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Employer education, agglomeration and workplace training: poaching vs knowledge spillovers ♠

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Abstract

This paper analyzes the role of the employer in workplace training, a novelty with respect to the literature on this topic. Taking advantage of a unique dataset on Italy, we study how individual employer profile and the agglomeration of employers influence firms' propensity to invest in training. Our findings show that highly educated employers have a greater propensity to invest in workplace training. Moreover, we are able to capture the effect of employers' human capital agglomeration on the training decision. We assert that such agglomeration leads to two different alternative scenarios: 1) a poaching effect may prevail, therefore competition among employers induces less propensity to train workers; 2) a positive knowledge spillover effect may prevail leading to a greater propensity to engage in training. We test these two options discovering that in the Italian case, where small businesses are prominent, the first effect is stronger. Several econometrics issues are considered in our empirical strategy: the skewed and bounded nature of the training decision indicator, the endogeneity issues derived from the agglomeration effect as well as the cross section dependence problems affecting standard errors.

Keywords: *workplace training; poaching; knowledge spillovers; entrepreneurship cluster; employer's education; social capital; proximity*.

JEL codes: J24; O15; O18; R23.

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1. Introduction

The economic literature has long recognized the key role of workplace training to foster technological adoption, skill upgrading of workers and, thus, to achieve productivity growth. The role of workplace training is further reinforced in periods of severe economic downturns, as a means to favour re-organization of internal labour markets and counter the negative effect on employment of the slowing down of the demand for firms' products (Brunello et al. 2007).

Understanding the determinants of workplace training then is a fundamental issue to be addressed for *policy makers* who aim at facing the economic recessions that most European economies are experiencing (Brunello 2011).

A large amount of studies on this field show that training increases with educational attainment of workforce and skill intensity of occupations as well as with firm size and innovation. This evidence however fails to account the role of employers characteristics.

This is quite surprising, given that employers are the key decision makers for firms personnel and training policy (Lazear 2010). Typically, a high educated employer is expected to know modern management practices and ought to put more emphasis on the skill accumulation of its employees (Bloom and Van Reenen 2010). Furthermore high level education employers agglomeration may affect workplace training.

With regards to the factors affecting a firm's training decision, we consider the effect of the educational level of the individual employer on the training in his/her firm. The focus of our analysis, however, is on the effect of human capital of employers on a local level. By exploiting the variability across local areas corresponding to the Italian provinces (NUTS 3), we consider whether further effects derive from local agglomeration of employers with different educational levels. In particular, we focus on the possible knowledge spillovers stemming from the share of college graduate employers in the area, positively influencing the firms' training decision, and contrast this with the negative effect that may derive from concentration of more educated employers if poaching prevails.

The paper exploits a new dataset drawn from a survey conducted in 2010, which has never been exploited until now in this field, collecting a rich set of information on the personal profile of employers and a large number of firm variables, as well as their training strategy. We estimate a Tobit and a Poisson model by means of an IV approach. Findings from both models show that the negative influence of poaching prevails so that in areas where the share of college graduate employers is larger, the incidence of training tends to be lower. To prove robustness of these results we include in the estimated equation a number of variables capturing the possible confounding effects of the aggregate level of human capital inside as well as outside the firm. Other variables controlling for the presence of innovations and the incidence of voluntary quits at the firm level are added. We also consider institutional factors

such as the share of firms that benefited from public grants provided for training and the presence of second-level collective bargaining in the firm. Finally, we introduce a proxy of local social capital.

The paper contributes to the existing literature in two ways. Firstly, it attempts to investigate a possible specific source of agglomeration economy generated by local agglomeration of employers with a high level of schooling. Accordingly to this view, the 'quality' of the employers may affect the amount of training investment realized by the firms which in turn has an impact on the productivity in the area.

Secondly, the richness of the dataset at our disposal enables us to insert a few largely unconsidered variables in the estimated equations. Thus, our results offer new insights on the influence exerted by the key-characteristics of the employer and the firm and by other selected features of the local economy on training investment.

The paper is organized as follows. Section 2 presents theoretical arguments and gives references to previous literature. Section 3 describes the dataset and shows descriptive evidence. Section 4 discusses the empirical strategy adopted to test the hypotheses while section 5 shows the results of econometric estimates. The last section offers some concluding remarks.

2. Hypotheses and previous literature

The overall goal of this paper is to enlarge the set of potential determinants of training choices by the firms. The individual profile of the employer is quite a neglected factor. In particular, his/her educational level has been proved to be a relevant factor underlying the performance of the firms, however, to the best of our knowledge, there are no papers focusing on the link between individual employer's education and training of his/her workforce. Doms et al. (2010) review a number of papers reporting associations between the employer's education and the success of the firm. Also Bugamelli et al. (2012) estimate the effects of a set of characteristics of entrepreneurs and management on various innovative activities. Van der Sluis and van Praag (2008) show a positive and significant effect of education on firm performance regardless of the performance measure used. This is consistent with the human capital theory predicting that education investment leads to benefits for the individual. Such benefits, in the case of entrepreneurs, do not consist only in income but also in a higher firm survival rate and growth.

Even though none of these studies directly tests the association between employer's education and training, the received results suggest that such association may exist. In particular, it seems reasonable to expect that in a firm managed by a more educated entrepreneur a higher amount of resources will be devoted to training. Thus, our first goal is

to provide fresh evidence of this link since our dataset, as opposed to most firm-based surveys, covers information on the individual profile of the employer.

Based on this, we try to take a further step forward in the analysis to test if an effect on training can derive from local agglomeration of more educated employers. Indeed, the literature on agglomeration shows that entrepreneurs tend to locate next to one another and that such entrepreneurial clusters can exert relevant influences through various channels on the performance of firms and workers located in the area (i.e. Duranton and Puga 2003; Rosenthal and Strange 2004; van Praag and Versloot 2007; Henderson 2007; Acs et al. 2009).

Thus, the second goal of this paper is to test whether such clusters do affect the firms' training choices. In particular, we assume that if employers with different schooling have a tendency to concentrate in specific areas, the average educational level of the employers will vary across areas. Then, we are interested to verify if an uncovered relationship exists between the share of high educated employers in an area and the firms' training investments. This analysis can represent a relevant innovation respect to the existing empirical evidence in a field where two different streams of literature meet, that on agglomeration and entrepreneurial clusters, on one hand, and that on firms training investments, on the other hand.

