Temporary Employment and Firm-Sponsored Training*

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Abstract

Using employees' longitudinal data, we study the causal effect of holding a temporary job rather than an open-ended contract on the probability of receiving firm-sponsored training. The empirical analysis is based on dynamic panel data models which control for unobserved heterogeneity and feedback from shocks in the training status to future propensity of having an open-ended or a temporary job contract. We find that in the Netherlands temporary workers are significantly less likely to receive firm-sponsored training. In order to avoid possible labour market segmentation due to unequal on-the-job acquisition of human capital, policies should be designed to create incentives for firms to invest in the training of temporary workers.

Keywords: firm-sponsored training, temporary employment, human capital, dynamic panel data model.
JEL classification codes: C33, C35, J41, M53

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1 Introduction

In the last two decades, in most of the OECD countries employment relations have changed and temporary contracts have replaced the "standard" open-ended job arrangement. Policy makers often see in temporary contracts an instrument for improving the ability of the economy to adapt to changing conditions and to an intense and rising international competition (OECD, 1995). Even if disadvantaged groups (youth, women, and long-term unemployed), excluded from employment by too strict regulations, may benefit most from this enhanced flexibility,[1] concerns have been expressed about the quality and possible social exclusion associated with temporary jobs. Job security, on-the-job training, and lifelong earnings are some of the dimensions of job quality at risk, especially if the labour market is segmented, the employment protection legislation of permanent workers is strict, and temporary jobs are mainly used as a buffer to face cyclical downturns.

This article analyses the on-the-job training that firms provide to their temporary workers. We aim at understanding whether temporary employees are as likely as permanent workers to receive firm-sponsored training. The importance of on-the-job training of employed workers has been stressed by the theoretical literature both at macro and micro levels. At macro level the accumulation of human capital is one of the main engine of growth (Lucas, 1993). At micro level, on-the job training provides employees with a refreshment and an update of their skills, making them, and thereby the organization where they work, more productive, more competent, and quicker in adapting to a changing economic and technological environment, which are key factors for firms' sustained competitive advantage (Wright et al., 1994). As a matter of fact, empirical studies find that on-the-job training has a positive impact on firms' productivity (e.g. Bartel, 1994, 1995; Barrett and O'Connell, 2001; Conti, 2005; Dearden et al., 2006; Zwick, 2006) and on employees' employment probability (Picchio and van Ours, 2011b). Moreover, to the extent that employees can learn general skills by firm-provided training,[2] trained workers are expected to return faster at work in case of job loss as they are more productive and more flexible in adapting to new tasks in different firms and sectors. Understanding whether firms invest less in temporary workers' human capital is therefore policy relevant to understand whether the spread of temporary contracts, especially among the new entrants in the labour market, might put at stake the human capital development of temporary workers and spur the segmentation in the labour market.

[1] Several empirical studies find that temporary jobs are a way out of unemployment and a stepping-stone to permanent jobs in Europe. See, among others, Booth et al. (2002b), Hagen (2003), Göbel and Verhofstadt (2008), Ichino et al. (2008), Picchio (2008), Berton et al. (2009), De Graaf-Zijl et al. (2011).

[2] Loewenstein and Spletzer (1999) empirically documented that most of the skills that employees learn by firm-provided training are general.

The economic theory does not provide clearcut predictions about the relation between the job arrangement and the incentives of firms to invest in training. On the one hand, firms' incentives to invest in training are negatively related to the probability of a job mismatch (see, e.g., Acemoglu and Pischke, 1999). Since the expected duration of the employer-employee match is shorter on average and, thereby, the probability of recouping the training investment is lower, firms will be less likely to provide temporary workers with training.[3] On the other hand, since training, in addition to fostering human capital, induces self-selection of more able workers and facilitates worker screening (Autor, 2001), firms might be willing to provide temporary workers with training before locking themselves in an open-ended job relationship. Moreover, we would expect that the higher the employment protection of permanent workers, the larger the firms' scope for providing temporary workers with training, as firms give more importance to the assessment of the true quality of workers before locking themselves in a permanent contract. Nevertheless, one could argue that high firing costs of permanent employees might induce firms to use temporary jobs simply as a flexibility buffer, reducing firms' incentives to invest in temporary employees' human capital.

Despite several studies have been conducted to understand the impact of temporary employment on several dimensions of employment quality like earnings, unemployment exit rate, probability of finding a permanent job, safety at work, and employment stability,[4] the empirical literature on temporary work and firm-provided training is scarce and far from identifying a causal effect. Apart from Alba-Ramirez (1994) who finds that Spanish firms hiring a larger number of training and apprenticeship contracts are more likely to provide their employees with training, the existing empirical literature finds that temporary workers are less likely to receive firm-provided training. Arulampalam and Booth (1998) find that employees with a seasonal, casual, or fixed-term contract are significantly less likely to receive work-related training in Britain. Draca and Green (2004) shows that in Australia firms invest in training of flexible workers but at a much lower rate: training received by flexible workers is 50%–80% less intense than the workforce average. Forrier and Sels (2003), Albert et al. (2005), and Sauermann (2006) find that temporary workers are associated to a lower probability of receiving firm-provided training in Belgium, Spain, and Germany, respectively.

The main contribution of this article is to use employees' longitudinal data based on retrospective training experiences to estimate the causal effect of holding a temporary job instead of an open-ended contract on the subsequent probability of receiving

[3] As a matter of fact, Picchio and van Ours (2011a) find that in the Netherlands when the labour market flexibility increases, firms are less likely to sponsor the training of their employees.

[4] See, e.g., Booth et al. (2002a) and the related special issue on temporary work.

firm-sponsored training. This is done by controlling for unobserved heterogeneity and by taking into account, in a dynamic framework, that a shock on the probability of receiving training might have feedback effects on the future probability of having a permanent/temporary contract. This article indeed also provides estimates of the effect of training on the subsequent probability of moving to a permanent position.

The empirical analysis exploits new Dutch longitudinal data. The Netherlands is an interesting country to conduct such an empirical investigation as the Netherlands started in the 1980s the process of reduction of the strictness of the regulation of temporary employment leaving untouched the employment protection of regular workers (OECD, 2004). We design and estimate a dynamic panel data model that describes the interrelated dynamics of work-related training and the type of contract, allowing for unobserved heterogeneity and accounting for initial conditions. We find that temporary workers are significantly less likely to receive firm-sponsored training in the subsequent 12 months than comparable permanent workers. The size of the effect ranges between 6.4 and 12.7 percentage points, depending on the model specification and the estimation method.

This paper is set up as follows. The data are described in Section 2. Section 3 formalizes the econometric model and clarifies the identification strategy. The estimation results are presented and discussed in Section 4. Section 5 concludes.

2 Data Description

The data used in this paper are from a new Dutch panel, the Longitudinal Internet Studies for the Social Sciences (LISS) panel. The LISS panel is administered by the CentERdata of Tilburg University. A representative sample of households is drawn from a population register by Statistics Netherlands and asked to join the panel by Internet interviewing. Households are provided with a computer and/or an Internet connection if they do not have one.[5] The LISS panel is made up of several study units. Different study units can have different timings and frequency over the year in data collection. Some background information on general characteristics, like demography, family composition, education, labour market position, and earnings, is measured on a monthly basis, from November 2007 until March 2011 (at the time of writing). Ten core studies are instead carried out once a year and cover a wide set of topics, like health, religion and ethnicity, social integration and leisure, family and household, work and schooling, personality, politics, and

[5]See Knoef and de Vos (2009) for an evaluation of the representativeness of the LISS panel and Scherpenzeel (2011, 2010) and Scherpenzeel and Das (2010) for methodological notes on the design of the LISS panel.

economic situation.[6] For this study we exploit the monthly information of the background variables and the core study on work and schooling, which was carried out mostly in April 2008, 2009, and 2010.[7] The core study on work and education comprises a broad range of questions about labour market participation, job characteristics, pensions, schooling and training. People are asked whether they attended work-related training courses in the last 12 months and, if so, who sponsored the training course. People are also asked whether they are at work at the moment of the interview and if they are employees, whether they have an open-ended or a temporary job.

