Agglomeration and workplace training: knowledge spillovers versus poaching

Giuseppe Croce, Edoardo di Porto, Emanuela Ghignoni and Andrea Ricci

ABSTRACT
Agglomeration and workplace training: knowledge spillovers versus poaching. Regional Studies. The paper aims at ascertaining whether and how a local agglomeration of highly educated employers affects firms’ propensity to invest in training. On a theoretical ground such agglomeration may favour two different scenarios: a knowledge spillover effect may foster larger investments, or a poaching effect may prevail inducing more competition and less training. Econometric estimates find that in the Italian environment, where small businesses are prominent, the second effect is stronger. Endogeneity issues are addressed by adopting an instrumental variables (IV) approach. Moreover, estimates show that an employer’s higher educational level is associated with a greater propensity to sponsor training.

KEYWORDS
workplace training; poaching; knowledge spillovers; entrepreneurs agglomeration; employer’s education; proximity

RÉSUMÉ
Agglomération et formation en milieu de travail: diffusion des connaissances ou débauchage. Regional Studies. Cette communication s’efforce d’établir si, et comment, une agglomération locale d’employeurs possédant une instruction de haut niveau affecte la propension des entreprises à investir dans la formation. Sur un plan théorique, une telle agglomération pourrait favoriser deux scénarios différents: une diffusion des connaissances pourra encourager des investissements plus substantiels, ou bien on pourra assister à la prévalence du débauchage, incitant la concurrence et limitant la formation. Des estimations économétriques révèlent que dans l’environnement de l’Italie, dominé par la petite entreprise, le deuxième effet est prévalent. On affronte les questions d’endogénéité en adoptant une approche de variables instrumentales (VI). En outre, des estimations montrent qu’un niveau d’instruction supérieur de l’employeur va de pair avec une propension majeure au parrainage de la formation.

MOTS-CLÉS
formation en milieu de travail; débauchage; diffusion des connaissances; agglomération des entrepreneur; instruction de l’employeur; proximité

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Workplace training has long been recognized as a factor driving skill upgrading and technological change. In the advanced economies, largely based on knowledge and innovation, it represents leverage to pursue productivity gains and better economic performance (Blundell, Dearden, Meghir, & Sianesi, 1999; Collier, Geen, Young-Bae, & Peirson, 2008). Yet the distribution of workplace training activities still remains widely heterogeneous among countries, regions and different categories of workers and firms. In particular, small firms tend to be poorly engaged in training (Bassanini, Booth, Brunello, & Leuven, 2007; Lynch & Black, 1998). Governments and public institutions set explicit priorities and policy goals in terms of increased levels of training as the lack of adequate flows of investments in workers’ skills raises serious concerns for economic growth and inequality (European Commission, 2013; International Labour Organization (ILO), 2010).

According to the human capital literature, the amount of employer-sponsored training depends on the comparison between its costs and benefits (Becker, 1964). Accordingly, empirical investigations have enlightened a number of workers and firms characteristics stimulating training investments. A large body of works show that training increases with workforce educational attainment, skill intensity, firm size and innovation (Asplund, 2005).

This paper investigates in depth the determinants of workplace training with a special focus on small businesses. To do this, two salient issues, that till now have been seldom considered, are taken into account: first, the impact of the entrepreneur’s education on the firm’s training choice; and, second, the potential heterogeneous effects stemming from local agglomeration on the training decision. Both these issues are crucial for small business behaviours.

Entrepreneur’s education in this study is considered as a possible relevant source of firms’ heterogeneity in their propensity to training. The absence of reliable empirical literature on the role of employers’ individual characteristics is quite surprising, since they are the most important decision-makers on firms’ personnel policies (Bloom & Van Reenen, 2010; Lazear, 2012). Adding employer’s education as a determinant of workplace training is a novelty (e.g., Bassanini et al., 2007) and represents the major contribution of this outlet.

Moreover, this paper takes into account the interaction between firms and their local context. In this regard, an association is established between the firms’ training choices and the possible effects stemming from local agglomeration of economic activities, which are nowadays studied by a flourishing literature (Combes & Gobillon, 2015; Duranton & Puga, 2004; Moretti, 2004). More specifically, the paper tests whether the agglomeration of university graduate employers influences firms’ training...
choices by exploiting the variability in the educational level of entrepreneurs across Italian provinces. This represents the second contribution of this study which, as far as the authors are concerned, is also an innovation with respect to the current literature.

However, the sign of this influence cannot be predicted a priori as it can go in opposite directions. On the one hand, university graduate employers may give rise to knowledge spillovers affecting positively the firms’ training decisions, because proximity and interactions with educated agents play a role in transmitting knowledge and ideas (Audretsch & Feldman, 2004). On the other hand, the concentration of more educated employers competing for skilled workers may induce the fear of poaching that might restrain training investment (Brunello & De Paola, 2004; Stevens, 1996). Understanding if these effects actually matter and which prevails is a question that calls for empirical analysis. This paper provides results for a representative sample of Italian firms, and describes peculiar different effects for small and large businesses.

In order to conduct a robust empirical analysis, a rich firm-level dataset is exploited. This collects information about the personal profile of the employer, training investments, and other firm and workforce characteristics. Data are from a survey conducted by the Italian Institute for the Development of Workers Professional Training (Istituto per lo Sviluppo della Formazione Professionale dei Lavoratori – ISFOL) in 2010 on a representative sample of limited and partnership firms.

The main results of the analysis are as follows. First, the presence of a tertiary-educated employer increases significantly the share of trained workers in his/her own firm. Second, in areas where the relative number of university graduate employers is higher, the firm-level incidence of training tends to be lower, suggesting that the negative effect of poaching prevails. Finally, this study shows that poaching occurs just for small firms, while large firms are substantially unaffected by the influence of employers’ human capital agglomeration.

It is worth noting that these findings are robust to several econometrics issues concerning the bounded nature of the dependent variable (the share of trained workers) and, most importantly, endogeneity. In order to achieve these objectives, the empirical analysis performs linear and non-linear regression models, and provides a credible identification strategy through the use of instrumental variables (IV). As a robustness check, alternative measures of human capital agglomeration have been considered (not only within geographical areas but also within similar industry; see Appendix A in the supplemental data online for clarification).

This analysis brings three major contributions to the literature. As mentioned above, for the first time in this literature the influence of the personal characteristics of the employer are taken into account, with a particular focus on education, as a determinant of training choice. Moreover, the received studies consider just the effect of employment density on training, while this one refines this measure taking into account the effect of the agglomeration of highly educated entrepreneurs. Finally, the empirical results provided show that small businesses are the most affected by both employment density and agglomeration of university graduate employers. As observed by Combes and Gobillon (2015), these results prove that small firms are more inclined to suffer and take advantage from local externalities.

This paper is organized as follows. The second section presents the theoretical arguments referring to the previous literature. The third section describes the dataset and shows descriptive evidences. The fourth section discusses the empirical strategy. The fifth section presents and comments on the results. The sixth section concludes.

RELATED LITERATURE AND HYPOTHESES

An employer’s education and training

In spite of the growing awareness of the relevance of personal characteristics for entrepreneurship and firms’ outcomes (Combes & Gobillon, 2015; Lazear, 2005), the economic literature analyzing the impact of the employer’s personal profile on the firm’s training choices is very limited.

In this regard, it is worth noticing that an employer’s education is considered a crucial factor underlying firm performance (Bechard & Toulouse, 1998; Vesper & Gartner, 1997).

