DOES INFORMAL LEARNING ON-THE-JOB IN OECD COUNTRIES DIFFER BY CONTRACT DURATION?

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Abstract

Several studies have shown that employees with temporary contracts have a lower training participation than those who have a contract of indefinite duration. 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 twenty OECD countries using unique data from the recent PIAAC survey. Using an instrumented 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 temp and permanent employees. Our findings then suggest that temporary employment need not be dead-end jobs. Instead, temp jobs with high learning content could be a stepping stone towards permanent employment. However, our results also suggest that labour market segmentation in OECD countries actually occurs within temporary employment due to the distinction between jobs with low and high learning opportunities.

JEL-Codes: E24, J24, J41.

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1. INTRODUCTION

The expansion of temporary work has raised concerns about undesirable labour market inequality 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. Comi and Grasseni, 2012; Cutulli and Guetto, 2013; O'Connell and Byrne, 2010; OECD, 2014; Pfeifer, 2014; Steijn et al., 2006). However, other studies show that temp jobs might increase transition probabilities into permanent employment, and could reduce unemployment rates (Booth et al., 2002; Cockx and Picchio, 2012; De Graaf-Zijl et al., 2011; Faccini, 2014; Gagliarducci, 2005; Jahn and Pozzoli, 2013).

Triggered by this trade-off, policy makers have stressed the importance of finding 'an appropriate balance between flexibility and security' (European Commission, 2003) in order to prevent a part of the labour force being trapped in 'dead-end' jobs. 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.

Access to opportunities to develop workers' human capital is a crucial issue for many governments to create such a balance. More on-the-job investments in human capital are expected to increase temp workers' chances of finding permanent employment (Autor, 2001; Booth et al., 2002; De Graaf-Zijl et al., 2011; Gagliarducci, 2005; 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 (2013; 2007) has explicitly considered lifelong learning strategies in the context of its so called *flexicurity* agenda.

Yet, due to a lack of appropriate data, in particular of international comparability, little is known about 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 training participation, although various studies have argued that employees spend much more time on informal learning activities that also contribute to the accumulation of human capital as a by-product of work (Cedefop, 2011; Koopmans et.al, 2006; Mincer, 1994; Nelen and De Grip, 2009). At the workplace, new skills and competences are informally acquired by workers while performing a combination of tasks, interacting with others, sensing the organisational culture, facing new job-related challenges, doing trial-and-error experimentation, and observing, reading, or simply executing their job (Billet, 2001; 2008; Koopmans et al., 2006; Marsick, 2009; Marsick et al., 2009; Tannenbaum et al., 2010).

On-the-job learning has been considered an investment that contributes to skills acquisition and, consequently, to have some positive effect on workers' productivity and wage gains (Blundell et al., 1999; Heckman, 1976; Killingsworth, 1982; Mincer 1968). The workplace plays an important role in human capital accumulation, since individuals continue learning during their working career. However, in previous literature a concern has been raised about the quality of the stock 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 to what extent 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 the on-the-job individual informal learning intensity across twenty OECD countries. Second, we raise the issue of endogeneity of temporary contracts due to possible selection into this kind of jobs, and account for the binary nature of the endogenous regressor. We estimate average treatment effects using an instrumented control function model with endogenous switching. Third, we explore the relation of substitution or complementarity between training and informal learning at the workplace for both temporary and permanent employees. For our empirical analyses we use the data from the OECD Programme for International Assessment of Adult Competences (PIAAC) study conducted in 2012. This survey contains very detailed information on workplace learning undertaken by workers.

Our results show that workers in temporary jobs engage more intensively in informal learning than their counterparts in permanent contracts, although the former, indeed, are less likely to participate in in formal training activities. In addition, we find evidence for a relation of complementarity between job-related training and informal learning for both temp and regular employees. On the assumption that workers strongly prefer permanent contracts, we argue that temp employees engage more intensively in informal workplace learning in order to increase their chances of upward mobility in the labour market.

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 presents 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.

2. RELATED LITERATURE

In most OECD countries, laying-off workers with permanent contracts is costly and time consuming. However, the opportunity to employ part of the workers by temporary contracts gives firms the option to adjust the size of its 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 has then the potential to impose a negative externality on welfare and skills development of the flex workforce (Arulampalam and Booth, 1998).

According to human capital theory, firms will be less inclined to invest in training temporary workers, since the expected period in which they could benefit from these investments is relatively short. There are several studies that provide empirical evidence of a negative relation between temporary contracts and training participation in different labour markets (e.g. Aruramplalan et al., 2011; Atkinson, 1998; Booth and Bryan, 2004; Cutulli and Guetto, 2013; Steijn et al., 2006; O'Connell and Byrne, 2010).

A significant nuance to this negative relationship has been introduced by means of the matching approach. As 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 temp contract on training may decrease with the quality of the job match (Akgündüz and Van Huizen, 2013; Jackson, 2012). Similarly, Acemoglu and Pischke (1999) show that employers will be encouraged to invest in general training of temporary employees due to the existence of 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 perform screening of high ability workers, prior to offering a permanent contract. He 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 the 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.

Apart from their participation in formal training activities, workers' human capital development is also affected by informal learning at the workplace. But due to a lack of adequate data, there are hardly any empirical studies that focus on the relation between informal learning investments and temporary contracts. In human capital literature, informal learning has mainly been seen as learning-by-doing. Arrow (1962) was one of the first authors who emphasised the importance of learning-by-doing, as an automatic by-product of the regular production process. Mincer (1974) claimed that informal learning may constitute the essential part and the major productivity building investments on human capital provided by firms. Following Mincer's analysis, many studies consider 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, accumulation of training reduces one's current earnings, while 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 it (Quinones et al., 1995; Tesluk and Jacobs, 1998) and not everyone is inherently good at learning from experiences (Maurer and Weiss, 2010). Besides, jobs widely differ 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 the workplace offer opportunities for undertaking challenging tasks, interacting with others, and organising one's work[1] (Billet, 2008; Cedefop, 2011).

A more recent framework of Destré et al., (2008), contemplates that workers can learn both by themselves and from others. This model yields a closed-form solution that revises the Mincer and Jovanovic's (1981) treatment of tenure in the human capital earnings function by relating earnings to the individual's job-specific learning potential. In such a setting, a worker's human capital is both increasing with training and tenure, and it converges towards the firm's 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 may be interpreted as attached into the workers' contract and that both 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 (De Grip and Smits, 2012; 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 temp contracts offer a path into permanent jobs[2]. 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; Cockx & Picchio, 2012; De Graaf-Zijl et al., 2011; Dekker, 2007; Gagliarducci, 2005; Jahn and Rosholm, 2014; Jahn and Pozzoli, 2013). It is often claimed that temporary work may 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 perspective of the worker, taking up a temp 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 temp contract at

[1] 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 at the workplace, what organisational factors influence particular learning styles at work and self-directed learning capability; and how to support and reward learning within firms (Billet, 2001; 2008; Cedefop, 2011; Keogh, 2009; Marsick et al., 2009; Svensson et al., 2004; Straka, 2000).