Theoretical predictions on the influences of the educational level of the entrepreneurial cluster on training are not univocal. Indeed, two opposite effects can derive from it, so that it is an empirical matter to establish which one actually prevails. The first effect derives from knowledge spillovers stemming from agglomeration of highly educated employers and positively affecting the training investments. To this regard it can be believed that a firm located in an area where the level of schooling of employers is higher may benefit from more information and knowledge which can make training more convenient. The second effect has a negative sign as it has to do with poaching. As more educated employers have a higher propensity to train, we may expect that in areas with a higher incidence of graduated employers every individual firm can behave more easily as a free-rider, searching for workers trained by other employers. This way, the employer in that area finds it more convenient to take advantage of the training carried out by the other firms without incurring costs. At the same time, the fear that other competing employers can poach skilled workers after training, lowers the expected benefits of training. Moreover, skilled wages can be higher where employers with a higher propensity to employ skilled labour are concentrated. Even this argument implies that incentives to training are lessened, as profits are more compressed where highly educated employers are more densely concentrated.

While poaching is a well known argument in training literature (i.e. Stevens 1996; Acemoglu and Pischke 1998; Leuven 2005; Combes and Duranton 2006), the former effect perhaps deserves some more discussion. We assume that training is a multifaceted complex activity with relevant qualitative dimensions that firms cannot precisely identify before

training has been accomplished. From this point of view, training can be seen as a form of innovation. Accordingly, the selection of successful practices of training requires the accumulation of some experience. Furthermore, this can exacerbate asymmetric information between providers and buyers in the market for training services. Thus, uncertainty and lack of relevant information can hamper training investments. It is worth noticing that, as long as we regard training as a managerial practice, this view fits well with some of the insights provided by Bloom and Van Reenen (2010), who state that the high persistence of different management practices across countries and firms despite their differential profitability, can be explained by imperfect information as firms learn from the experiences of others while experimenting with different practices.

Thus, if an employer is located in an area where other firms train intensively, forming an entrepreneurial cluster with a high density of firms involved in training practices, he/she will have the possibility of gaining information and take advantage from their experiences by imitating and learning from them. As long as the employer has closer social interactions with other employers, sharing information will be more effective. Following Henderson (2007), we consider that both accidental spillover and deliberate exchanges can be relevant in our context.

Then, we assume that also the human capital of the employers in a local area matters and can influence the training of an individual firm. If a firm is located in an area where it can take advantage of information spillovers, training will be more profitable. Based on this argument, the aggregate education of the employers located in an area might positively affect the training decisions of a firm located in the same area. In our hypothesis, more educated employers better appreciate the potential benefits of training and are less reluctant to train. Moreover, the quality of the shared knowledge increases with their level of education since highly educated employers are more conscious about the meanings and the quality of training experimented and can relay this through a more careful description.

This process of interactive learning requires some proximity between the actors involved (Boschma 2005). Firstly, geographical proximity is required as, when tacit knowledge is considered, knowledge spreads through co-location and face-to-face relationships (Acs et al. 2009; Fantino et al. 2012). In our case, geographical proximity is important because the knowledge concerning workplace training has a relevant tacit and localized component concerning local providers, institutional routines, and past experiences that depend on local specific evolutions.

In principle also cognitive as well as social proximity might be relevant in this context. Indeed, as for the former one, if actors share the same knowledge base and expertise, they may learn from each other more effectively (Boschma 2005). Moreover, as for the latter one, economic relationships are embedded in social ties which can reinforce interactive learning (Breschi and Lissoni 2005; Agrawal et al. 2008). However, in this paper we focus on geographical proximity and take into account the possible effect of knowledge spillover by

measuring the aggregate educational level of the employers located in each area by the share of employers with a university degree, under the hypothesis that a larger agglomeration of highly educated employers may beget a larger positive effect on training sponsored by the firms in the area.

As for the role of spillovers in Italian local economies, Guiso and Schivardi (2008) report evidence showing that they actually influence economic outcomes. In particular, their results confirm that knowledge spillovers do positively affect the average local level of total factor productivity. On the other hand, previous papers by Brunello and Gambarotto (2007) and Brunello and De Paola (2008) find that training decreases where employment density is higher, and conclude that possible local spillover positive effects are less strong than the negative effects caused by higher congestion and poaching. In an analysis based on a worker-based dataset, Croce and Ghignoni (2012) find that the local level of schooling tends to increase the probability of training and interpret this result in terms of a strategy directed to acquire absorptive capacity in presence of knowledge spillovers (Cohen and Levinthal 1990).

In order to better clarify our theoretical framework and some intricacies of our empirical analysis we can refer to Fig. 1. The equilibrium level of training τ for a firm is given by the equality of marginal benefits of training (*MB*) and its marginal costs (*MC*). Under the hypothesis of knowledge spillover we assume that $\partial MB/\partial X \geq 0$, where X represents a measure of the local educational level of the employers. As a consequence, the *MB* curve shifts upward if the firm is located in an area where such level is higher, and this increases the equilibrium value of τ. On the other hand, if poaching is more intense where X is higher, there can also be $\partial MB/\partial X \leq 0$, causing a downward shift of the MB curve and a decrease of the equilibrium level of τ. Indeed, if the employer fears that competing firms can poach his/her workers after training, the expected benefits of training lowers. Which effect prevails cannot be predicted *a priori*, so empirical analysis is required to uncover it. The sign of the estimated coefficient of the variable X will reveal if poaching or knowledge spillover exerts the stronger effect.

However, a few possible confounding effects can arise if X also affects *MC*. First, we must take into account the possibility that $\partial MC/\partial X \leq 0$, which implies a downward shift of the *MC* curve. This could be the case if in areas where employers are more educated and, as a consequence, the overall propensity to training is higher, there is a fiercer pressure on local authorities to subsidize firms' training expenditures. In this case, of course, an observed positive relationship between X and training could not be interpreted as a result of knowledge spillovers. In order to control for this confounding effect we include in our equation a measure of the incidence of external subsidy on the total training expenditure at provincial level. Second, to control for the tightness of the skilled labour market, we include a variable measuring the difficulty faced by the firm in filling their vacancies. Indeed, it seems likely that where X is higher, the demand for skilled labour is also higher. Whenever this makes it more difficult to recruit skilled workers in the market, the profitability of training increases,

implying $\partial MB/\partial X \geq 0$. Third, as the level of education of the employers is positively associated to propensity to innovate, we can expect that in the local areas where X is larger, there can be more innovation. As a result, if training complements innovation, the benefits of training will be higher, implying $\partial MB/\partial X \geq 0$. For this reason we include in the equation a control to distinguish innovating from non- innovating firms.

3. Data and descriptive evidences

The empirical analysis is based on the Employer and Employee Survey (RIL) conducted by ISFOL in 2010 on a representative sample of over 25,000 partnership and limited firms operating in the non-agricultural private sector.

The RIL survey collects a rich set of information about personnel organization, industrial relations and other workplace characteristics. In particular, RIL survey allows to detect the educational level and other demographic characteristics of entrepreneurs[1] along with the intensity of training investments and other information about firm personnel policy, industrial relations and productive specialization.

