sufficient, and 3) a higher level would be needed.

[17] According to the OECD (2014b), this item aims to measure the extent of elaborate learning, based on the approach of Kirby *et al.* (2003). It is considered a stable personal characteristic, named by the OECD (2014b) as readiness to learn. Elaborate learning is the metacognitive ability to integrate new information with previous knowledge, synthesise new material and make connections to form a wider perspective. It structures the learning process and affects the efficiency with which new information is processed. Therefore, it also describes learners' interest in learning and information-processing strategies. In the context of PIAAC, elaborate learning aims to capture how people approach learning situations especially in the workplace. We use the standardised index of readiness to learn derived by PIAAC from the following questions, all measured on a five-point Likert scale: 1) When I hear or read about new ideas, I try to relate them to real life situations to which they might apply, 2) I like learning new things, 3) When I come across something new, I try to relate it to what I already know, 4) I like to get to the bottom of difficult things, 5) I like to figure out how different ideas fit together, and 6) If I don't understand something, I look for additional information to make it clearer.

[18] Transitions from unemployment to temporary or permanent employment and from temporary contracts to permanent contracts are likely to depend on the labour market's response to aggregate factors and to the business cycle (Wasmer, 1999). During economic downturns, as the pool of unemployed builds up, transition rates from unemployment into temporary jobs are larger than the flow from unemployment to permanent jobs (Wasmer, 1999; Holmlund and Storrie, 2002). Similarly, when the unemployment rate is high, the probability that a temporary contract is converted into a permanent contract is lower (Wasmer; 1999; Givord and Wilner, 2015).

supply in the labour market (Wasmer, 1999; Gagliarducci, 2005; Givord and Wilner, 2015).[19] Temporary employment then comprises more employable individuals who could have had permanent contracts if the economic conditions had been better (Wasmer, 1999; Givord and Wilner, 2015).

Second, there is no reason to expect that unemployment rates at the country level directly affect individual decisions on informal learning investments on the job, except through the kind of contract the employee has. Higher unemployment rates might raise tenure uncertainty and, therefore, incentivise greater on-the-job investments in informal learning. Nonetheless, this uncertainty mainly depends on whether the contract is permanent or temporary. Both temporary and permanent workers will respond to changes in economic conditions; however, the learning behaviour of those on temporary contracts will be far more responsive to the rate of unemployment.

The relation between unemployment and the probability of having a temporary contract may, however, differ by country because of the strictness of EPL. Stricter rules applicable to permanent employment may tend to increase the incidence of temporary work and to limit the extent to which temporary contracts will be converted into permanent ones (Booth *et al.*, 2002; Holmlund and Storrie, 2002; OECD, 2004; Gagliarducci, 2005; Kahn, 2010; Sala *et al.*, 2012). As an alternative specification, we therefore use version 3 of the EPL indicator for regular employment[20] (standardised and categorised in three dummies) to interact with our selection instrument.

### *4.3 Descriptive Statistics*

Table 2 presents summary statistics for permanent and the temporary workers, respectively. As expected, the temporary employees in our sample are generally younger and have fewer years of work experience and tenure than permanent workers. Moreover, among individuals in temporary positions, there is a higher share of overeducated workers and a lower proportion employed in skilled occupations, large firms, and the tertiary sector of the economy. It is worth mentioning that there is no descriptive difference between permanent and temporary employees regarding years of education and elaborate learning.

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[19] The greater value of hiring a worker with a temporary contract rather than a permanent contract comes from the employer's right to dismiss unproductive or mismatched workers at a lower cost. In Wasmer's (1999) model, when the unemployment rate is relatively high, firms are more willing to make use of temporary contracts with lower turnover costs due to uncertainty in demand. Accordingly, the effect of a lower growth and a higher unemployment rate is to increase the share of temporary jobs. His model predicts that a decrease of one percentage point in productivity growth implies a 0.2 percentage point higher unemployment rate, which will increase the number of temporary workers by 2.5 percentage points and the share of temporary jobs by 2.8 percentage points.

[20] This indicator is the weighted sum of 13 data items concerning the regulations for individual dismissals and additional provisions for collective dismissals. It is measured on a scale of zero (least restrictions/strictness) to six (most restrictions/strictness), where a higher score indicates a higher level of employment protection.

Regarding our variables of interest, we first observe that practically every person learns something on the job (98 percent informal learning incidence), with no significant difference by type of contract. However, the informal learning intensity of flex workers has a higher mean, which makes more interesting to analyse the intensity of informal learning than its incidence. In contrast, we observe that permanent employees participate more often in job-related training. In our sample, 91.7 percent of training participation was totally or mostly financed by firms while 8.3 percent was financed by the workers themselves. Similarly, 83.3 percent of trained workers participated in training only or mostly during working hours, while 16.7 percent did so mostly or entirely outside working hours. All this suggests that firms are the main initiators and funders of training, although there is also room for employee initiative.

Finally, our data confirm that the average value of the lagged unemployment rate for the group of temporary workers was three percentage points higher than for permanent employees. We confirm that the unemployment rate for 2011 has a significant Pearson's correlation of 0.50 to the country incidence of temporary contracts in 2012 and 0.56 to the temporary contract dummy of our sample (see Figure A1 in the Appendix). Similarly, we observe that the average value of EPL applicable to regular employment is slightly higher for the group of temporary workers in our sample.

*[Insert Table 2 about here]*

## 5. On-the-job Informal Learning Intensity

### *5.1 Main Findings*

The main results of the regressions for on-the-job informal learning intensity are presented in the upper panel of Table 3. To assess the results of taking into account selection into temporary jobs, Table 3 proceeds stepwise. The first specification gives the results of an ordinary OLS regression. Specifications (2) and (3) show the coefficients from standard 2SLS estimations. The last specifications (4) and (5) provide the CF estimates derived in the context of the endogenous switching regression model described in Section 3, which not only consider the endogeneity of the type of contract but also account for the binary nature of the endogenous regressor. The second section of Table 3 shows the corresponding first-stage/treatment estimates of the temporary contract equation.[21]

Overall, the results in Table 3 provide remarkable evidence of a positive difference in on-the-job informal learning intensity between temporary and permanent employees, in favour of the former group. Compared with the OLS estimates, the other coefficients that account for the endogeneity of

[21] Tables A1 and A2 in the Appendix show other more restricted specifications of the endogenous switching model to see how the main estimated coefficient of temporary contracts changes with the progressive introduction of control variables.

temporary contract selection are adjusted upwards, as we expected. We consider the estimates generated by the CF more precise and proceed with interpretation. Further arguments on the accuracy of these estimates follow.

The results in columns (4) and (5) confirm that the OLS coefficient of temporary contracts is biased downwards. Once selection into the contract type is controlled for, the estimated ATE of interest increases from 0.095 to 0.17 of a standard deviation. This implies that workers in temporary jobs invest, on average, 0.17 of a standard deviation more in on-the-job informal learning than their counterparts in permanent employment[22]. The estimated correlation between the temporary contract equation errors and the outcome errors $\rho$ is negative (-0.075), indicating that unobservables that raise informal learning intensity tend to occur with unobservables that lower temporary contract selection. This result is coherent with our hypothesis of unobservables mentioned in Section 3. For instance, people with greater ability or motivation and greater time preferences for the future are less likely to be selected into temporary jobs and are at the same time more likely to engage more in job training and informal learning (Mincer, 1997).

In comparison with the OLS estimates, the CF coefficients and standard errors of the exogenous regressors change much less. Most of the control variables in our regressions affect the dependent variable in the expected direction according to human capital theory. We find that on-the-job informal learning intensity decreases with age, as the lifecycle theory of human capital predicts. The squared term of age is positive and significant, which denotes an upwards turning point of investments at the end of employees' working life. It might be seen as a rational action to counterbalance the depreciation of human capital at an older age, as suggested in the literature (e.g. Heckman, 1976; Killingsworth, 1982; Destré *et al.*, 2008).

Years of education are positively correlated with intensity of learning in the workplace. On average, one additional year of schooling increases informal learning by 0.016 of a standard deviation. This complementarity may arise because of the self-productivity of human capital accumulated through formal schooling, which could increase ability to learn and could be useful for informal learning on the job (Rosen 1972). Educational mismatches seem to have an important impact on this relation. With respect to workers in a well-matched job, overeducated employees tend to invest, on average, 0.11 of a standard deviation less in informal learning, while undereducated employees invest 0.15 of a standard

[22] In specification (5), which includes three instruments (the standardised unemployment rate and its interaction with two of the three dummies of EPL for permanent employment), the coefficient of interest becomes increases slightly but is not significantly different from the estimate in specification (4). Including the EPL measures as exclusion restriction has very little effect on the coefficients, which suggests that the country-specific dummies included in the selection equation absorb most of the explanatory power of the national differences in employment regulations on the probability of having a temporary contract.

deviation more. This finding is consistent with Jahn and Pozzoli (2013) study, which hypothesises that temporary workers employed below their skill level are less likely to improve their human capital.[23]

There is also a positive relation of informal learning intensity with elaborate learning and actual working hours and a negative relation with tenure. The latter is attributed to the greater learning exposure of workers when they are new to their jobs. We also find that informal learning intensity in the workplace tends to be significantly higher for individuals employed in high-skilled occupations and larger firms.

*[Insert Table 3 about here]*

We favour the CF specifications for various reasons. First, we observe that they provide more accurate predicted probabilities in the temporary contract equation. Linear predictions from the 2SLS first stage range from -0.20 to 0.76, leaving 16 percent of the sample predicted probabilities below 0. In contrast, probit predicted probabilities range from zero to 0.92, providing better common support for the treatment parameters to be defined. Therefore, we presume the outcome equation estimates to be more efficient in the second case. Second, the sizes of the instrument coefficients differ significantly between the 2SLS and CF specifications. In column (4), for instance, an increase of one standard deviation in the unemployment rate, on average, increases the probability of being in a temporary job by 1.6 percentage points. In column (2), the same effect predicted by the 2SLS first stage is approximately 4.7 percentage points, three times bigger. The size of the probit marginal effect is closer to that in related research, for example, Kahn’s (2010).

Third, we are carefully selective in the inclusion of covariates in the temporary contract equation in columns (4) and (5), which is not allowed in the standard 2SLS framework. As suggested by related literature, we do not include tenure, working hours, or educational mismatches as determinants of temporary contract selection. Even so, we perform further robustness checks of this treatment equation specification. Fourth, we observe some implausible estimates in the 2SLS outcome equations, such as positive non-significant coefficients for age and tenure. Fifth, the Wald tests for specifications (4) and (5) indicate with 95 percent confidence that we can reject the null hypothesis of no correlation between the errors of the temporary contract and outcome equations, so that our instrumented endogenous switching regression models fit well overall. Concerning the admissibility of our selection instrument, it is worth mentioning that Wald and F-tests after nonlinear and linear first-stage estimations, respectively, show that the unemployment rate in addition to the other covariates makes a

[23] Our estimations control for the fact that workers have a job at the appropriate level. Nonetheless, estimations that do not control for educational mismatches yield a very similar and significant coefficient for temporary contracts (0.163 and 0.165 of a standard deviation using one and three instruments, respectively; see specification (5) in Tables A1 and A2).

significant contribution to the model of interest. Last but not least, in contrast to the CF approach, 2SLS does not provide ATEs but, instead, local ATEs, the former being more policy relevant in the context of our research question.

We conclude that the difference in the intensity of on-the-job informal learning between workers with temporary and permanent contracts is positive and approximately 0.17 of a standard deviation in the OECD countries included in our sample. The size of this coefficient is substantial if we consider that it is almost the same as the impact of 10 years of schooling. Assuming that full-time male workers have generally stronger preferences for permanent contracts (Wasmer, 1999; Booth *et al.*, 2002; Holmlund and Storrie, 2002; Jahn and Bentzen, 2012), we hypothesise that flex employees will rationally engage more in workplace informal learning to increase their chances of transition to more stable jobs with current or potential future employers. Thus, it could be that those individuals with expectations of upward mobility in the labour market will be more likely to invest more in on-the-job informal learning.[24]

### *5.2 Robustness of Main Results*

In this section we present various robustness checks of the previous results, mainly related to the sensitivity of our main estimation to alternative treatment specifications. All the results in this section are shown in the Appendix.

The first concern we address is the robustness of our CF estimations with respect to different specifications of the probit model. We tested a range of models and present the summary results in the Appendix, Table A3.

Specifications (2) to (6) include variables that we do not consider determinants of temporary contract selection in Table 3. We note that including these regressors does not substantially change the main estimates. Only when tenure is included as an explanatory variable for temporary contracts do we see that the estimated ATE of interest increases from 0.17 to 0.22 of a standard deviation, which indicates that our results are conservative. Moreover, the predicted values of $\rho$ remain negative and the Wald tests are significant in all these specifications, indicating that our main results hold.