Between 5,701 and 6,951 individuals were interviewed each year for the core study on work and schooling, resulting in a total of 19,018 records. We focus on employees who are older than 16 and younger then 64 year of age. We drop observations with missing values in the variables used in the econometric analysis and employees with on-call jobs. We eliminate employees that are not always in the sample across the three waves. The latter restriction is due to the fact that we estimate a dynamic model of order one with unobserved effects, which requires (at least) three time observations per individual. One more time period is indeed needed because of the model dynamic. A further period is needed as initial values are used to correct for initial conditions induced by the presence of the unobserved effects. After the application of these sample selection criteria, we are left with a balanced panel of 2,102 individuals for a total of 4,204 individual-year observations for the years 2009 and 2010.[8]

We are primarily interested in whether and to what extent temporary employees receive less firm-sponsored training than permanent workers. We denote by y_{it} the indicator variable equal to 1 if employee i received firm-sponsored training in the 12 months preceding the interview at time t and 0 otherwise. We denote by w_{it} the indicator variable equal to 1 if employee i is a temporary worker (either fixed-term or worker for a temporary work agency) at the interview time t and 0 if employed with an open-ended contract. Table 1 reports raw conditional and unconditional probabilities of receiving firm-sponsored training and of having a temporary job. Panel a of Table 1 shows the raw probability of receiving firm-sponsored training during the year conditional on the contractual arrangement at the beginning of the year. Temporary employees are less likely

[6] See http://www.lissdata.nl/dataarchive/study_units/view/1 for the full list of studies of the LISS panel.

[7] About 5.5% of the 2008 interviews were conducted in July, whilst respectively 6.8% and 7.8% of the 2009 and 2010 interviews were collected in May.

[8] When we keep individuals who were in the sample in 2008, 2009, and 2010, we are left with 4,376 individuals. The age selection reduces the sample size to 3,530 individuals. When we keep only employees with a permanent job, a fixed-term job, or a job for a temporary work agency, we are left with about 2,400 individual observations per year. When we focus on those who were at work in all the time periods (balanced panel), we are left with 2,102 individuals.

to receive firm-sponsored training in the next 12 months. Whereas the probability that temporary workers receive firm-sponsored training in the next 12 months is 22.2%, the same probability is equal to 32.2% for permanent employees. Panel b of Table 1 reports

Table 1: Raw Conditional and Unconditional Probabilities of Firm-Sponsored Training and Temporary Contract (Absolute Frequencies in Parenthesis)

a.	Firm-sponsored training in $[t-1,t)$		
Temporary worker at $t-1$	No	Yes	Total
No	0.648 (2,495)	0.352 (1,353)	1.000 (3,848)
Yes	0.778 (277)	0.222 (79)	1.000 (356)
Total	0.659 (2,772)	0.341 (1,432)	1.000 (4,204)
b.	Temporary worker at t		
Firm-sponsored training in $[t-1,t)$	No	Yes	Total
No	0.908 (2,516)	0.092 (256)	1.000 (2,772)
Yes	0.949 (1,359)	0.051 (73)	1.000 (1,432)
Total	0.922 (3,875)	0.078 (329)	1.000 (4,204)
c.	Temporary worker at t		
Temporary worker at $t-1$	No	Yes	Total
No	0.983 (3,781)	0.017 (67)	1.000 (3,848)
Yes	0.264 (94)	0.736 (262)	1.000 (356)
Total	0.922 (3,875)	0.078 (329)	1.000 (4,204)
d.	Firm-sponsored training in $[t-1,t)$		
Temporary worker in $[t-2,t-1)$	No	Yes	Total
No	0.821 (2,105)	0.188 (487)	1.000 (2,592)
Yes	0.414 (667)	0.586 (945)	1.000 (1,612)
Total	0.659 (2,772)	0.341 (1,432)	1.000 (4,204)

the probability of having a temporary job conditional on firm-sponsored training in the preceding 12 months. The raw probability of having a temporary job at time t decreases from 9.2% to 5.1% if firm-sponsored training courses were attented in the preceding 12 months. These raw probabilities suggest that there might be some interdependence between firm-sponsored training and the contractual arrangement. However, most of the effect might be spurious and determined by individual observed and unobserved heterogenety. For instance, those employees willing or selected to attend a training course might also be more endowed with skills, motivated, able, and attached to the workforce: hence, they are also more likely to get or keep a permanent position in the future. Moreover, panel b of Table 1 suggests that a strict exogeneity assumption (conditional on observed and unobserved heterogeneity) on the temporary work variable in a regression model for the probability of receiving firm-sponsored training might be potentially violated as a shock in the training variable might generate feedback to future probabilities of getting a permanent job. Panel c of Table 1 reports the raw probabilities of having a temporary job as a function of the previous contractual arrangement. There is a strong raw state dependence in temporary jobs: the probability of having a temporary job, conditional on a temporary position one year before, is equal to 74%. The raw probability of moving from a temporary to a permanent position is equal to 26%. Lasly, the panel at the bottom of Table 1 reports raw probabilities of receiving firm-provided training as a function of past training. Those workers who received training in the past are more likely to receive it also in the future.

Table 2 presents summary statistics of the outcome variables and of the variables used in the econometric analysis. More than one third of the employees attended at least one training course sponsored by the employer in the preceding 12 months and almost 8% have a temporary job (either fixed-term job or temporary work agency job).[9] The average age is about 44 years with 12 years of job tenure. Almost 52% of the people in the sample are women and more than 45% have at least a higher secondary degree. On average each household has 3 members and 1.1 children. Almost 19% of the people are single, 58% declare to be the head of the household, and 39% live in a very or extremely urban area. More than 61% of the employees work on a full-time basis (the contractual working hours per week are larger than 30). Almost 40% of the employees work in a public or semi-public company, almost one third work in the sector of education, health, or welfare, and almost two third work in firms with more than 20 employees.

3 Econometric Modelling

We are primarily interested in understanding whether employees' probability of receiving firm-sponsored training in the next 12 months might be affected by the current temporary arrangement of the job. The temporary contract indicator is a potentially endogenous variable for several reasons. First, there might be self-selection issues determined by unobserved heterogeneity. Temporary workers might have different motivations, skills, and attachment to the labour market than permanent workers. Second, there might be feedback effects, i.e. shocks in the training indicator affecting the future type of employment contract. For instance, temporary workers with a positive transitory shock in the probability of receiving training might have the opportunity to accumulate human capital, so that their future probability of making a transition towards a permanent position increases. Furthermore, the positive shock in firm-sponsored training might reveal some of temporary workers' abilities and skills. To the extent that they reveal (un)appealing information, their probability of getting a permanent position will increase (decrease). Alternatively, if there is a negative shock in the probability of receiving firm-sponsored

[9] We do not include in the sample on-call workers as they are deemed to have structurally different jobs, given the production technology of the sectors where they are employed. We deleted from the balanced panel 107 observations with on-call jobs in the period 2009–2010.