Furthermore, RIL data allows to perform an updated analysis on a key and almost unknown feature of the Italian productive system: the behavior of partnership firms. Actually, to the best of our knowledge, there is no empirical study based on rich information about a representative sample of both limited and partnership Italian firms, sampled without any sectorial, geographical and dimensional constraints[2]. Thus, this work is the first controlling for employer's schooling, voluntary dismissals, and the share of public grants provided for training at local level. We can also identify if the firm has introduced some innovations in the production process and in which firms decentralized negotiations on wages take place.

Given the focus of the paper, the empirical analysis is limited to firms with more than five employees to guarantee a minimum level of organizational structure. Moreover, the sample is

[1] As "entrepreneur" we mean the individual who exercises the direct management of the firm (Isfol_RIL questionnaire, Section I).

[2] The RIL Survey sample is stratified by size, sector, geographic area and legal form of firms. The sample design of the RIL involves the use of variable probability of inclusion in the sample, where the range of inclusion depends on firm size, measured by the total number of employees. This choice has required the construction of a "direct estimator", able to take account of the different probability of inclusion among the firms belonging to a specific stratum. In particular the direct estimator is defined for each sample unit (firm) as the inverse of the probability of inclusion in the sample. The estimates obtained without the use of the direct estimator are therefore biased as large firms are over-represented with respect to their effective incidence in the reference population, having a probability of inclusion in the sample higher than that associated with small firms. Furthermore, the direct estimator has been modified by suitable calibration techniques, obtaining a final estimator calibrated according to a set of constraints. Thus, this estimator is able to reproduce, through the RIL sample, the total of active firms for each stratum and, simultaneously, the total number of employees in the same stratum (size, sector, etc..).

restricted to those firms with no missing data on the key-variables, so that the final sample over which the analysis is performed counts about 7,000 firms.

3.1 Descriptive statistics

Tab. 1 displays the weighted descriptive statistics for the main variables used in the empirical analysis. To begin with, it appears evident a limited diffusion of the employers' human capital: on average, no more than 24% of firms are managed by an employer with a university degree, 50% of them are managed by employers with an upper secondary level of education while 23% has an employer with lower secondary education. Such an evidence may be related to the significant incidence of partnership and family-owned firms in Italy. Actually, the management of these firms is expected to require less formal education and skills than those used in limited and market-owned firms, which are typically associated to complex organizational and business structure (Bandiera et al. 2011; Lazear, 2010).

Similarly, the human capital of the workforce is quite limited in our sample, coherently with what was previously found about the weakness of labour demand for qualified workers in Italy (Naticchioni et al. 2010). In particular, the share of employees with a tertiary degree is only 8% while the share of employees with upper secondary and lower secondary education are 48% and 49%, respectively.

Furthermore, the share of employees who have attended a training course organized by firms is only 19% on average, a result in line with both the low propensity of Italian firms to invest in formal training and the positive complementary between training investment and schooling at the workplace (Colombo and Stanca 2008; Brunello 2001). In addition, the incidence of external subsidies on total training expenditure is less than 4%.

Tab. 1 also reports that the composition of the workforce is significantly biased against females (36%) and that the incidence of voluntary quits is low although quite differentiated by firms. As for other sample characteristics, a decentralized bargaining scheme is adopted by 7% of the firms and over 30% of them have invested in innovation over the period 2007-2010. Moreover, firms are predominantly localized in Northern regions and are small in size: 69% of firms employ less than 15 workers while only 1% of them employ more than 250 workers. As for sectoral activity, we observe that partnership and limited firms in Italy are mainly specialized in manufacturing (27%), in construction (13%) and in retail and the wholesale sector (19%). Conversely, there emerges a limited presence in highly human-capital-intensive service sectors: financial intermediation and insurance (1%), information, communication and other business services (7%) and health, education and private social services (2%).

As far as our key aggregate variables are concerned, Tab. 1 indicates that the incidence of firms managed by an employer with a tertiary degree calculated by province on RIL data is on

average 27.8%, even though the geographical distribution of this variable is extremely differentiated by province, ranging between 11% in Brindisi and 51% in Milan. Finally, the percentage of tertiary graduates of the population aged 15-64, was calculated at province level on 2001 Census data. This variable has an average value of 4% and a very low variation between Italian provinces, underlying a sort of temporal and spatial inertia of schooling attainments in Italy.

Fig. 2a and Fig. 2b integrate the picture shown by Tab. 1, reporting the relationship between our variables of interest. Fig. 2a describes an almost negligible positive correlation between the share of employers with a tertiary degree by province and the share of workers in training by province. Fig. 2b shows similar evidence but it is based on the share of employers with a tertiary degree and the percentage of training firms by province

4. Econometric strategy

The econometric analysis about the relations between the workplace training and employers' education is performed by estimating the following equation:

$$TW_i = \alpha * TDE_i + \beta * D_p + \delta * W_i + \gamma * F_i + \varepsilon_i \quad (1)$$

where the dependent variable TW_i is the share of trained workers in firm i, TDE_i is a dummy variable indicating whether the employer of firm i is tertiary graduated and D_p it is the number of tertiary educated employers in the province p on the population (aged 15-64) in province p, that is our indicator of entrepreneurial human capital agglomeration. The vector W_i contains workforce characteristics in firm i, F_i is a vector containing firms characteristics and ε_i is an idiosyncratic error term[3].

We use Tobit and Poisson regression models to estimate different specifications of equation (1). The dependent variable TW_i is a fractional skewed variable with a high number of observations equal to zero. It is worth to notice that Poisson regression assumes generically $E[Y|X]=\exp(X\beta)$ to get a consistent estimate of β, so it is appropriate for a wide variety of models where the dependent variable is nonnegative (zero or positive), not just where the dependent variable measures counts of events. Moreover, recent literature (Brock and Durlauf 2007) highlights that linear models are not able to identify social interaction parameters. In this case, the use of non-linear estimates (as Tobit and Poisson models) supports model's identification.

[3] Note that we preferred to estimate a model whose independent variable is the percentage of employees trained instead of a dichotomous training model. Indeed the binary choice "do training- do not training" may be dictated by legal requirements, rather than a business decision, and could involve very few employees for a very small number of hours.

In this framework, we assume the event in which no workers received training (TW_i=0) as the revealed employer preference for no training. Then no selection on observables has to be made in order to adjust our data and model such as Heckman or the like are not needed. This is perfectly in line with the line of reasoning provided by Angrist and Pischke (2009).

However, a potential problem with standard Tobit and Poisson estimates of equation (1) is the presence of endogeneity issues.

In particular, if there are unobservable factors influencing both the average incidence of employers with a tertiary level of education in province p and firms' propensity to train, Tobit and Poisson estimates would suffer from an omitted variable bias. This happens when highly educated employers tend to be agglomerated in areas characterized by high quality management practices, technological investments and cooperative industrial relations (that are more favorable to workplace training). In this case, the estimated correlation between D_p and firms' training might reflect the effect of unobserved characteristics rather than the real effect of agglomeration.