[2] Besides, flex employees may increase learning investments for signalling reasons, due to the fact that employers can use temporary contracts to investigate the match and for screening of workers ability.

the beginning of one's 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[3]. All this suggests that temp 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

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

where IL is a continuous variable, the on-the-job informal learning intensity for worker i, X is a vector of covariates composed by worker's and firm's characteristics along with a set of country dummies, and T is a binary indicator for the type of contract (T = 1 for employees on temporary contracts, T = 0 for employees on permanent contracts). All variables are described in the next section. For this model, the impact of temporary contracts on individual's informal learning intensity is measured by the estimate of δ.

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 characteristics of workers such as ability and motivation (Autor, 2001; Booth et al., 2002; Givord and Wilner, 2014; Loh, 1994; Mincer, 1994), but also time preferences and risk aversion (Belzil and Leonardi, 2007; Berton and Garibaldi, 2012; Mincer, 1994; Weiss, 1986) 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 who is selected into temporary contracts would have relatively lower ability or lower motivation, then the OLS estimate of δ will actually underestimate the treatment effect. We might expect the bias to also be negative if most temp employees would be workers who tend to have stronger time preferences for the present (or higher discount rate), or use to be below average risk-aversion persons. 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 the temporary job selection by estimating an endogenous switching regression model of informal learning intensity where workers face two regimes, temporary and

[3] Usually workers with a less favoured labour position (youth, women and low educated) fall into this segment of temporary dead-end jobs.

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 $\mathrm{T} = (0, 1)$ is assumed to depend linearly upon observable variables X and unobservables μ_i as in equation (1). The decision process for the temporary contract indicator is posed as a nonlinear function of observables z and unobservables υ, and linked to the observed outcome IL_i through the latent variable T^*, as follows.

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

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

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

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

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

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 ϕ and Φ are the standardised normal density and distribution functions respectively.

The model is identified through exclusion restrictions. First, the nonlinearity of the selection equation, thus the correlation between μ_i and υ_i, and second, by including variables in $\boldsymbol{z}$ that satisfy the following constraints: $\mathrm{Cov}(z, \mu_i) = 0$, and $\gamma \neq 0$. In order to take account of selection into temporary employment based on observable and unobservable characteristics, we need a selection instrument that directly affects the incidence of temporary contracts but not the individual informal learning intensity.

For the model to be identified we use as instrument the unemployment rate of the year preceding the interview date by the corresponding country, gender and age group of the individual. We establish the admissibility of this instrument in Sections 4 and 5.

Control function (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, like 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 methods simultaneously fit the continuous equation (1)-(3) and the binary equation (2) of the model in order 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 μ_i and υ_i, the logarithmic likelihood function[4] for the system of (1–2) is given in Maddala (1983):

$$\ln \mathrm{IL}_i \begin{cases} \ln\Phi\left\{\dfrac{\mathbf{z}_i\gamma + (\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta} - \delta)\,{}^{\rho}/_{\sigma}}{\sqrt{1-\rho^2}} - \dfrac{1}{2}\left(\dfrac{\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta} - \delta}{\sigma}\right)^2 - \ln\left(\sqrt{2\pi}\sigma\right)\right. & \mathrm{T}_i = 1 \\ \ln\Phi\left\{\dfrac{-\mathbf{z}_i\gamma + (\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta})\,{}^{\rho}/_{\sigma}}{\sqrt{1-\rho^2}} - \dfrac{1}{2}\left(\dfrac{\mathrm{IL}_i - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}\right)^2 - \ln\left(\sqrt{2\pi}\sigma\right)\right. & \mathrm{T}_i = 0 \end{cases} \tag{4}$$

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

$$\mathrm{IL}_i = \mathbf{x}_i\boldsymbol{\beta}_0 + \delta\mathrm{T}_i + \mathrm{T}_i(\mathbf{x}_i - \bar{\mathbf{x}})\psi + \mu_0 + \mathrm{T}_i(\mu_1 - \mu_0) \tag{5}$$

This model is very restrictive, because the treatment may create interaction effects with observed or unobserved personal characteristics (Maddala, 1983). This particular way of expressing the outcome model emphasises that we are primarily interested in δ, 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 consistently estimate nonconstant treatment effects and average effects on the treated –ATT (Wooldridge, 2010). If the variance–covariance matrix of unobservables and $(\mu_i, v_i) \sim N(0, \Sigma)$, we obtain an identical representation to the endogenous switching regression model described above, also estimated by (4).

This control function 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 gives better approximation to the conditional expected function of the treatment variable than

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

the linear model, the resulting linear estimates will be more efficient than those using a linear first stage (Angriest & Pischke, 2009; Newey, 1990; Wooldridge, 2010). This approach has some further advantages. It is appropriate for continuous selection instruments to be used for binary endogenous regressors (Imbens and Wooldridge, 2009). It 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 effects on the treated –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 control function estimator hinges on the bivariate normality assumption of μ_i and υ_i; thus the probit equation be correctly specified in order to predict effectively which observations are selected into treatment. The better the prediction, the more precise estimates will be. Successful use of the control function method usually requires that at least one selection instrumental variable in $\boldsymbol{z}$ not be included in **x** (Heckman, 1978; Heckman and Vytlacil, 2005; Wooldridge, 2010).

Since the benefit of increased precision of estimation might be at the cost of greater chance of misspecification error, we perform various robustness checks of our CF estimations. One important robustness check is based on the Wooldridge's (2003, 2010) robust approach. He demonstrates that, under weaker distributional and functional assumptions, an alternative instrumental variables estimator can be consistently applied to estimate homogeneous and heterogeneous effects of a discrete endogenous variable. The alternative is using the probit fitted values for each T_i as valid generated IVs in a simple 2SLS procedure. Then, the first-stage estimations are not needed to be correctly specified as it is required in the control function 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 control function estimator if the additional assumptions needed for control function consistency hold (Wooldridge 2003, 2010).

4. DATA AND DESCRIPTIVE STATISTICS

4.1 Data and sample

We use data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey, which was conducted between 2011 and 2012 in 24 industrialised countries, based on a representative sample of the population of the OECD participant countries[5]. This is a unique dataset that measures the incidence of training as well as the intensity of on-the-job informal learning.