Table 2: Summary Statistics of the Pooled Sample

	Mean	Std. Dev.	Minimum	Maximum
Firm-sponsored training in $[t-1,t)$	0.341	0.474	0.000	1.000
Temporary job at t	0.078	0.269	0.000	1.000
Female	0.517	0.500	0.000	1.000
Age in years	44.062	11.004	17.000	64.000
Education				
Primary	0.043	0.204	0.000	1.000
Intermediate secondary (vmbo/mbo)	0.502	0.500	0.000	1.000
Higher secondary (havo/hbo)	0.369	0.483	0.000	1.000
University or more	0.086	0.281	0.000	1.000
# of household components	2.959	1.312	1.000	9.000
# of kids in the household	1.121	1.142	0.000	6.000
Head of the household	0.578	0.494	0.000	1.000
Single	0.189	0.391	0.000	1.000
Urban area	0.390	0.488	0.000	1.000
$\ln$(net income) ($\ln$€)	6.821	1.873	0.000	11.986
Net income is not reported	0.064	0.244	0.000	1.000
Job tenure in years	12.049	10.385	0.000	47.000
Public employment	0.395	0.489	0.000	1.000
Full-time[(a)]	0.613	0.487	0.000	1.000
Sector				
Agriculture/Mining/Manufacturing	0.165	0.371	0.000	1.000
Retail trade/Transport/Communication	0.126	0.331	0.000	1.000
Finance	0.049	0.215	0.000	1.000
Services	0.168	0.374	0.000	1.000
Education/Health/Welfare	0.308	0.462	0.000	1.000
Other	0.185	0.389	0.000	1.000
Occupation				
High skilled white collar[(b)]	0.136	0.343	0.000	1.000
Low skilled white collar[(c)]	0.654	0.476	0.000	1.000
High skilled blue collar[(d)]	0.076	0.266	0.000	1.000
Low skilled blue collar[(e)]	0.133	0.340	0.000	1.000
Firm size (number of employees)				
$(0-10]$ employees	0.191	0.393	0.000	1.000
$(10-20]$ employees	0.132	0.339	0.000	1.000
$(20-100]$ employees	0.328	0.470	0.000	1.000
more than 100 employees	0.310	0.463	0.000	1.000
Number of employees unknown	0.039	0.194	0.000	1.000
# of observations (individuals)	4,204 (2,102)			

[(a)] The full-time indicator is built on the basis of the contractual weekly working hours. We define as full-timers those employees with more than 30 contractual working hours per week.

[(b)] We define as high skilled white collar workers those employees having a higher academic profession (e.g. architect, physician, scholar, engineer) or a higher supervisory profession (e.g. manager, director, supervisory civil servant).

[(c)] We define as low skilled white collar workers those employees having an intermediate academic profession (e.g. teacher, nurse, social worker, policy assistant) or an intermediate supervisory or commercial profession (e.g. head representative, department manager, shopkeeper) or other mental work.

[(d)] We define as high skilled blue collar workers those employees having a skilled and supervisory manual work (e.g. electrician).

[(e)] We define as low skilled blue collar workers those employees having a semi-skilled (e.g. driver) or an unskilled manual work (e.g. cleaner).

training, temporary workers might not be able to signal their skills: then the imperfectly informed employers might prefer to make the temporary contracts expire instead of locking themselves in open-ended job matches of uncertain quality. Lastly, there might be a problem of time-varying heterogeneity. Temporary workers are expected to have a more fragmented labour market career. Hence, when measuring the impact of having a temporary job on the probability of receiving firm-sponsored training in the subsequent 12 months, we should control for the number of months workers are effectively at work, as this number is likely to be correlated both to the contract type and to the probability of receiving firm-sponsored training.

In order to deal with these endogeneity issues, we jointly model the type of contract at each interview time and the firm-sponsored training participation during the subsequent 12 months. In a sensitivity analysis we also control for the number of months the individual was at work during the year. The model is designed with a dynamic recursive structure. The firm-sponsored training indicator depends on the temporary position at the beginning of the year. Similarly, whether individuals have a temporary job at the interview time depends on whether employees participated to firm-sponsored training in the last 12 months.

We design a multivariate discrete response model for panel data. Its estimation takes into account time-invariant individual characteristics, unobservable by the econometrician, that could be important in jointly determining the probability of having a temporary job and the training participation. Innate ability, intelligence, motivations, and labour market attachments are some examples of such endowments that, if ignored, may lead to biased parameter estimates. This selection on unobservables is controlled for under the assumption that the unobserved determinants of the training participation and the temporary job are dependent and jointly normally distributed. In a robustness check we adopt a more flexible specification, i.e. a discrete distribution with a flexible cross-equation correlation structure. Moreover, following Hyslop (1999) and Alessie et al. (2004) and in order to avoid the parametric restrictions of correlated random effects discrete response models, we compare the results with those of linear probability models where we get rid of the unobserved (time-invariant) heterogeneity by first-differencing.

Finally, as for a dynamic unobserved effects panel data model, three time observations per individual are needed, we had to exclude from our sample those employees who were not always at work at the three survey dates or that reported missing information in one or more waves. In what follows, we assume that attrition and missing information are random.

3.1 Constructing the Likelihood Function

The econometric model is similar to the state dependence model with feedback effects of Biewen (2009). In our panel data, at the interview date t, employee i can have either an open-ended job ($w_{it} = 0$) or a temporary position ($w_{it} = 1$) and, during the preceding 12 months, either they participated to some firm-sponsored training programme ($y_{it} = 1$) or not ($y_{it} = 0$). Let us denote the joint density of $y_{i1}, \dots, y_{iT}, w_{i1}, \dots, w_{iT}$ conditional on a set of strictly exogenous covariates $\mathbf{x}_i = (\mathbf{x}_{i1}, \dots, \mathbf{x}_{iT})$ and individual unobserved heterogeneity $\mathbf{c}_i$, possibly correlated with the covariates, as

$$f(y_{i1}, \dots, y_{iT}, w_{i1}, \dots, w_{iT} | \mathbf{x}_i, \mathbf{c}_i; \Psi), \tag{1}$$

where Ψ is the set of true parameters of the conditional joint distribution. We impose now an assumption on the dynamic of the model: the dynamics are of first order, once $\mathbf{x}_{it}$ and $\mathbf{c}_i$ are conditioned on. Under this assumption and the strict exogeneity assumption, the conditional density of the outcome variables can be expanded as

$$\prod_{t=1}^{T} f(y_{it}, w_{it} | y_{it-1}, w_{it-1}, \mathbf{x}_{it}, \mathbf{c}_i; \Psi). \tag{2}$$

Given the time sequencing of the outcome variables and without further assumptions, we can equivalently rewrite the joint density in (2) as

$$\prod_{t=1}^{T} f(y_{it} | y_{it-1}, w_{it-1}, \mathbf{x}_{it}, \mathbf{c}_i; \Theta) f(w_{it} | y_{it}, y_{it-1}, w_{it-1}, \mathbf{x}_{it}, \mathbf{c}_i; \Gamma), \tag{3}$$

where $\Theta \cup \Gamma = \Psi$. This decomposition of the conditional sample density allows us to focus on the effect of the contractual arrangement w_{it-1} on the firm-sponsored training y_{it} that is received by the employee in the subsequent 12 months, i.e. in the time interval $[t-1, t)$. Moreover, the sample density in (3) sheds light on the existence and direction of possible feedback from shocks in the training status (y_{it}) in the last 12 months to the contractual arrangement (w_{it}).