To deal with this problem, a large set of variables that capture firms' and workers' observable and unobservable characteristics is included, and different econometric specifications of Eq. 1 are provided.

Moreover we take into account the potential reverse causality deriving from the non-random localization of the employers (employers with certain characteristics may select themselves in particular areas). This is a key element to test for the poaching vs knowledge spillover hypothesis, as motivated in the previous theoretical section.

To address this issue we adopt an instrumental variable approach. The instrument Z_p is the lagged share of individuals with a tertiary degree in province p over the total provincial population (as obtained from Census data in 2001). The rationale behind this choice is that tertiary graduate employers can appear with more probability where other tertiary graduates are located, therefore using Z_p we are able to catch out this sort of "network effect" from the variance of D_p. A similar strategy is advised in Combes et al. (2011) where they aim at identifying spillover effects in agglomeration economies.

Indeed, human capital endowments found in the local markets in 2001 are persistent over time and are associated with the current employers schooling level. In other words, a large share of graduates in 2001 predicts a higher probability of finding a highly educated employer in firms operating in the same area ten years later. Conversely, the province share of individuals with a tertiary level of schooling in 2001 is unlikely to be correlated with the share of trained workers in firm i operating in the same area in the year 2010. This is because the share of trained workers is typically affected by the exogenous process of labour market policy and economic conditions and it is significantly variable over time (Brunello et al. 2007).

It is worth mentioning something on the identification of the coefficients of our key variable. D_p coefficient can identify only that an agglomeration effect is at work and describes

if the poaching effect prevails on the spillover effect (or viceversa). Intuitively, the D_p coefficient jointly identifies the two effects. It is impossible to disentangle the two effects in our micro-econometric setting. Therefore, we can test if one (and which) of the two effects prevails and, in line with Brunello & Gambarotto 2007, Brunello & De Paola 2007, we consider a non significant result as an indication that the two opposite effects have a similar magnitude.

As already mentioned we test if an employer with a tertiary level of education has a greater propensity to invest in workplace training. In doing so, we estimate the effect of employers' individual level of education TDE_i on workplace training. This is important in order to identify D_p coefficient too. In fact, if we believe that agglomerated human capital can affect the propensity to invest in workplace training, we expect that the estimates confirm that individual employer's education also matters. Intuitively, individual human capital is the channel through which the agglomeration effect comes up, therefore it is the engine that let the agglomeration effect work out. Thus, if the coefficient of TDE_i is significant, then D_p coefficient can be significant, while a different result should seem very counterintuitive. To put it differently, we can infer that a significant estimated coefficient for TDE_i is a necessary condition to identify a significant D_p coefficient.

5. Estimation Results

The richness of our dataset allows to control for different employer and firm specific variables which may be seen as confounding factors that can move the exogenous choices of the employer. Most of the related literature in the field dealing with workplace training is unable to perform this kind of controls while usual estimations suffer from omitted variable bias problems.

Tables 2 and 3 respectively show the Tobit and Poisson estimates of different specifications of equation (1). In particular our baseline model only includes employers' characteristics: the variable of employers human capital agglomeration D_p and two dummies that formalize the maximum level of the employer's education: tertiary (TDE_i), upper secondary ($USDE_i$) and lower secondary (omitted category).

From column 1 of Table 2 and 3 it emerges that both TDE_i and $USDE_i$ are positive and strongly significant, meaning that a better educated employer provides workplace training to a larger share of his/her workforce. Also D_p appears to be positive and significant both in the Tobit and in the Poisson regression. Thus, the first evidence emerging from our estimates is that density exerts a positive effect on training, which is consistent with the idea of knowledge spillovers.

To verify further this result, column 2 of Table 2 and 3 shows the Tobit and Poisson estimates of equation (1) when we control for other workforce and firms characteristics too. As for workforce composition, we consider the human capital endowments of workers (the

percentage of workers with a tertiary or an upper secondary education, respectively: *%tert_edu* and *%upsec_edu*), the share of female (*%female*) and the share of voluntary dismissals (*quit rate*)[4]. As for firm characteristics, we take into account a dummy for the adoption of innovation in the production process during the last 3 years (*innov_proc*), a dummy pointing out if a decentralized bargaining occurs at the firm level (*firm_level_barg*), and the share of firms that benefited from public grants provided for training in the province (*share_finpub*). Further we included in the equation the percentage of the population of the province holding a tertiary degree in 2009 (*%tert_edu_prov*) drawn from ISTAT data in order to take into account the effect of local human capital.

This broader specification of equation (1) confirms previous results about the positive effect of the individual level education and the existence of spillovers associated with agglomeration of highly educated employers. Indeed, column 2 of Table 3 and 4 makes it apparent that the positive relation between the human capital of employers and workplace training is not significantly affected by the inclusion of workforce composition, labour turnover, incidence of public subsidies and firms' attitudes towards innovation and industrial relation. In particular, these findings show that in firms with a higher share of workers with a tertiary or a upper secondary educational level, a larger portion of the workforce is involved in training. This result can be the consequence of the well-known "complementarity effect", according to which firms are more likely to train well educated workers (Brunello, 2001; Riphahn and Trübswetter, 2007). Conversely, we do not find any significant effect of the workforce composition by gender. As expected, both Tobit and Poisson estimates indicate that firm-sponsored training investments are depressed by voluntary quits. At the same time, the local availability of public grants supporting training activities are positively associated to the incidence of training in a firm located in the area. Neither estimate finds any significant influence of the share of population in the province with a tertiary degree (*%tert_edu_prov*) on our dependent variable. On the contrary, the share of trained employees is strongly and positively affected by the occurrence of process innovations in the firm which appears to be an outstanding factor in increasing the share of workers in training. This result points out that employers view training as a complement of innovation.

A further relevant factor exerting a positive influence on training relates to industrial relations. The coefficient of *firm_level_barg* is positive and statistically significant meaning that the incidence of training tends to be larger in firms where a firm-level bargaining occurs. This result suggests that in workplaces where the unions and the employer make collective agreements, more attention is devoted to the participation in training of a larger portion of the workforce. Indeed the development of organizational structures that foster trade unions'

[4] We adopt this measure with caution as it only applies to the same year the training measure refers to, which is also a year of macroeconomic downturn due to economic global crisis, so that voluntary separations could be underrepresented.

cooperation inside the firm can favour employer-provided training. In this regard, economic theory has traditionally shown that training provided at firm level is expected to encourage workers and firms to bargain over the expected returns of firm specific skills accumulation (Hashimoto, 1982). Recent empirical evidence for Italy confirms these theoretical predictions showing a positive relationship between firm level bargaining and training investment (Damiani and Ricci, 2012). Our result is coherent with this explanation. In particular, the presence of unions and the adoption of firm level bargaining increase the share of the trained as they play a role in helping employees to protect the quasi-rents generated by job-related training and human capital investments. Indeed, ample divergences may be found in beneficial effects of training since, in some cases, the magnitude of wage gains is only half that on productivity, as shown by Dearden, Reed and Van Reenen (2005). Thus firm wage agreements may lower the divergences between the overall gains of workplace training. In addition, it is worth recalling also that, according to specific regulations, the unions consent may represent a requirement to apply for public subsidies for training.