[5] See OECD (2014b) for further details about validation of data.

The latter measure which is not available in any other large scale dataset is based on a conceptual framework that takes account of three pathways of learning, namely learning by doing, learning from others and learning from keeping up to date with new products or services.

We restricted the sample to include full-time[6] employed males[7], excluding self-employed and armed force, aged 17 to 65, not participating in any formal education programme, that have an employment contract different from apprenticeship. The sample size is 25,366 observations balanced[8] in 20 OECD countries[9], 88.2 percent permanent positions 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

Dependent (outcome) variables

1. On-the-job informal learning intensity, a standardised index[10] derived from the following questions, all three measured in a five-point Likert scale[11]:

  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 the three questions were answered 'never' and the highest if 'every day'. To facilitate interpretation of results, the variable was standardised. In addition, a dummy

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

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

[8] In Canada the sample existed 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.

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

[10] This index was derived by PIAAC from the d_q13 set of questions using the generalised partial credit model (GPCM) and estimated by weighted likelihood estimation (WLE). Its validity was assessed based on cross-country comparability, scale reliability and scale correlations. For further details, see OECD (2014b). The index cannot be estimated for 554 respondents in our sample that reported 'never' in all three d_q13 questions; therefore, the lowest value of the index by country was imputed to those observations. The findings are robust to different constructions of the index, e.g. very similar results are obtained by using the standardised principal component factor of the three statements.

[11] Item response rate to these questions was about 98%. 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.

variable for on-the-job informal learning incidence was derived. It takes the value 0 when the above questions are all answered ‘never’, 1 otherwise.

2. Training incidence, a dummy variable of participation in job-related training during the previous 12 months. It is based on the set of questions b_q12 that ask: 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 1 if the person participated in any of the mentioned training activities and the current/last training activity was reported to be mainly job-related. It takes the value 0 otherwise[12].

Explanatory variable

Temporary contract[13]: a dummy variable that takes the value 1 for temporary contracts and 0 for permanent contracts. Temporary contracts in our sample include fixed-term positions (90.5 percent) and agency work (9.5 percent).[14]

Control variables: The questionnaire contains detailed information about individual, current job and firm characteristics. As suggested by earlier research, we control for age, educational levels (highest level of education obtained imputed into years of education), educational mismatch (dummies for overeducation and undereducation[15]), employer tenure, actual weekly working hours (top-coded at 60), readiness to learn[16]; and firm size (five categories), occupation (nine ISCO 1-digit categories), industry (ten ISIC 1-digit categories) and country dummies.

[12] Item response rate to these questions was about 90%.

[13] According to the OECD concepts, permanent workers are, in general, 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.

[14] It is derived from the d_q09 question which asks for the kind of contract employees 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, 5) no contract.

[15] These dummies are derived from the d_q12b 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.

[16] According to OECD (2014b), this item aims to measure the extent of elaborate or deep learning, based on the approach of Kirby et al. (2003). In view of these authors, deep 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 being processed. Therefore, deep learning also describes learners’ interest in learning and information-processing strategies. Deep learners seek meaning and understanding; they are intrinsically motivated towards learning and interested in achieving competence in the area. In the context of PIAAC, deep learning aims to capture how learners would approach situations in general, but especially in the context of their current workplace. We use the standardised index of readiness to learn which was derived by PIAAC from the i_q04 questions, all measured in 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 info to make it clearer.

Selection instrument variable

We use unemployment rate as selection instrument in our estimations. We collected OECD data on annual male unemployment by country and five-year age groups for the years 2010 and 2011. We matched this data to the individuals by corresponding country, age and year of the interview.

The unemployment rates likely represent a suitable instrument for the individual probability of having a temp contract, which is uncorrelated with the error term μ_i, due to the following two reasons. First, unemployment measures have been shown to be correlated to subsequent temporary employment incidence. The average likelihood that workers will be in temporary jobs rises primarily when the unemployment rate is relatively high (Jahn and Bentzen, 2012; Kahn, 2010). That is expected since temp 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 means often a risk for active working population and job seekers that reduces the chance of finding more stable employment (European Commission, 2010). When economic prospects are poor, workers anticipate that opportunities on the labour market will be scarce, and they will thus accept temporary contracts with higher probability (Abraham, 1990; Givord and Wilner, 2014). From a demand side point of view, employers add greater value to the use of temporary employment as a low cost short-run buffer when there is excess supply in the labour market or if the labour market is regulated by stringent permanent job security provisions (Gagliarducci, 2005; Kahn, 2010).

Second, there is no reason to expect that unemployment rates at the country level directly affect decisions on informal learning investments on-the-job, except through the kind of contract an employee has. Higher unemployment rates might raise tenure uncertainty at the firm and therefore incentive greater investments in human capital on-the-job; however uncertainty mainly depends on whether the contract is of indefinite or fixed duration.

The relationship between unemployment and the probability of having a temp contract may however differ by country due to the strictness of employment protection legislation (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; Gagliarducci, 2005; Kahn, 2010; OECD, 2004; Sala et al., 2012). We therefore use version 3 of the EPL indicator for regular employment[17] (standardised and categorised in 3 dummies) to interact with our selection instrument.

[17] This 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 from 0 (least restrictions/strictness) to 6 (most restrictions/strictness). A higher score means a higher level of employment protection.

4.3 Descriptive statistics

Table 2 presents summary statistics for the permanent and the temporary workers, respectively. As expected, temporary employees in our sample are generally younger, and have fewer years of work experience and tenure than permanent workers. Besides, among individuals in temp 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 remarkable that there is no descriptive difference between permanent and temporary employees regarding years of education and readiness to learn.

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, flex workers show a greater mean of informal learning intensity. This makes it more interesting to analyse the intensity of informal learning rather than the incidence. On the other hand, we observe that permanent employees more often participate in job-related training. In our sample, 91.7 percent of training participation was totally or mostly financed by firms while 8.3 percent, by workers. Likewise, 83.3 percent of trained workers followed training only or mostly during working hours, while 16.7 percent did it 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, data confirm that temp workers faced on average 3 percentage points higher unemployment rates during the previous year than the rates corresponding to permanent employees. The simple Pearson's correlation confirmed that the unemployment rate is significantly correlated to the country incidence of temporary contracts by 0.50 and to the temporary contract dummy of our sample by 0.2. In the same way, we observe that the average level of EPL applicable to permanent employment is higher for the group of temporary workers.

[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 selection into temporary jobs into account, 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 that only take account of self-selection. The last specifications (4) and (5) provide the control function estimates derived in the context of the endogenous switching regression model as described in Section 3, which not only take the endogeneity of the type of contract into consideration but in addition explicitly account for the binary nature of the endogenous regressor. The latter coefficients were obtained by maximum likelihood. The second section of Table 3 shows the correspondent first stage/treatment estimates of the temporary contract equation.