In order to empirically model the interrelated dynamics between employment situation and training participation, we are now going to impose some parametric functional restrictions on the determinants of the sample density. For individual i and $t = 1, \dots, T$

we assume that the two dichotomous outcome variables follow probit models, i.e.

$$\mathrm{P}(y_{it}=1|\quad y_{it-1},w_{it-1},\mathbf{x}_{it},\mathbf{c}_i) = \Phi(\qquad y_{it-1}\delta_1+w_{it-1}\theta_1+\mathbf{x}_{it}'\beta_1+c_{1i}), \quad (4)$$
$$\mathrm{P}(w_{it}=1|y_{it},y_{it-1},w_{it-1},\mathbf{x}_{it},\mathbf{c}_i) = \Phi(y_{it}\alpha_2+y_{it-1}\delta_2+w_{it-1}\theta_2+\mathbf{x}_{it}'\beta_2+c_{2i}), \quad (5)$$

where Φ denotes the standard normal CDF.

Equation (4) shows that, the probability of individual i of receiving firm-sponsored training in the last 12 months is influenced by the contractual arrangement in the past year, w_{it-1}, by the past firm-sponsored training, y_{it-1}, by a vector of observed variables, $\mathbf{x}_{it}$, and by an unobserved heterogeneity term c_{1i}.

Similarly, equations (5) allows the probability of having a temporary job at the interview data t to be determined by the firm-sponsored training in the last 12 months, y_{it}, and in the preceding year, y_{it-1}, by the past contractual arrangement w_{it-1}, by a vector of observed characteristics, and by an unobserved component c_{2i}.

On the basis of the sample density in (3) and the empirical specifications in (4) and (5), the contribution to the likelihood function of individual i is

$$\mathscr{L}_i(y_{i1},\dots,y_{iT},w_{i1},\dots,w_{iT}|\mathbf{x}_i,\mathbf{c}_i;\Psi)=\prod_{t=1}^{T}\Phi[(2y_{it}-1)(y_{it-1}\delta_1+w_{it-1}\theta_1+\mathbf{x}_{it}'\beta_1+c_{1i})]$$
$$\Phi[(2w_{it}-1)(y_{it}\alpha_2+y_{it-1}\delta_2+w_{it-1}\theta_2+\mathbf{x}_{it}'\beta_2+c_{2i})]. \quad (6)$$

Estimation of the model parameters cannot be based on this likelihood function, as $\mathbf{c}_i \equiv (c_{1i}, c_{2i})$ is not observed and the inclusion of individual dummy indicators would generate the incidental parameters problem (e.g. Heckman, 1981). The unobserved term $\mathbf{c}_i$ is likely to be correlated with the covariate vector $\mathbf{x}_{it}$. Innate ability, intelligence, motivations, and labour market attachment are all determinants of our dependent variables but also very likely to be correlated with covariates like education, job tenure, and sector. Hence, we do not treat $\mathbf{c}_i$ as a random effect but we allow for dependence between observed and unobserved characteristics by using a Mundlak (1978) version of Chamberlain's (1984) approach. Moreover, as the model is dynamic, the likelihood function in (6) suffers also from an initial conditions problem generated by the plausible correlation between the initial values of the outcome variables (y_{i0}, w_{i0}) and $\mathbf{c}_i$. The initial conditions problem is addressed by using Wooldridge's (2005) approach.[10] Formally, the parametric

[10] An alternative correction of the initial conditions problem is in Heckman (1981) and it is based on a separate formulation of the processes leading to the first realizations of the outcome variables, in order to get an approximation of the conditional distribution of the initial conditions. In this study, we prefer Wooldridge's (2005) approach because the true processes are already ongoing when the first observations are recorded and they are likely to be generated in the same way as later observations. Moreover, Wooldridge's (2005)

specification of the unobserved heterogeneity terms is assumed to be, for $j = 1, 2$,

$$c_{ji} = \bar{\mathbf{x}}_i' \beta_{0j} + y_{i0}\delta_{0j} + w_{i0}\theta_{0j} + v_{ji}, \tag{7}$$

where $\bar{\mathbf{x}}_i$ is the individual time average of $\mathbf{x}_{it}$, and y_{i0} and w_{i0} are the realizations of the outcome variables at the date of entry into our sample. The term $\mathbf{v}_i \equiv (v_{1i}, v_{2i})$ is the residual unobserved heterogeneity component and is assumed to be independent of observed characteristics and to have a bivariate normal distribution, with zero mean, unit variance, and correlation equal to $\rho_{\mathbf{v}}$. The unobserved time-invariant factors are allowed therefore to be cross-correlated, so as to capture cross-equation correlation, and we control for selection on unobservables by integrating out these unobserved factors from the likelihood function.

To check whether the parametric assumptions on the distribution of the random unobserved heterogeneity $\mathbf{v}_i$ are too strict and might bias the estimation results, in a robustness check we follow Heckman and Singer (1984) and assume that the vector $\mathbf{v}_i$ is a random draw from a bivariate discrete distribution function. More in detail, we assume that v_{1i} and v_{2i} have two points of support each with the following four probabilities:

$$\begin{aligned} p^1 &\equiv \Pr(v_1 = v_{1i}^1, v_2 = v_{2i}^1) \quad & p^2 &\equiv \Pr(v_1 = v_{1i}^2, v_2 = v_{2i}^1) \\ p^3 &\equiv \Pr(v_1 = v_{1i}^1, v_2 = v_{2i}^2) \quad & p^4 &\equiv \Pr(v_1 = v_{1i}^2, v_2 = v_{2i}^2) = 1 - \sum_{r=1}^{3} p^r \end{aligned}$$

The probabilities associated to the mass points are specified as logistic transforms:[11]

$$p^m = \frac{\exp(\lambda_m)}{\sum_{r=1}^{4} \exp(\lambda_r)} \quad \text{with} \quad \lambda_4 = 0.$$

Substituting equation (7), for $j = 1, 2$, into (6) and integrating out the unobserved heterogeneity $\mathbf{v}_i$ on the basis of the assumed distribution $G(\mathbf{v}_i)$ yield the unconditional

approach is computationally much simpler.

[11]Note that v_{1i} and v_{2i} are independent if and only if $p^1 p^4 = p^2 p^3$ (see van den Berg and Lindeboom, 1998; van den Berg and Ridder, 1994). This makes it easy to test whether the nonemployment and training equations are independent. Furthermore, it can be shown that the correlation $\rho_{\mathbf{v}}$ between v_{1i} and v_{2i} is given by $\rho_{\mathbf{v}} = \frac{p^1 p^4 - p^2 p^3}{\sqrt{(p^1+p^3)(p^2+p^4)(p^1+p^2)(p^3+p^4)}}$.

individual contribution to the likelihood function

$$
\begin{aligned}
&\mathscr{L}_i\left(y_{i1},\dots,y_{iT},w_{i1},\dots,w_{iT}|y_{i0},w_{i0},\mathbf{x}_i;\Psi,\Sigma\right)= \\
&\int_{\Re^2}\ \prod_{t=1}^{T}\Phi\Big[\left(2y_{it}-1\right)\left(y_{it-1}\delta_1+w_{it-1}\theta_1+\mathbf{x}_{it}'\beta_1+c_{1i}(v_{1i})\right)\Big] \\
&\times\ \Phi\Big[\left(2w_{it}-1\right)\left(y_{it}\alpha_2+y_{it-1}\delta_2+w_{it-1}\theta_2+\mathbf{x}_{it}'\beta_2+c_{2i}(v_{2i})\right)\Big]\mathrm{d}G(\mathbf{v}_i),
\end{aligned}
\tag{8}
$$

where Σ is the set of parameters to be estimated that characterizes the discrete distribution function of the unobserved heterogeneity term $\mathbf{v}_i$.