Doms, Lewis, and Robb (2010) and Unger, Rauch, Frese, and Rosenbusch (2011) show that an employer’s education is associated with a firm’s success. Colombo and Grilli (2005) find that an entrepreneur’s education has a major influence on high-tech firm growth. Other contributions show that an entrepreneur’s human capital attributes affect firm survival (Brüderl, Preisendörfer, & Ziegler, 1992; Gimeno, Foltz, Cooper, & Woo, 1997), whereas Van der Sluis and Van Praag (2008) find a positive effect of education on firm performance. Bugamelli, Cannari, Lotti, and Magri (2012) estimate the effects of a set of entrepreneurs’ and management characteristics on various innovative activities. Kolympiris, Kalaitzandonakes, and Miller (2015) find that education and other personal attributes affect the interactions between the entrepreneur and the local context.

Moreover, highly educated employers are able to implement more effective management practices and put higher value on workforce skills accumulation (Bloom & Van Reenen, 2010; Zwick, 2004).

Summing up, this evidence implies that identifying the determinants of training is impossible if the employer’s education is not taken into account. Moreover, it provides the ground for a first hypothesis:

Hypothesis 1: A tertiary-educated employer trains a larger share of workforce than a less educated employer.

Agglomeration of tertiary-educated employers and training

After testing the effect of the employer’s education on training, it is investigated whether there is a further effect
of employers’ human capital on training stemming from its local concentration. The literature reviewed points out that entrepreneurial clusters can exert relevant influences on firms’ and workers’ performance located in the area (Acs, Braunerhjelm, Audretsch, & Carlsson, 2009; Brouwer, Budil-Nadvornikova, & Kleinknecht, 1999; Folsa, Cooper, & Saik, 2006; Henderson, 2007; Rosenthal & Strange, 2004; Van Praag & Versloot, 2007). Moreover, employment density has been considered as a factor particularly influencing training activities. However, theoretical predictions on the sign of this effect are not univocal (Brunello & De Paola, 2008). On the one hand, agglomeration might generate a spillover effect with a potentially positive impact on training; on the other hand, as Combes and Duranton (2006) suggest, it might favour a poaching effect, which discourages investment in training by employers.

A spillover effect consists of a knowledge externality stemming from the agglomeration of economic activities (Duranton & Puga, 2004; Henderson, 2007). Training is a multifaceted activity characterized by qualitative features, which firms cannot fully assess before training has been accomplished. This fact is particularly relevant for small businesses, which pay a relatively high cost for uncertainty. Indeed, the resulting impact of training on skills and firm profitability is highly uncertain ex ante. Thus, training can be seen as a form of innovation. Accordingly, the selection of successful training practices can only proceed through a process of trial and error which requires the accumulation of experience.

In this context, highly educated employers may play a relevant role since, as argued above, they consider training investments to be a valuable managerial option and are more inclined towards training. As a consequence, they are able to elaborate a ‘knowledge’ about training, its possible positive implications for a firm’s performance as well as practical solutions to implement it. This knowledge may circulate in the local economy through direct contacts (informal chats or deliberate exchanges) between employers (Henderson, 2007) or through the local networks of service providers and business consultants (Acs & Varga, 2005). A large body of studies shows that such interactions shape knowledge and entrepreneurial behaviour (Carlino & Kerr, 2015) and are especially significant for small businesses, as these firms are more likely to lack management qualification (Erickson & Jacoby, 2003; Muller & Zenker, 2001; Robertson, Swan, & Newell, 1996).

Therefore, in areas where a large share of firms train intensively, each employer has a good chance to gain information from neighbours’ training experience. This process of interactive learning necessarily occurs in the local context. It requires some spatial proximity as knowledge about workplace training contains a relevant tacit component concerning local providers, institutional routines and other local specific factors (Boschma, 2005; Johannisson, 1998; Lechner & Dowling, 2003; Witt, 2004).

Following this reasoning, it can be presumed that each firm located in an area where the education level of the employers is higher, and the share of training firms is larger, will benefit from more information and knowledge, which will make training activities more profitable. Then, the agglomeration of highly educated employers is expected to affect training decisions positively.

Yet such agglomeration may have a negative effect due to the risk of poaching. Previous studies document that more qualified and skilled workers show a larger job-to-job mobility (Greenhalgh & Mavrotas, 1996; Trivellato, Paggiaro, Leombruni, & Rosati, 2005) and that trained people are more likely to leave their employer after training (Brunello & De Paola, 2004) due to better outside options.

This well-known behaviour related to workplace training (Acemoglu & Pischke, 1999; Leuven, 2005; Stevens, 1996) has been studied recently also in relation to the agglomeration of entrepreneurial activities (Combes & Duranton, 2006). If better-educated employers exhibit a higher propensity to train, then ceteris paribus, in areas where they are more numerous, every firm can more easily engage in free-riding and hire workers trained by other employers. So employers take advantage of the training provided by other firms. At the same time, the fear that competing employers might poach skilled workers reduces the expected benefits of training and depresses training investments (Moen & Rosen, 2004).

Accordingly, the second hypothesis is:

**Hypothesis 2:** The agglomeration of tertiary-educated employers in an area affects the share of workers trained by each firm located in that area. To this regard, two opposite effects may be distinguished:

**Hypothesis 2a:** If the knowledge spillover effect prevails, the share of trainees is expected to increase with the agglomeration of graduate employers; while

**Hypothesis 2b:** The opposite holds if the poaching effect prevails.

**Small versus large firms**

Finally, this analysis focuses on the distinction between small and large firms. As already noted, small businesses train their employees less intensively. This fact calls for a specific investigation into which factors depress small businesses’ training investments. Previous evidence about the negative correlation between the firm’s size (as measured by the number of employees) and workplace training may be motivated by financial constraints, lack of internal resources, organizational rigidities and less advanced technology (Bassanini et al., 2007).

Moreover, these firms are especially exposed to the influence of the local context as they depend heavily on inputs and knowledge available from the outside (Combes & Gobillon, 2015).

A strand of literature points out that smaller firms are at greater risk from poaching than larger firms since the former ones usually pay lower wages and offer worse job conditions (Asplund, 2005; Brown, Hamilton, & Medoff, 1990; Contini & Revelli, 1992; Lynch, 2004; Patton, 2004; Storey & Westhead, 1997). Workforce turnover is usually higher for small firms, confirming that they are
weaker when facing poaching and competition (Greenhalgh & Mavrotas, 1996). By contrast, larger firms face a lower risk of losing their skilled workers since they are more attractive and their bargaining power in the local labour market is higher (Organisation for Economic Co-operation and Development (OECD), 1996). Moreover, large firms may be seen as those that over the years have been shown to be more able to extract enough benefits from agglomeration to counteract the costs of competition. The Marshallian idea that agglomeration benefits are ‘in the air’ is currently being criticized in the regional economic debate. Fitjar and Rodriguez-Pose (2016) demonstrate that interactions are important to obtain agglomeration benefits, but this does not come from ‘pure chance’ but rather from the precise research of the opportunities deriving from agglomeration. Large firms are more skilled to perform this research.

Thus, the empirical specification is estimated separately for small and large firms in order to test the following hypothesis:

Hypothesis 3: Small and large firms are affected differently by the agglomeration of tertiary-educated employers: the smaller ones are expected to be relatively more influenced. However, as under Hypothesis 2, two opposite cases must be distinguished:

Hypothesis 3a: The share of trainees is expected to increase with the agglomeration of graduate employers if the knowledge spillover effect prevails; while

Hypothesis 3b: The share of trainees is expected to decrease if the poaching effect prevails.