Overall, 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 first group. Compared with the standard OLS estimates, the other coefficients that account for the endogeneity of temp contract selection are adjusted upwards, as we expected. We consider the estimates generated by the control function approach more precise and proceed with interpretation. Further argumentation on the accuracy of these estimates will follow.

The results in columns (4) and (5) indicate, indeed, that the OLS coefficient of temporary contracts is biased downwards. Once the 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 informal learning on-the-job than their counterparts in permanent employment. The estimated correlation between the temporary contract equation errors and the outcome errors ρ is negative (-0.075), indicating that unobservables that raise informal learning intensity tend to occur with unobservables that lower temporary contract selection. This is coherent with our hypothesis of unobservables mentioned in Section 3. For instance, persons with greater ability or motivation and larger time preference for the future are less likely to be selected into temp jobs at the same time that they are also more likely to engage more in job training and informal learning (Mincer, 1994).

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

Years of education correlate positively to intensity of learning at 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 may increase ability to learn and be useful for informal learning on-the-job (Rosen 1972). Yet, educational mismatches seem to have an important impact on this relationship.

With respect to the well matched, overeducated employees tend to invest, on average, 0.11 of a standard deviation less in informal learning while undereducated invest 0.15 of a standard deviation more. This is consistent with Jahn and Pozzoli (2013) who hypothesize that temporary workers employed below their skill level will be less likely to improve their human capital.[18]

There is also a positive relation of informal learning intensity with readiness to learn and actual working hours, and a negative relation with tenure. The latter is attributed to the larger learning exposure of workers when they are new to their jobs. Even though not shown in Table 3, we also find that informal learning intensity at the workplace tends to be significantly higher for individuals employed in high-skilled occupations and larger firms. There are also some significant differences across industries and countries.

[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 prediction from the 2SLS first stage runs from -0.20 to 0.76, leaving 16 percent of the sample predicted probabilities below 0. On the other hand, probit predicted probabilities run from 0 to 0.92, allowing 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 size of the instruments coefficients significantly differ between 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 ending up in a temporary job by 1.6 percentage points. In column (2), the same effect predicted by the 2SLS first stage is about 4.7 percent, 3 times bigger. The size of the probit marginal effect is relatively closer to related research, e.g. Kahn (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, and 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 the positive non-significant coefficients of age and tenure. Fifth, the Wald tests for specifications (4) and (5) indicate that, at 95 percent confidence, we can reject the null hypothesis of no correlation between the errors of the temporary contract and the outcome equations, so that our instrumented

[18] Our estimations control for the fact that workers have a job at the appropriate level. Nonetheless, estimations that do not control for educational mismatches give a very similar and significant coefficient for temporary contracts (0.163 and 0.165 of a standard deviation using one and three instruments, respectively).

endogenous switching regression models fit well overall. An important argument in favour of these models and our instrument is that the Wald test after the CF estimation that does not include any instrument, which means relying identification only upon nonlinearities, cannot reject the null. Additionally, concerning the admissibility of our instrument, it is worth mentioning that Wald and F-tests after nonlinear and linear first-stage estimations, respectively, show that our instrumental variable included in addition to the other covariates makes a significant contribution to the model of interest. Last but not least, in contrast to the CF approach, 2SLS does not provide average treatment effects but local average treatment effects, the former being more policy-relevant in the context of our research question.

We conclude that the ATE of temporary contracts on the intensity of informal learning on-the-job is positive and about 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 about the same as the impact of ten years of schooling. Assuming that full-time male workers have generally stronger preferences for permanent contracts (Booth et al., 2002; Jahn and Bentzen, 2012), we hypothesise that flex employees will rationally engage more on workplace informal learning in order to increase their chances of transition to more stable jobs with current or potential future employers. Thus, it could be expected that those individuals with expectations for upward mobility into the labour market will be more likely to invest more in informal learning on-the-job.[19]

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 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 summary results in the appendix, Table A1.

Specifications (2) to (6) include variables that we do not consider as 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 explanatory variable for temporary contracts we see that the estimated ATE of interest increases from 0.17 to 0.22 of a standard deviation, which indicates

[19] This finding might be related to Engellandta and Riphahn (2005) study who found that temporary workers in Switzerland provide higher effort than permanent employees by using indicators for unpaid overtime work. They also suggest that implicit incentives of shifting to permanent employment might explain those results.

that our results are conservative. Moreover, the predicted values of ρ remain negative and the Wald tests are significant in all these specifications, meaning that our main results hold.

The specifications (7) to (12) exclude variables that we included as determinants of temporary contract selection in our main estimations. The results in Table A1 show that the ATE of temporary contracts on informal learning intensity is almost identical to that of Table 3. Only when country dummies are excluded from the probit model we observe an increase in the estimated ATE of interest from 0.17 to 0.22 of a standard deviation. This suggests that country-fixed effects are important controls for unobserved heterogeneity between countries. Also, the predicted values of ρ remain negative in these alternative models. The Wald tests are all significant at 95% confidence with the only exception of models excluding occupation dummies that are significant at 90% 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 the 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 A2). These estimators are downwards adjusted in comparison with the standard 2SLS results of Table 3; however they are about seven and four times larger than the corresponding OLS and CF estimators, respectively. This shows that although Wooldridge's approach is more efficient that the direct 2SLS procedure and fully robust to misspecification of the probit model, it is less efficient than the control function method in this particular case.

5.3 Heterogeneous effects

Heterogeneous workers

Although temporary workers are on average more intensively engaged in informal learning, this might differ among temporary workers with different characteristics. Temporary employees could for instance have different expectations on their career perspectives. If that is the case, we might expect distinct levels of informal learning intensity of temporary workers depending on their age and tenure: particularly younger workers and those with lower tenure might have stronger incentives to engage in learning when they are employed in a temporary job as this might help them to acquire a permanent contract. We might expect that these investments in informal learning are more gainful for temporary workers earlier in the career when they have better perspectives 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 it has been explained in Section 3. The results shown in Table 4 indicate that after allowing for heterogeneous response 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 temp contracts invest, on average, 0.13 of a standard deviation[20] more in workplace learning than workers with permanent contracts. The ATT shows that temporary employees actually invest 0.18 of a standard deviation more in informal learning than if they had contracts of indefinite duration.

These models allowing for heterogeneity show that coefficients on age, age square, tenure and working hours significantly differ by type of contract while years of education, overeducation, undereducation, and learning readiness do not. The coefficients confirm our expectations that the rate at which informal learning intensity decrease with age and tenure is larger when holding a temporary contract. This suggests that the mean estimate of temporary contracts in our informal learning model is mainly driven by the temp employees who are younger and have few years of tenure.

