Workplace training and entrepreneurs clusters: poaching vs knowledge spillovers [*]

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1. Introduction

This paper considers the determinants of workplace training provided by the entrepreneurs. Among these, we focus firstly on the effect of the educational level of the individual entrepreneur on the training in his/her firm. Secondly, exploiting variability across local areas corresponding to Italian provinces, we consider potential local knowledge spillovers generated by the aggregate educational level of the cluster of entrepreneurs. In particular, we focus on the possible positive influence of the share of college graduate entrepreneurs in the area on the firm's decision to invest in training and contrast this with the negative effect that may derive from concentration of more educated entrepreneurs if poaching prevails.

The paper exploits a new dataset derived from a survey conducted in 2010 and reporting a rich information set on entrepreneurs and firms, and on their training strategy. Our findings show that the negative influence of poaching prevails so that in areas where the share of college graduate entrepreneurs is larger, both the share of training firms and the incidence of trained workers tend to be lower.

The next section motivates the paper, presents theoretical arguments and gives references to previous literature. Section 3 provides a descriptive depiction of our variables. Section 4 presents the empirical strategy adopted to test our hypotheses while the following section shows the results of econometric estimates. The last section concludes.

2. Hypotheses and previous literature

The overall goal of this paper is to enlarge the set of factors considered as potential determinants of training choices by the firms. A quite neglected factor is the individual profile of the entrepreneur. 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 entrepreneur's education and training. Doms et al. (2010) review a number of papers reporting associations between the employer education and the success of an individual firm and also their results confirm a positive effect of it on a few firm outcomes. Van der Sluis and van Praag (2008) show a positive and significant effect of education on entrepreneurship performance regardless of the performance measure used. This is consistent with human capital theory predicting that education investment leads to benefits for the individual. Such benefits, in case of entrepreneurs, do not consist only in income but also in a higher firm survival rate and growth. Also Bugamelli et al. (2012) estimate the effects of a set of characteristics of entrepreneurs and management on various innovative activities.

Even though none of these studies directly tests the association between employer's education and training, we consider that received results are sufficient to hypothesize that such association may exist. According to the findings reported in the literature, it is reasonable to assume that a firm managed by a more educated entrepreneur trains more intensively. Thus, our first goal is to provide some evidence about this link as our data, differently from most firm-based surveys, report information on the individual profile of entrepreneurs.

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 entrepreneurs. Indeed, the literature on agglomerations and clusters shows that entrepreneurs tend to agglomerate and that such entrepreneurial clusters can exert relevant influences on the performance of the firms located in the area (e.g. Duranton and Puga 2003, Henderson 2007).

Thus, our second goal is to test whether such clusters do affect also the firms' training choices. In particular, we assume that if entrepreneurs with different schooling have a tendency to concentrate in specific areas the average educational level of the entrepreneurs will vary across areas. Then, we are interested to verify if an uncovered relationship exists between the share of entrepreneurs holding a university degree in an area and the firms' training investments. We believe that this piece of 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.

As for this, theoretical predictions on the influences of the educational level of the entrepreneurial cluster on training are not univocal. Indeed, we can predict two opposite effects so that it is an empirical matter to establish which one actually prevails. The first effect may derive from knowledge spillovers stemming from agglomeration of highly educated entrepreneurs 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 entrepreneurs is higher can 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 entrepreneurs have a higher propensity to train, we may expect that in areas with a higher incidence of graduated employers each individual firm can behave more easily as a free-rider, searching for workers trained by other employers. By this way, the employer in that area finds convenient to take advantage of the training carried out by the other firms without incurring the costs of it. At the same time, the fear that other competing employers can poach his/her workers after training, lowers the expected benefits of training. We can also consider that even skilled wages can be higher where entrepreneurs with a higher propensity to employ skilled labour are concentrated. This argument leads to conclude that the individual incentives to training are lessened where more educated entrepreneurs are more densely concentrated.

While poaching is a well known argument in the training literature (see for example Stevens 1996, Acemoglu and Pischke 1998, Brunello and De Paola 2004, Leuven 2005, Combes and Duranton 2006), the former effect perhaps deserves some more discussion. Indeed, we try to detect if a discernible effect of knowledge spillovers on training exists, where training is an outcome variable which, to the best of our knowledge, has never been considered so far (even if it can be seen as a natural complement of innovation and R&D, that conversely have been extensively studied).