Previous empirical evidence finds a significant effect of agglomeration and knowledge spillovers in Italian local economies. De Blasio and Di Addario (2005), Di Addario and Patacchini (2008), Mion and Naticchioni (2009), and Andini, De Blasio, Duranton, and Strange (2013) find that agglomeration affects wages. Guiso and Schivardi (2011) show that knowledge spillovers increase the local level of total factor productivity. Croce and Ghignoni (2012) find that a higher level of education among the local population increases the probability of training.

However, Brunello and De Paola (2008), using Italian data, provide evidence that training decreases where employment density is higher, and conclude that positive spillovers are outweighed by the negative effects of higher congestion (i.e., poaching). Similar results are found by Brunello and Gâmbaretto (2007) when using UK data, and by Muehlemann and Wolter (2011) in a study of apprenticeship training in Switzerland. Finally, Andini et al. (2013) also confirm that poaching prevails as in their results training is negatively related to density.

DATA AND DESCRIPTIVE EVIDENCE

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

collects a unique set of information on the personal profile of the employer, training investments, and other firm and workforce characteristics. In particular, it asks about the educational level of the employer and the incidence of training (the share of trained workers in the firm). It also provides information on productive specialization and industrial relations.

In addition, RIL data allow updated empirical analysis on the behaviour of partnership firms, a key and almost neglected feature of the Italian productive system. As far as is known, there are no empirical studies based on such a rich source of information concerning a representative sample of both partnership and limited Italian firms.

This analysis is restricted to firms with more than four employees in order to guarantee a minimum level of organizational structure. Firms involved in a merger, spin-off or acquisition event during the period 2007–09 are excluded in order to minimize the probability that recent changes in ownership and corporate governance were affecting the characteristics of the employer and, thus, training investment decisions. After deleting observations with missing data, a final sample of around 10,000 firms is obtained.

Descriptive statistics

Weighted descriptive statistics for the variables used in the empirical analysis are presented in Table A1 in Appendix A in the supplemental data online. On average, the share of employees who have attended a training course provided by the firm (\(TW\)) is 18%, in line with both the low propensity of Italian firms to invest in formal training (OECD, 1999, 2003), and the complementarity in the workplace between training investment and schooling (Brunello, 2004; Colombo & Stanca, 2014). As for employers’ characteristics, on average 22% of firms are managed by an employer with tertiary education (\(TDE\), with around 55% managed by employers with upper secondary education (\(USDE\)). Clearly, the sample shows a lower incidence for firms with employers aged under 40 years (\(You\), with 61% managed by employers aged between 40 and 59 years and 27% older than 59 years. Italian employers’ demographic profile may be associated with the predominance of small and family firms whose management typically requires less formal education than large and market-owned companies (Bandiera, Guiso, Prat, & Sadun, 2011; Lazear, 2012).

In relation to workforce composition, Table A1 indicates that the share of employees with tertiary education (\(\%\text{tert\_edu}\)) is 8%, while the shares of employees with upper secondary (\(\%\text{upsec\_edu}\)) or lower secondary education (\(\%\text{lowsec\_edu}\)) are 44% and 48%, respectively. Workforce low education attainment reflects the weaker demand for qualified workers in Italy highlighted in previous studies (Naticchioni, Ricci, & Rustichelli, 2010).

A wide set of firm characteristics such as investment in innovations, the incidence of firm-level bargaining and exposure to international trade are available in the dataset. In particular, the adoption of a decentralized bargaining scheme including a productivity clause (\(\text{Prod\_clause}\)) affects 8% of the sampled firms, while about 29% invested in process innovations over the period 2007–10 (\(\text{Innov}\)).

REGIONAL STUDIES
Participation in international trade is measured by the share of exporting firms (Export), which is equal to 22%, and by the percentage of those belonging to multinational groups (Foreign), equal to 2%.

As described by RIL, the majority of Italian firms are located in the Northern regions, and are mostly small: on average, 78% employ fewer than 15 workers and less than 1% have more than 249 employees. As for the distribution of firms by industry, 28% of them are in the manufacturing sector, 14% in construction, 22% in retail and wholesale, and 11% in hotels and restaurants. The share of firms in services that rely on higher education and good skills is low (financial intermediation and insurance 1%, information, communication and other business services 8%, and health, education and private social service 2%).

In relation to the local labour market, the indicators of employers’ human capital agglomeration $D_{TDEp}$ and $D_{TDEp}$ are defined, respectively, as the number of tertiary-educated employers in the province $p$, and in the province $p$ and branch of economic activity $s$, on the total population aged between 15 and 64 years (/10,000) in the province $p$. Employment density ($DENp$) corresponds to the number of employees per square kilometre (/100). Note that on average there are 1.83 tertiary graduate employers per 10,000 inhabitants in each province, and 198 employees per square kilometre. Table 1 reports high standard deviations in the geographical distribution of both $D_{TDEp}$ and $DENp$, which are widely different across provinces (see Table A2 in Appendix A in the supplemental data online for further details).

Finally, Figure A1 indicates the large geographical variability of the number of employers with a tertiary degree, and describes a positive but almost negligible correlation of this variable and the local share of trained workers.

**Econometric strategy**

This paper estimates a relationship between training incidence and employers’ human capital agglomeration by regressing the following equation:

$$TW_i = \alpha \cdot DENp + \beta \cdot D_{TDEp} + \chi \cdot DEp + \delta \cdot Ei + \phi \cdot W_i + \gamma \cdot Fi + \epsilon_i$$

(1)

where the dependent variable $TW_i$ measures training incidence defined as the share of trained workers in total employment in firm $i$; $D_{TDEp}$ is the key explanatory variable, the share of tertiary-educated employers in province $p$; and $DENp$ is employment density. The vector $DEp$ includes a set of variables measuring the incidence of various entrepreneurial, corporate governance characteristics and labour market conditions at provincial level, as well as other potential local confounding factors. Among the firm-level control variables, the vector $Ei$ indicates the socio-demographic profile of the employer in the firm $i$; $W_i$ represents the workforce composition; and $Fi$ describes the productive characteristics (see Table A2 in Appendix A in the supplemental data online for details). Finally, $\epsilon_i$ is an idiosyncratic error term.

According to the theoretical hypotheses, the estimated coefficient of the variable $D_{TDEp}$ indicates whether an agglomeration effect is at work, and if so, whether a knowledge spillover or poaching effect prevails. Of course, the coefficient might identify only the net effect of these two opposite effects. Therefore, in line with previous papers, a non-significant coefficient should be considered as indicating that the two effects balance out (e.g., Brunello & De Paola, 2008; Brunello & Gambaretto, 2007).

As argued above in the second section, this study is particularly interested in investigating the influence of the local economic environment on firms’ training decisions. To this end, the paper draws on the urban economics literature highlighting that the agglomeration of workers and businesses may have an influence on the economic outcomes in the area. However, the proposed analysis refines this hypothesis and contributes to this literature by considering the specific effect of the agglomeration of university graduate employers.

Thus, by estimating equation (1), the study tests whether and how the share of tertiary-educated employers by province affects the incidence of training in each single firm in the same area. Since small firms are expected to be more exposed to the influence of the local environment, separate regressions for small and larger firms are run in order to detect differences in the results according to firm size.