Specifications (7) to (12) exclude variables we included as determinants of temporary contract selection in our main estimations. The results in Table A3 show that the ATE of temporary contracts

[24] This finding might be related to the study of Engellandta and Riphahn (2005), who, using indicators for unpaid overtime work, found that temporary workers in Switzerland exert greater effort than permanent employees. They also suggest that implicit incentives of shifting to permanent employment could explain those results. As shown by Guell (2000), temporary workers are motivated by the possibility of moving to a permanent job.

on informal learning intensity is almost identical to that of Table 3. Only when country dummies are excluded from the probit model do we observe an increase in the estimated ATE of interest from 0.17 to 0.22 of a standard deviation. This result suggests that country-fixed effects are important controls for unobserved heterogeneity between countries. Moreover, the predicted values of $\rho$ remain negative in these alternative models. The Wald tests are all significant with 95 percent confidence, the only exception being models excluding occupation dummies that are significant at 90 percent instead.

A second concern is a possible misspecification of the treatment equation due to relevant covariates we do not observe. When we assess the accuracy of our main results in contrast to those provided by Wooldridge's robust estimator described in Section 3, we find that the coefficients of the temporary contract indicator remain highly significant and positive (see Table A4). These estimators are downwards adjusted in comparison with the standard 2SLS results of Table 3; however, they are approximately seven and four times larger than the corresponding OLS and CF estimators, respectively. This finding shows that, although Wooldridge's approach is more efficient than the direct 2SLS procedure and fully robust to misspecification of the probit model, it is less efficient than the CF method in this particular case.

### *5.3 Heterogeneous Effects*

#### *5.3.1 Heterogeneous Workers*

Although temporary workers are, on average, more intensively engaged in informal learning, this could differ among temporary workers with different characteristics. Temporary employees could, for instance, have different expectations for their career prospects. If that is the case, we might expect distinct levels of the informal learning intensity of temporary workers, depending on their age and tenure: In particular, younger workers and those with shorter tenure could have stronger incentives to engage in learning when they are employed in a temporary job, since this could help them to acquire a permanent contract. We expect these investments in informal learning to be more beneficial for temporary workers earlier in their career, when they have higher expectations of transferring to a permanent position.

To investigate the possible heterogeneity of informal learning intensity, we estimate full endogenous switching regression models to allow all coefficients of covariates to vary over the treatment level, as explained in Section 3. The results shown in Table 4 indicate that, after allowing for heterogeneous responses to treatment, our main conclusion still holds. Both the ATE and ATT remain significant and positive, the latter being of similar size to the ATE estimated in Table 3. We find that workers with temporary contracts invest, on average, 0.13 of a standard deviation[25] more in informal learning than workers with permanent contracts do. The ATT shows that temporary employees invest, on average, 0.18 of a standard deviation more in informal learning than if they had a permanent contract.

These models allowing for heterogeneity show that the coefficients of age, age squared, tenure, and working hours differ significantly by type of contract while years of education, overeducation, undereducation, and elaborate learning do not. The coefficients confirm our expectations that the rate at which informal learning intensity decreases with age and tenure is greater for those with a temporary contract. This result suggests that the mean estimate of temporary contracts in our informal learning model is mainly driven by temporary employees who are younger and have had tenure for fewer years.

*[Insert Table 4 about here]*

More precisely, the significant difference in the coefficient of age between temporary and permanent employees suggests that being a year older decreases the intensity of informal learning, on average, by 0.0218 of a standard deviation in the case of employees with permanent contracts and by 0.0265 in the case of temporary contract workers. As mentioned previously, larger investments in informal learning of temporary workers are expected to be more beneficial earlier in the job career when workers have better prospects of gaining a permanent position. This suggests that, at some point in employees' life course, the difference in informal learning between those with permanent and temporary contracts will vanish; nevertheless, the difference is not just a young, early career effect. According to the estimations (1) and (2) in Table 4, the positive marginal effect of temporary contracts on informal learning intensity becomes insignificant (at the 95 percent confidence level) after the age of 47 (see Figure 1). The table also shows that the coefficient of age squared is only significantly different from zero for permanent employees. This finding suggests that the upwards turning point of informal learning investments at the end of an employee's working life holds particularly for workers with a permanent contract.

*[Insert Figure 1 about here]*

Similarly, the results in Table 4 show that the negative coefficient of tenure is significantly larger for employees with temporary contracts. For permanent employees, one additional year of tenure reduces the informal learning intensity by 0.0024 of a standard deviation, compared with 0.0082 for temporary workers. This result suggests that the higher intensity of informal learning for temporary workers

[25] The corresponding ATE estimated by running two separate OLS regressions is 0.075, significant with 99 percent confidence.

holds particularly for employees with fewer years of tenure. This again indicates that this effect ends gradually. We find with 95 percent confidence that the positive marginal effect of temporary contracts on informal learning intensity disappears after approximately seven years of tenure (see Figure 2). This effect may be due to temporary workers adjusting their expectations of labour mobility when they feel trapped in a temporary job. As mentioned previously, this finding suggests that workers who remain employed in a temporary job for a long time are actually employed in dead-end jobs with no career prospects.

*[Insert Figure 2 about here]*

*5.3.2 Heterogeneous Job Tasks*

Our estimates could be driven by different correlated job tasks. For instance, it could be that employees in high-skilled jobs or in jobs that offer more task complexity, task discretion, and flexibility are more often engaged in informal learning at work. To test this expectation, we construct dummy variables for different job content characteristics and calculate heterogeneous effects on informal learning via interaction terms between these dummies and temporary contracts, as explained in Section 3. The corresponding results are presented in Table 5.

*[Insert Table 5 about here]*

The estimation results show that all employees, regardless of the kind of contract they have, tend to engage more intensively in informal learning when they are employed in high-skilled jobs[26] or have a job in which they have higher levels of task discretion, [27] are more often confronted with simple[28] and complex[29] problems, are more often involved in team-work[30], use ICT at work more often[31], and more

[26] This dummy takes the value one for employees in ISCO occupation categories 1 to 3 and the value zero for employees in ISCO occupation categories 4 to 9.

[27] This dummy takes the value one for the highest two quantiles of an index derived from the following questions, all measured on a five-point Likert scale: To what extent can you choose or change: a) the sequence of your tasks, b) how you do your work, c) the speed or rate at which you work, and d) your working hours? The variable takes the value zero otherwise.

[28] This dummy takes the value one if the person responded with of the two highest-frequency answers to the question how often are you usually faced by relatively simple problems that take no more than five minutes to think about a good solution? The variable takes the value zero otherwise.

[29] This dummy takes the value one if the employee responded with one of the two highest-frequency answers to the question how often are you usually confronted with more complex problems that take at least 30 minutes to think about a good solution? The variable takes the value zero otherwise.

[30] This dummy takes the value one if the employee answered one of the two highest values to the question, in your job, what proportion of your time do you usually spend collaborating with co-workers? The variable takes the value zero otherwise.

[31] This dummy takes the value one for the two highest quantiles of an index derived from the following questions, all measured on a five-point Likert scale: In your job, how often do you usually: a) use email, b) use the internet to better understand issues related to your work, c) conduct transactions on the internet?, d) use

often perform planning[32] tasks. These results suggest that our main conclusion holds, even after controlling for observable job content characteristics. In all cases, the ATE remains highly significant and very close to that of Table 3, again supporting the idea that differences in career prospects due to the type of contract drives our findings.

## 6. INFORMAL LEARNING AND TRAINING: SUBSTITUTION OR COMPLEMENTARITY?

### *6.1 Training Incidence*

To assess the substitutability or complementarity between informal learning and training, we first perform estimations to validate in our sample the negative association of temporary contracts to training participation found in other studies. For this analysis, the sample size is reduced to 22,447 observations of employees who reported valid information on the job-related training variable, excluding those who were unemployed when participated in the training.[33] Table 6 provides the results.

*[Insert Table 6 about here]*

The temporary contract indicator yields the expected negative coefficient in all the estimations. The coefficient given by the standard probit specification (2) is just slightly higher compared with the OLS specification (1). The results in columns (3) and (4) indicate that the OLS and probit estimations can be considered biased downwards to some extent. Once the selection into the contract types is controlled for, the estimated temporary contract penalty for participating in training increases from 6.5 to 7.6 percentage points. This implies that workers in temporary jobs are, on average, 7.6 percentage points less likely to take part in job-related training activities than individuals in permanent employment are.

The negative value of $\rho$ suggests that unobservables that decrease temporary contract selection probably occur with unobservables that increase training participation. This result is again in line with our hypothesis of unobservables mentioned in Section 3. However, in the CF[34] specifications (3) and

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spreadsheet software, e) use a word processor, and f) participate in real-time discussions on the internet? The variable takes the value zero otherwise.

[32] This dummy takes the value one for the two highest quantiles of an index derived from the following questions, all measured on a five-point Likert scale: How often does your job usually involve a) planning your own activities, b) planning the activities of others, and c) organising your own time? The variable takes the value zero otherwise.

[33] For this reason, we excluded 364 observations from the estimations.

[34] Since maximum likelihood estimations of endogenous switching models for binary outcome variables follow a different structure and notation, the Stata command *etregress* is not appropriate. We then used the wrapper

(4), the Wald tests indicate that we cannot reject the null hypothesis of $\rho = 0$ with 95 percent confidence, but we can do so with 90 percent confidence. This means that, with 95 percent confidence, temporary contract selection could still be considered exogenous to the model of training participation; therefore, probit estimation (2) would be reliable. In any case, the probit and CF estimates are of comparable size and significance.

The results in Table 6 confirm the disadvantage of temporary workers accessing job-related training, widely evidenced in the literature (e.g. Arulampalam *et al.*, 2004; Booth and Bryan, 2004; Steijn *et al.*, 2006; Albert *et al.*, 2010; O'Connell and Byrne, 2010; Cutulli and Guetto, 2013). In addition, we find that the effect of age on training probability is positive early in the employee's working career but rapidly turns into a negative, as the significant coefficient of age squared indicates. Specifications (3) and (4) show that the probability of participation in training is positive until workers reach nearly age 35 and subsequently starts decreasing. This result is consistent with the lifecycle model of human capital accumulation (Ben Porath, 1967) and empirical findings (e.g. O'Connell and Byrne, 2010; Grund and Martin, 2012).

The probability of training also rises with years of education. On average, every additional year of schooling increases the chances of participating in job-related training by 1.7 percentage points. Educational mismatches also have an important impact on training, as they do on informal learning. With respect to well-matched workers, overeducated employees are 1.8 percentage points less likely to take part in training activities, while undereducated employees are 2.8 percentage points more likely. There is also a positive relation between training probability and elaborate learning, actual working hours, and tenure,[35] the latter because it may be optimal to delay training if there is belated information about good matches and employees' future mobility (Loewenstein and Spletze, 1997).

### *6.2 Complementarity*

We have found that, although workers with temporary contracts are less likely to participate in training, they engage more intensively in informal learning. This raises the question of whether informal workplace learning is a substitute of training for temporary workers.

To answer this question we first observe whether there is a difference in the informal learning intensity of employees who undertook training and those who did not. Figures 3 and 4 illustrate this difference among temporary and permanent workers, respectively. Both figures suggest a positive relation between job-related training and informal learning, since the intensity of investments in the latter is

program *ssm* to obtain the do-file to fit the correspondent models (4) and (5) with the *gllamm* command. For a detailed description, see Miranda and Rabe-Hesketh (2006) and Rabe-Hesketh *et al.* (2005).

[35] After age squared is controlled for, the squared term of tenure was not significant in any of the equations. Therefore we kept the former and did not include the latter.

shown to be consistently greater when the incidence of training is positive. Figure 3 indicates that workers with temporary contracts do not seem to substitute for the lack of formal training with informal learning: When they have the opportunity to participate in training, they engage more in informal learning.

*[Insert Figure 3 and Figure 4 about here]*

To test whether there is, indeed, complementarity between training and informal learning, we include training participation and its interaction with the type of contract in our main equation for informal learning. Table 7 shows that the positive relation between informal learning and job-related training holds after controlling for various individual and employer characteristics. Moreover, the magnitude of this complementarity does not differ by type of contract, since the interaction term of training and temporary contract is not statistically significant in any of the three estimations, which means that the direction and size of the complementarity in question runs equally for temporary workers and permanent employees. On average, taking part in job-related training increases informal learning by 0.19 of a standard deviation. Moreover, the results show that temporary workers engage more intensively in informal learning, even after controlling for job-related training participation.

*[Insert Table 7 about here]*

## 7. CONCLUSIONS AND DISCUSSION

In this paper, we analysed the difference in informal learning intensity at work between permanent and temporary male employees across 20 OECD countries. Human capital theory predicts both firms and employees to be less willing to invest in skills if workers are hired under temporary contracts. Remarkably, we find that workers in temporary jobs engage more intensively in informal learning on the job than workers in permanent employment, although the former are, indeed, less likely to participate in formal training activities.

These results account for the endogeneity of the selection into temporary contracts and for the binary nature of the endogenous regressor. The results are robust to changes in our model specification and more efficient in comparison with alternative 2SLS specifications. We conclude that the difference in the intensity of on-the-job informal learning between workers with temporary and permanent contracts is positive and approximately 0.17 of a standard deviation in the OECD countries included in our sample. This result is substantial if we consider that it is approximately the same as the impact of 10 years of schooling. Consistent with human capital theory, we also find that workers' informal learning intensity decreases with both age and tenure. Conversely, it increases with years of education, actual working hours, elaborate learning and undereducation. The groups that benefit most are individuals employed in high-skilled occupations and larger firms.