3.2 Discussion on Identification

This study deals with the contractual arrangement of a job relationship (temporary or permanent) and firm-sponsored training. It treats them as outcome variables which evolve with an endogenous pattern through the employees' labour market career. The model is designed to recover the potentially endogenous interrelated dynamics of these outcomes, which are also determinants of later outcomes. Identification of the main causal effects crucially depends on the capacity to control for different sources of endogeneity: (i) outcome variables are determinants of later outcomes; (ii) time-invariant unobserved heterogeneity; (iii) time-variant heterogeneity.

We exploit two main identification sources. First, the sequencing of the training realizations and of the temporary indicator is such that the contractual arrangement at the interview time can be considered as predetermined with respect to the training participation during the subsequent 12 months. In other words, as pointed out by Biewen (2009) in a different framework, the two equations are not simultaneous. Thanks to the recursive structure of the model, identification is attained without exclusion restrictions. Second, we have multiple observations per individual which are exploited to identify the cross-equation correlation structure due to residual unobserved heterogeneity and therefore to control for selection on unobservables.

Nevertheless, a possible identification pitfall might be due to time-variant heterogeneity. For example, take two identical employees but with different contractual arrangement at the interview time. The temporary worker is more likely to have job interruptions in the subsequent 12 months: exogenous shocks, like those generated by the business cycle, are going to affect more the employment stability and the number of months at work of the temporary worker. If the temporary worker will spend less time in employment on average, she will have less opportunity to receive firm-sponsored training. How can we disentangle the effect of having a temporary job by other relevant time-variant heterogeneity, like the fact that temporary workers are more likely to spend more time out of employment? We will address this problem by adding in a sensitivity analysis further covariates controlling for the number of months spent in non-employment during each year. This is aimed at controlling for different career patterns within the year. We anticipate that the results are robust to this kind of heterogeneity: employment persistences are indeed very strong and the time-constant unobserved heterogeneity might already pick up most of the heterogeneity due to the within year career patterns.

4 Estimation Results

4.1 Correlated Random Effects Probit Models

Table 3 reports the estimation results of the dynamic bivariate probit model with correlated random effects as described in Subsection 3.1. In specification 1 the distribution of the residual unobserved heterogeneity terms is assumed to be bivariate normal. In specification 2, we adopt a bivariate discrete distribution. In both specifications, the correlation of the unobserved heterogeneity distribution is estimated to be small and not significantly different from zero. As a matter of fact, the tests of independent equations cannot reject the null hypothesis, meaning that the firm-sponsored training equation could be treated as a univariate model.

Therefore, Tables 4 and 5 display the estimation results of univariate unobserved heterogeneity probit models for the firm-sponsored training equation. We try different specification to check the robustness of the estimated parameters of primary interest. Specification 3 is the univariate counterpart of specification 1. In specification 4 we include indicators for the number of months spent in employment in the last 12 months to control for heterogeneous career patters during the year. As many job characteristics are potentially endogenous due to possible failure of the strict exogeneity assumption, in specification 5 the model is re-estimated by removing them. The model estimated in specification 6 adopts instead an opposite strategy: we include 14 indicators aimed at providing a better description of the job type, like whether the job is dangerous, physically demanding, requiring mental effort, characterized by irregular hours, *et cetera*. By doing so, we try to capture possible time-varying heterogeneity omitted from the benchmark specification that might be jointly correlated with the probability of having a temporary job and the probability of receiving firm-sponsored training. Finally, in specification 7 we add an indicator variable equal to one if the employee has received training courses sponsored by other means in the last 12 months as a weakly exogenous regressor.

In the upper panel of Tables 3, 4, and 5 we report usual coefficient estimates. In the second panel we report instead estimated predicted probabilities and average partial effects (APE) that are of focal interest in this paper. They are aimed at quantifying the size of the effects under analysis. There are different ways in which the marginal effect of w_{it-1} on the probability of receiving firm-sponsored training can be estimated in a dynamic probit model with correlated random effects. At the sample mean of the exogenous regressor ($\bar{\mathbf{x}}$) and of the lag training status ($\bar{y}_{t-1}$), we define:

- π_1 as the probability of receiving firm-sponsored training in the next 12 months if the employee has currently a permanent job;
- π_2 as the probability of receiving firm-sponsored training in the next 12 months if the employee has currently a temporary job.

Consistent estimators of these probabilities are:

$$\widehat{\pi}_1 = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\sum_{t=1,2}\Phi(y_{it-1}\widehat{\delta}_1 + \mathbf{x}'_{it}\widehat{\beta}_1 + \bar{\mathbf{x}}'_i\widehat{\beta}_{01} + y_{i0}\widehat{\delta}_{01} + w_{i0}\widehat{\theta}_{01}); \quad (9)$$

$$\widehat{\pi}_2 = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\sum_{t=1,2}\Phi(\widehat{\theta}_1 + y_{it-1}\widehat{\delta}_1 + \mathbf{x}'_{it}\widehat{\beta}_1 + \bar{\mathbf{x}}'_i\widehat{\beta}_{01} + y_{i0}\widehat{\delta}_{01} + w_{i0}\widehat{\theta}_{01}). \quad (10)$$

We obtain the APE by taking the difference between $\widehat{\pi}_2$ and $\widehat{\pi}_1$.[12] It measures the effect of having a temporary job rather than a permanent contract on the probability of receiving firm-sponsored training in the next 12 months.

The bivariate model of specification 1 in Table 3 returns an APE of firm-sponsored training for temporary workers, instead of permanent workers, of -0.075, statistically significant at 5%. An employee with a given set of observed and unobserved characteristics is 7.5 percentage points less likely to receive firm-sponsored training in the subsequent 12 months if she currently has a temporary job than if she has a permanent job. It is a sizeable effect, since the probability of receiving firm-sponsored training decreases from 35.2% to 27.6%, i.e. by 21.6%. When we move to the bivariate discrete distribution of the residual unobserved heterogeneity component we get very similar results but we lose in precision. The APE is equal to -0.068 and not significantly different from zero.

The bivariate model is able to reveal the interrelated dynamics of contractual arrangements and firm-sponsored training and therefore we are able to identify the impact of firm-sponsored training of future probabilities of holding a permanent job. The estima-

[12]The standard errors of $\widehat{\pi}_1$, $\widehat{\pi}_2$, and $APE = \widehat{\pi}_2 - \widehat{\pi}_1$ are estimated by bootstrapping the results (individual-cluster bootstrap with replacement).