Different specifications of equation (1) using both linear ordinary least squares (OLS) model and IV are estimated. However, given the nature of the dependent variable, it is advisable to specify the regression via non-linear models too. There is no compulsory prescription for the functional form to be used in this case. Tobit models seems appropriate since the dependent variable $TW_i$ is a fractional skewed variable with a high number of observations equal to zero, thus the event in which no worker received training ($TW_i = 0$) is assumed to be the employer’s revealed preference for no training. Tobit regressions in this case should be interpreted as Type II Tobit that allows the process of participation/selection and the process of ‘outcome’ to be independent, conditional on covariates (Amemiya, 1985). An example of this case among many is Jappelli, Pica, and Padula (2014), who use Tobit to regress square metres transferred from donors to recipients after an inheritance fiscal reform.

The Tobit model, however, can be debatable since it implies that observations beyond the threshold are feasible. One possible solution is to employ an ordered probit model, building thresholds in order to fit consistently the distribution of the dependent variable. For this purpose, the fractional dependent variable ($TW_i$) is divided into four classes: the first containing all the zeros and the other grouping according to tertiles. Subsequent econometric analysis focuses specifically on the effect of agglomeration of highly educated employers. This requires solving unobserved heterogeneity issues and the potential endogeneity of this covariate and of employment density ($DENp$). These are potential problems related to standard OLS, Tobit and ordered probit estimates of equation (1).
### Table 1. Employment density and agglomeration of tertiary graduate employers by province: ordinary least squares (OLS), Tobit and ordered probit estimates with instrumental variables (IV) (second stage).

| Variables | IV-2SLS (a) Coefficient | IV-Tobit (b) dy/dx Coefficient | IV-ordered probit (c) Coefficient | IV-2SLS (d) Coefficient | IV-Tobit (e) dy/dx Coefficient | IV-ordered probit (f) Coefficient |
|-----------|--------------------------|---------------------------------|---------------------------------|--------------------------|---------------------------------|---------------------------------|
|           |                         |                                 |                                 |                          |                                 |                                 |
| $D_{TDE}$ | -0.006***               | -0.002***                       | -0.029***                       | -0.053**                 | -0.016**                        | -0.174**                        |
|           | (0.002)                 | (0.001)                         | (0.008)                         | (0.025)                  | (0.008)                         | (0.078)                         |
| $DEN$     | 0.080                   | 0.012                           | 0.087                           | -0.029                   | -0.020                          | -0.262                          |
|           | (0.106)                 | (0.034)                         | (0.378)                         | (0.003)                  | (0.001)                         | (0.006)                         |
| $D_{old}$ | 0.373**                 | 0.128**                         | 1.415**                         | 0.032                    | 0.024                           | 0.299                           |
|           | (0.192)                 | (0.064)                         | (0.671)                         | (0.266)                  | (0.086)                         | (0.849)                         |
| $D_{priv}$| -0.316*                 | -0.116*                         | -1.385**                        | -0.253                   | -0.097                          | -1.178*                         |
|           | (0.191)                 | (0.060)                         | (0.629)                         | (0.213)                  | (0.066)                         | (0.607)                         |
| $D_{prod}$| -0.122                  | -0.028                          | -0.354                          | -0.125                   | -0.038                          | -0.472                          |
|           | (0.203)                 | (0.066)                         | (0.748)                         | (0.244)                  | (0.076)                         | (0.800)                         |
| $TDE$     | 0.027**                 | 0.011***                        | 0.110***                        | 0.026**                  | 0.011***                        | 0.110***                        |
|           | (0.011)                 | (0.004)                         | (0.040)                         | (0.011)                  | (0.004)                         | (0.040)                         |
| $USDE$    | 0.017**                 | 0.007***                        | 0.075**                         | 0.016**                  | 0.007***                        | 0.074**                         |
|           | (0.007)                 | (0.003)                         | (0.031)                         | (0.007)                  | (0.003)                         | (0.031)                         |
| $Old$     | 0.028**                 | 0.009**                         | 0.105**                         | 0.029**                  | 0.009**                         | 0.106**                         |
|           | (0.011)                 | (0.004)                         | (0.044)                         | (0.012)                  | (0.004)                         | (0.044)                         |
| $Mat$     | 0.015                   | 0.004                           | 0.048                           | 0.016                    | 0.004                           | 0.050                           |
|           | (0.010)                 | (0.004)                         | (0.042)                         | (0.010)                  | (0.004)                         | (0.042)                         |
| $Priv$    | -0.027*                 | -0.005                          | -0.062                          | -0.023                   | -0.005                          | -0.061                          |
|           | (0.015)                 | (0.005)                         | (0.050)                         | (0.015)                  | (0.005)                         | (0.050)                         |
| $Fam$     | 0.002                   | -0.001                          | -0.042                          | 0.004                    | -0.001                          | -0.040                          |
|           | (0.011)                 | (0.003)                         | (0.038)                         | (0.011)                  | (0.003)                         | (0.038)                         |
| $Prod\_clause$ | 0.068***               | 0.020***                        | 0.240***                        | 0.068**                  | 0.020**                         | 0.239**                         |
|           | (0.013)                 | (0.003)                         | (0.040)                         | (0.013)                  | (0.003)                         | (0.040)                         |
| $Innov$   | 0.067***                | 0.038***                        | 0.251***                        | 0.067**                  | 0.038**                         | 0.251**                         |
|           | (0.004)                 | (0.003)                         | (0.015)                         | (0.004)                  | (0.003)                         | (0.015)                         |
Table 1. Continued.

| Variables          | IV-2SLS (a) Coefficient | IV-Tobit (b) dy/dx | IV-ordered probit (c) Coefficient | IV-2SLS (d) Coefficient | IV-Tobit (e) dy/dx | IV-ordered probit (f) Coefficient |
|--------------------|-------------------------|--------------------|-----------------------------------|-------------------------|--------------------|-----------------------------------|
| Export             | -0.026***               | -0.004             | -0.077**                         | -0.026***               | -0.004             | -0.073***                         |
|                    | (0.008)                 | (0.003)            | (0.033)                           | (0.007)                 | (0.003)            | (0.033)                           |
| Foreign            | 0.077***                | 0.018***           | 0.182***                         | 0.077***                | 0.019***           | 0.191***                         |
|                    | (0.018)                 | (0.005)            | (0.057)                           | (0.018)                 | (0.005)            | (0.058)                           |
| %tert_edu_prov     | 0.079                   | 0.024              | 0.237                             | 0.599*                  | 0.182*             | 1.937**                          |
|                    | (0.184)                 | (0.058)            | (0.631)                           | (0.313)                 | (0.103)            | (0.934)                           |
| Share_finpub       | 0.602***                | 0.234***           | 2.481***                         | 0.710***                | 0.269***           | 2.864***                         |
|                    | (0.163)                 | (0.054)            | (0.610)                           | (0.204)                 | (0.062)            | (0.644)                           |
| 15<n. employees<50 | 0.029***                | 0.014***           | 0.184***                         | 0.027***                | 0.014***           | 0.183***                         |
|                    | (0.008)                 | (0.002)            | (0.026)                           | (0.008)                 | (0.002)            | (0.026)                           |
| 49<n. employees<250| 0.061***                | 0.029***           | 0.353***                         | 0.052***                | 0.028***           | 0.350***                         |
|                    | (0.014)                 | (0.004)            | (0.042)                           | (0.013)                 | (0.004)            | (0.042)                           |
| n. employees>249   | 0.098***                | 0.035***           | 0.489***                         | 0.080***                | 0.036***           | 0.498***                         |
|                    | (0.022)                 | (0.005)            | (0.060)                           | (0.021)                 | (0.005)            | (0.059)                           |
| Workforce composition | Yes                    | Yes                | Yes                               | Yes                    | Yes                | Yes                              |
| Region             | Yes                     | Yes                | Yes                               | Yes                    | Yes                | Yes                              |
| Sectors            | Yes                     | Yes                | Yes                               | Yes                    | Yes                | Yes                              |
| Constant           | 0.059                   |                    | 0.352*                           |                       |                    |                                  |
|                    | (0.123)                 |                    | (0.202)                           |                       |                    |                                  |
| res1               |                         |                    |                                  | -0.137*                |                    |                                  |
|                    |                         |                    |                                  | (0.082)                |                    |                                  |
| res2               | 0.027                   |                    | 0.038                             |                       |                    |                                  |
|                    | (0.044)                 |                    | (0.040)                           |                       |                    |                                  |
| R²                 | 0.136                   | 0.133              |                                  |                       |                    |                                  |
| Observations       | 10,164                  | 10,164             | 10,164                            | 10,164                 | 10,164             | 10,164                           |