On the assumption that full-time male workers prefer permanent contracts (Wasmer, 1999; Booth *et al.*, 2002; Holmlund and Storrie, 2002; Jahn and Bentzen, 2012), we hypothesise that temporary workers would rationally invest more in informal learning to increase their possibility of transition towards more stable employment. Thus, it is expected that individuals with positive prospects of upward mobility in the labour market are more likely to invest more in informal learning on the job. This may be incentivised by different attributes of informal learning in contrast to training, primarily the lower opportunity costs (Destré *et al.*, 2008). In line with this hypothesis, our heterogeneous effects analyses show that temporary workers invest more in informal learning earlier in their working career, likely when they have higher expectations of moving to a permanent job.

Research on the stepping stone effects of temporary employment is in line with this hypothesis. These studies often evoke the idea that odds of transition most probably increase with improvements in human capital, work experience, and general labour skills while being on assignment (Abraham, 1990; Autor, 2001; Booth *et al.*, 2002; Gagliarducci, 2005; de Graaf-Zijl *et al.*, 2011; Cockx and Picchio, 2012; Jahn and Pozzoli, 2013; Jahn and Rosholm, 2014). Human capital investments in on-the-job learning are seen as the main mechanism through which temporary employment offers a path to permanent jobs.

Hence, temporary workers' expectations of later promotion in the labour market could be responsible for the stronger incentives to invest in informal learning. Temporary workers may perceive more intense learning as a profitable investment in their career development. These decisions probably depend on the manner in which uncertainty affects the returns to investment in relation to possible changes in the future, such as the wage gains of shifting to a better job. Weiss (1986) provides some theoretical support for this explanation. The author states that, if the returns to learning are affected by uncertainty, supplementary investments in human capital become a way of hedging against risk. In addition, if these investments are positively influenced by a decreased discount rate because the future becomes more important, incentives for self-investment increase and give rise to capital accumulation until a more stable job is obtained.

This result has two important implications. First, if optimal human capital investments decline over the lifecycle by a search for a proper match or a better job, the learning intensity in temporary employment is likely to be higher, as we actually find, the earlier in employees' working life and/or the earlier the job occurs in a worker's career. Second, accepting a temporary job that might pay less initially but involves higher learning potential[36] can be a good strategy for workers in their early careers, to maximise lifetime income. That is because such jobs are more likely to be a stepping-stone for occupational mobility within or across firms (Sicherman and Galor, 1990).

In addition, this paper shows evidence of complementarity between job-related training and informal learning for both temporary and permanent employees. This result suggests that, at the individual level, the higher informal learning investment of temporary workers does not substitute for the lack of formal training. This complementarity can arise because of the self-productivity of human capital, so that human capital accumulated through training is useful for informal learning on the job (Nelen and De Grip, 2009). It can also be associated with higher previous investments in formal schooling, which not only provide higher skills but also may increase a worker's learning capacity. Since more educated individuals are more likely of greater ability, they are more efficient learners who also tend to invest more in job training and informal learning (Mincer, 1997; Rosen, 1972). One initial repercussion of this complementarity is that studies on returns to job training might have overestimated their results, since they usually attribute all the benefits of skill acquisition to workers' participation in training without considering the informal learning costs.

A second implication is that the policy objective of promoting flexicurity in several European countries is still a challenge regarding the learning potential of temporary jobs. If flexible work is taken by people in lieu of unemployment in search for further individual promotion into the labour market, it should be on the condition that they can continue learning. Since human capital in the workplace is accumulated through both training and informal learning and they complement each other, our results imply that there are at least two easily differentiable kinds of flex employment in terms of learning content. The first consist of 'good temporary jobs' with high task autonomy and more team-work, requiring a high level of problem solving. These jobs offer plenty of opportunities for training and informal learning, likely involving positive career expectations of upward mobility. Second, there are 'bad temporary jobs', which have no or very few opportunities to participate in training and informal learning, causing most workers to be trapped in precarious employment. The latter group is in a disadvantaged situation to build on job career skills. Moreover, such jobs limit the adaptability of the flexible part of the workforce that is presumed to play a key role in economic and labour market adjustment processes. This underlines the importance of improving firms' learning strategies in the workplace to optimise the benefits of both training and informal learning as means of fostering human capital development and the sustainable employability of flex workers.

[36] In this respect, the job's learning potential can refer to informal learning as well as to opportunities for participation in formal training.

Therefore, our results suggest that labour inequality among OECD countries should also be investigated between jobs that offer temporary employment because of the fragmentation between temporary jobs of low and high learning content. Temporary jobs are not necessarily dead-end jobs. Instead, by offering sufficient opportunities to learn on the job, such jobs could be a stepping stone towards more stable employment. As indicated by Cedefop (2011) and the European Commission (2010b), the flexicurity concept assumes that it is the worker who needs employability support for a successful transition either within the same organisation or to a different firm. Both formal and informal investments in the human capital of workers with temporary contracts need to be incentivised and complemented in the workplace to strengthen their employability and to facilitate the required flexibility in the labour market.

## REFERENCES


Abraham, K. (1990) Restructuring the employment relationship: The growth of market-mediated work arrangements. In Abraham, K. and McKersie, R. (Eds.), *New developments in the labour market: Toward a new institutional Paradigm*. Cambridge, MA, MIT Press, 85-119.

Acemoglu, D. and. Pischke J. (1999) Beyong Becker: Training in imperfect Labour Markets. *The Economic Journal* 109 (453): 112-142.

Akgündüz, Y., and Van Huizen, T. (2013) Training in Two-Tier Labour Markets: The Role of Job Match Quality. Working paper, Utrecht University School of Economics.

Albert, C., García-Serrano, C. and Hernanz, V. (2010) On-the-job training in Europe: Determinants and wage returns. *International Labour Review* 149(3): 315-341.

Angrist, J. and Pischke J. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, Princeton University Press.

Arrow, K. (1962) The economic implications of learning-by-doing. *Review of Economic Studies* 24(3): 155-173.

Arulampalam, W. and Booth, A. (1998) Training and Labour Market Flexibility: Is there a Trade-off? *The British Journal of Industrial Relations* 36(4): 521-536.

Arulampalam, W., Booth, A. and Bryan, M. (2004) Training in Europe. *Journal of the European Economic Association* 2(2-3): 346–360.

Atkinson, A. (1998). Exclusion, Employment and Opportunity. CASE Working Paper, Centre for Analysis of Social Exclusion, London School of Economics.

Autor, D. (2001) Why Do Temporary Help Firms Provide Free General Skills Training? *The Quarterly Journal of Economics* 116 (4): 1409-1448.

Belzil C. and Leonardi, M. (2007) Can Risk Aversion Explain Schooling Attainments? Evidence from Italy. Labour Economics 14 (6): 957-970.

Ben-Porath, Y. (1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy* 75: 352-365.

Berton, F. and Garibaldi, P. (2012) Workers and Firms Sorting into Temporary Jobs. *The Economic Journal* 122 (562): 125 - 154.

Berton, F., Devicienti, F. and Pacelli, L. (2011) Are temporary jobs a port of entry into permanent employment?: Evidence from matched employer-employee. *International Journal of Manpower* 32(8): 879 – 899.

Billet, S. (2008) Emerging Perspectives on Workplace Learning. In Billet, S., Harteis, C., and Eteläpelto, A. (Eds.), *Emerging Perspectives of Workplace Learning*. Rotterdam, Netherlands, Sense Publishers, 1-15.

Blundell, R., Dearden, L., Meghir, C. and Sianesi, B. (1999) Human Capital Investment: The Returns from Education and Training to the Individual, the Firm and the Economy. *Fiscal Studies* 20 (1): 1- 23.

Booth, A. and Bryan, M. (2004) Training in Europe. *Journal of the European Economic Association* 2 (2-3): 346-360.

Booth, A., Francesconi, M. and Frank, J. (2002) Temporary jobs: Stepping stones or dead ends? *The Economic Journal* 112 (480): 189-213.

Bover, O, Arellano, M. and Bentolila, S (2002) Unemployment duration, benefit duration and the business Cycle. *The Economic Journal* 112 (479): 223–265.

Cedefop (2011) *Learning while working. Success stories on workplace learning in Europe*. Luxembourg: Publications Office of the European Union, The European Centre for the Development of Vocational Training.

Cockx, B., and M. Picchio (2012). Are short-lived jobs stepping stones to long-lasting jobs? *Oxford Bulletin of Economics and Statistics* 74(5): 646-675.

Comi, S. and Grasseni, M. (2012) Are Temporary Workers Discriminated Against? Evidence from Europe. *The Manchester School* 80(1): 28–50.

Cutulli, G. and Guetto, R. (2013) Fixed-Term Contracts, Economic Conjuncture, and Training Opportunities: A Comparative Analysis across European Labour Markets. *European Sociological Review* 29 (3): 616-629.

Destré, G, Lévy-Garboua, L. and Sollogoub, M. (2008) Learning from experience or learning from others? Inferring informal training from a human capital earnings function with matched employer–employee data. *The Journal of Socio-Economics* 37: 919–938.

De Graaf-Zijl, M., van den Berg, G. and Heyma, A. (2011) Stepping stones for the unemployed: the effect of temporary jobs on the duration until (regular) work. *Journal of Population Economics* 24(1): 107-139.

De Grip, A. (2008) Economic perspectives of workplace learning. In Nijhof, W. and Nieuwenhuis, L. (Eds), *The Learning Potential of the Workplace*. Rotterdam, Netherlands, Sense Publishers, 15-29.

Dekker, R. (2007). *Non–Standard Employment and Mobility in the Dutch, German and British Labour Market*. Ridderkerk: Ridderprint.

Engellandta, A. and Riphahn, R. (2005) Temporary contracts and employee effort. *Labour Economics* 12(3): 281–299.

European Commission (2013) Flexicurity in Europe. Administrative Agreement. Final Report. Luxembourg: Publications Office of the European Union.

__________ (2010) *Employment in Europe* 2010. Luxembourg: Publications Office of the European Union.

__________ (2010b). Changing patterns of working, learning and career development across Europe. Final Report. Luxembourg: Publications Office of the European Union.

__________ (2007) *Towards Common Principles of Flexicurity: More and better jobs through flexibility and security*. Luxembourg: Publications Office of the European Union.

__________ (2003) *Employment in Europe*. Luxembourg: Publications Office of the European Union.

Faccini, R. (2014) Reassessing Labour Market Reforms: Temporary Contracts as a Screening Device. *The Economic Journal* 124 (575): 167–200.

Gagliarducci, S. (2005) The dynamics of repeated temporary jobs. *Labour Economics* 12 (4): 429 – 448.

Gebel, M. (2013) Is a Temporary Job Better Than Unemployment? A Cross-country Comparison Based on British, German, and Swiss Panel Data. *Journal of Applied Social Science Studies* 133(2): 143-155.

Givord, P., and Wilner, L. (2015) When Does The Stepping-Stone Work? Fixed-Term Contracts versus Temporary Agency Work In Changing Economic Conditions. *Journal of Applied Econometrics* 30(5): 787-805.

Greene, W. (2012) *Econometric Analysis*, seventh edition. New York, Pearson Education.

Grund, C. and Martin, J. (2012) Determinants of further training – evidence for Germany. *The International Journal of Human Resource Management* 23(17): 3536–3558.

Guell, M. (2000) Fixed-term Contracts and Unemployment: an Efficiency Wage Analysis. Working Paper No. 433, Princeton University, Department of Economics, Industrial Relations Section.

Heckman, J. (1978) Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica* 46(4): 931–959.

__________ (1976) A Life-Cycle Model of Earnings, Learning, and Consumption. *Journal of Political Economy* 84 (4): 11-44.

Heckman, J. and Navarro-Lozano, S. (2004) Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models. *The Review of Economics and Statistics* 86(1): 30–57.

Heckman, J., Tobias, J. and Vytlacil, E. (2001) Four Parameters of Interest in the Evaluation of Social Programs. *Southern Economic Journal* 68(2): 210–223.

Heckman, J. and Vytlacil, E. (2005) Structural Equations, Treatment Effects, and Econometric Policy Evaluation. *Econometrica* 73(3): 669–738

____________ (1999). Local instrumental variables and latent variable models for identifying and bounding treatment effects. *Proceedings of the National Academy of Sciences* 96: 4730-4734.

Holmlund, B. and Storrie, D. (2002) Temporary work in turbulent times: the Swedish experience. *The Economic Journal* 112 (480): 245–269.

ILO (2010) The impact of the economic and financial crisis on youth employment: Measures for labour market recovery in the European Union, Canada and the United States. Employment Working Paper No. 70. International Labour Office, Youth Employment Programme. Geneva: ILO.

Imbens, G. and Wooldridge, J. (2009) Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47(1): 5–86.