Table 3: Dynamic Correlated Random Effects Bivariate Probit Models

	Specification 1						Specification 2					
	Firm-sponsored training equation			Temporary job equation			Firm-sponsored training equation			Temporary job equation		
Variable	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.
Firm-sponsored training$_t$	–		–	.177		.353	–		–	-.082		.257
Firm-sponsored training$_{t-1}$	.759	***	.062	-.182		.177	.521	***	.118	-.004		.267
Temporary worker$_{t-1}$	-.282	*	.149	2.597	***	.235	-.281		.259	2.294	***	.368
Female	.005		.066	.136		.135	-.002		.085	.272		.232
Time dummy 2010	-.098	**	.045	.156	*	.092	-.125	**	.057	.062		.237
Age/10	.247	**	.109	-.004		.201	.295	**	.144	.092		.463
Age squared/100	-.062	***	.021	-.016		.042	-.743	***	.269	-.584		1.077
Education - Reference: Primary												
Interm. secondary	.197		.126	.099		.239	.231		.156	.426		.530
Higher secondary	.190		.129	.162		.244	.228		.159	.368		.507
University or more	.222		.151	.057		.300	.260		.180	.125		.622
# of household components	-.121		.314	-.264		.187	-.154		.606	-.482		14.235
# of kids in the household	-.093		.341	.079		.306	-.085		.601	.091		14.265
Head of the household	.307		.310	.683		.679	.333		.417	.850		1.449
Single	.163		.552	.034		.736	.071		.769	.057		14.385
Urban area	-.462		.519	.304		.779	-.578		.571	1.123		1.899
Net income (€)	.313		.277	-.157		.292	.030		.028	-.047		.104
Net income is not reported	1.749		2.082	-.618		2.143	1.556		1.943	-2.728		6.809
Job tenure/10	-.890	**	.394	-3.733	***	.628	-.917	*	.478	-6.482	***	1.522
Job tenure squared/100	.272	**	.128	.721	***	.237	2.695		1.669	13.475	**	5.757
Public employment	-.214		.289	.198		.514	-.311		.580	.428		.873
Part-timer	-.247		.231	-.059		.340	-.239		.309	-.226		.738
Sector – Reference: Agriculture/Mining/Manufacturing												
Retail tr./Transp./Commun.	1.078	**	.486	1.085		.708	1.039		.820	1.587		3.488
Finance	.893		.584	2.484	***	.739	.936		2.675	3.546		26.360
Services	.948		.647	.797		.861	.975		.858	1.048		4.318
Educ./Health/Welfare	1.401	**	.591	-.395		.790	1.485		.969	-1.571		4.360
Other	1.022	***	.379	.422		.739	.991		.772	.742		3.418
Occupation indicators – Reference: High-skilled white collar worker												
Low skilled white collar	.562		.370	.700		.626	.684		.825	1.430		1.889
High skilled blue collar	-.556		.981	-.016		1.455	-.540		1.040	-.330		2.931
Low skilled blue collar	-.700		.625	1.332	*	.740	-.686		.933	2.247		2.597
Initial conditions and unobserved heterogeneity support points												
Firm-sponsored training$_0$	.299	***	.062	-.014		.157	.569	***	.137	-.263		.317
Temporary worker$_0$	.131		.152	-.292		.234	.105		.232	2.529	***	.725
$\widehat{v}_j^1$	-2.648	***	.500	1.183		.929	-2.474	***	.782	.492		3.808
$\widehat{v}_j^2$	–		–				-3.475	***	.818	4.525		3.847
$\widehat{\rho}_{\mathbf{v}}$	-.162		.174				.092		.237			
Predicted probability $\widehat{\pi}_1$	.352	***	.019				.351	***	.017			
Predicted probability $\widehat{\pi}_2$	.276	***	.038				.283	***	.040			
APE: $\widehat{\pi}_2 - \widehat{\pi}_1$	-.075	**	.037				-.068		.042			
# of observations NT (N)	4,204 (2,102)						4,204 (2,102)					
Log-likelihood	-2,604.0						-2,582.9					
# of parameters	118						122					
Pseudo-R^2	.322						.327					
Test of independent eq.	χ^2_1=.828 p-value=.363						χ^2_1=.151 p-value=.698					

Notes: * Significant at 10% level; ** significant at 5% level; *** significant at 1% level. The firm size indicators and the individual time averages of the time-varying covariates are included in the model specification but not reported for the sake of brevity. The standard errors are robust to within-individual correlation and heteroskedasticity. The standard errors of the predicted probabilities, APE, and $\rho_{\mathbf{v}}$ are obtained by bootstrapping the resuls 250 times (individual-cluster bootstrap with replacement).

Table 4: Dynamic Correlated Random Effects Univariate Probit Models of the Firm-Sponsored Training Equation

	Specification 3			Specification 4			Specification 5		
Variable	Coeff.		S.E.	Coeff.		S.E.	Coeff.		S.E.
Firm-sponsored training$_{t-1}$	.759	***	.062	.750	***	.062	.790	***	.060
Temporary worker$_{t-1}$	-.274	*	.148	-.241	*	.147	-.306	**	.146
Number of months out of the workforce - Reference: Never									
$[1, 6]$ months	–		–	-.214		.294	–		–
$(6, 12]$ months	–		–	-.557	*	.300	–		–
Female	.004		.066	.001		.066	.026		.057
Time dummy 2010	-.097	**	.045	-.096	**	.046	-.095	**	.042
Age/10	.250	**	.109	.153		.116	.241	**	.094
Age squared/100	-.063	***	.021	-.045	**	.022	-.056	***	.018
Education - Reference: Primary									
Intermediate secondary	.199		.126	.208	*	.126	.268	**	.121
Higher secondary	.192		.129	.215	*	.129	.430	***	.122
University or more	.224		.152	.246		.151	.485	***	.138
# of household components	-.117		.301	-.038		.330	-.104		.363
# of kids in the household	-.097		.330	-.171		.355	-.109		.387
Head of the household	.300		.308	.313		.305	.319		.302
Single	.167		.542	.295		.558	.233		.574
Urban area	-.471		.522	-.511		.535	-.466		.510
Net income (€)	.315		.278	.305		.288	–		–
Net income is not reported	1.755		2.087	1.687		2.178	–		–
Job tenure/10	-.886	**	.396	-.935	**	.401	–		–
Job tenure squared/100	.272	**	.129	.271	**	.132	–		–
Public employment	-.210		.287	-.245		.299	–		–
Part-timer	-.243		.230	-.262		.229	–		–
Sector – Reference: Agriculture/Mining/Manufacturing									
Retail trade/Transport/Communication	1.083	**	.486	1.099	**	.489	–		–
Finance	.898		.584	.912		.589	–		–
Services	.946		.646	.958		.656	–		–
Education/Health/Welfare	1.415	**	.589	1.484	**	.621	–		–
Other	1.016	***	.378	1.024	***	.386	–		–
Occupation indicators – Reference: High-skilled white collar worker									
Low skilled white collar	.568		.371	.560		.365	–		–
High skilled blue collar	-.535		.981	-.540		.983	–		–
Low skilled blue collar	-.707		.624	-.695		.612	–		–
Firm size indicators – Reference: $(0-10]$ employees									
$(10-20]$ employees	-.155		.238	-.151		.242	–		–
$(20-100]$ employees	-.251		.268	-.251		.273	–		–
more than 100 employees	-.198		.384	-.211		.387	–		–
# of employees unknown	.344		.432	.326		.437	–		–
Constant	-2.682	***	.494	-2.086	***	.528	-1.379	***	.209
Initial conditions									
Firm-sponsored training$_0$	.300	***	.062	.299	***	.062	.383	***	.060
Temporary worker$_0$	.137		.151	.140		.150	.116		.148
Predicted probability $\widehat{\pi}_1$	.352	***	.017	.350	***	.017	.340	***	.015
Predicted probability $\widehat{\pi}_2$	.278	***	.036	.286	***	.035	.244	***	.041
APE: $\widehat{\pi}_2 - \widehat{\pi}_1$	-.073	**	.035	-.064	*	.034	-.096	**	.042
# of observations NT (N)	4,204 (2,102)			4,204 (2,102)			4,204 (2,102)		
Log-likelihood	-2,200.5			-2,193.1			-2,287.5		
# of parameters	58			62			22		
Pseudo-R^2	.184			.187			.152		

Notes: * Significant at 10% level; ** significant at 5% level; *** significant at 1% level. The firm size indicators and the individual time averages of the time-varying covariates are included in the model specification but not reported for the sake of brevity. The standard errors are robust to within-individual correlation and heteroskedasticity. The standard errors of the predicted probabilities and APE are obtained by bootstrapping the resuls 500 times (individual-cluster bootstrap with replacement).