Note: Omitted variables: employers with a lower secondary education, employers with fewer than 40 years, share of employees with a lower secondary education, number of employees less than 15, and a firm’s age. Workforce composition includes the educational level of the employees, the share of women, the incidence of hirings, and separations. Robust (bootstrapped) standard errors are shown in parentheses; standard errors are clustered at the province level; ***p < 0.01, **p < 0.05, *p < 0.1.
More specifically, if there are unobservable factors influencing the local agglomeration of human capital and the firms’ propensity to train, the estimates will suffer from omitted variables bias. This can occur if, for example, tertiary-educated employers tend to be concentrated in areas characterized by managerial practices, social norms and cooperative industrial relations that tend to favour workplace training. In these cases, the standard estimates of $D_{TDEp}$ might reflect the role played by these unobserved factors rather than the ‘true’ effect deriving from the spatial agglomeration of educated employers. In addition, the presence of unobserved heterogeneity that, affecting both employment density and training activities, might lead to biased estimates of the variable $DENp$, it cannot be excluded.

Including a large set of firm-level and local explanatory variables in equation (1) allows one to control for a number of the aforementioned unobserved factors and also to minimize the potential omitted variables bias. In addition, an IV approach is developed to deal with the endogeneity deriving from the non-random localization of graduate employers and employment density.\textsuperscript{11}

In particular, the lagged number of employees per square kilometre by province in 1991 is used as an additional instrument ($Z^1_p$) for employment density ($DENp$). This choice relies on the consideration that employment patterns show significant inertia over time and across geographical areas. Then the lagged local value of employment density in 1991 can be expected to be positively correlated with the value of employment density found in the same province in the year 2010. On the other hand, the instrument $Z^2_p$ is unlikely to be correlated with firms’ training activities 20 years later.

Analogously, the lagged share of individuals with a tertiary degree in province $p$ over the total provincial population (based on 1991 Census data) is used as an instrument ($Z^3_p$) for the agglomeration of employers’ human capital ($D_{TDEp}$). To rationalize this choice it can be argued that tertiary graduate employers are more likely to occur in locations where other tertiary graduates reside, as Berry and Glaeser (2005) show. Furthermore, the average education level of the population tends to be persistent over time and across different geographical areas. Then the lagged local share of graduate individuals in 1991 is expected to predict the share of tertiary-educated employers operating in the same province in 2010 (see also Combes, Duranton, & Gobillon, 2011). Conversely, the local share of the graduate population in 1991 is too far back in time to be correlated with the share of trained workers by $i$th firm in 2010 since training investments are typically affected by firms’ current economic conditions, and by the exogenous changes in training and labour market policies (Bassanini et al., 2007).\textsuperscript{12} Having chosen the additional instruments $Z^1_p$ and $Z^2_p$ for the explanatory variables $DENp$ and $D_{TDEp}$, equation (1) can be estimated by both IV-two stage least squares (2SLS) and IV-Tobit regressions.\textsuperscript{13}

Instrumenting an ordered probit model is less straightforward. A practical solution proposed by Wooldridge (2015) consists in employing a control function method in order to estimate non-linear models with endogenous covariates. This method is especially appropriate when there can be difficulties in optimizing likelihood functions. A similar tool in the case of spatial probit is used by Di Porto, Parenti, Paty, and Abidi (2016). Following Woolridge (2015), the estimation procedure involves different stages. In a first linear regression stage the endogenous variable is regressed on the instruments. In the present case, having two endogenous variables and two instruments, the first stage involves two linear regressions, one for each endogenous variable (both regressions use the two instruments mentioned above). Residuals are predicted from these linear models and in the last stage a traditional ordered probit model is regressed on endogenous covariates, exogenous covariates and predicted residuals.\textsuperscript{14}

Results obtained by applying the different methodologies report similar results. This ensures that the analysis is not biased by the subjective choice of the econometric specification.

**MAIN ESTIMATION RESULTS**

**Whole sample**

OLS, Tobit and ordered probit estimates for two different specifications of equation (1) are reported in Table A3 in Appendix A in the supplemental data online.\textsuperscript{15} First, consider the regression results obtained if the agglomeration of tertiary-educated employers is excluded from the set of explanatory variables. In this case, all estimates in columns (a) to (c) in Table A3 show that employment density ($DENp$) is negatively related to training incidence. In line with the previous literature, this result can be interpreted as preliminary evidence of the prevalence of the poaching effect over the spillover effect (Andini et al., 2013; Brunello & De Paola, 2008; Brunello & Gambarotto, 2007; Muchlemann & Wolter, 2011).\textsuperscript{16}

In addition, the same columns (a) to (c) reveal that the event of an employer with a tertiary education ($TDEi$) predicts a higher incidence of training compared with employers with upper secondary ($USDEi$) and lower secondary education (omitted category). It is crucial to verify that workplace training increases with the educational profile of the employer, as this is a prerequisite for the agglomeration effect to emerge. That is, the positive estimates found for the variable $TDEi$ support the hypothesis that the spatial agglomeration of highly educated employers might generate further effects on training investments.

This issue is investigated by estimating a second specification of equation (1) which includes $D_{TDEp}$ as an additional explanatory variable. In such a case, the OLS, Tobit and ordered probit estimates in columns (d) to (f) of Table A3 show that the agglomeration of tertiary-educated employers exerts an (additional) negative influence on training incidence, and may represent a distinct source of poaching for the firms located in the area with respect to the effect deriving from employment density.

In relation to the other control variables, Table A3 shows that a number of firm characteristics appear to...
drive training activities. Among these, there is a significant role of second-level bargaining (Prod_clause), innovation and exposure to international competition, as well as of firm size. These results are discussed more in detail below.  

It is worth noting that the standard estimates associated with the key variables (DEN_r and D_TDE_p) are confirmed when alternative regression models are taken into account; thus, they represent a first reliable step toward a better understanding of the relation between firm-sponsored training and the externalities deriving from the agglomeration of the employers’ human capital.

At the same time, empirical evidence reported in Table A3 cannot be considered conclusive since both the linear and non-linear estimates might be biased by the endogeneity issue, as mentioned above.

To deal with this problem the (second-stage) IV-2SLS, IV-Tobit and IV-ordered probit estimates of equation (1) are reported in Table 1. First, note that the effect of the employer’s education is still positive and statistically significant. These estimates confirm hypothesis 1, formalized above, which predicts that a tertiary-educated employer trains a larger share of workforce than a less educated employer. As for the first specification, linear (column (a) in Table 1) and non-linear (columns (b) and (c)) IV estimates confirm a negative and significant effect associated with the employment density. According to the results displayed in columns (a) and (b), it may be computed that an increase of 1 SD (standard deviation) in the variable DEN_r reduces the firm’s training incidence by 1.41% and 0.47%, respectively, when IV-2SLS and IV-Tobit estimates are considered. Ordered probit estimates (column c) are in line with those obtained by other models, and show a negative coefficient for employment density.