The results concerning our density variable change markedly if firm size, sector of activity and geographical areas are also considered. As reported by columns 3 of Tables 2 and 3, the D_p does not play a role any longer in predicting workplace training, while the sign and the statistical significance of the employer's education, as well as of the other variables, are not affected. Thus, the spillover hypothesis seems to fail when equation (1) is estimated by including a comprehensive set of variables in order to control for the role of unobserved heterogeneity in firms' training policy. The dummies for different firm sizes are positive and statically significant showing that the percentage of trained workers increases with the total number of firm employees.

As a further control, in our equation we add the percentage of voters in the 2001 referendum on Title V of the Italian Constitution (*ref_2001*) as a proxy for local social capital. Indeed, in principle interactions between entrepreneurs can be influenced by the quality of social relationships prevailing at local level. As social capital should measure "the ability of people to work together for common purposes in groups and organizations" (Fukuyama 1995, p. 10), it may represent a factor fostering the spread of information and cooperation which, in turn, favor knowledge spillovers. Accordingly, the inclusion of such a measure could help us to single out the relative strength of knowledge spillovers and poaching effects but, as a matter of fact, it does not bring about any change in our results.

Tobit regression is presented with (Table 2, cols. 4 and 5) and without (Table 2, cols. 1-3) bootstrapped cluster standard errors and proves the robustness of our results.

However the results shown in Tables 2 and 3 cannot be taken as conclusive as both the magnitude and statistical significance of the Tobit and Poisson estimates may depend crucially on the endogeneity issue mentioned earlier.

5.1 Instrumental variable estimates

In this section we use an instrumental variable approach to identify a causal impact of the "agglomeration effect" D_p. In particular, Newey's minimum chi-squared estimator can be invoked for this particular situation (Newey 1987). This is an efficient two step procedure in which general results on asymptotic efficiency of two-stage and Amemiya GLS (Amemiya 1979, 1981, 1983) estimators are used to obtain a simple, asymptotically efficient estimator of the structural coefficients. In particular this estimator can be calculated by applying GLS to estimates of the reduced form coefficients that are obtained by using reduced form residuals as additional explanatory variables. Using block bootstrap method we are able to compute provincial clustered standard errors for this type of model. This is needed in our case because we have to deal with an agglomeration effect and therefore we should relax the assumption that observations are i.i.d. (Combes et al. 2011). In addition, we implement a second method, which is a Generalized Method of Moments (GMM) estimator of Poisson regression (Mullahy 1997) that allows endogenous variables to be instrumented by excluded instruments

The results of the instrumental variable regression of equation (1) are displayed in Tables 4 and 5. For sake of simplicity, we do not report first stage regressions that show Z (the percentage of population with at least a tertiary degree in 2001, by province) to be always strongly significant and F stats greater than 10 for all the models.

As shown by Tables 4 and 5 the instrumental variable estimates of D_p vary with the inclusion in the equation (1) of an increasing number of control variables. Indeed our estimates show that D_p turns out to be negative in both regressions and even highly significant in the Poisson regression (Table 5, cols. 3 and 4). Then, when we instrument the density variable, we unearth that knowledge spillovers and poaching effects can counteract each other and the latter one tends to prevail.

The relevance of poaching effects is also brought to light by the indicator of voluntary quits we include in the regressions. We interpret this variable as a proxy of the incidence of poaching which, according to theory, is expected to depress training activities sponsored by the employer. As already found in the Tables above, findings reported in Tables 4 and 5 too confirm that voluntary quits have a strongly negative influence on the share of trained workers.

As for the other covariates we do not find major deviations from previous results. In particular, both dummies for the employer's educational level, TDE_i and $USDE_i$, keep their positive and significant effect. As expected, also the strong and positive impact of the firm workforce composition by educational level is confirmed. Indeed, both the percentage of workers holding a university degree (*%tert_edu*) and the percentage of workers with an upper secondary level of education (*%upsec_edu*) contribute to significantly increase the share of trained workforce. Even the sizable role of process innovations and firm-level bargaining, that

have been discussed above, are confirmed. It is worth noticing that all our results confirm that the firm size is a highly influential factor, with a positive and strong effect on training incidence.

Finally, after including fixed effect controls, the effect of local human capital (*%tert_edu_prov*) becomes positive and statistically significant (Table 4, cols. 4 and 5, Table 5, cols. 3 and 4). This variable has been included in order to capture the effects of knowledge spillovers generated by the education level of the population in the area. The literature has repeatedly highlighted the problem of endogeneity and spatial sorting affecting this variable (Croce and Ghignoni 2012) and we use it just as a necessary control. The result is consistent with the prediction that training should be more frequent in provinces where the aggregate educational level is higher. At the same time, the main results are not affected.

Overall, our results show that the negative effect of poaching dominates the possible positive effect of knowledge spillovers. That is, when surrounded by highly educated employers in the same location (province) entrepreneurs are less prone to finance workplace training. Although, from an individual point of view, a more educated employer is likely to offer more training to his employees, when agglomeration of graduate employers is taken into account, poaching effects seem to prevail.

6. Conclusions

Based on a rich dataset covering information on the personal profile of employers and on a number of firm variables, as well as on their training strategies, the paper tries to shed new light on the factors affecting the provision of training at the workplace. The first focus of the analysis concerns the influence of the personal profile of the employer, namely his/her educational level. Secondly, we investigate if a further effect derives from local agglomeration of employers with different educational levels. In this regard, we test if a positive effect, caused by knowledge spillovers, prevails on the negative one, due to poaching.

As for the first focus, our findings show a positive and significant effect of the employer's education. In particular, after controlling for other relevant covariates, we find that an employer holding a university degree tends to train a larger share of the workforce. To test the second hypothesis, we cope with endogeneity issues by adopting an IV strategy and include a number of variables to control for possible confounding effects in the estimated equations. The results show that, *ceteris paribus*, in the areas where a larger share of employers hold a university degree, the segment of workers receiving employer-sponsored training tends to be lower. Thus, we must conclude that the negative effect of poaching dominates the possible positive effect of knowledge spillovers.

As for policy implications, when poaching represents a relevant issue, public subsidies targeted to training firms represent the standard solution to internalize the effects of training.

Moreover, since our results show that the lowest incidence of training mostly concerns small firms, special measures targeted to small businesses and greater effectiveness of the institutions supporting cooperative attitudes (such as training sectoral funds) ought to be recommended.