Jackson, C. (2012) Match quality, worker productivity, and worker mobility: Direct evidence from teachers. *The Review of Economics and Statistics* 95(4): 1096-1116.

Jahn, E. and Bentzen, J. (2012) What Drives the Demand for Temporary Agency Workers? *LABOUR* 26 (3): 341–355.

Jahn, E. and Pozzoli, D. (2013) The pay gap of temporary agency workers — Does the temporary sector experience pay off? *Labour Economics* 24: 48–57.

Jahn, E. and Rosholm, M. (2014) Looking beyond the bridge: The effect of temporary agency employment on labor market outcomes. *European Economic Review* 65: 108–125.

Kahn, L. (2010) Employment protection reforms, employment and the incidence of temporary jobs in Europe: 1996–2001. *Labour Economics* 17: 1–15.

Keogh, H. (2009). The state and development of adult learning and education in Europe, North America and Israel. Regional Synthesis Report. Hamburg: UNESCO Institute for Lifelong Learning.

Kirby, J., Knapper, C., Evans, C., Carty, A., and Gadula, C. (2003). Approaches to learning at work and workplace climate. *International Journal of Training and Development* 7(1): 31-52.

Killingsworth, M. (1982) "Learning-by-doing" and "Investment in Training": A Synthesis of Two "Rival" Models of the Life Cycle. *The Review of Economic Studies* 49 (2): 263-271.

Koopmans, H., Doornbos, A., and Eekelen, I. (2006). Learning in interactive work situations: It takes two to tango; why not invite both partners to dance? *Human Resource Development Quarterly* 17: 135-158.

Loewenstein, M. And Spletzer, J. (1997) Delayed Formal On-The-Job Training. *Industrial and Labor Relations Review* 51(1): 82-99.

Loh, E. (1994): Employment probation as a sorting mechanism. *Industrial and Labor Relations Review* 47 (3): 471-486.

Maddala, G. (1983) Limited-Dependent and Qualitative Variables in Econometrics (Econometric Society Monographs, 3) (Kindle Locations 5759-5766). Cambridge University Press. Kindle Edition.

Marsick, V., Watkins, K., Callahan, M., and Volpe, M. (2009). Informal and incidental learning in the workplace. In Smith, M. and DeFrates-Densch, N. (Eds.), *Handbook of research on adult learning and development.* New York, NY: Routledge, 570-599.

Maurer, T. and Weiss, E. (2010) Continuous Learning Skill Demands: Associations with Managerial Job Content, Age, and Experience. *Journal of Business and Psychology* 25(1): 1–13.

Miranda, A and Rabe-Hesketh, S. (2006) Maximum likelihood estimation of endogenous switching and sample selection models for binary, count, and ordinal variables. *Stata Journal* 6 (3): 285-308.

Mincer, J. (1997) The Production of Human Capital and the Lifecycle of Earnings: Variations on a theme. *Journal of Labor Economics* 15(1): 26-47.

_________ (1974). *Schooling, Experience and Earnings*. New York: Columbia University Press.

_________ (1968) Job Training, Wage Growth and Labour Turnover. NBER Working paper series No. 2690. Massachusetts, National Bureau of Economic Research.

Mincer, J. and Jovanovic, B. (1981) Labour mobility and wages. In: Rosen, S. (Ed.), *Studies in Labour Markets*. Chicago, Chicago University Press, 21–64.

Nelen, A. and De Grip, A. (2009) Why do Part-Time Workers invest less in Human Capital than Full Timers? *LABOUR* 23(s1): 61-83.

Newey, W. (1990) Semiparametric Efficiency Bounds. *Journal of Applied Econometrics* 5: 99-135.

O'Connell, P. and Byrne, D. (2010). The determinants and effects of training at work: bringing the workplace back in. *European Sociological Review*, DOI: 10.1093/esr/jcq063.

OECD (2014) *OECD Employment Outlook 2014*, OECD Publishing.

______ (2014b) Technical Report of the Survey of Adult Skills, Reader's Companion. OECD Publishing.

______ (2010) Recognising Non-Formal And Informal Learning Outcomes, Policies and Practices. OECD Publishing.

______ (2006) *OECD Employment Outlook 2006*. OECD Publishing.

______ (2004) *OECD Employment Outlook 2004*. OECD Publishing.

Pfeifer, C. (2014) A Note on Dual Internal Labor Markets and Wages of Temporary Workers: Evidence from Linked-Employer-Employee Data. *Journal of Labor Research* 35 2): 133-142.

Quinones, M., Ford, J., and Teachout, M. (1995). The relationship between work experience and job performance: A conceptual and meta-analytic review. *Personnel Psychology* 48: 887-910.

Rabe-Hesketha, S., Skrondalb, A. and Picklesc, A. (2005) Maximum likelihood estimation of limited and discrete dependent variable models with nested random effects. *Journal of Econometrics* 128: 301–323.

Rosen, S. (1972) Learning and Experience in the Labour Market. *Journal of Human Resources* 7: 326-342.

Sala, H., Silva, J. and Toledo, M. (2012) Flexibility at the Margin and Labor Market Volatility in OECD Countries. *The Scandinavian Journal of Economics* 114(3): 991–1017.

Sicherman, N. and Galor, O. (1990). A theory of career mobility. *Journal of Political Economy* 98(1): 169-92.

Steijn, B., Need, A. and Gesthuizen, M. (2006) Well Begun, Half Done? Long-Term Effects of Labour Market Entry in the Netherlands, 1950–2000. *Work, Employment and Society* 20(3): 453–72.

Stevens, M. (1994). An investment model for the supply of training by employers. *The Economic Journal* 104 (424): 556–570.

Straka, G. (2000). Conditions promoting self-directed learning at the workplace. *Human Resources Development International* 3(2): 241-251.

Svensson, L., Ellström, P. and Aberg, C. (2004). Integrating formal and informal learning at work. *Journal of Workplace Learning* 16(7/8): 479-492.

Tannenbaum, S., Beard, R., McNall, L., and Salas, E. (2010). Informal learning and development in organizations. In Kozlowski, S. and Salas, E. (Eds.), *Learning, training, and development in organizations*. New York: Routledge, 303-332.

Tesluk, P., and Jacobs, R. (1998). Toward an integrated model of work experience. *Personnel Psychology* 51: 321-355.

Virtanen, M., Kivimäki, M, Joensuu, M., Virtanen, P., Elovainio, M. and Vahtera, J. (2005) Temporary employment and health: a review. *International Journal of Epidemiology* 34 (3): 610–622

Wasmer, E. (1999) Competition for jobs in a growing economy and the emergence of dualism. *The Economic Journal* 109 (457): 349–71.

Weiss, Y. (1986) The determination of life cycle earnings: A survey. In Ashenfelter O., Layard, R. and Card, D. (Eds.) Handbook of Labor Economics. Elsevier, doi:10.1016/S1573-4463(86)01014-3, 603-640.

Wooldridge, J. (2003). Further results on instrumental variables estimation of average treatment effects in the correlated random coefficient model. *Economics Letters* 79: 185–191.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*, second edition. Cambridge, MA: MIT Press.

**Table 1. Sample description***

| COUNTRY | TOTAL OBS. | FINAL SAMPLE | % | PERMANENT | % | % OECD* | TEMP | % | % OECD* |
|---|---|---|---|---|---|---|---|---|---|
| 1 Austria | 2,530 | 1,249 | 4.9 | 1,171 | 93.8 | 90.7 | 78 | 6.2 | 9.3 |
| 2 Belgium | 2,700 | 1,196 | 4.7 | 1,144 | 95.7 | 92.9 | 52 | 4.3 | 7.1 |
| 3 Canada | 12,728 | 1,164 | 4.6 | 1,052 | 90.4 | 87.0 | 112 | 9.6 | 13.0 |
| 4 Czech Republic | 2,769 | 1,176 | 4.6 | 1,013 | 86.1 | 92.6 | 163 | 13.9 | 7.4 |
| 5 Denmark | 4,560 | 1,743 | 6.9 | 1,634 | 93.7 | 92.2 | 109 | 6.3 | 7.8 |
| 6 Estonia | 3,464 | 1,577 | 6.2 | 1,434 | 90.9 | 95.3 | 143 | 9.1 | 4.7 |
| 7 Finland | 2,757 | 1,259 | 5.0 | 1,157 | 91.9 | 87.2 | 102 | 8.1 | 12.8 |
| 8 France | 3,430 | 1,616 | 6.4 | 1,477 | 91.4 | 85.6 | 139 | 8.6 | 14.4 |
| 9 Germany | 2,676 | 1,345 | 5.3 | 1,212 | 90.1 | 86.1 | 133 | 9.9 | 13.9 |
| 10 Ireland | 2,744 | 931 | 3.7 | 801 | 86.0 | 90.1 | 130 | 14.0 | 9.9 |
| 11 Italy | 2,235 | 925 | 3.6 | 835 | 90.3 | 87.1 | 90 | 9.7 | 12.9 |
| 12 Japan | 2,517 | 1,494 | 5.9 | 1,332 | 89.2 | 91.4 | 162 | 10.8 | 8.6 |
| 13 Korea | 3,102 | 1,162 | 4.6 | 905 | 77.9 | 78.9 | 257 | 22.1 | 21.1 |
| 14 Netherlands | 2,546 | 1,168 | 4.6 | 1,032 | 88.4 | 81.4 | 136 | 11.6 | 18.6 |
| 15 Norway | 2,655 | 1,147 | 4.5 | 1,090 | 95.0 | 93.3 | 57 | 5.0 | 6.7 |
| 16 Poland | 4,733 | 1,495 | 5.9 | 923 | 61.7 | 72.6 | 572 | 38.3 | 27.4 |
| 17 Slovak Republic | 2,706 | 1,183 | 4.7 | 1,014 | 85.7 | 93.6 | 169 | 14.3 | 6.4 |
| 18 Spain | 2,964 | 1,061 | 4.2 | 894 | 84.3 | 78.0 | 167 | 15.7 | 22.0 |
| 19 Sweden | 2,253 | 1,156 | 4.6 | 1,081 | 93.5 | 85.7 | 75 | 6.5 | 14.3 |
| 20 United Kingdom | 3,737 | 1,319 | 5.2 | 1,172 | 88.9 | 94.1 | 147 | 11.1 | 5.9 |
| Total | 69,806 | 25,366 | 100 | 22,373 | 88.2 | 87.8 | 2,993 | 11.8 | 12.2 |

* Four countries are excluded from our study: Australia, Cyprus, the Russian Federation, and the United States. Australian data were not available due to confidentiality reasons. OECD statistics for Cyprus were not available. Data from the Russian Federation were preliminary and considered by the OECD (2014b) to be not representative of the population. Last, because of the particular characteristics of the US labour market, particularly its very poor employment protection, the distinction between temporary and permanent employment is of much less significance (ILO, 2010). In the PIAAC survey, 58 percent of all workers in the United States stated not having any kind of formal contract, which would leave only 387 non-random observations in our sample. This suggests that temporary contracts in the United States are not comparable to those in other countries.