Turning to the second specification of equation (1), the IV-2SLS, IV-Tobit and IV-ordered probit results reported in columns (d) to (f) in Table 1 confirm that the effect exerted by the agglomeration of tertiary-educated employers is negative, statistically significant and greater in magnitude than that found for employment density. In particular, an increase of 1 SD in the variable D_TDE_p reduces the share of trained workers in the range between 4.93% (IV-2SLS) and 1.49% (IV-Tobit), whereas a change of 1 SD in DEN_r leads to a decrease in the share of trained workers between 1.175% (IV-2SLS) and 0.47% (IV-Tobit). Once again, IV-ordered probit estimates are perfectly in line with the other results, confirming that they are not driven by functional form choice.

There is a coherent picture emerging from IV regressions in Table 1 and the estimates in Table A3 in Appendix A in the supplemental data online. Indeed, the results support hypothesis 2b expressed above, predicting that the agglomeration of graduate employers generates a poaching effect which counteracts and dominates the possible knowledge spillover effect, so that the share of trainees decreases with the agglomeration of graduate employers. In other words, when located in areas with a large share of highly educated employers, firms are less likely to finance workplace training as they find it easier to recruit skilled workers who received training from other employers, and at the same time fear that skilled workers will be more likely to be poached by rival firms. Although, from an individual point of view, a better educated employer is likely to invest more in training, when the agglomeration of graduate employers is taken into account, the poaching effect prevails.

IV estimates provide evidence that both firm level bargaining (Prod_clause) and innovative strategies (Innov) enhance training investment (Table 1). That is, the adoption of firm-level bargaining may be an efficient mechanism to help firms and employees to protect the quasi-rents generated by job-related training (Damiani & Ricci, 2014a). Likewise, the implementation of new technologies in productive processes fosters training investments since they generally require an updating of workers’ skills (Croce, Di Porto, Ghignoni, & Ricci, 2015).

Another interesting finding is related to the competitive pressure from international trade. All the regressions in Table 1 show a positive and statistically significant relationship between foreign-owned firms (Foreign) and the share of trained workers. Indeed, a number of studies show that multinational firms are likely to adopt efficient managerial practices that use training investments in order to adapt human resources to organizational changes demanded by international competition (Bloom & Van Reenen, 2010). On the other hand, exporters of goods and services (Export) seem less prone to train their employees than non-exporters. To rationalize this result, it is noteworthy that a large portion of Italian exporting firms are small sized and specialized in low-tech, semi-artisanal activities. These features tend to favour human capital accumulation in the workplace mainly through informal learning-by-doing than through formal training courses.

Other potential sources of local human capital externalities are considered in this analysis; the effect of the local human capital (%tert edu prov.) appears to be positive and statistically significant in columns (d) to (f) of Table 1. This variable is included to capture the possible effects of knowledge spillovers generated by the education level of the population in the area; that is, training should be more common in provinces where the aggregate education level is higher. Furthermore, the empirical strategy controls the effect of the local availability of publicly provided training grants (Share_finpub) since this represents a potential local confounding factor affecting training incidence. As expected, the estimates show that the share of firms receiving public support for training activities is positively associated with training incidence.

Finally, the estimates reported in Table 1 indicate a positive relationship between the share of trained workers and firm size dummies. This confirms that data are in line with previous studies showing that workers in small enterprises face a lower probability of receiving employer-sponsored training (OECD, 2003).  

The role of firms’ size
In order to understand the results discussed so far, the remaining part of this study investigates whether there is
any relevant role of the firms’ size in shaping the relation between the agglomeration of graduate employers and training investments. As explained above, it may be argued that small firms are more heavily affected by local agglomeration, so a careful consideration of the differential behaviour of small and large firms is required to shed more light on this topic (see hypothesis 3).

In particular, to verify whether hypothesis 3a or 3b prevails, equation (1) is re-estimated by distinguishing the subsamples of small firms (with fewer than 50 employees) and that of larger firms.21

Accordingly, Table A4 in Appendix A in the supplemental data online displays the results obtained by linear and non-linear regression models disaggregated by firm size. Comparing the estimates in columns (a) to (c) and those in (d) to (f) makes it evident that employment density and agglomeration of university graduate employers retain a negative and statistically significant impact on training incidence only in the subsample of firms with fewer than 50 employees.

Firms’ size effect is further confirmed by using an IV approach, as shown by Table 2 which reports the (second-stage) IV-2SLS, IV-Tobit and IV-ordered probit estimates for each subsample considered. More specifically, columns (a) and (b) of Table 2 indicate that in firms with fewer than 50 employees an increase of 1 SD in the variable $D_{TDE}$ reduces the share of trained workers in the range between 6.97% (IV-2SLS) and 1.95% (IV-Tobit), whereas a change of 1 SD in $DEN$ leads to a decrease in the share of trained workers of −1.41% (IV-2SLS) and 0.47% (IV-Tobit). Furthermore, the IV-ordered probit estimates indicate that the IV results for small firms are not driven by the functional choice of the regression model.

Conversely, the IV estimates in columns (d) to (f) point out that the impact of the key variables are virtually zero and lose their statistical significance in the subsample of firms with more than 50 employees (with the exception of a positive estimate of the $D_{TDE}$ variable in the IV-Tobit).

Overall, evidence from Table 2 reinforces the idea, underlying hypothesis 3b, that the negative influence of employment density and agglomeration of university graduate employers found in the whole sample (Table 1) depends mostly on the behaviour of smaller firms. On the other hand, to test hypotheses 3a and 3b, a regression model with interaction terms was developed instead of splitting the sample. More specifically, a full-sample-based linear model is performed by interacting $D_{TDE}$ with a dummy indicator (small) which is equal to 1 if firms employ fewer than 50 workers, and zero otherwise. In this framework, the OLS estimate associated with the interaction term $D_{TDE} \times \text{small}$ is negative (−0.018) and statistically significant at 10%, with a standard error of 0.011. As for the (second-stage) IV-2SLS regressions, the negative estimate of $D_{TDE} \times \text{small}$ is higher in magnitude (−0.069) and statistically significant at 5%, with a standard error of 0.029. In other words, the OLS and IV-2SLS coefficient estimates of the interaction term are perfectly in line with those found for the variable $D_{TDE}$ when the regressions are performed only in the subsample of firms with fewer than 50 employees (see column (a) in Table 2).23

In sum, the contrasting evidence for small and large firms supports the view that these results are consistent with the poaching argument formalized by hypothesis 3b.

As for the other control variables reported in Table A4 in Appendix A in the supplemental data online and in Table 2, it is interesting to observe that the positive impact of the employers’ human capital on training activities holds only for the subsample of small firms, while the opposite it is true for other management characteristics. That is, both standard and IV estimates reveal that the presence of a private/dynastic management (Priv), rather than an externally hired manager, tends to reduce the share of trained workers exclusively in the firms with more than 50 employees. This leads one to argue that in larger firms an external manager is more likely to adopt formal human resource strategies intended to raise labour productivity while ‘dynastic’ managers (i.e., selected through informal ties by family owners) rely more on informal and less structured practices (Damiani & Ricci, 2014b; Damiani, Pompei, & Ricci, 2016).24

CONCLUSIONS

Based on a unique dataset containing information on the personal profile of employers, firms’ characteristics and firm-sponsored training, this paper sheds a new light on the factors affecting the provision of training at the workplace. These results uncover that, even after controlling for the other relevant covariates, training investments by the firm increases with the employer’s education: a university graduate employer trains on average a significantly larger portion of employees than his/her less-educated peers. While the complementarity between workers’ education and training represents a well-known fact, this analysis points out for the first time in this literature the influence of the employer’s education on workplace training.