[Insert Table 4 about here]

More precisely, the significant difference in the coefficient of age between temp 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 above, larger investments in informal learning of temporary workers are expected to be more gainful earlier in the job career when workers have better perspectives on gaining a permanent position. This suggests that at some point in the life course the difference in informal learning between permanent and temporary employees will vanish. 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% confidence level) after the age of 48. The table also shows that the coefficient of age square is only significantly different from zero for permanent employees. This suggests that the turning up point of informal learning investments at the end of the working life particularly holds for workers with a permanent contract.

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 temp workers. This suggests that the higher intensity of informal learning for temporary workers particularly holds for employees with fewer years of tenure. This again indicates that this effect ends gradually. We find that at 95% of confidence the positive marginal effect of temporary contracts on

[20] The correspondent ATE estimated by running two separate OLS regressions is 0.075, significant at 99% confidence.

informal learning intensity disappears after approximately 9 years of tenure. This may be due to temp workers adjusting their expectations of labour mobility when they feel to be locked in a temp job. As mentioned above, this suggests that workers who remain employed in a temp job for a long time are actually employed in dead-end jobs without any career perspectives.

Heterogeneous job tasks

One might also wonder whether our estimates are driven by different correlated job tasks. For instance, one could imagine that employees in jobs that offer more task discretion and flexibility, or more task complexity 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, disregarding the kind of contract they have, tend to engage more intensively in informal learning when they have a job in which they have higher levels of task discretion[21], are more often confronted to simple[22] and complex[23] problems, are more often involved in team work[24], more often use ICT at work[25], and more often perform planning[26] tasks. However, this does not differ between those with temporary or permanent contracts. 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 perspectives due to the type of contract is the driver of our findings.

[21] This dummy takes the value 1 for the highest two quantiles of an index derived from the following questions, all measured in 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?. It takes the value 0 otherwise.

[22] This dummy takes the value 1 if the person answered one of the two highest frequency values to the question: how often are you usually faced by relatively simple problems that take no more than 5 minutes to think about a good solution? It takes the value 0 otherwise.

[23] This dummy takes the value 1 if the employee answered one of the two highest frequency values 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? It takes the value 0 otherwise.

[24] This dummy takes the value 1 if the employee answered one of the two highest proportion values to the question: In your job what proportion of your time do you usually spend collaborating with co-workers? It takes the value 0 otherwise.

[25] This dummy takes the value 1 for the highest two quantiles of an index derived from the following questions, all measured in a five-point Likert scale. In your job, how often do you usually: a) use email?; b) use the internet in order to better understand issues related to your work?; c) conduct transactions on the internet?; d) use spreadsheet software?; e) use a word processor?; and f) participate in real-time discussions on the internet? It takes the value 0 otherwise.

[26] This dummy takes the value 1 for the highest two quantiles of an index derived from the following questions, all measured in a five-point Likert scale. How often does your usually involve: a) planning your own activities?; b) planning the activities of others?; and c) organising your own time? It takes the value 0 otherwise.

6. INFORMAL LEARNING AND TRAINING: SUBSTITUTION OR COMPLEMENTARITY?

6.1 Training incidence

In order 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 followed the training[27]. Table 6 provides the results and proceeds stepwise.

[Insert Table 6 about here]

The temporary contract indicator yields the expected negative coefficient in all estimations. The coefficient given by the standard probit (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 type is controlled for, the estimated temporary contract penalty to participate in training increases from 6.5 to 7.6 percentage points. This implies that workers in temporary jobs are, on average, 7.6 percent less likely to take part of job-related training activities than individuals in permanent employment.

The negative value of ρ suggest that unobservables that decrease temporary contract selection probably occur with unobservables that increase training participation chances. This is again coherent with our hypothesis of unobservables mentioned in Section 3. However, note that in the CF[28] specifications (3) and (4), the Wald tests indicate that we cannot reject the null hypothesis of $\rho = 0$ at 95 percent confidence, but at 90 percent. That means that at 95 percent of 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 to access job-related training as it has been widely evidenced in the literature (e.g. Albert et al., 2010; Arulampalam et al., 2004; Booth and Bryan, 2004; Cutulli and Guetto, 2013; Steijn et al., 2006; O'Connell and Byrne, 2010). In

[27] Due to this reason, we excluded 364 observations from the estimations.

[28] Since maximum likelihood estimation of endogenous switching models for binary outcome variables follows a different structure and notation, the Stata command *etregress* is not appropriate. Then, we used the wrapper program *ssm* to obtain the do-file to fit the correspondent models (4) and (5) with the *gllamm* command. For a detail description, see Miranda and Rabe-Hesketh (2006) and Rabe-Hesketh et al. (2005).

addition, we find that the effect of age on training probability is positive early in the working career, but rapidly turns into negative as the significant coefficient of age square indicates. It is shown in specifications (3) and (4) that the probability of participation in training is positive until workers nearly reach age 35 and subsequently it starts decreasing, consistent with the lifecycle model of human capital accumulation (Ben Porath, 1967) and empirical studies' findings (e.g. Grund and Martin, 2012; O'Connell and Byrne, 2010).

The probability of training also rises with years of education. On average, every additional year of schooling increases the chances to participate in job-related training by 1.7 percentage points. Educational mismatches also have an important impact on training as they have on informal learning. With respect to the well matched, overeducated employees are 1.8 percent less likely to take part in training activities while undereducated are 2.8 percent more likely. There is also a positive relation of training probability with readiness to learn, actual working hours, and tenure[29]. The latter because it may be optimal to delay training if there is belated information about well matches and employees' future mobility (Loewenstein and Spletze, 1997).