Table 5: Dynamic Correlated Random Effects Univariate Probit Models of the Firm-Sponsored Training Equation

	Specification 6			Specification 7		
Variable	Coeff.		S.E.	Coeff.		S.E.
Firm-sponsored training$_{t-1}$	.752	***	.062	.757	***	.062
Other training$_{t-1}$	–		–	-.034		.127
Temporary worker$_{t-1}$	-.278	*	.149	-.268	*	.148
Female	.030		.066	.002		.066
Time dummy 2010	-.092	**	.046	-.096	**	.045
Age/10	.209	*	.111	.234	**	.111
Age squared/100	-.054	**	.021	-.060	***	.021
Education - Reference: Primary						
Intermediate secondary	.192		.126	.200		.126
Higher secondary	.188		.131	.195		.130
University or more	.238		.153	.227		.152
# of household components	-.137		.311	-.113		.308
# of kids in the household	-.095		.339	-.101		.335
Head of the household	.296		.302	.301		.309
Single	.239		.539	.177		.545
Urban area	-.531		.515	-.469		.523
Net income (€)	.330		.285	.313		.279
Net income is not reported	1.794		2.137	1.735		2.094
Job tenure/10	-.932	**	.399	-.890	**	.396
Job tenure squared/100	.288	**	.132	.273	**	.129
Public employment	-.215		.288	-.211		.288
Part-timer	-.239		.234	-.245		.231
Sector – Reference: Agriculture/Mining/Manufacturing						
Retail trade/Transport/Communication	1.138	**	.495	1.066	**	.487
Finance	.944		.610	.904		.583
Services	.945		.655	.942		.646
Education/Health/Welfare	1.538	**	.615	1.414	**	.592
Other	1.142	***	.385	1.006	***	.378
Occupation indicators – Reference: High-skilled white collar worker						
Low skilled white collar	.631	*	.382	.578		.371
High skilled blue collar	-.424		.927	-.557		.981
Low skilled blue collar	-.638		.635	-.734		.629
Firm size indicators – Reference: $(0-10]$ *employees*						
Constant	-1.831	***	.552	-2.626	***	.498
14 task description indicators		Yes[(a)]			No	
Initial conditions						
Firm-sponsored training$_0$	.289	***	.063	.298	***	.062
Other training$_0$	–		–	.144		.151
Temporary worker$_0$	.107		.153	-.076		.125
Predicted probability $\widehat{\pi}_1$	.354	***	.016	.351	***	.017
Predicted probability $\widehat{\pi}_2$	.282	***	.035	.280	***	.036
APE: $\widehat{\pi}_2 - \widehat{\pi}_1$	-.072	**	.034	-.071	**	.034
# of observations NT (N)		4,204 (2,102)			4,204 (2,102)	
Log-likelihood		-2,164.3			-2,199.9	
# of parameters		86			60	
Pseudo-R^2		.197			.184	

Notes: * Significant at 10% level; ** significant at 5% level; *** significant at 1% level. The firm size indicators and the individual time averages of the time-varying covariates are included in the model specification but not reported for the sake of brevity. The standard errors are robust to within-individual correlation and heteroskedasticity. The standard errors of the predicted probabilities and APE are obtained by bootstrapping the resuls 500 times (individual-cluster bootstrap with replacement).

[(a)] Fourteen job task indicators (and the corresponding individual time averages) are included in the training equation but not reported for the sake of brevity.

tion results of the temporary job equation reveals that receiving firm-sponsored training in the last 12 months does not matter in determining the probability of having a temporary position. There is instead a strong state dependence in temporary jobs: even after controlling for a set of observed characteristics and taking into account time-invariant unobserved heterogeneity, the persistence in temporary positions is strong. This reflects the segmentation of the labour market in well protected workers against dismissals, the permanent workers, and less protected ones, the temporary employees.

As said before, Tables 4 and 5 focus on univariate models as the tests of independent equations cannot reject the null hypothesis quite confidently. The estimated APEs are quite stable across different specifications. The most important difference is when we control for the number of months spent out of the workforce during the reference year (specification 4): the APE is estimated to be smaller in size, significant only at the 10% level, and equal to -0.064. The direction of the change is as expected, under the assumption that temporary workers are less likely to be continuously in employment during the year and, as such, less likely to receive on-the-job training. However, it should also be noted that the difference is negligibile, especially with respect to the size of the standard errors of the estimated APEs.

If we focus on the other regressors, we note that those employees who received firm-sponsored training in the past are more likely to receive it also in the future. Women are as likely as men to receive firm-sponsored training. There is evidence of an inverted U-shaped relationship between age and the probability of receiving firm-sponsored training. Finally, the probability of receiving firm-sponsored training decreases with job tenure.

4.2 Robustness Check: Linear Probability Models

The aim of this subsection is to check whether the parametric restrictions on the correlated random effects of the dynamic discrete response models might be too strict and therefore biased the estimation the average partial effect. Following Hyslop (1999) and Alessie et al. (2004), we estimate dynamic linear probability models and we get rid of the unobserved (time-invariant) heterogeneity by simply first-differencing. By doing so we do need to impose any particular restriction about the distribution of the unobserved heterogeneity and its correlation with the explanatory variables. Moreover, the estimated coefficients of the covariates of linear probability models seem to give good estimates of the partial effects (Wooldridge, 2002, § 15.2).

The dynamic linear model for the probability of receiving firm-sponsored training is

$$y_{it} = y_{it-1}\delta + w_{it-1}\theta + \mathbf{x}'_{it}\beta + c_i + \varepsilon_{it} \qquad (\, i = 1, \cdots, N,\ t = 1, 2), \tag{11}$$

where c_i is the fixed effect, ε_{it} is the serially uncorrelated error term, and $\mathbf{x}_{it}$ are strict exogenous variables that are allowed to be correlated with the individual fixed effects. First-differencing equation (11) eliminates the fixed effect c_i and gives

$$\Delta y_{it} = \Delta y_{it-1}\delta + \Delta w_{it-1}\theta + \Delta \mathbf{x}_{it}'\beta + \Delta\varepsilon_{it} \qquad (\, i = 1, \cdots, N,\ t = 2). \tag{12}$$

As well known in dynamic models, Δy_{it-1} is correlated with $\Delta\varepsilon_{it}$ and therefore endogenous. We exploit the time dimension of the data to find a valid instrument. Under the assumption of dynamic completeness of the model in equation (11), y_{it-2} is uncorrelated with $\Delta\varepsilon_{it}$ and can therefore be exploited as instrument.