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Figure 1 - The equilibrium level of training

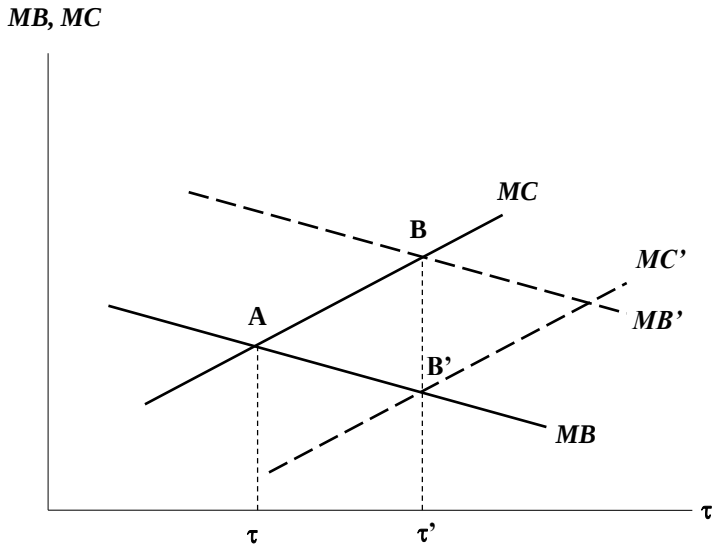

Table 1 - Descriptive statistics (sampling weights)

	Mean	St dev	Min	Max
Employer characteristics				
tertiary education (0/1)	0.24	0.42	0	1
secondary education (0/1)	0.53	0.50	0	1
elementary education (0/1)	0.23	0.42	0	1
Workforce characteristics				
% trained	0.19	0.33	0	1
% tertiary education	0.08	0.16	0	1
% secondary education	0.43	0.30	0	1
% primary education	0.48	0.34	0	1
% female	0.39	0.29	0	1
quit rate	0.10	0.15	0	1
Firms characteristics				
firm level bargaining (0/1)	0.07	0.26	0	1
innovation (0/1)	0.32	0.47	0	1
4< n. employees<15	0.68	0.47	0	1
14< n. employees<50	0.24	0.43	0	1
49< n. employees<250	0.07	0.25	0	1
n. employees>249	0.01	0.11	0	1
North Ovest	0.28	0.45	0	1
North East	0.28	0.45	0	1
Centre	0.22	0.41	0	1
South	0.22	0.42	0	1
Quarrying, Mining etc	0.00	0.04	0	1
manufacturing	0.27	0.44	0	1
gas, water and gas distribution	0.01	0.10	0	1
Construction	0.13	0.34	0	1
retail and wholesale	0.19	0.39	0	1
trasportation	0.04	0.18	0	1
hotels and restaurants	0.17	0.38	0	1
insurance, monetary and financial intermediation	0.01	0.10	0	1
real estate and rental	0.05	0.23	0	1
information, comunication and other business services	0.07	0.25	0	1
health, education and social services	0.02	0.14	0	1
sports, entertainment and other	0.03	0.17	0	1
Local labour markets (province)				
% pop with tertiary education at 2001	0.05	0.01	0.03	0.08
% of public financing	0.10	0.04	0.00	0.21
D_p	1.84	0.96	0.27	11.85
N of Obs		6,766		

Source: ISFOL-RIL Survey 2010

Figure 2.a - Employers with a tertiary degree and workers in training by Province