6.2 Complementarity

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

To answer this question one could first observe whether there is a difference in the informal learning intensity of employees who undertook any training and those who did not. Figures 1 and 2 graphically present 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 shown to be consistently greater when the incidence of training is positive. Figure 1 indicates that workers on temp contracts do not seem to substitute 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 1 and Figure 2 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 of informal learning. Table 7 shows that the positive relation between informal learning and job-related training

[29] After controlling for age square, the square term of tenure was not significant in any of the equations. Therefore we kept the former and did not include the latter.

holds after controlling for various individual and employer characteristics. Moreover, the magnitude of this complementarity does not differ by type of contract as the interaction term of training and temporary contract is not statistically significant in all three estimations, which means that the direction and size of the regarded complementarity for temp workers runs equally to the complementarity estimated for permanent employees. On average, taking part in job-related training increases informal learning by 0.19 of a standard deviation. Moreover, the estimated results show that flex workforce 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 have analysed the difference in informal workplace learning intensity between permanent and temporary male employees across twenty OECD countries. Human capital theory would expect both firms and employees to be less willing to invest in skills if workers are hired under temp contracts. Remarkably, we found significant evidence that workers in temporary jobs engage more intensively in informal learning on-the-job than their counterparts in permanent employment; although the former, indeed, are 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. Results are robust to changes in our model specification and more efficient in comparison with alternative 2SLS specifications. We conclude that the ATE of temporary contracts on the intensity of informal learning on-the-job is positive and about 0.17 of a standard deviation in the OECD countries included in our sample. This result is substantial if we consider that it is about the same as the impact of ten years of schooling. Consistent with human capital theory, we also found that workers' informal learning intensity decreases with age and tenure. Conversely, it increases with years of education, actual working hours, learning readiness 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 (Booth et al., 2002; Jahn and Bentzen, 2012); we hypothesise that flex workforce would rationally invest more in informal learning to increase their possibilities of transition towards more stable employment. Thus, it would be expected that those individuals with positive prospects of upward mobility in the labour market would be 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 (De Grip and Smits, 2012; Destré et al., 2008).

Research on the 'stepping stone' effects of temporary employment is in line with this hypothesis. These studies often evoke the idea that transition odds most probably 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; Cockx & Picchio, 2012; de Graaf-Zijl et al., 2011; Gagliarducci, 2005; Jahn and Rosholm, 2014; Jahn and Pozzoli, 2013). 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 into the labour market may be responsible for the stronger incentives to invest in informal learning. Flex workforce may perceive more intense learning as a profitable investment for job career development. These decisions probably depend on the manner in which uncertainty affects the returns to investments 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. He 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 increases and give rise to capital accumulation until finding a job that offers better stability conditions.

This has two important implications. First, if optimal human capital investments decline over the lifecycle by the search for a proper match or a better job, the learning intensity in temporary employment is likely to be higher, as we actually found, the earlier in the working life and/or the earlier the job occurs. Second, accepting a temporary job that might pay less initially but involves higher learning potential[30] 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 (de Grip and Smits, 2012; Sicherman and Galor, 1990).

In addition, this paper shows evidence for complementarity between job-related training and informal learning for both temp and permanent employees. This suggests that the higher informal learning investment of temporary workers does not substitute for the lack of formal training at the individual level. This complementarity may 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 to higher previous investments in formal schooling, which not only provide higher skills, but may also 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

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

more in job training and informal learning (Mincer, 1994; Rosen, 1972). One initial repercussion of this complementarity is that studies on returns to job training might have overestimated results as they usually attribute all the benefits of skill acquisition to workers' participation in training without taking into consideration the informal learning costs.

A second implication is that the policy objective of promoting flexicurity in several OECD countries is still a challenge regarding the learning potential of temporary jobs. If flexible work is taken by people against unemployment in search for further individual promotion into the labour market, it would 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. First, 'good' temp jobs with plenty opportunities for training and informal learning, likely involving positive career expectations of upward mobility and, second, 'bad' temp jobs in which there are none or very few possibilities to participate in training and informal learning activities that would cause most workers to be trapped in precarious employment. The latter group is in a disadvantaged situation to build on skills for their job careers. 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.

Thus, our results suggest that labour inequality among OECD countries should also be investigated within temporary employment because of the fragmentation between low and high learning content jobs. The important policy conclusion from our work is then that temporary jobs need not be dead-end jobs. Instead, by offering sufficient opportunities to learn on the job, they could function as a stepping-stone towards more stable employment. As indicated by the Cedefop (2011) and the European Commission (2010b), the flexicurity concept assumes that it is the worker who needs support for a successful transition either with the same or with another employer. Thus, formal and informal investments in human capital need to be provided and complemented in the workplace to strengthen the employability of temporary workers and to facilitate the adjustment of the economy. All this implies further efforts in research and policy responses towards the balance between flexibility and security sought by the OECD countries.

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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

* OECD statistics 2012

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
Readiness to learn (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). It is due to lower response rate and the exclusion of respondents who followed training while being unemployed.

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

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS (1 instrument)	2SLS (3 instruments)	CF-ML (1 instrument)	CF-ML (3 instruments)
Informal Learning Equation					
Temp 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)
Learning Readiness	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)
Occupation dummies	yes	yes	yes	yes	Yes
Industry & firm size dummies	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)		
Learning readiness		0.0005	0.0005	0.0027	0.0028
		(0.0027)	(0.0027)	(0.0023)	(0.0023)
Occupation, Industry & firm size dummies		yes	yes	yes	yes
Country dummies		yes	yes	yes	yes
First-stage Tests *Admissibility of instrument*		F(49, 25316) = 58.60	F(51, 25314) = 56.97	Wald chi2(45) = 2243.8	Wald chi2(47) = 2245.6
Adj. R^2 First-stage		0.1400	0.1413	0.1305	0.1320
athrho				-0.0746***	-0.0774***
_cons				(0.0223)	(0.0219)
lnsigma				-0.103***	-0.103***
_cons				(0.0351)	(0.0351)
IV Test of endogeneity / *Wald test of indep. Eqns. (rho = 0)*		F(1,19) = 16.0 (p = 0.0008)	F(1,19) = 9.47 (p = 0.0062)	Chi2(1) = 4.72 (p = 0.0299)	Chi2(1) = 5.60 (p = 0.0179)
N	25,366	25,366	25,366	25,366	25,366
R^2	0.1744	0.0798	0.1024	.	.