We assume that training is a multifaceted complex activity involving qualitative dimensions that firms cannot precisely identify before the training has been realized. From this point of view, training can be seen as a sort of innovation. More information on training would require a lot of experience useful to select good practices. As a consequence, the market for training services is not transparent due to asymmetric information between providers and buyers. 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 various management practices across countries and firms despite their differential profitability, can be explained by imperfect information as firms learn from experiences of others in experimenting with different practices.

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

For this reason we assume that the human capital of the entrepreneurs 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 informational spillovers, training will be more profitable. Accordingly to this reasoning, it can be assumed that the aggregate education of the employers located in an area might positively affect the training decisions (whether train or not and how many workers train) of a firm located in that area. In our hypothesis, more educated entrepreneurs better appreciate the potential benefits of training and are less reluctant to train. In addition, the quality of the knowledge shared increases with their level of education as highly educated employers are more conscious about the meanings and the quality of training experimented and can communicate them through a more careful description. Finally, if the individual employer has personal characteristics, like education, similar to these of the other employers in the area, we can credibly assume that they belong to the same social network and this further helps the sharing of information.

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

However, also cognitive proximity and social proximity may be required as actors sharing the same knowledge base and expertise may learn from each other more effectively (Boschma 2005) and, due to the fact that economic relationships are embedded in social ties which can reinforce interactive learning (Breschi and Lissoni 2005, Agrawal et al. 2008). To take into account the possible effect of knowledge spillover we measure the aggregate educational level of the entrepreneurs located in each area by the share of entrepreneurs with a university degree.

In order to better clarify our theoretical framework and some intricacies of our empirical analysis we can refer to the Figure 1. The equilibrium level of training τ for a firm is given by the equality of training marginal benefits (MB) and 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 entrepreneurs. As a consequence MB 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, we have also $\partial MB/\partial X \leq 0$ causing a downward shift of 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, his/her 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. In order to attempt to disentangle these two opposite effects we exploit further information provided by the dataset about the incidence of voluntary quits in total workforce during 2009. As this measure can represent a proxy of poaching, we include it as a tentative to capture this effect. However, we adopt such measure with some cautions as it refers only to the same year that training measures refer to, which is also a year of macroeconomic downturn due to economic global crisis, so that voluntary separations could be underrepresented.

As for previous literature regarding Italian local economies, the role of local externalities as a major determinant of local economic outcomes has been verified for example by Guiso and Schivardi (2008). Their result confirms that knowledge spillovers do positively affect economic outcomes and, in particular, 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 a quite different analysis, based on a worker-based dataset, Croce and Ghignoni (2012) find that knowledge spillovers associated to local human capital tend to increase the probability of training and interpret this result in terms of a strategy directed to acquire absorptive capacity (Cohen and Levinthal 1990).

However, a possible confounding effect can arise if different X levels can also affect MC. It could be argued, for example, that where entrepreneurs are more educated and, as a consequence, the overall propensity to train is higher, there will be a bigger pressure on local authorities to subsidize firms' training expenditures meaning that we must take into account that $\partial MC/\partial X \leq 0$ which implies a downward shift of the MC curve. In this case, of course, the 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.

3. Data and descriptive evidence

The empirical analysis is based on employer and employee survey (RIL) conducted by ISFOL in 2010 on a representative sample of over 20000 Italian firms operating in non agricultural sectors. The RIL survey for 2010 collects information about training investment, management characteristics and other workplace practices prevalent in the sampled firms (see the appendix for a detailed description of the dataset). However before performing the empirical analysis we select only those firms with at least five employees to guarantee a minimum level of organizational structure of the firms under study.

Our sample consists of 24,459 firms distributed on 110 Italian Provinces. Our dependent variables are a dummy variable (*trdum*) assuming value 1 if the firm provides training to at least one of its workers (and zero otherwise), and the share of trained workers by firm (*trshare*). Table 2 shows that the percentage of workers in training in Italy is rather low (21%), whereas the percentage of training firms scarcely reaches 36%. In addition, the incidence of external subsidies on total training expenditure is less than 4%.

The average value of our main variable of interest, the percentage of entrepreneurs with a college degree by province and branch of economic activity, is only 27.8%. Beside this result, the geographical distribution of college graduate entrepreneurs is extremely differentiated by province, ranging between 11% in Brindisi and 51% in Milan.