**Table 2. Summary statistics**

| Variable | Permanent | | Temporary | | All | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Min | Max |
| Informal learning intensity (standarised index) | -0.03 | 0.98 | 0.03 | 1.09 | -3.39 | 2.05 |
| Informal learning incidence | 0.98 | 0.14 | 0.97 | 0.17 | 0 | 1 |
| Training (participation)* | 0.52 | 0.50 | 0.39 | 0.49 | 0 | 1 |
| | | | | | | |
| Age | 42.08 | 11.11 | 36.04 | 12.83 | 17 | 65 |
| Years of education | 13.30 | 2.89 | 12.93 | 3.09 | 3 | 22 |
| Work experience (years) | 21.31 | 11.67 | 14.59 | 12.59 | 0 | 47 |
| Overeducated | 0.23 | 0.42 | 0.30 | 0.46 | 0 | 1 |
| Undereducated | 0.07 | 0.26 | 0.05 | 0.23 | 0 | 1 |
| Elaborate learning (standardised index) | -0.02 | 1.00 | -0.04 | 1.09 | -6.89 | 8.86 |
| Tenure (years) | 11.90 | 10.26 | 4.44 | 7.33 | 0 | 51 |
| Weekly working hours | 42.52 | 7.28 | 42.58 | 8.37 | 35 | 60 |
| | | | | | | |
| Firm size 1-10 | 0.20 | 0.40 | 0.24 | 0.43 | 0 | 1 |
| Firm size 11-50 | 0.30 | 0.46 | 0.32 | 0.47 | 0 | 1 |
| Firm size 51 -250 | 0.26 | 0.44 | 0.24 | 0.43 | 0 | 1 |
| Firm size 251-1000 | 0.14 | 0.35 | 0.12 | 0.33 | 0 | 1 |
| Firm size >1000 | 0.10 | 0.30 | 0.07 | 0.25 | 0 | 1 |
| | | | | | | |
| *Occupation* | | | | | | |
| Managers | 0.10 | 0.30 | 0.05 | 0.21 | 0 | 1 |
| Professionals | 0.18 | 0.39 | 0.15 | 0.36 | 0 | 1 |
| Technicians | 0.18 | 0.39 | 0.11 | 0.31 | 0 | 1 |
| Clerks | 0.07 | 0.25 | 0.08 | 0.27 | 0 | 1 |
| Services and sales workers | 0.09 | 0.28 | 0.11 | 0.32 | 0 | 1 |
| Skilled agricultural and fishery workers | 0.01 | 0.10 | 0.02 | 0.13 | 0 | 1 |
| Craft workers | 0.18 | 0.39 | 0.21 | 0.41 | 0 | 1 |
| Operators | 0.13 | 0.34 | 0.17 | 0.37 | 0 | 1 |
| Elementary occupations | 0.05 | 0.22 | 0.11 | 0.31 | 0 | 1 |
| | | | | | | |
| *Industry* | | | | | | |
| Agriculture, forestry and fishing | 0.02 | 0.13 | 0.03 | 0.16 | 0 | 1 |
| Manufacturing | 0.30 | 0.46 | 0.30 | 0.46 | 0 | 1 |
| Construction | 0.11 | 0.31 | 0.14 | 0.34 | 0 | 1 |
| Sales, transportation, accomodation and food services | 0.22 | 0.42 | 0.20 | 0.40 | 0 | 1 |
| Information and communication | 0.05 | 0.21 | 0.03 | 0.16 | 0 | 1 |
| Finance | 0.03 | 0.18 | 0.02 | 0.13 | 0 | 1 |
| Real estate | 0.01 | 0.09 | 0.01 | 0.10 | 0 | 1 |
| Professional, technical and administration services | 0.08 | 0.26 | 0.09 | 0.29 | 0 | 1 |
| Public administration, education and health | 0.17 | 0.38 | 0.15 | 0.36 | 0 | 1 |
| Other services | 0.02 | 0.15 | 0.04 | 0.19 | 0 | 1 |
| | | | | | | |
| Observations | 22,373 | | 2,993 | | 25,366 | |
| | | | | | | |
| *Selection instrument* | | | | | | |
| Unemployment rate (by country and age groups) | 0.07 | 0.04 | 0.10 | 0.06 | 0 | 0.57 |
| Unemployment rate (standardised) | -0.07 | 0.90 | 0.55 | 1.46 | -1.25 | 10.63 |
| EPL regular employment (standardised) | 0.03 | 0.98 | 0.10 | 0.90 | -1.88 | 1.98 |

* For this particular variable, we have fewer observations (22447), due to lower response rate and the exclusion of respondents who participated in training while unemployed.

**Table 3. Estimations of on-the-job informal learning intensity**

| | (1) OLS | (2) 2SLS (1 instrument) | (3) 2SLS (3 instruments) | (4) CF-ML (1 instrument) | (5) CF-ML (3 instruments) |
|---|---|---|---|---|---|
| ***Informal Learning Equation*** | | | | | |
| Temporary contract | 0.0953$^{***}$ | 1.5036$^{***}$ | 0.9877$^{***}$ | 0.1667$^{***}$ | 0.1698$^{***}$ |
| | (0.0280) | (0.3995) | (0.2753) | (0.0502) | (0.0501) |
| Age | -0.0271$^{***}$ | 0.0156 | 0.0054 | -0.0249$^{***}$ | -0.0248$^{***}$ |
| | (0.0050) | (0.0120) | (0.0116) | (0.0049) | (0.0050) |
| Age$^2$ | 0.0002$^{***}$ | -0.0003$^{**}$ | -0.0002 | 0.0002$^{***}$ | 0.0002$^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Years of education | 0.0155$^{***}$ | 0.0204$^{***}$ | 0.0193$^{***}$ | 0.0156$^{***}$ | 0.0156$^{***}$ |
| | (0.0033) | (0.0050) | (0.0048) | (0.0034) | (0.0034) |
| Overeducated | -0.1045$^{***}$ | -0.1284$^{***}$ | -0.1227$^{***}$ | -0.1046$^{***}$ | -0.1046$^{***}$ |
| | (0.0162) | (0.0202) | (0.0194) | (0.0161) | (0.0161) |
| Undereducated | 0.1544$^{***}$ | 0.1565$^{***}$ | 0.1560$^{***}$ | 0.1543$^{***}$ | 0.1543$^{***}$ |
| | (0.0278) | (0.0268) | (0.0267) | (0.0277) | (0.0277) |
| Working hours | 0.0068$^{***}$ | 0.0075$^{***}$ | 0.0074$^{***}$ | 0.0067$^{***}$ | 0.0067$^{***}$ |
| | (0.0012) | (0.0013) | (0.0013) | (0.0012) | (0.0012) |
| Tenure | -0.0031$^{***}$ | 0.0063$^{**}$ | 0.0041 | -0.0031$^{***}$ | -0.0031$^{***}$ |
| | (0.0009) | (0.0030) | (0.0029) | (0.0009) | (0.0009) |
| Elaborate learning | 0.2041$^{***}$ | 0.2042$^{***}$ | 0.2042$^{***}$ | 0.2040$^{***}$ | 0.2040$^{***}$ |
| | (0.0148) | (0.0149) | (0.0147) | (0.0148) | (0.0148) |
| _cons | -0.1483 | -1.4037$^{***}$ | -0.6646$^{***}$ | -0.2095 | -0.2125 |
| | (0.1209) | (0.3553) | (0.1691) | (0.1288) | (0.1293) |
| Other controls | yes | yes | yes | yes | yes |
| Country dummies | yes | yes | yes | yes | yes |
| ***Temporary Contract Equation*** | | | | *AME* | *AME* |
| Unemployment | | 0.0467$^{***}$ | 0.0479$^{***}$ | 0.0160$^{***}$ | 0.0239$^{***}$ |
| | | (0.0057) | (0.0075) | (0.0056) | (0.0073) |
| Unemployment *EPL moderate | | | 0.0016 | | -0.0117 |
| | | | (0.0083) | | (0.0065) |
| Unemployment * EPL low | | | -0.0713$^{***}$ | | -0.0625$^{***}$ |
| | | | (0.0135) | | (0.0078) |
| Age | | -0.0180$^{***}$ | -0.0192$^{***}$ | -0.0203$^{***}$ | -0.0213$^{***}$ |
| | | (0.0019) | (0.0019) | (0.0023) | (0.0019) |
| Age$^2$ | | 0.0002$^{***}$ | 0.0002$^{***}$ | 0.0002$^{***}$ | 0.0002$^{***}$ |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Years of education | | -0.0035$^{***}$ | -0.0035$^{***}$ | -0.0010 | -0.0010 |
| | | (0.0009) | (0.0009) | (0.0017) | (0.0017) |
| Overeducated | | 0.0169$^{***}$ | 0.0167$^{***}$ | | |
| | | (0.0048) | (0.0048) | | |
| Undereducated | | -0.0018 | -0.0010 | | |
| | | (0.0068) | (0.0068) | | |
| Working hours | | -0.0006$^{*}$ | -0.0006$^{**}$ | | |
| | | (0.0003) | (0.0003) | | |
| Tenure | | -0.0067$^{***}$ | -0.0067$^{***}$ | | |
| | | (0.0002) | (0.0002) | | |
| Elaborate learning | | 0.0005 | 0.0005 | 0.0027 | 0.0028 |
| | | (0.0027) | (0.0027) | (0.0023) | (0.0023) |
| Other controls | | yes | yes | yes | yes |
| Country dummies | | yes | yes | yes | yes |
| *First-stage Tests* | | F(49, 25316) | F(51, 25314) | Wald chi2(45) | Wald chi2(47) |
| | | = 58.60 | = 56.97 | = 2243.9 | = 2245.6 |
| *Adj. $R^2$ First-stage* | | 0.1400 | 0.1413 | 0.1305 | 0.1325 |
| *athrho* | | | | -0.0746$^{***}$ | -0.0774$^{***}$ |
| | | | | (0.0223) | (0.0219) |
| *lnsigma* | | | | -0.1033$^{***}$ | -0.1055$^{***}$ |
| | | | | (0.0351) | (0.0351) |
| *IV Test of endogeneity /* | | F(1,19) = 16.0 | F(1,19) = 9.47 | Chi2(1) = 4.72 | Chi2(1) = 5.60 |
| *Wald test of indep. Eqns. (rho = 0)* | | ($p$ = 0.0008) | ($p$ = 0.0062) | ($p$ = 0.0299) | ($p$ = 0.0179) |
| *N* | 25,366 | 25,366 | 25,366 | 25,366 | 25,366 |
| *$R^2$* | 0.1744 | 0.0798 | 0.1024 | . | . |

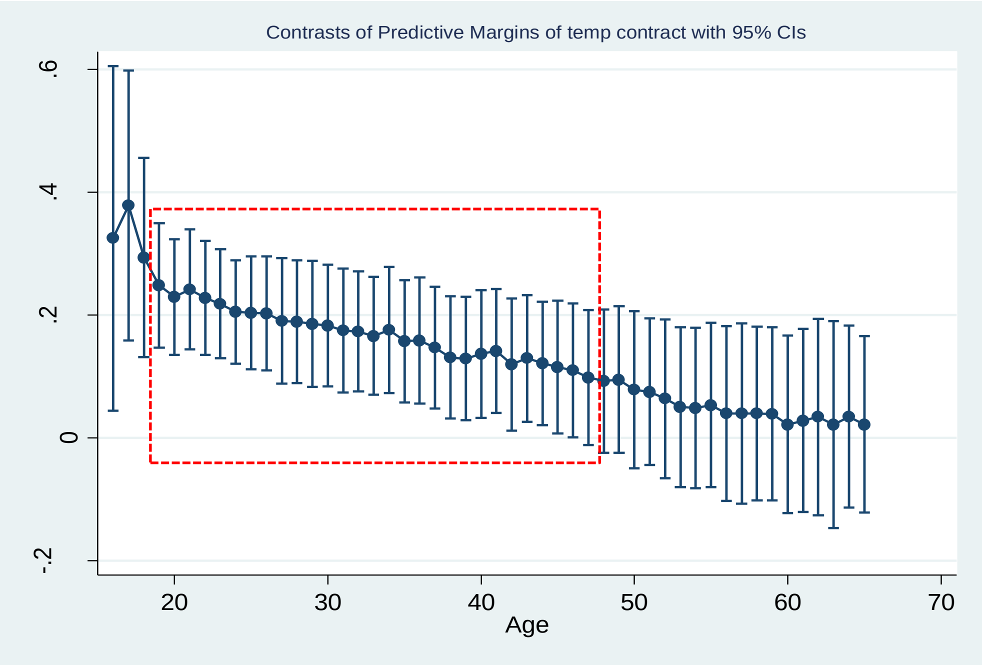
The informal learning dependent variable is standardised. The standardised unemployment rate is used as an instrument in columns (2) and (4) and columns (3) and (5) add as instruments the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. The term AME denotes average marginal effects. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table 4. Estimations of on-the-job informal learning intensity with heterogeneous employees**