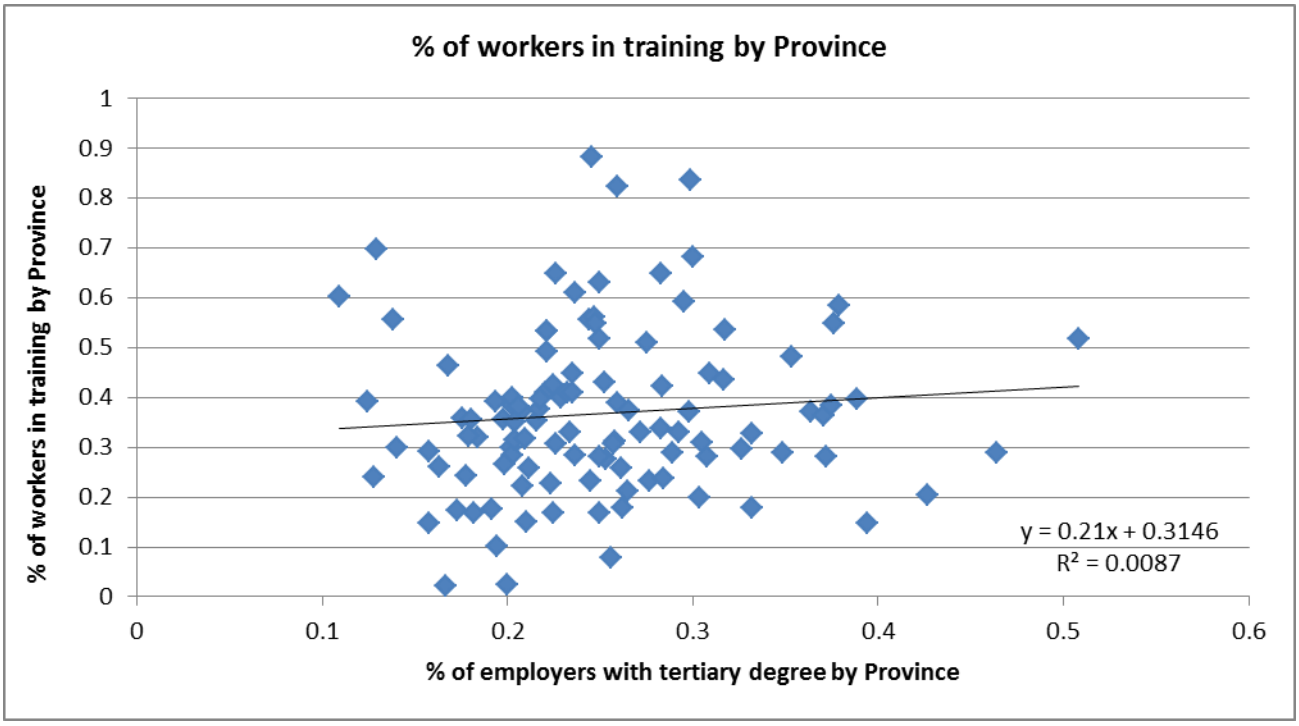

Figure 2.b. - Employers with a tertiary degree and training firms by Province

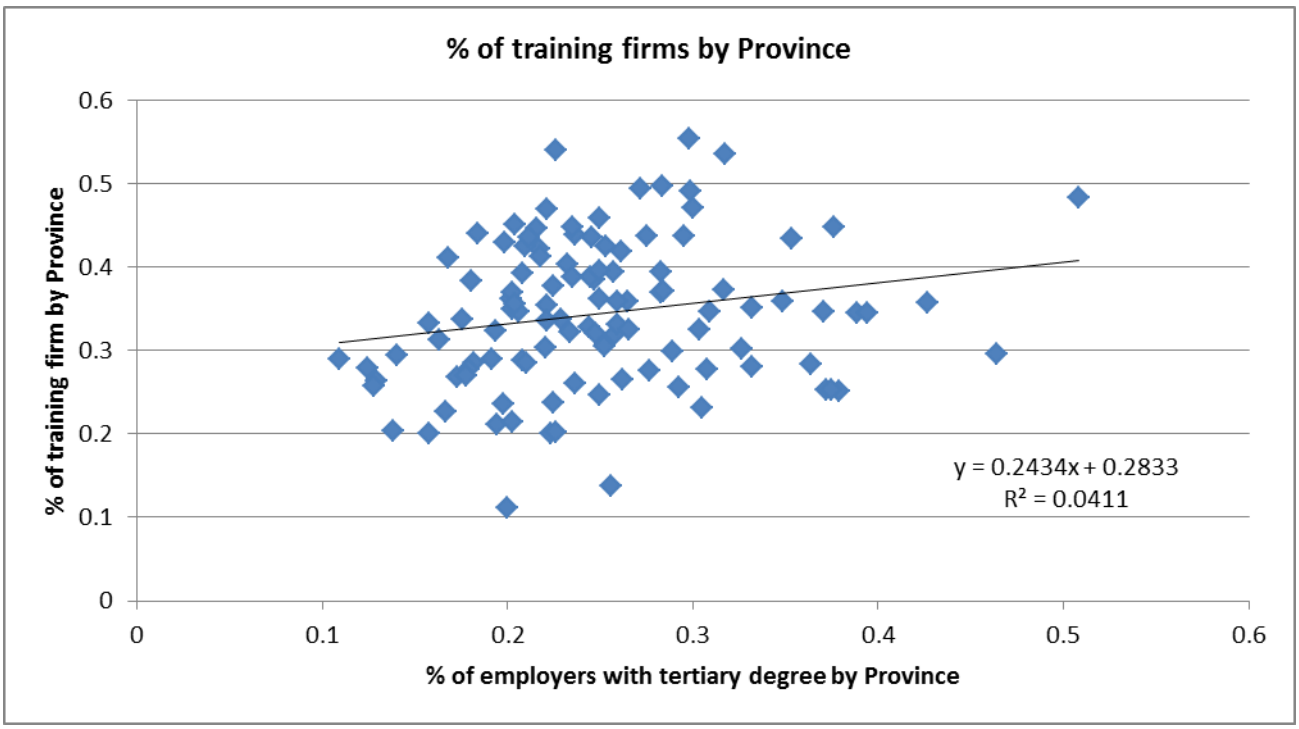

Table 2 – Tobit estimates (without instrumental variable)

	(1)		(2)		(3)		(4)		(5)	
VARIABLES	*TW*	sigma	*TW*	sigma	*TW*	sigma	*TW*	sigma	*TW*	sigma
D_p	0.019***		0.018***		-0.022		-0.022		-0.021	
	(0.006)		(0.007)		(0.019)		(0.026)		(0.015)	
TDE	0.344***		0.115***		0.063**		0.063**		0.064**	
	(0.024)		(0.031)		(0.031)		(0.029)		(0.030)	
USDE	0.134***		0.066**		0.054**		0.054*		0.055**	
	(0.023)		(0.028)		(0.027)		(0.029)		(0.026)	
%tert_edu			0.531***		0.259***		0.259***		0.256***	
			(0.057)		(0.063)		(0.076)		(0.062)	
%upsec_edu			0.112***		0.076**		0.076*		0.078*	
			(0.038)		(0.038)		(0.042)		(0.043)	
%female			-0.050		-0.086*		-0.086		-0.087*	
			(0.036)		(0.045)		(0.066)		(0.050)	
quit rate			-0.209***		-0.157***		-0.157**		-0.202***	
			(0.062)		(0.061)		(0.068)		(0.066)	
firm_level_barg			0.323***		0.218***		0.218***		0.219***	
			(0.025)		(0.027)		(0.028)		(0.026)	
innov_proc			0.198***		0.227***		0.227***		0.225***	
			(0.020)		(0.020)		(0.024)		(0.018)	
%tert_edu_prov			-0.218		-0.042		-0.042		-0.199	
			(0.328)		(0.491)		(0.571)		(0.469)	
share_finpub			1.565***		1.249***		1.249***		1.209***	
			(0.247)		(0.433)		(0.430)		(0.428)	
14< n. employees<50					0.129***		0.129***		0.126***	
					(0.023)		(0.025)		(0.020)	
49< n.employees<250					0.228***		0.228***		0.224***	
					(0.028)		(0.027)		(0.033)	
n.employees>249					0.267***		0.267***		0.263***	
					(0.042)		(0.038)		(0.033)	
ref_2001									0.002	
									(0.003)	
Sector of economic activity					yes		yes		yes	
Macro-area					yes		yes		yes	
Region					yes		yes		yes	
Constant	-0.356***	0.825***	-0.486***	0.690***	-0.408***	0.658***	-0.408***	0.658***	-0.478***	0.657***
	(0.024)	(0.010)	(0.051)	(0.011)	(0.098)	(0.010)	(0.118)	(0.015)	(0.151)	(0.018)
bootstrapped cl. SE	NO		NO		NO		YES		YES	
Observations	13,733	13,733	6,795	6,795	6,795	6,795	6,795	6,795	6,766	6,766

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3 – Poisson estimates (without instrumental variable)

VARIABLES	(1) *TW*	(2) *TW*	(3) *TW*	(4) *TW*
D_p	0.025**	0.026	-0.028	-0.025
	(0.012)	(0.017)	(0.052)	(0.052)
TDE	0.493***	0.181**	0.128	0.126
	(0.053)	(0.083)	(0.085)	(0.085)
USDE	0.201***	0.119	0.106	0.106
	(0.052)	(0.076)	(0.077)	(0.077)
%tert_edu		0.852***	0.395**	0.394**
		(0.128)	(0.156)	(0.157)
%upsec_edu		0.226**	0.134	0.139
		(0.097)	(0.105)	(0.105)
%female		-0.001	-0.112	-0.112
		(0.093)	(0.124)	(0.124)
quit rate		-0.431**	-0.359*	-0.438**
		(0.195)	(0.196)	(0.204)
firm_level_barg		0.450***	0.330***	0.330***
		(0.058)	(0.067)	(0.067)
innov_proc		0.289***	0.345***	0.341***
		(0.049)	(0.051)	(0.051)
%tert_edu_prov		-0.265	-0.032	-0.239
		(0.826)	(1.318)	(1.369)
share_finpub		1.719***	1.588	1.559
		(0.619)	(1.135)	(1.147)
14< n. employees<50			0.141**	0.136**
			(0.062)	(0.062)
49< n.employees<250			0.236***	0.229***
			(0.075)	(0.075)
n.employees>249			0.274***	0.267***
			(0.102)	(0.102)
ref_2001				0.003
				(0.007)
Sector of economic activity			yes	yes
Macro-area			yes	yes
Region			yes	yes
Constant	-1.752***	-2.095***	-2.046***	-2.110***
	(0.051)	(0.129)	(0.269)	(0.360)
Observations	13,733	6,795	6,795	6,766