The standardised unemployment rate is used as instrument in columns (2) and (4), and columns (3) and (5) add as instruments the interactions of the standardised unemployment rate with 2 of the 3 dummies of EPL for permanent employment. AME correspond to Average Marginal Effects. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1) CF-ML (1 instrument)	Difference Permanent and Temp contract	(2) CF-ML (3 instruments)	Difference Permanent and Temp contract
ATE	**0.1255**** (0.0500)		**0.1292**** (0.0517)	
ATT	**0.1822***** (0.0489)		**0.1856***** (0.0505)	
Permanent contract * Age	-0.0218*** (0.0046)	-0.0047** (0.0021)	-0.0218*** (0.0047)	-0.0046** (0.0020)
Temp contract * Age	-0.0265*** (0.0051)		-0.0264*** (0.0051)	
Permanent contract * Age^2	0.0002*** (0.0001)		0.0002*** (0.0001)	
Temp contract * Age^2	-0.0000 (0.0002)		-0.0000 (0.0002)	
Permanent contract * Years of education	0.0157*** (0.0032)	-0.0004 (0.0068)	0.0157*** (0.0032)	-0.0003 (0.0068)
Temp contract * Years of education	0.0153** (0.0077)		0.0154** (0.0077)	
Permanent contract * Overeducated	-0.1102*** (0.0190)	0.0495 (0.0369)	-0.1102*** (0.0190)	0.0495 (0.0369)
Temp contract * Overeducated	-0.0606*** (0.0230)		-0.0606*** (0.0230)	
Permanent contract * Undereducated	0.1409*** (0.0296)	0.1218 (0.0937)	0.1410*** (0.0296)	0.1242 (0.0937)
Temp contract * Undereducated	0.2627*** (0.0864)		0.2652*** (0.0864)	
Permanent contract * Tenure	-0.0024** (0.0010)	-0.0059** (0.0029)	-0.0023** (0.0010)	-0.0058** (0.0028)
Temp contract * Tenure	-0.0082*** (0.0031)		-0.0082*** (0.0031)	
Permanent contract * Working hours	0.0078*** (0.0011)		0.0078*** (0.0011)	
Temp contract * Working hours	0.0016 (0.0022)		0.0016 (0.0022)	
Permanent contract * Learning readiness	0.2049*** (0.0132)	-0.0048 (0.0283)	0.2088*** (0.0132)	-0.0087 (0.0290)
Temp contract * Learning readiness	0.2001*** (0.0345)		0.2001*** (0.0345)	
Temp contract	0.5957** (0.2746)		0.5993** (0.2785)	

_cons	-0.3196***	-0.3220***
	(0.1098)	(0.1105)
Treatment interactions with:		
Occupation dummies	yes	yes
Industry & firm size dummies	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
Occupation dummies	yes	yes
Industry & firm size dummies	yes	yes
Country dummies	yes	yes
athrho	-0.0509***	-0.0532***
_cons	(0.0171)	(0.0178)
lnsigma	-0.1072***	-0.1072***
_cons	(0.0358)	(0.0359)
Wald test of indep. Eqns	Chi2(1) = 8.85	Chi2(1) = 8.90
(rho = 0)	(p = 0.0029)	(p = 0.0028)
N	25,366	25,366

The standardised unemployment rate is used as instrument in column (1), and column (2) adds as instruments the interactions of the standardised unemployment rate with 2 of the 3 dummies of EPL for permanent employment. AME correspond to average marginal effects. All regressions include the same control variables as reported in Table 3. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1) CF-ML (1 instrument)	(2) CF-ML (3 instruments)
ATE Temp Contract	**0.1656***** **(0.0511)**	**0.1695***** **(0.0508)**
Permanent contract * Task discretion	0.0794*** (0.0134)	0.0794*** (0.0134)
Temp contract * Task discretion	0.0809*** (0.0272)	0.0812*** (0.0272)
Difference	0.0014 (0.0299)	0.0018 (0.0298)
athrho *_cons*	-0.0404** (0.0200)	-0.0428** (0.0192)
Wald test of indep. Eqns. *(rho = 0)*	Chi2(1) = 4.09 (*p* = 0.0430)	Chi2(1) = 4.97 (*p* = 0.0258)
N	25365	25365
ATE Temp Contract	**0.1643***** **(0.0552)**	**0.1680***** **(0.0547)**
Permanent contract * Complex problems	0.3549*** (0.0164)	0.3549*** (0.0164)
Temp contract * Complex problems	0.3950*** (0.0574)	0.3950*** (0.0573)
Difference	0.0402 (0.0541)	0.0401 (0.0541)
athrho *_cons*	-0.0407* (0.0210)	-0.0431** (0.0202)
Wald test of indep. Eqns. *(rho = 0)*	Chi2(1) = 3.96 (*p* = 0.0466)	Chi2(1) = 4.56 (*p* = 0.0327)
N	25334	25334
ATE Temp Contract	**0.1761***** **(0.0577)**	**0.1800***** **(0.0576)**
Permanent contract * Simple problems	0.3138*** (0.0177)	0.3138*** (0.0176)
Temp contract * Simple problems	0.3190*** (0.0477)	0.3191*** (0.0477)
Difference	0.0051 (0.0476)	0.0053 (0.0476)
athrho *_cons*	-0.0457** (0.0223)	-0.0481** (0.0216)
Wald test of indep. Eqns. *(rho = 0)*	Chi2(1) = 4.18 (*p* = 0.0409)	Chi2(1) = 4.96 (*p* = 0.0259)
N	25343	25343
ATE Temp Contract	**0.1531***** **(0.0487)**	**0.1565***** **(0.0490)**
Permanent contract * Team work	0.2284*** (0.0228)	0.2284*** (0.0229)

Temp 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**
_cons	(0.0196)	(0.0193)
Wald test of indep. Eqns.	Chi2(1) = 3.92	Chi2(1) = 4.52
(rho = 0)	(*p* = 0.0478)	(*p* = 0.0336)
N	25349	25349
ATE Temp Contract	**0.1752*** **	**0.1786*** **
	(0.0502)	**(0.0503)**
Permanent contract * ICT use	0.2035***	0.2035***
	(0.0209)	(0.0209)
Temp contract * ICT use	0.2211***	0.2215***
	(0.0495)	(0.0495)
Difference	0.0176	0.0179
	(0.0437)	(0.0438)
athrho	-0.0414**	-0.0436**
_cons	(0.0199)	(0.0194)
Wald test of indep. Eqns.	Chi2(1) = 4.33	Chi2(1) = 5.05
(rho = 0)	(*p* = 0.0374)	(*p* = 0.0246)
N	25366	25366
ATE Temp Contract	**0.1690*** **	**0.1723*** **
	(0.0538)	**(0.0536)**
Permanent contract * Planning tasks	0.2056***	0.2056***
	(0.0204)	(0.0204)
Temp contract * Planning tasks	0.1740***	0.1742***
	(0.0337)	(0.0338)
Difference	-0.0316	-0.0313
	(0.0274)	(0.0275)
athrho	-0.0415**	-0.0436**
_cons	(0.0204)	(0.0198)
Wald test of indep. Eqns.	Chi2(1) = 4.13	Chi2(1) = 4.86
(rho = 0)	(*p* = 0.0422)	(*p* = 0.0276)
N	25366	25366

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

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*
Temp 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)
Learning Readiness	0.0356***	0.0378***	0.0377***	0.0382***
	(0.0039)	(0.0045)	(0.0041)	(0.0042)
_cons	-0.3756***			
	(0.0684)			
Occupation dummies	yes	yes	yes	Yes
Industry & 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)
Overeducated				

Undereducated				
Working hours				
Tenure				
Learning readiness			0.0020	0.0015
			(0.0131)	(0.0019)
Occupation, industry & firm size dummies			yes	yes
Country dummies			yes	yes
First-stage Tests			Wald chi2(45)	Wald chi2(47)
Admissibility of instrument			= 2071.1	= 2102.6
Adj. R2 First-stage			0.1230	0.1262
athrho			-1.2761***	-1.2880***
_cons			(0.0872)	(0.3194)
lnsigma			-8.6042	-8.3152**
_cons			(5.5440)	(0.9946)
Wald test of indep. eqns.			Chi2(1) = 3.17	Chi2(1) = 3.51
(rho = 0)			(p = 0.0750)	(p = 0.0609)
N	22447	22447	22447	22447
R^2	0.1895	0.1489	.	.