| | (1) CF-ML (1 instrument) | Difference Permanent and Temporary contract | (2) CF-ML (3 instruments) | Difference Permanent and Temporary contract |
|---|---|---|---|---|
| ***ATE*** | **0.1255**$^{**}$ | | **0.1292**$^{**}$ | |
| | (0.0500) | | (0.0517) | |
| ***ATT*** | **0.1822**$^{***}$ | | **0.1856**$^{***}$ | |
| | (0.0489) | | (0.0505) | |
| Permanent contract * Age | -0.0218$^{***}$ | | -0.0218$^{***}$ | |
| | (0.0046) | -0.0047$^{**}$ | (0.0047) | -0.0046$^{**}$ |
| Temporary contract * Age | -0.0265$^{***}$ | (0.0021) | -0.0264$^{***}$ | (0.0020) |
| | (0.0051) | | (0.0051) | |
| Permanent contract * Age$^2$ | 0.0002$^{***}$ | | 0.0002$^{***}$ | |
| | (0.0001) | | (0.0001) | |
| Temporary contract * Age$^2$ | -0.0000 | | -0.0000 | |
| | (0.0002) | | (0.0002) | |
| Permanent contract * Years of education | 0.0157$^{***}$ | | 0.0157$^{***}$ | |
| | (0.0032) | -0.0004 | (0.0032) | -0.0003 |
| Temporary contract * Years of education | 0.0153$^{**}$ | (0.0068) | 0.0154$^{**}$ | (0.0068) |
| | (0.0077) | | (0.0077) | |
| Permanent contract * Overeducated | -0.1102$^{***}$ | | -0.1102$^{***}$ | |
| | (0.0190) | 0.0495 | (0.0190) | 0.0495 |
| Temporary contract * Overeducated | -0.0606$^{***}$ | (0.0369) | -0.0606$^{***}$ | (0.0369) |
| | (0.0230) | | (0.0230) | |
| Permanent contract * Undereducated | 0.1409$^{***}$ | | 0.1410$^{***}$ | |
| | (0.0296) | 0.1218 | (0.0296) | 0.1242 |
| Temporary contract * Undereducated | 0.2627$^{***}$ | (0.0937) | 0.2652$^{***}$ | (0.0937) |
| | (0.0864) | | (0.0864) | |
| Permanent contract * Tenure | -0.0024$^{**}$ | | -0.0023$^{**}$ | |
| | (0.0010) | -0.0059$^{**}$ | (0.0010) | -0.0058$^{**}$ |
| Temporary contract * Tenure | -0.0082$^{***}$ | (0.0029) | -0.0082$^{***}$ | (0.0028) |
| | (0.0031) | | (0.0031) | |
| Permanent contract * Working hours | 0.0078$^{***}$ | | 0.0078$^{***}$ | |
| | (0.0011) | | (0.0011) | |
| Temporary contract * Working hours | 0.0016 | | 0.0016 | |
| | (0.0022) | | (0.0022) | |
| Permanent contract * Elaborate learning | 0.2049$^{***}$ | | 0.2088$^{***}$ | |
| | (0.0132) | -0.0048 | (0.0132) | -0.0087 |
| Temporary contract * Elaborate learning | 0.2001$^{***}$ | (0.0283) | 0.2001$^{***}$ | (0.0290) |
| | (0.0345) | | (0.0345) | |
| Temporary contract | 0.5957$^{**}$ | | 0.5993$^{**}$ | |
| | (0.2746) | | (0.2785) | |
| _cons | -0.3196$^{***}$ | | -0.3220$^{***}$ | |
| | (0.1098) | | (0.1105) | |
| *Treatment interactions with:* | | | | |
| Other controls | yes | | yes | |
| Country dummies | yes | | yes | |
| ***Temporary Contract Equation*** | *AME* | | *AME* | |
| Unemployment | 0.0145$^{**}$ | | 0.0226$^{***}$ | |
| | (0.0059) | | (0.0080) | |
| Unemployment * EPL moderate | | | -0.0122$^{*}$ | |
| | | | (0.0072) | |
| Unemployment * EPL low | | | -0.0525$^{***}$ | |
| | | | (0.0061) | |
| Other controls | yes | | yes | |
| Country dummies | yes | | yes | |
| *athrho* | -0.0509$^{***}$ | | -0.0532$^{***}$ | |
| | (0.0171) | | (0.0178) | |
| *lnsigma* | -0.1072$^{***}$ | | -0.1072$^{***}$ | |
| | (0.0358) | | (0.0359) | |
| *Wald test of indep. Eqns (rho = 0)* | Chi2(1) = 8.85 | | Chi2(1) = 8.90 | |
| | ($p$ = 0.0029) | | ($p$ = 0.0028) | |
| *N* | 25,366 | | 25,366 | |

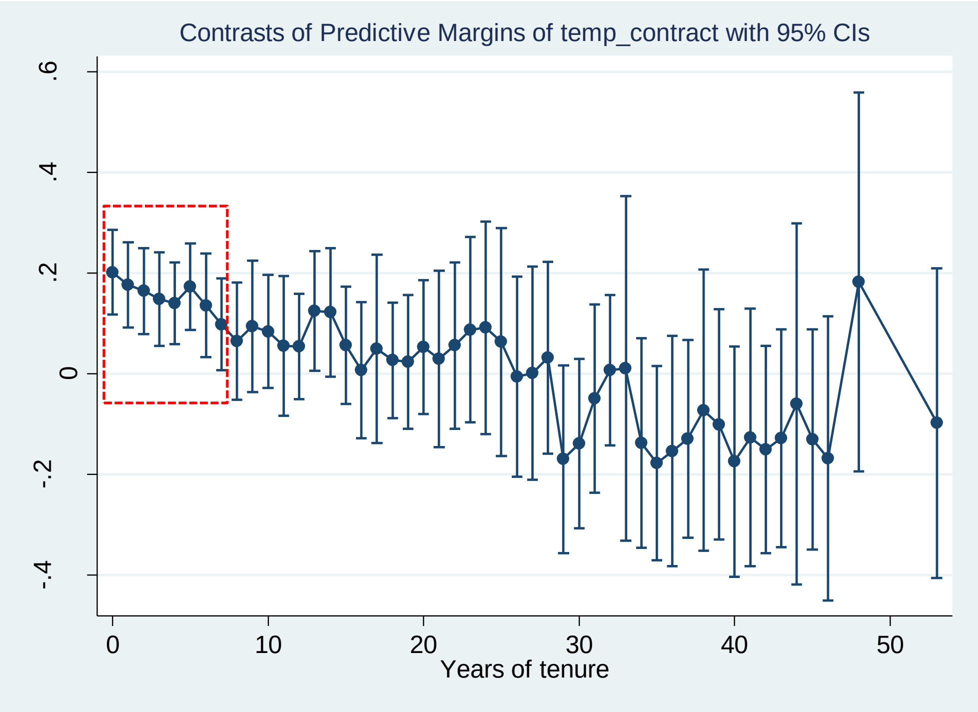
The informal learning dependent variable is standardised. The standardised unemployment rate is used as an instrument in column (1), and column (2) adds as instruments the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. The term AME denotes average marginal effects. All the regressions include the same control variables as reported in Table 3. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Figure 1. Estimated difference in informal learning between temporary and permanent employees over age**




Marginal effects computed based on the full endogenous switching regression model (2) in Table 4. The dotted line shows marginal effects that are significant with 95 percent confidence at a minimum.

**Figure 2. Estimated difference in informal learning between temporary and permanent employees over years of tenure**




Marginal effects computed based on the full endogenous switching regression model (2) in Table 4. The dotted line shows marginal effects that are significant with 95 percent confidence at a minimum.

**Table 5. Heterogeneous effects of temporary contracts by various job content characteristics**

| | (1)<br>CF-ML<br>(1 instrument) | (2)<br>CF-ML<br>(3 instruments) |
|---|---|---|
| ***ATE Temporary Contract*** | **0.1455**$^{***}$ | **0.1497**$^{***}$ |
| | **(0.0514)** | **(0.0507)** |
| Permanent contract * High skilled occupations | 0.2194$^{***}$ | 0.2195$^{***}$ |
| | (0.0181) | (0.0180) |
| Temporary contract * High skilled occupations | 0.1920$^{***}$ | 0.1926$^{***}$ |
| | (0.0465) | (0.0464) |
| Difference | -0.0274 | -0.0269 |
| | (0.0441) | (0.0441) |
| *athrho* | -0.0357$^{**}$ | -0.0383$^{**}$ |
| | (0.0214) | (0.0206) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 3.93 | Chi2(1) = 4.04 |
| | (*p* = 0.0474) | (*p* = 0.0444) |
| *N* | 25,366 | 25,366 |
| ***ATE Temporary Contract*** | **0.1656**$^{***}$ | **0.1695**$^{***}$ |
| | **(0.0511)** | **(0.0508)** |
| Permanent contract * Task discretion | 0.0794$^{***}$ | 0.0794$^{***}$ |
| | (0.0134) | (0.0134) |
| Temporary contract * Task discretion | 0.0809$^{***}$ | 0.0812$^{***}$ |
| | (0.0272) | (0.0272) |
| Difference | 0.0014 | 0.0018 |
| | (0.0299) | (0.0298) |
| *athrho* | -0.0404$^{**}$ | -0.0428$^{**}$ |
| | (0.0200) | (0.0192) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 4.09 | Chi2(1) = 4.97 |
| | (*p* = 0.0430) | (*p* = 0.0258) |
| *N* | 25,365 | 25,365 |
| ***ATE Temporary Contract*** | **0.1643**$^{***}$ | **0.1680**$^{***}$ |
| | **(0.0552)** | **(0.0547)** |
| Permanent contract * Complex problems | 0.3549$^{***}$ | 0.3549$^{***}$ |
| | (0.0164) | (0.0164) |
| Temporary contract * Complex problems | 0.3950$^{***}$ | 0.3950$^{***}$ |
| | (0.0574) | (0.0573) |
| Difference | 0.0402 | 0.0401 |
| | (0.0541) | (0.0541) |
| *athrho* | -0.0407$^{*}$ | -0.0431$^{**}$ |
| | (0.0210) | (0.0202) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 3.96 | Chi2(1) = 4.56 |
| | (*p* = 0.0466) | (*p* = 0.0327) |
| *N* | 25,334 | 25,334 |
| ***ATE Temporary Contract*** | **0.1761**$^{***}$ | **0.1800**$^{***}$ |
| | **(0.0577)** | **(0.0576)** |
| Permanent contract * Simple problems | 0.3138$^{***}$ | 0.3138$^{***}$ |
| | (0.0177) | (0.0176) |
| Temporary contract * Simple problems | 0.3190$^{***}$ | 0.3191$^{***}$ |
| | (0.0477) | (0.0477) |
| Difference | 0.0051 | 0.0053 |
| | (0.0476) | (0.0476) |
| *athrho* | -0.0457$^{**}$ | -0.0481$^{**}$ |
| | (0.0223) | (0.0216) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 4.18 | Chi2(1) = 4.96 |
| | (*p* = 0.0409) | (*p* = 0.0259) |
| *N* | 25,343 | 25,343 |
| ***ATE Temporary Contract*** | **0.1531**$^{***}$ | **0.1565**$^{***}$ |
| | **(0.0487)** | **(0.0490)** |
| Permanent contract * Team work | 0.2284$^{***}$ | 0.2284$^{***}$ |
| | (0.0228) | (0.0229) |
| Temporary contract * Team work | 0.2694$^{***}$ | 0.2693$^{***}$ |
| | (0.0349) | (0.0350) |
| Difference | 0.0409 | 0.0408 |
| | (0.0359) | (0.0360) |
| *athrho* | -0.0388$^{**}$ | -0.0410$^{**}$ |
| | (0.0196) | (0.0193) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 3.92 | Chi2(1) = 4.52 |
| | (*p* = 0.0478) | (*p* = 0.0336) |
| *N* | 25,349 | 25,349 |

| | | |
|---|---|---|
| ***ATE Temporary Contract*** | **0.1752*****<br>**(0.0502)** | **0.1786*****<br>**(0.0503)** |
| Permanent contract * ICT use | 0.2035***<br>(0.0209) | 0.2035***<br>(0.0209) |
| Temporary contract * ICT use | 0.2211***<br>(0.0495) | 0.2215***<br>(0.0495) |
| Difference | 0.0176<br>(0.0437) | 0.0179<br>(0.0438) |
| *athrho* | -0.0414**<br>(0.0199) | -0.0436**<br>(0.0194) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 4.33<br>($p$ = 0.0374) | Chi2(1) = 5.05<br>($p$ = 0.0246) |
| *N* | 25,366 | 25,366 |
| ***ATE Temporary Contract*** | **0.1690*****<br>**(0.0538)** | **0.1723*****<br>**(0.0536)** |
| Permanent contract * Planning tasks | 0.2056***<br>(0.0204) | 0.2056***<br>(0.0204) |
| Temporary contract * Planning tasks | 0.1740***<br>(0.0337) | 0.1742***<br>(0.0338) |
| Difference | -0.0316<br>(0.0274) | -0.0313<br>(0.0275) |
| *athrho* | -0.0415**<br>(0.0204) | -0.0436**<br>(0.0198) |
| *Wald test of indep. Eqns. (rho = 0)* | Chi2(1) = 4.13<br>($p$ = 0.0422) | Chi2(1) = 4.86<br>($p$ = 0.0276) |
| *N* | 25,366 | 25,366 |