Before proceeding with instrumental variables (IV) estimation of model (12), we need to make an assumption on the exogeneity of the temporary work indicator w_{it-1}. We assume that it is strict exogenous, i.e. $E(\varepsilon_{it}|y_{it-1}, \mathbf{w}_i, \mathbf{x}_i, c_i) = 0$ for $t = 1, 2$. It implies that feedback effects from shocks in firm-sponsored training to future temporary employment are not allowed. Strict exogeneity of w_{it-1} seems to be supported by the estimation results of the temporary employment equation in Table 3, where there is evidence of no significant effect of past training on future probability of having a permanent job. In what follows, we will formally test whether the strict exogeneity is valid against the sequential exogeneity assumption of w_{it-1}, i.e. $E(\varepsilon_{it}|y_{it-1}, w_{it-1}, \mathbf{x}_i, c_i) = 0$ for $t = 1, 2$, which allows instead for feedbacks. Under sequential exogeneity of w_{it-1}, we need to instrument Δw_{it-1} as it might be correlated with $\Delta\varepsilon_{it}$. Once again we use the lag of order two of the endogenous variable as valid instrument, since sequential exogeneity implies that $E(w_{it-2}\Delta\varepsilon_{it}) = 0$. A regression-based Hausman test cannot reject the null hypothesis of strict exogeneity of w_{it-1}. The endogeneity tests are reported at the bottom of Table 6.

The columns of Table 6 under Model 1 report the ordinary least squares (OLS) estimation results of equation (11). The effect of having a temporary job on the likelihood of receiving firm-sponsored training in the subsequent 12 months is small (around 1.6 percentage points) and not significantly different from zero. The OLS estimate is however likely to be biased upward if there is positive correlation between the temporary job indicator and the fixed effect, for instance if temporary workers are more motivated to gain human capital and more willing to participate in training courses. As a matter of fact, when we get rid of the fixed effect by first-differencing, the impact of having a temporary job on the probability of receiving training is significantly negative and about 10 percentage points (see the estimation results in the columns under Model 2). The columns under Models 3 and 4 display the IV and efficient generalized method of moments (GMM) estimation results of equation (12), where Δy_{it-1} is instrumented by y_{it-2} in the IV framework and by $(y_{it-2}, \mathbf{x}_{it-2})$ in the overidentified framework. The estimated

Table 6: Linear Probability Models of the Firm-Sponsored Training Equation

	Model 1			Model 2			Model 3			Model 4		
	OLS			First-difference			First-difference IV			First difference Efficient GMM		
Variable	Coeff.		S.E.[a]	Coeff.		S.E.[a]	Coeff.		S.E.[a]	Coeff.		S.E.[a]
Firm-sponsored training$_{t-1}$	.333	***	.022	-.414	***	.020	.170	***	.044	.159	***	.043
Temporary worker$_{t-1}$	-.016		.033	-.099	**	.044	-.132	***	.049	-.136	***	.048
Female	.021		.027	–		–	–		–	–		–
Age/10	.012		.038	–		–	–		–	–		–
Age squared/100	-.005		.007	.061		.040	.067		.047	.064		.043
Education - Reference: Primary												
Intermediate secondary	.036		.041	–		–	–		–	–		–
Higher secondary	.032		.043	–		–	–		–	–		–
University or more	.065		.057	–		–	–		–	–		–
# of household components	.013		.043	-.061		.060	-.039		.087	-.067		.085
# of kids in the household	-.003		.043	.024		.066	-.015		.096	.011		.093
Head of the household	.012		.028	.079		.078	.098		.094	.098		.092
Single	.000		.049	-.114		.135	.040		.164	.041		.161
Urban area	.009		.019	-.233	**	.104	-.165		.141	-.165		.138
Net income (€)	.053	***	.019	.073		.056	.079		.069	.057		.067
Net income is not reported	.342	**	.139	.355		.392	.398		.506	.255		.493
Job tenure/10	.015		.031	-.138		.097	-.206	*	.113	-.190		.110
Job tenure squared/100	-.006		.008	.024		.045	.059		.043	.046		.042
Public employment	.029		.027	-.121		.077	-.062		.083	-.070		.082
Part-timer	.061	**	.026	-.011		.052	-.053		.061	-.049		.060
Sector – Reference: Agriculture/Mining/Manufacturing												
Retail tr./Transport/Commun.	-.039		.033	-.019		.102	.245	**	.125	.226	*	.123
Finance	.184	***	.055	.152		.150	.217		.160	.219		.158
Services	.064	*	.038	.121		.176	.240		.201	.273		.199
Education/Health/Welfare	.151	***	.038	.206		.161	.388	**	.164	.380	**	.162
Other	-.020		.032	.043		.104	.254	**	.108	.248	**	.107
Occupation indicators – Reference: High-skilled white collar worker												
Low skilled white collar	.060	*	.033	.242	**	.108	.160		.106	.137		.105
High skilled blue collar	.075		.051	.051		.216	-.088		.290	-.062		.283
Low skilled blue collar	.036		.041	.111		.147	-.099		.169	-.114		.166
Constant	-.435	**	.168	-.093	***	.024	-.075	***	.028	-.071	***	.025
# of observations N	2,102			2,102			2,102			2,102		
R^2	.215			.191			–			–		
Excluded instruments	–			–			y_{it-2}			$(y_{it-2}, \mathbf{x}_{it-2})$		
F test of excluded instruments[b]	–			–			$F(1, 2075)$=871.96			$F(25, 2051)$=36.41		
Hansen J statistics[b]	–			–			–			$\chi^2(24)$=28.36		
	–			–			–			p-value=.245		
Hausman test for endogeneity	–			–			$\chi^2(1)$=1.74			$\chi^2(1)$=.09		
of Temporary worker$_{t-1}$[b]	–			–			p-value=.188			p-value=.764		

Notes: * Significant at 10% level; ** significant at 5% level; *** significant at 1% level. The firm size indicators are included in the model specification but not reported for the sake of brevity.

[a] The standard errors are robust to heteroskedasticity.

[b] The tests are made robust to heteroskedasticity.

effect of temporary employment on the probability of receiving firm-sponsored training is now highly significant and slightly bigger in size: temporary workers are about 13 percentage points less likely to receive training in the subsequent 12 months than permanent employees.

The diagnostic tests at the bottom of Table 6 delivers three points worth of mentions. First, the F tests for explanatory power of excluded instruments as suggested by Staiger and Stock (1997) show no sign of weakness of the instruments. Second, the Hansen J statistics support the exogeneity of the instruments. Lastly, the regression-based Hausman tests on the temporary work indicator suggest that its strict exogeneity is supported by the data.

Summarizing, fully controlling for unobserved heterogeneity without parametric restrictions on its distribution indicates that temporary workers are significantly less likely to receive firm-sponsored training than permanent workers by about 13 percentage points. This finding gives robustness to the estimation results of dynamic correlated random effects probit models.

5 Conclusions

This article investigated whether temporary employees are as likely as permanent workers to receive firm-sponsored training. On-the job training provides employees with a refreshment and an update of their skills, making them more productive, competent, employable. Moreover, to the extent that employees can learn some general skills by way of firm-sponsored training, trained workers return faster at work in case of job loss as they are more productive and more flexible in adapting to new tasks in different firms and sectors. Understanding whether firms invest less in temporary workers' human capital is therefore policy relevant to understand whether the spread of temporary contracts, especially among the new entrants in the labour market, might put at stake the employability of temporary workers and spur the development of a segmented labour market.

As the economic theory does not provide clearcut predictions about the relation between the job arrangement and firm-sponsored training, we empirically investigate it by way of new Dutch longitudinal data. We found that temporary workers are significantly less likely to receive firm-sponsored training in the subsequent 12 months than comparable permanent workers. The size of the effect ranged between 6.4 and 12.7 percentage points, depending on the model specification and the estimation method.

CONCLUSIONS TO BE CONTINUED.

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