The standardised unemployment rate is used as instrument in columns (3) and (4), and column (5) adds as instruments the interactions of the standardised unemployment rate with 2 of the 3 dummies of EPL for permanent employment. AME correspond to Average Marginal Effects. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. Informal learning and training Temporary workers

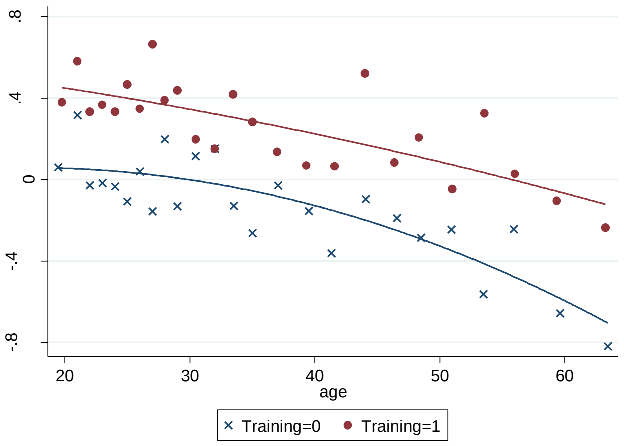

Figure 2. Informal learning and training Permanent workers

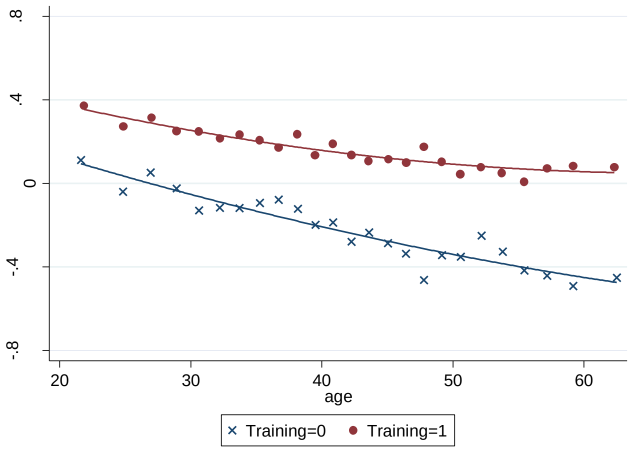

Table 7. Estimations on complementarity between informal learning and training participation

	(1)	(2)	(3)
	OLS	CF-ML (1 instrument)	CF-ML (3 instrument)
Informal Learning Equation			
Temp 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)
Temp contract*Training	-0.0164	-0.0106	-0.0106
	(0.0316)	(0.0303)	(0.0303)
	-0.0282***	-0.0248***	-0.0249***
Age	(0.0057)	(0.0055)	(0.0055)
	0.0002***	0.0002**	0.0002**
Age^2	(0.0001)	(0.0001)	(0.0001)
	0.0131***	0.0135***	0.0135***
Years of education	(0.0028)	(0.0030)	(0.0030)
	-0.0955***	-0.0955***	-0.0955***
Overeducated	(0.0185)	(0.0185)	(0.0185)
	0.1483***	0.1485***	0.1486***
Undereducated	(0.0321)	(0.0320)	(0.0320)
	0.0064***	0.0064***	0.0064***
Working hours	(0.0013)	(0.0013)	(0.0013)
	-0.0032***	-0.0024**	-0.0024**
Tenure	(0.0008)	(0.0010)	(0.0010)
	0.1947***	0.1949***	0.1949***
Learning Readiness	(0.0150)	(0.0150)	(0.0150)
_cons	-0.0954	-0.1938	-0.1928
	(0.1233)	(0.1302)	(0.1309)
Occupation dummies	yes	yes	yes
Industry & firm size dummies	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***
_cons		(0.0225)	(0.0226)
lnsigma		-0.1102***	-0.1102***
_cons		(0.0361)	(0.0361)
Wald test of indep. Eqns.		Chi2(1) = 10.2	Chi2(1) = 9.91
(rho = 0)		(*p* = 0.0014)	(*p* = 0.0016)
N	22447	22447	22447
R^2	0.1849	.	.

APPENDIX

Table A1. Estimations of informal learning intensity under alternative treatment specifications

	ATE (1 instrument)	ρ	Wald test ρ=0	ATE (3 instruments)	ρ	Wald test ρ=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, overeducated and undereducated	0.2236***	-0.0798***	Chi2(1) = 10.9	0.2273***	-0.0822***	Chi2(1) = 11.7
	(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 firm size dummies	0.1567***	-0.0369*	Chi2(1) = 2.84	0.1613***	-0.0394*	Chi2(1) = 3.53
	(0.0550)	(0.0219)	(*p* = 0.0918)	(0.0547)	(0.0209)	(*p* = 0.0603)
(12) Occupation, industry, firm size and country dummies	0.2209***	-0.0746***	Chi2(1) = 8.15	0.2214***	-0.0743***	Chi2(1) = 8.69
	(0.0609)	(0.0261)	(*p* = 0.0043)	(0.0584)	(0.0252)	(*p* = 0.0032)

All above estimations are based on the same sample of 25,633 observations. Estimations with 1 instrument use the standardised unemployment rate and estimations with 3 instruments add the interactions of the standardised unemployment rate with 2 of the 3 dummies of EPL for permanent employment. All regressions include the same control variables as reported in Table 3, with the only exception mentioned for each robustness check. The outcome model remains the same as reported in Table 3. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Wooldridge's IV robust estimations of informal learning intensity

	(1) Robust IV (1 instrument)	(2) Robust IV (3 instruments)
Informal Learning Equation		
Temp 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)
Learning readiness	0.2041***	0.2041***
	(0.0145)	(0.0145)
_cons	-0.6280***	-0.6440***
	(0.1496)	(0.1562)
Occupation dummies	yes	yes
Industry & 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 instrument in column (1), and column (2) adds as instruments the interactions of the standardised unemployment rate with 2 of the 3 dummies of EPL for permanent employment. AME correspond to Average Marginal Effects. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.