The informal learning dependent variable is standardised. The standardised unemployment rate is used as an instrument in column (1), and column (2) adds as instruments the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. All the regressions include the same control variables as reported in Table 3. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table 6. Estimations of job-related training participation**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | OLS | Probit | CF – ML (1 instrument) | CF – ML (3 instruments) |
| ***Training Equation*** | | *AME* | *AME* | *AME* |
| Temporary contract | -0.0619*** | -0.0648*** | -0.0751*** | -0.0763*** |
| | (0.0124) | (0.0133) | (0.0131) | (0.0134) |
| Age | 0.0116*** | 0.0114*** | 0.0161*** | 0.0158*** |
| | (0.0022) | (0.0021) | (0.0038) | (0.0029) |
| Age$^2$ | -0.0002*** | -0.0002*** | -0.0002*** | -0.0002*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Years of education | 0.0161*** | 0.0163*** | 0.0165*** | 0.0173*** |
| | (0.0016) | (0.0016) | (0.0016) | (0.0017) |
| Overeducated | -0.0168** | -0.0167** | -0.0180** | -0.0198** |
| | (0.0078) | (0.0077) | (0.0079) | (0.0082) |
| Undereducated | 0.0293** | 0.0280*** | 0.0278*** | 0.0284*** |
| | (0.0110) | (0.0102) | (0.0102) | (0.0104) |
| Working hours | 0.0031*** | 0.0030*** | 0.0030*** | 0.0029*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Tenure | 0.0020*** | 0.0020*** | 0.0029*** | 0.0024*** |
| | (0.000335) | (0.000326) | (0.000338) | (0.000407) |
| Elaborate learning | 0.0356*** | 0.0378*** | 0.0377*** | 0.0382*** |
| | (0.0039) | (0.0045) | (0.0041) | (0.0042) |
| _cons | -0.3756*** | | | |
| | (0.0684) | | | |
| Industry and firm size dummies | yes | yes | yes | yes |
| Country dummies | yes | yes | yes | yes |
| ***Temporary Contract Equation*** | | | *AME* | *AME* |
| Unemployment | | | 0.0131** | 0.0186** |
| | | | (0.0061) | (0.0087) |
| Unemployment * EPL moderate | | | | -0.0107 |
| | | | | (0.0082) |
| Unemployment * EPL low | | | | -0.0613*** |
| | | | | (0.0073) |
| Age | | | -0.0218*** | -0.0223*** |
| | | | (0.0029) | (0.0019) |
| Age$^2$ | | | 0.0002*** | 0.0002*** |
| | | | (0.0000) | (0.0000) |
| Years of education | | | -0.0025 | -0.0006 |
| | | | (0.0017) | (0.0017) |
| Elaborate learning | | | 0.0020 | 0.0015 |
| | | | (0.0131) | (0.0019) |
| Other controls | | | yes | yes |
| Country dummies | | | yes | yes |
| *First-stage Tests* | | | Wald chi2(45) = 2071.1 | Wald chi2(47) = 2102.6 |
| *Adj. R2 First-stage* | | | 0.1230 | 0.1262 |
| *athrho* | | | -1.2761*** | -1.2880*** |
| | | | (0.0872) | (0.3194) |
| *lnsigma* | | | -8.6042 | -8.3152** |
| | | | (5.5440) | (0.9946) |
| *Wald test of indep. eqns. (rho = 0)* | | | Chi2(1) = 3.17 (p = 0.0750) | Chi2(1) = 3.51 (p = 0.0609) |
| *N* | 22,447 | 22,447 | 22,447 | 22,447 |
| $R^2$ | 0.1895 | 0.1489 | . | . |

The training participation dependent variable is binary. The standardised unemployment rate is used as an instrument in columns (3) and (4) and column (5) adds as instruments the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. The term AME denotes average marginal effects. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Figure 3. Informal learning and training**
**Temporary workers**

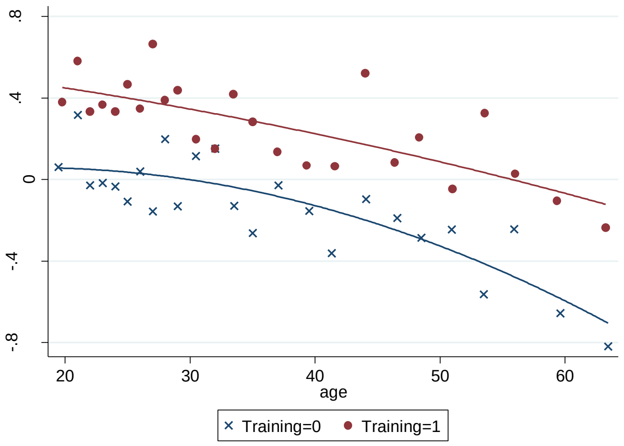



**Figure 4. Informal learning and training**
**Permanent workers**

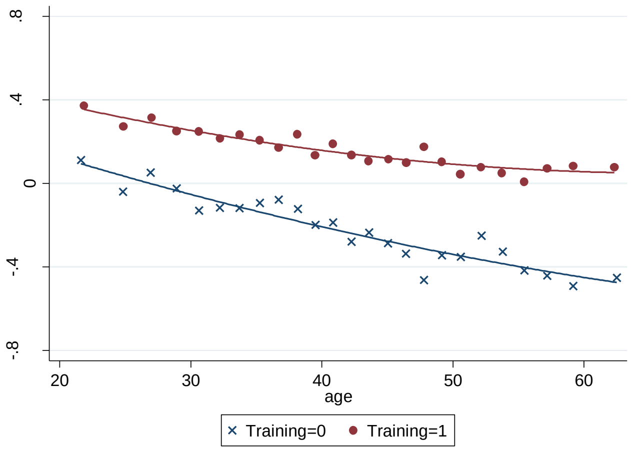


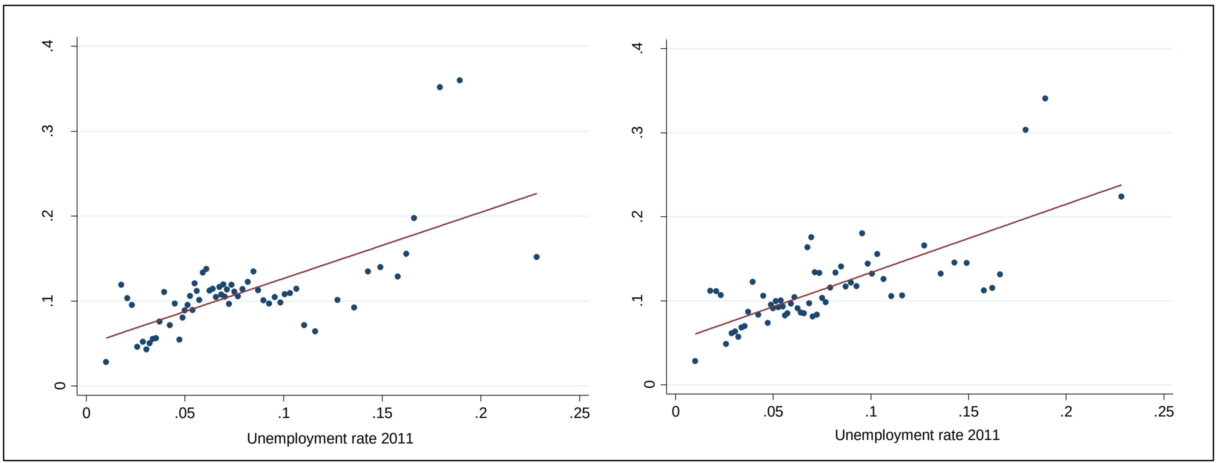
**Table 7. Estimations on complementarity between informal learning and training participation**

| | (1) | (2) | (3) |
|---|---|---|---|
| | OLS | CF-ML (1 instrument) | CF-ML (3 instrument) |
| ***Informal Learning Equation*** | | | |
| Temporary contract | 0.1040*** | 0.1679*** | 0.1661*** |
| | (0.0326) | (0.0510) | (0.0513) |
| Training | 0.1906*** | 0.1900*** | 0.1899*** |
| | (0.0136) | (0.0135) | (0.0134) |
| Temporary contract*Training | -0.0164 | -0.0106 | -0.0106 |
| | (0.0316) | (0.0303) | (0.0303) |
| Age | -0.0282*** | -0.0248*** | -0.0249*** |
| | (0.0057) | (0.0055) | (0.0055) |
| Age$^2$ | 0.0002*** | 0.0002** | 0.0002** |
| | (0.0001) | (0.0001) | (0.0001) |
| Years of education | 0.0131*** | 0.0135*** | 0.0135*** |
| | (0.0028) | (0.0030) | (0.0030) |
| Overeducated | -0.0955*** | -0.0955*** | -0.0955*** |
| | (0.0185) | (0.0185) | (0.0185) |
| Undereducated | 0.1483*** | 0.1485*** | 0.1486*** |
| | (0.0321) | (0.0320) | (0.0320) |
| Working hours | 0.0064*** | 0.0064*** | 0.0064*** |
| | (0.0013) | (0.0013) | (0.0013) |
| Tenure | -0.0032*** | -0.0024** | -0.0024** |
| | (0.0008) | (0.0010) | (0.0010) |
| Elaborate learning | 0.1947*** | 0.1949*** | 0.1949*** |
| | (0.0150) | (0.0150) | (0.0150) |
| _cons | -0.0954 | -0.1938 | -0.1928 |
| | (0.1233) | (0.1302) | (0.1309) |
| Other controls | yes | yes | yes |
| Country dummies | yes | yes | yes |
| ***Temporary Contract Equation*** | | *AME* | *AME* |
| Unemployment | | 0.0118** | 0.0190** |
| | | (0.0058) | (0.0093) |
| Unemployment * EPL moderate | | | -0.0115 |
| | | | (0.0079) |
| Unemployment * EPL low | | | -0.0570*** |
| | | | (0.0075) |
| *athrho* | | -0.0717*** | -0.0710*** |
| | | (0.0225) | (0.0226) |
| *lnsigma* | | -0.1102*** | -0.1102*** |
| | | (0.0361) | (0.0361) |
| *Wald test of indep. Eqns. (rho = 0)* | | Chi2(1) = 10.2 | Chi2(1) = 9.91 |
| | | ($p$ = 0.0014) | ($p$ = 0.0016) |
| *N* | 22,447 | 22,447 | 22,447 |
| $R^2$ | 0.1849 | . | . |

The informal learning dependent variable is standardised. The standardised unemployment rate is used as an instrument in column (2) and column (3) adds as instruments the interactions of the standardised unemployment rate with two of three 3 EPL dummies for permanent employment. All the regressions include the same control variables as reported in Table 3. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**APPENDIX**

**Figure A1. Correlation graph between temporary contracts and unemployment rate**




These figures show the correlation between the unemployment rate in 2011 and the share of temporary contracts in 2012, both variables collapsed by the corresponding country and age group. Each point in the graphs is a bin for three observations. The figure on the left uses OECD statistics for the percentage of temporary contracts and the figure on the right is based on our sample data.

**Table A1. CF-ML estimations of on-the-job informal learning intensity with one instrument**

| CF - ML regressions | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ***Informal Learning Equation*** | | | | | | |
| Temporary contract | 0.4368*** | 0.1370** | 0.1475** | 0.1541** | 0.1632*** | 0.1667*** |
| | (0.1012) | (0.0652) | (0.0624) | (0.0605) | (0.0505) | (0.0502) |
| Age | | -0.0198*** | -0.0247*** | -0.0253*** | -0.0247*** | -0.0249*** |
| | | (0.0051) | (0.0050) | (0.0050) | (0.0049) | (0.0050) |
| Age$^2$ | | 0.0001 | 0.0001** | 0.0002*** | 0.0002*** | 0.0002*** |
| | | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Years of education | | 0.0612*** | 0.0279*** | 0.0248*** | 0.0154*** | 0.0156*** |
| | | (0.0045) | (0.0038) | (0.0037) | (0.0032) | (0.0034) |
| Overeducated | | | | | | -0.1046*** |
| | | | | | | (0.0161) |
| Undereducated | | | | | | 0.1543*** |
| | | | | | | (0.0277) |
| Working hours | | | 0.0076*** | 0.0080*** | 0.0068*** | 0.0067*** |
| | | | (0.0013) | (0.0013) | (0.0012) | (0.0012) |
| Tenure | | | -0.0027*** | -0.0035*** | -0.0028*** | -0.0031*** |
| | | | (0.0010) | (0.0009) | (0.0009) | (0.0009) |
| Elaborate learning | | | | | 0.2084*** | 0.2040*** |
| | | | | | (0.0150) | (0.0148) |
| _cons | 0.0399*** | -0.0740 | -0.2432** | -0.4289*** | -0.2484* | -0.2095 |
| | (0.0038) | (0.1153) | (0.1203) | (0.1294) | (0.1277) | (0.1288) |
| Occupation dummies | no | no | yes | yes | yes | yes |
| Industry and firm size dummies | no | no | no | yes | yes | yes |
| Country dummies | yes | yes | yes | yes | yes | yes |
| ***Temporary Contract Equation*** | *AME* | *AME* | *AME* | *AME* | *AME* | *AME* |
| Unemployment | 0.0624*** | 0.0161*** | 0.0156*** | 0.0158*** | 0.0160*** | 0.0160*** |
| | (0.0054) | (0.0056) | (0.0054) | (0.0056) | (0.0056) | (0.0056) |
| Age | | -0.0215*** | -0.0208*** | -0.0203*** | -0.0203*** | -0.0203*** |
| | | (0.0023) | (0.0022) | (0.0023) | (0.0023) | (0.0023) |
| Age$^2$ | | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Years of education | | -0.0033* | -0.0007 | -0.0008 | -0.0009 | -0.0010 |
| | | (0.0017) | (0.0019) | (0.0017) | (0.0017) | (0.0017) |
| Elaborate learning | | | | | 0.0027 | 0.0027 |
| | | | | | (0.0023) | (0.0023) |
| Occupation dummies | no | no | yes | yes | yes | yes |
| Industry and firm size dummies | no | no | no | yes | yes | yes |
| Country dummies | yes | yes | yes | yes | yes | yes |
| *First-stage Wald test* | Chi2(20) = 1653.9 | Chi2(43) = 2007.2 | Chi2(31) = 2142.4 | Chi2(44) = 2239.6 | Chi2(45) = 2243.9 | Chi2(45) = 2243.9 |
| *Adj. $R^2$ First-stage* | 0.0996 | 0.1136 | 0.1228 | 0.1305 | 0.1305 | 0.1305 |
| *athrho* | -0.1887*** | -0.0364* | -0.0426** | -0.0549*** | -0.0738*** | -0.0746*** |
| | (0.0264) | (0.0217) | (0.0204) | (0.0202) | (0.0254) | (0.0223) |
| *lnsigma* | -0.0345 | -0.0675* | -0.0849** | -0.0869** | -0.1031*** | -0.1033*** |
| | (0.0368) | (0.0350) | (0.0356) | (0.0354) | (0.0361) | (0.0351) |
| *Wald test of indep. Eqns (rho = 0)* | Chi2(1) = 51.3 (*p* = 0.0000) | Chi2(1) = 2.83 (*p* = 0.0925) | Chi2(1) = 3.85 (*p* = 0.0497) | Chi2(1) = 4.27 (*p* = 0.0388) | Chi2(1) = 4.83 (*p* = 0.0280) | Chi2(1) = 4.72 (*p* = 0.0299) |
| *N* | 25,366 | 25,366 | 25,366 | 25,366 | 25,366 | 25,366 |