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 –Tobit estimates with instrumental variable (second stage)

IVTOBIT	(1)	(2)	(3)	(4)	(5)
dependent variable	*TW*	*TW*	TW	TW	TW
D_p	0.059***	-0.035	-0.143*	-0.143*	-0.148**
	(0.021)	(0.028)	(0.076)	(0.077)	(0.072)
TDE	0.339***	0.115***	0.067**	0.067**	0.067**
	(0.024)	(0.031)	(0.031)	(0.030)	(0.030)
USDE	0.133***	0.064**	0.056**	0.056**	0.056**
	(0.023)	(0.028)	(0.027)	(0.026)	(0.026)
%tert_edu		0.519***	0.276***	0.276***	0.277***
		(0.057)	(0.065)	(0.063)	(0.063)
%upsec_edu		0.108***	0.078**	0.078*	0.078*
		(0.038)	(0.039)	(0.043)	(0.043)
%female		-0.046	-0.085*	-0.085*	-0.086*
		(0.036)	(0.045)	(0.050)	(0.050)
quit rate		-0.253***	-0.199***	-0.199***	-0.199***
		(0.066)	(0.064)	(0.066)	(0.066)
firm_level_barg		0.321***	0.216***	0.216***	0.216***
		(0.025)	(0.028)	(0.026)	(0.026)
innov_proc		0.194***	0.224***	0.224***	0.224***
		(0.020)	(0.020)	(0.017)	(0.017)
%tert_edu_prov		0.271	1.664	1.664*	1.660*
		(0.414)	(1.161)	(0.970)	(0.977)
share_finpub		1.582***	1.942***	1.942***	1.981***
		(0.249)	(0.623)	(0.741)	(0.722)
14< n. employees<50			0.123***	0.123***	0.123***
			(0.023)	(0.020)	(0.020)
49< n.employees<250			0.224***	0.224***	0.224***
			(0.029)	(0.033)	(0.033)
n.employees>249			0.272***	0.272***	0.273***
			(0.042)	(0.034)	(0.034)
ref_2001					0.002
					(0.004)
Sector of economic activity			yes	yes	yes
Macro-area			yes	yes	yes
Region			yes	yes	yes
Constant	-0.433***	-0.435***	-0.456***	-0.456***	-0.513***
	(0.047)	(0.057)	(0.105)	(0.121)	(0.156)
bootstrapped cl. SE	NO	NO	NO	YES	YES
Observations	13,667	6,766	6,766	6,766	6,766

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 –Poisson estimates with instrumental variable (second stage)

IVPOISSON	(1)	(2)	(3)	(4)
dependent variable	*TW*	*TW*	*TW*	*TW*
D_p	0.063**	-0.054*	-0.260***	-0.252***
	(0.030)	(0.030)	(0.079)	(0.079)
TDE	0.481***	0.193***	0.128*	0.126*
	(0.040)	(0.064)	(0.069)	(0.069)
USDE	0.196***	0.119**	0.153**	0.151**
	(0.040)	(0.060)	(0.065)	(0.065)
%tert_edu		0.897***	0.636***	0.633***
		(0.100)	(0.130)	(0.130)
%upsec_edu		0.155**	0.161*	0.161*
		(0.079)	(0.095)	(0.094)
%female		-0.069	-0.239**	-0.235**
		(0.071)	(0.111)	(0.111)
quit rate		-0.515***	-0.579***	-0.583***
		(0.144)	(0.150)	(0.149)
firm_level_barg		0.430***	0.347***	0.346***
		(0.038)	(0.051)	(0.051)
innov_proc		0.306***	0.408***	0.412***
		(0.036)	(0.042)	(0.042)
%tert_edu_prov		0.410	2.970**	3.246**
		(0.640)	(1.400)	(1.480)
share_finpub		1.990***	2.415**	2.420**
		(0.473)	(1.033)	(1.022)
14< n. employees<50			0.156***	0.159***
			(0.053)	(0.053)
49< n.employees<250			0.314***	0.318***
			(0.062)	(0.062)
n.employees>249			0.401***	0.398***
			(0.086)	(0.084)
ref_2001				-0.008
				(0.006)
Sector of economic activity			yes	yes
Macro-area			yes	yes
Region			yes	yes
Constant	-1.822***	-1.993***	-1.955***	-1.717***
	(0.068)	(0.115)	(0.237)	(0.327)
Observations	13,667	6,766	6,766	6,766

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1 - Variables definition

Variables	Definition	Sources (*)
TW	Proportion of employees that have attended a training course organized by the firm	(a)
D_p	Index of employers' human capital agglomeration	(a)
TDE	Dummy variable that equals 1 if an employer has a tertiary level of education, 0 otherwise.	(a)
USDE	Dummy variable that equals 1 if an employer has an upper secondary level of education, 0 otherwise	(a)
%tert_edu	Proportion of employees with a tertiary education degree	(a)
%upsec_edu	Proportion of employees with an upper secondary education degree	(a)
%female	Proportion of female employees	(a)
quit rate	Proportion of employees who quit in 2009	(a)
firm_level_barg	Dummy variable that equals 1 if the firm has implemented a decentralized scheme on wage and labour issues, 0 otherwise	(a)
innov_proc	Dummy variable that equals 1 if the firm has invested in process innovation three years before the survey, 0 otherwise	(a)
%tert_edu_prov	Percentage of population (15-64 years old) with a tertiary education degree by province, 2009	(b)
share_finpub	Percentage of firms in the province who obtained a full or partial funding for training activity, on the number of firms in the province	(a)
Firm size	4 dummies variables for: 4< n. employees<15 (ref. cat.), 14< n. employees<50, 49< n. employees<250, n. employees>249	(a)
Ref_2001	Percentage of voters in the 2001 referendum on Title V of the Italian Constitution	(c)
Sector of economic activity	11 dummies variables for: Quarrying (ref. cat.), Mining etc; manufacturing; gas, water and gas distribution; Construction; retail and wholesale; transportation hotels and restaurants; insurance, monetary and financial intermediation ; real estate and rental; information, communication and other business services; health, education and social services; sports, entertainment and other	(a)
Macro-area	4 dummies variables for: North West (ref. cat.), North East, Centre and South regions	(a)
Region	20 dummies variables for Italian regions (NUTS 2)	(a)

(*)Sources: (a) RIL- ISFOL Survey 2010; (b) ISTAT; Census data 2001; (c) Italian Ministry of Interior.

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