Most importantly, separate estimates for small and large firms reveal that while the employer’s education does not make any difference for large firms, it has a positive and significant impact on training propensity of smaller ones. This may have important policy implications as it suggests that, apart from financial and organizational constraints, the skills and the managerial culture of the employer affects his/her evaluation of the costs and benefits of different human resource management practices.

Moreover this analysis focuses on the effects deriving from the local agglomeration of highly educated employers. In addition to the effect of employment density, already taken into account by previous studies, a new and insightful form of agglomeration of employers’ human capital is considered. More precisely, the paper tests whether the agglomeration of university graduate employers in a geographical area plays any role in encouraging or, alternatively, discouraging training at the workplace. The first effect may derive from knowledge spillovers that positively affect the propensity to train, while the second may be due to poaching.

Empirical results show that, ceteris paribus, in areas where a larger share of employers holds a university degree,
Table 2. Employment density and agglomeration of tertiary graduate employers by firms’ size: ordinary least squares (OLS), Tobit and ordered probit estimates with instrumental variables (IV) (second stage).

| Variables | IV-2SLS (a) Coefficient | IV-Tobit (b) dy/dx | IV-ordered probit (c) Coefficient | IV-2SLS (d) Coefficient | IV-Tobit (e) dy/dx | IV-ordered probit (f) Coefficient |
|-----------|--------------------------|--------------------|----------------------------------|--------------------------|--------------------|----------------------------------|
| D_TDE     | -0.075**                 | -0.021***          | -0.270***                        | 0.066                    | 0.039***            | 0.371                           |
|           | (0.030)                  | (0.001)            | (0.100)                          | (0.065)                  | (0.008)             | (0.255)                         |
| DEN       | -0.006**                 | -0.002***          | -0.033***                        | -0.004                   | -0.001              | -0.013                          |
|           | (0.003)                  | (0.001)            | (0.008)                          | (0.007)                  | (0.004)             | (0.027)                         |
| D_old     | 0.039                    | -0.011             | -0.122                           | -0.257                   | -0.079              | -0.664                          |
|           | (0.149)                  | (0.041)            | (0.507)                          | (0.398)                  | (0.172)             | (1.255)                         |
| D_fam     | -0.092                   | -0.022             | -0.332                           | 0.256                    | 0.287               | 3.349                           |
|           | (0.293)                  | (0.061)            | (0.940)                          | (0.687)                  | (0.306)             | (2.542)                         |
| D_priv    | -0.204                   | -0.058             | -0.868                           | 0.034                    | -0.079              | -1.311                          |
|           | (0.224)                  | (0.062)            | (0.659)                          | (0.638)                  | (0.345)             | (2.197)                         |
| D_prod    | -0.069                   | 0.013              | 0.103                            | -0.138                   | -0.062              | -0.333                          |
|           | (0.259)                  | (0.080)            | (0.898)                          | (0.711)                  | (0.390)             | (2.440)                         |
| TDE       | 0.027**                  | 0.009***           | 0.108***                         | 0.022                    | 0.021               | 0.143                           |
|           | (0.011)                  | (0.003)            | (0.041)                          | (0.031)                  | (0.015)             | (0.113)                         |
| USDE      | 0.021**                  | 0.007***           | 0.081**                          | 0.002                    | 0.008               | 0.071                           |
|           | (0.008)                  | (0.003)            | (0.033)                          | (0.029)                  | (0.015)             | (0.101)                         |
| Old       | 0.032***                 | 0.010***           | 0.132***                         | 0.023                    | 0.007               | 0.032                           |
|           | (0.012)                  | (0.004)            | (0.045)                          | (0.037)                  | (0.023)             | (0.139)                         |
| Mat       | 0.021*                   | 0.006              | 0.081*                           | -0.007                   | -0.010              | -0.104                          |
|           | (0.011)                  | (0.004)            | (0.044)                          | (0.033)                  | (0.021)             | (0.126)                         |
| Priv      | -0.016                   | -0.003             | -0.038                           | -0.063***                | -0.029              | -0.197**                        |
|           | (0.017)                  | (0.005)            | (0.059)                          | (0.023)                  | (0.011)             | (0.080)                         |
| Fam       | -0.008                   | -0.004             | -0.08                            | 0.008                    | 0.001               | -0.039                          |
|           | (0.013)                  | (0.004)            | (0.049)                          | (0.020)                  | (0.010)             | (0.062)                         |
| Prod_clause | 0.081***                | 0.023***           | 0.308***                         | 0.055***                 | 0.031***            | 0.241***                        |
|           | (0.017)                  | (0.004)            | (0.054)                          | (0.021)                  | (0.010)             | (0.066)                         |
| Innov     | 0.069***                 | 0.021***           | 0.261***                         | 0.056***                 | 0.053***            | 0.216***                        |
|           | (0.005)                  | (0.002)            | (0.017)                          | (0.014)                  | (0.011)             | (0.050)                         |
| Export    | -0.026***                | -0.004             | -0.046                           | -0.058**                 | -0.020              | -0.197**                        |
|           | (0.009)                  | (0.003)            | (0.038)                          | (0.023)                  | (0.014)             | (0.088)                         |
| Foreign   | 0.040                    | 0.007              | 0.102                            | 0.082***                 | 0.038***            | 0.232**                         |
|           | (0.037)                  | (0.009)            | (0.124)                          | (0.031)                  | (0.014)             | (0.111)                         |
| %tert_edu_prov | 0.722**            | 0.206***           | 2.719**                          | 0.030                    | -0.093              | -1.661                          |
|           | (0.320)                  | (0.069)            | (1.062)                          | (0.807)                  | (0.309)             | (2.884)                         |
| Share_finpub | 0.818***             | 0.270***           | 3.358***                         | 0.305                    | 0.184               | 1.312                           |
|           | (0.225)                  | (0.065)            | (0.747)                          | (0.452)                  | (0.224)             | (1.529)                         |

Workforce composition: Yes, Yes, Yes, Yes, Yes, Yes
Region: Yes, Yes, Yes, Yes, Yes, Yes
Sectors: Yes, Yes, Yes, Yes, Yes, Yes

(Continued)
Table 2. Continued.

| Variables               | <50 employees | ≥50 employees |
|-------------------------|---------------|---------------|
|                         | IV-2SLS       | IV-Tobit      | IV-2SLS       | IV-Tobit      | IV-ordered probit |
|                         | (a) coefficient | (b) dy/dx | (c) coefficient | (d) coefficient | (e) dy/dx | (f) coefficient |
| Constant                | 0.422*        |              | –0.310        |              | 0.388        |
|                         | (0.219)       |              | (0.578)       |              | (0.258)      |
| res1                    | –0.223**      |              |              | 0.287***      |              |
|                         | (0.104)       |              |              | (0.104)       |              |
| res2                    | –0.011        |              |              |              |              |
|                         | (0.045)       |              |              |              |              |
| R²                      | 0.113         | 0.143        |              |              |              |
| Observations            | 8707          | 8707         | 8707          | 1457          | 1457         | 1457          |

Note: Omitted variables: employers with a lower secondary education, employers with fewer than 40 years, share of employees with a lower secondary education, number of employees less than 15, and a firm’s age. Workforce composition includes the educational level of the employees, the share of women, the incidence of hirings, and separations. Robust (bootstrapped) standard errors are shown in parentheses; standard errors are clustered at the province level; ***p < 0.01, **p < 0.05, *p < 0.1.

firms tend to train a lower portion of their workforce. Similarly, higher employment density depresses workplace training in the area. This leads to the conclusion that the negative effect of poaching prevails over the possible positive effect of knowledge spillovers.