The informal learning dependent variable is standardised. The standardised unemployment rate is used as an instrument in all specifications. The term AME denotes average marginal effects. Specification (6) is our preferred specification, reported as specification (4) in Table 3. Standard errors clustered at the country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table A2. CF-ML estimations of on-the-job informal learning intensity with three instruments**

| CF - ML regressions | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ***Informal Learning Equation*** | | | | | | |
| Temporary contract | 0.4356*** | 0.1381** | 0.1484** | 0.1548** | 0.1649*** | 0.1698*** |
| | (0.0619) | (0.0653) | (0.0623) | (0.0602) | (0.0503) | (0.0501) |
| Age | | -0.0198*** | -0.0247*** | -0.0253*** | -0.0246*** | -0.0248*** |
| | | (0.0051) | (0.0051) | (0.0050) | (0.0049) | (0.0050) |
| Age$^2$ | | 0.0001 | 0.0001** | 0.0002*** | 0.0002*** | 0.0002*** |
| | | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Years of education | | 0.0612*** | 0.0279*** | 0.0248*** | 0.0154*** | 0.0156*** |
| | | (0.0045) | (0.0038) | (0.0037) | (0.0032) | (0.0034) |
| Overeducated | | | | | | -0.1046*** |
| | | | | | | (0.0161) |
| Undereducated | | | | | | 0.1543*** |
| | | | | | | (0.0277) |
| Working hours | | | 0.0076*** | 0.0080*** | 0.0068*** | 0.0067*** |
| | | | (0.0013) | (0.0013) | (0.0012) | (0.0012) |
| Tenure | | | -0.0027*** | -0.0035*** | -0.0028*** | -0.0031*** |
| | | | (0.0010) | (0.0009) | (0.0009) | (0.0009) |
| Elaborate learning | | | | | 0.2084*** | 0.2040*** |
| | | | | | (0.0150) | (0.0148) |
| _cons | 0.0400*** | -0.0748 | -0.2439** | -0.4294*** | -0.2505* | -0.2126 |
| | (0.0039) | (0.1166) | (0.1216) | (0.1302) | (0.1282) | (0.1293) |
| Occupation dummies | no | no | yes | yes | yes | yes |
| Industry and firm size dummies | no | no | no | yes | yes | yes |
| Country dummies | yes | yes | yes | yes | yes | yes |
| ***Temporary Contract Equation*** | *AME* | *AME* | *AME* | *AME* | *AME* | *AME* |
| Unemployment | 0.0712*** | 0.0245*** | 0.0236*** | 0.0236*** | 0.0238*** | 0.0239*** |
| | (0.0107) | (0.0072) | (0.0070) | (0.0073) | (0.0073) | (0.0073) |
| Unemployment * EPL moderate | -0.0119 | -0.0127 | -0.0121 | -0.0116 | -0.0116 | -0.0117 |
| | (0.0129) | (0.0084) | (0.0080) | (0.0078) | (0.0078) | (0.0078) |
| Unemployment * EPL low | -0.0387** | -0.0614*** | -0.0612*** | -0.0623*** | -0.0625*** | -0.0625*** |
| | (0.0157) | (0.0072) | (0.0064) | (0.0064) | (0.0064) | (0.0064) |
| Age | | -0.0226*** | -0.0219*** | -0.0214*** | -0.0214*** | -0.0213*** |
| | | (0.0019) | (0.0018) | (0.0019) | (0.0019) | (0.0019) |
| Age$^2$ | | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Years of education | | -0.0033* | -0.0008 | -0.0009 | -0.0010 | -0.0010 |
| | | (0.0017) | (0.0019) | (0.0017) | (0.0017) | (0.0017) |
| Elaborate learning | | | | | 0.0029 | 0.0028 |
| | | | | | (0.0023) | (0.0023) |
| Occupation dummies | no | no | yes | yes | yes | yes |
| Industry and firm size dummies | no | no | no | yes | yes | yes |
| Country dummies | yes | yes | yes | yes | yes | yes |
| *First-stage Wald test* | Chi2(22) = 1644.6 | Chi2(25) = 2012.2 | Chi2(33) = 2145.1 | Chi2(46) = 2241.6 | Chi2(47) = 2245.6 | Chi2(47) = 2245.6 |
| *Adj. $R^2$ First-stage* | 0.1006 | 0.1155 | 0.1247 | 0.1324 | 0.1325 | 0.1325 |
| *athrho* | -0.1882*** | -0.0361* | -0.0435** | -0.0567*** | -0.0752*** | -0.0774*** |
| | (0.0266) | (0.0216) | (0.0202) | (0.0201) | (0.0238) | (0.0219) |
| *lnsigma* | -0.0345 | -0.0675* | -0.0848** | -0.0869** | -0.1031*** | -0.1055*** |
| | (0.0368) | (0.0350) | (0.0356) | (0.0354) | (0.0361) | (0.0361) |
| *Wald test of indep. Eqns (rho = 0)* | Chi2(1) = 50.1 (*p* = 0.0000) | Chi2(1) = 3.03 (*p* = 0.0817) | Chi2(1) = 4.08 (*p* = 0.0434) | Chi2(1) = 4.82 (*p* = 0.0281) | Chi2(1) = 5.53 (*p* = 0.0187) | Chi2(1) = 5.60 (*p* = 0.0179) |
| *N* | 25,366 | 25,366 | 25,366 | 25,366 | 25,366 | 25,366 |

The informal learning dependent variable is standardised. The standardised unemployment rate and its interaction with two of the three EPL dummies for permanent employment are used as instruments in all the specifications. The term AME denotes average marginal effects. Specification (6) is our preferred specification, reported as specification (5) in Table 3. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table A3. Estimations of informal learning intensity under alternative treatment specifications**

| | ATE (1 instrument) | $\rho$ | Wald test $\rho$=0 | ATE (3 instruments) | $\rho$ | Wald test $\rho$=0 |
|---|---|---|---|---|---|---|
| (1) Baseline CF-ML results in Table 3 | 0.1667*** | -0.0746*** | Chi2(1) = 4.72 | 0.1698*** | -0.0774*** | Chi2(1) = 5.60 |
| | (0.0502) | (0.0223) | ($p$ = 0.0299) | (0.0501) | (0.0219) | ($p$ = 0.0179) |
| _Probit models including_ | | | | | | |
| (2) Overeducated and undereducated | 0.1632*** | -0.0408** | Chi2(1) = 4.75 | 0.1671*** | -0.0432** | Chi2(1) = 5.75 |
| | (0.0496) | (0.0187) | ($p$ = 0.0293) | (0.0494) | (0.0180) | ($p$ = 0.0165) |
| (3) Working hours | 0.1675*** | -0.0434** | Chi2(1) = 5.68 | 0.1713*** | -0.0458*** | Chi2(1) = 6.78 |
| | (0.0484) | (0.0182) | ($p$ = 0.0172) | (0.0484) | (0.0176) | ($p$ = 0.0092) |
| (4) Tenure | 0.2211*** | -0.0782*** | Chi2(1) = 9.99 | 0.2244*** | -0.0804*** | Chi2(1) = 10.7 |
| | (0.0607) | (0.0247) | ($p$ = 0.0016) | (0.0609) | (0.0246) | ($p$ = 0.0011) |
| (5) Tenure and working hours | 0.2250*** | -0.0806*** | Chi2(1) = 11.2 | 0.2285*** | -0.0829*** | Chi2(1) = 11.9 |
| | (0.0594) | (0.0241) | ($p$ = 0.0008) | (0.0597) | (0.0239) | ($p$ = 0.0005) |
| (6) Tenure, working hours, | 0.2236*** | -0.0798*** | Chi2(1) = 10.9 | 0.2273*** | -0.0822*** | Chi2(1) = 11.7 |
| overeducated and undereducated | (0.0595) | (0.0242) | ($p$ = 0.0010) | (0.0598) | (0.0240) | ($p$ = 0.0006) |
| _Probit models excluding_ | | | | | | |
| (7) Occupation dummies | 0.1586*** | -0.0378* | Chi2(1) = 2.98 | 0.1629*** | -0.0403* | Chi2(1) = 3.69 |
| | (0.0539) | (0.0219) | ($p$ = 0.0844) | (0.0534) | (0.0209) | ($p$ = 0.0546) |
| (8) Industry dummies | 0.1585*** | -0.0384** | Chi2(1) = 4.09 | 0.1626*** | -0.0408** | Chi2(1) = 5.05 |
| | (0.0505) | (0.0190) | ($p$ = 0.0430) | (0.0503) | (0.0182) | ($p$ = 0.0246) |
| (9) Firm size dummies | 0.1628*** | -0.0409** | Chi2(1) = 4.34 | 0.1667*** | -0.0429** | Chi2(1) = 5.03 |
| | (0.0513) | (0.0196) | ($p$ = 0.0372) | (0.0513) | (0.0191) | ($p$ = 0.0249) |
| (10) Country dummies | 0.2134*** | -0.0700*** | Chi2(1) = 13.4 | 0.2122*** | -0.0698*** | Chi2(1) = 13.7 |
| | (0.0508) | (0.0191) | ($p$ = 0.0002) | (0.0491) | (0.0188) | ($p$ = 0.0002) |
| (11) Occupation, industry and | 0.1567*** | -0.0369* | Chi2(1) = 2.84 | 0.1613*** | -0.0394* | Chi2(1) = 3.53 |
| firm size dummies | (0.0550) | (0.0219) | ($p$ = 0.0918) | (0.0547) | (0.0209) | ($p$ = 0.0603) |
| (12) Occupation, industry, firm size | 0.2209*** | -0.0746*** | Chi2(1) = 8.15 | 0.2214*** | -0.0743*** | Chi2(1) = 8.69 |
| and country dummies | (0.0609) | (0.0261) | ($p$ = 0.0043) | (0.0584) | (0.0252) | ($p$ = 0.0032) |

The informal learning dependent variable is standardised. All the above estimations are based on the same sample of 25,633 observations. Estimations with one instrument use the standardised unemployment rate and estimations with three instruments add the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. All the regressions include the same control variables as reported in Table 3, the only exception being that mentioned for each robustness check. The outcome model remains the same as reported in Table 3. Standard errors clustered at the country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table A4. Wooldridge's IV robust estimations of informal learning intensity**

| | (1)<br>Robust IV<br>(1 instrument) | (2)<br>Robust IV<br>(3 instruments) |
|---|---|---|
| ***Informal Learning Equation*** | | |
| Temporary contract | 0.6334*** | 0.6513*** |
| | (0.1089) | (0.1155) |
| Age | -0.0108** | -0.0108** |
| | (0.0046) | (0.0046) |
| Age$^2$ | -0.0000 | -0.0000 |
| | (0.0001) | (0.0001) |
| Years of education | 0.0174*** | 0.0174*** |
| | (0.0038) | (0.0039) |
| Overeducated | -0.1136*** | -0.1139*** |
| | (0.0163) | (0.0165) |
| Undereducated | 0.1551*** | 0.1552*** |
| | (0.0266) | (0.0266) |
| Working hours | 0.0071*** | 0.0071*** |
| | (0.0012) | (0.0012) |
| Tenure | 0.0005 | 0.0006 |
| | (0.0015) | (0.0016) |
| Elaborate learning | 0.2041*** | 0.2041*** |
| | (0.0145) | (0.0145) |
| _cons | -0.6280*** | -0.6440*** |
| | (0.1496) | (0.1562) |
| Occupation dummies | yes | yes |
| Industry and firm size dummies | yes | yes |
| Country dummies | yes | yes |
| ***Temporary Contract Equation*** | *AME* | *AME* |
| Unemployment | 0.0140** | 0.0219*** |
| | (0.0059) | (0.0044) |
| Unemployment * EPL moderate | | -0.0119*** |
| | | (0.0045) |
| Unemployment * EPL low | | -0.0523*** |
| | | (0.0098) |
| *N* | 25,366 | 25,366 |
| $R^2$ | 0.1479 | 0.1461 |

The standardised unemployment rate is used as an instrument in column (1) and column (2) adds as instruments the interactions of the standardised unemployment rate with two of the three EPL dummies for permanent employment. The term AME denotes average marginal effects. Standard errors clustered at the country level are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.