Even in this case the results show neatly that small businesses are those that suffer the most the negative impact of fiercer local competition, while large firms stay unaffected by it. Small firms are more exposed to the influence of the local environment and this may contribute to an explanation of their reluctance to train.

All the results are confirmed after controlling for endogeneity, which has been addressed by adopting a credible IV strategy and by including a number of covariates correlated with several confounding factors.

Since poaching is a relevant issue, there is room for policies aimed at mitigating its effect and to support firm-provided training. Public subsidies targeted to training firms, or regulations establishing the provision of a minimum amount of training by employers may be appropriate solutions to internalize the benefits of training and to limit free-riding (Stevens, 2001). Measures targeted to small businesses should be especially considered. Moreover, as many small businesses lack appropriate managerial skills, the creation of local networks of small firms, business associations and knowledge-intensive services providers should be supported in order to provide guidance to local entrepreneurs.

Further research might focus on achieving a better understanding of how economic and social interactions among agents operating in the same local environment shape employers’ choices and investments concerning training and human resources management.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at http://dx.doi.org/10.1080/00343404.2016.1230270

NOTES

1. By ‘employer’ is meant the individual who directly manages the firm and makes major decisions about personnel policies (ISFOL RIL questionnaire, Section I).
2. The RIL Survey sample is stratified by size, sector, geographical area and a firm’s legal form. The sample design 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 required the construction of a ‘direct estimator’ to take account of the different probabilities of inclusion among 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 biased since large firms are over-represented with respect to their effective incidence on the population, having a probability of inclusion in the sample higher than that associated with small firms. Also, the direct estimator is modified by suitable calibration techniques to obtain a final estimator calibrated according to a set of constraints (Cochran, 1977).
3. As specified in note 2, the sample weight is defined for each firm as the inverse of the probability of inclusion in the sample, corrected using calibration techniques. Using this weight for the descriptive statistics allows the target population to be reproduced, i.e., the total number of Italian firms active in the non-agricultural sector (Deville & Sardal, 1992).
4. TIW is defined as the ratio of the number of employees who participated in firm-provided training activities in 2009 against the total number of the firm’s employees at 31 December 2009. Although data provide information
on firms’ training investments, it is preferable to use an indicator of training incidence. In the dataset, responses to questions concerning monetary values (e.g., wages, training investments) are subject to substantial problems of misreporting or measurement error, and, therefore, are not reliable.

5. It is preferable to estimate a model where the dependent variable is the percentage of employees trained rather than estimating a dichotomous training model. This is because the binary choice ‘do training–do not training’ might not be very informative since training could be dictated by legal requirements rather than being a business decision, and might involve very few employees in each firm.

6. In particular, equation (1) includes the percentage of the provincial population with a tertiary degree (%tert_mean), and the share of firms that benefited from public grants provided for training in the province (Share_finpub).

7. The same reasoning applies to the coefficient of the variable DENP.

8. Also, Brock and Durlauf (2007) highlight that non-linear models are well suited to identify social interaction parameters, hence the use of Tobit regressions supports the model’s identification.

9. The authors thank the associate editor for this suggestion.

10. The choice of tertiles is due to the need of having a consistent sample size within each class. Other choices can be proposed, but this seems to fit the data better.

11. The empirical strategy employs the two-step procedure suggested by Newey (1987).

12. To control for whether the instruments can solve endogeneity issues related to new firms as well as whether these are included in the regression model.

13. As suggested by Angrist and Pischke (2009), in an IV framework the use of 2SLS estimates identifies the causal effect of an endogenous regressor, and this is true also in the case of a limited dependent variable model.

14. In order to have robust standard errors, it is advisable to bootstrap the procedure instead of performing the regression separately. Note too that residual significance in the second stage verifies the presence of endogeneity (this can be seen as a Hausman test for endogeneity). However, it is important to enlighten that the first-stage regression shows that at least one instrument is always significant to explain the specific endogenous covariate. This is enough to ensure that the instruments are not weak. Finally, in order to save space, the paper reports only coefficient estimates of standard and IV-ordered probit models.

15. Tobit estimates of the average marginal effects are obtained using the block bootstrap method to compute provincial clustered standard errors. This is necessary because the empirical analysis has to deal with an agglomeration effect, and, therefore, should relax the assumption that observations are independent and identically distributed (i.i.d.) (Combes et al., 2011).

16. Investment in training can decline also because density improves the quality of the match and shortens the duration of the search for skilled workers. In denser local labour markets, employers face a wider labour supply and a higher likelihood of finding the required skills (Hesley & Strange, 1990). Consequently, the relative cost of training tends to increase and an inverse relationship between density and training investments might be observed. The matching and the poaching effects are difficult to disentangle empirically since both imply an inverse relationship between density and training. However, as argued in the fifth section, the poaching argument is consistent with the contrasting evidence for small and large firms, which results from the estimates.

17. Estimates also indicate that the composition of the workforce generally does not exert a significant influence on the share of trained workers, except for the presence of women and the occurrence of separations. For brevity, these results are not displayed in the tables. For a deeper discussion on this point, however, see note 20 below.

18. The first-stage regressions (not reported here) show that the instruments $Z_1^p$ (lagged employment density by province) and $Z_2^p$ (lagged percentage of population with a tertiary degree by province) are always strongly significant, and the $F$-stats are greater than 10 for all the models. However, these regressions and the endogeneity tests are available from the authors upon request.

19. The regression models also include the workforce composition by education level in order to control for the presence of the well-known complementarity between workers’ education and training, predicting that firms are more likely to train highly educated workers (Lynch, 1994; Riphahn & Trübswetter, 2007). However, these variables are not statistically significant in both standard and IV estimates, suggesting that the employers’ profile may be more influential than the workforce composition in determining training activities.

20. Table A3 in Appendix A in the supplemental data online and Table 1 do not report the regression estimates disaggregated by sectors of economic activity. These estimates (available from the authors upon request) provide some evidence that firms operating in high-tech industries (i.e., electricity, water and gas distribution) and knowledge-intensive sectors (insurance, financial intermediation and other business services) train more intensively than those specialized in low-tech industries (mining, quarrying, etc.). At the same time, the statistical link between the firm’s productive specialization and training incidence might be mitigated as a result of the inclusion in equation (1) of other explanatory variables (i.e., innovative investment, international competition, etc.), which, at least partially, capture sector-specific technological factors. However, to prove the robustness of these findings, Appendix A in the supplemental data online provides some additional tests to investigate whether the main regression results are confirmed taking into account the sectoral dimension of possible knowledge spillover.

21. Following EUROSTAT’s Continuing Vocational Training Survey (CVTS), the threshold of 50 employees
is adopted as a suitable demarcation between small and large enterprises in the context of workplace training (EUROSTAT, 2012).

22. The negative impact of $D_{TDE'}$ on the share of trained workers is more relevant in the subsample of small firms than in the whole sample.

23. These results are available from the authors upon request.

24. Consider that the vast majority of firms in Italy are family owned (Bianco, Bontempi, Golinelli, & Parigi, 2013). Thus, the incentives to save training costs in large firms may also be favoured if the close connection between a family’s wealth and enterprise assets overlap with the myopic behaviour of dynastic management.

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