As to the composition of workforce by firm, it is significantly biased in favour of males (60%) and blue collars (56%, versus 39% of white collars). The number of voluntary quits (*dimissioni*) is quite low (which is a not surprising result, given that 2009 was a crisis year), although quite differentiated by firm.

The percentage of innovating firms is low for both products (34%) and processes (28%) innovations and almost stable by province, as shown by the standard deviation reported in Table 2. As well known, Italian productive system is characterized by small firms concentrated in Northern and Central Italy (see variables *size* and *_area* in Table 2). At the same time, employment density (about 181 workers per square Km on average) is extremely different from province to province (from 10 in Ogliastra to 871 in Milan). Also the cultural, financial and transportation infrastructures characterizing the different Italian provinces present a wide range of variation. The % of tertiary graduates in the population aged 15-64 in 2004 (that we use as an instrument) barely reaches 4%, and is characterized by a very low variation between provinces.

4. Econometric strategy

We develop three different empirical methodologies to describe how the share of college graduates in sector "a" and province "j" affects different indicators of workplace training. Our analysis is based on survey data collected in 2010 and therefore our results have to be read as cross firm comparisons. The first two methods are developed using the variable *trshare* as dependent: this is a continuous variable always greater than zero. This indicator shows to be clearly skewed and the number of observations equal to zero is slightly high. In the third model we use as dependent the dummy variable *trdum* which is 1 when the specific firm provides workplace training.

On the right-hand side of our empirical models we are particularly interested to identify the effect of two covariates. First, *locprovsett* as observed before represents the share of college graduates in sector "a" and province""j". This variable is an endogenous continuous covariate and we would like to identify its contribution in order to test for poaching or alternatively knowledge spillover, as motivated above in the theoretical part. Second, *man_col* is an exogenous dummy that describes whether the employer of the specific firm is a college graduate.

In order to take into account of these peculiarities we decided to develop firstly a tobit model where one of the regressors is endogenously determined, assuming 0 as a lower limit for left censoring. 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. Secondly, always using *trashare* as dependent, we implement a Generalized Method of Moments (GMM) estimator of Poisson regression (Mullahy, 1997) that allows endogenous variables to be instrumented by excluded instruments. It is worth to notice that Poisson regression assumes $E[Y|X]=\exp(X\beta)$ 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. The last model on *trdum* is a classical probit model where one regressor is endogenously determined and continuous. A maximum likelihood estimation is performed in order to derive the estimator.

In all the empirical models proposed we instrument *locprovsett* using *Z* lagged values of the share of college graduates. In particular we take values in 2004 as a predictor of *locprovsett*. The rationale behind this choice is that college graduate employer can appear with more probability where other college graduate are located, therefore using *Z* we are able to catch out this sort of "network effect" from the variance of *locprovsett.* A strategy like this is advised in Combes et al. (2011) when we aim to identify spillover effects in agglomeration economies[1].

We include a number of covariates in the model as explained in the data sections, here in particular we would stress on the role of the variable *dimissioni,* measuring the number of voluntary quits in each firm. We repeat the estimation of the three models including and excluding this covariate in order to test if our results are identifying poaching behavior or other effects.

5. Results and comments

Table 3 and 4 report results for our three empirical models. We do not report first stage regressions that show anyway *Z* to be always strongly significant and F stats greater than 10 for all the 6 models. Results are not sensible to the inclusion of the covariate measuring the incidence of voluntary quits (*dimissioni*). The variable *man_col* is always positive and strongly significant, meaning that a better educated employer tend to train more workers and to provide workplace training with a higher probability. The variable of interest for our test of knowledge spillover VS poaching *locprovsett* is always negative and strongly significant. According to what we have discussed above, this can be seen as a signal that negative poaching effect dominates positive spillovers influence and that when surrounded by educated employers in the same sector and same location (province) entrepreneurs are less prone to finance workplace training. This behavior seems to be orthogonal to any effect that can be driven by the public or other external subsidies that are provided to training firms. The coefficient of *share_finpubb_prov* is in fact always not significant.

6. Conclusions

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[1] Other instruments developed following Card (2010) are right now in progress and the results from these estimations will be presented in a following version.

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Figure 1. The equilibrium level of training

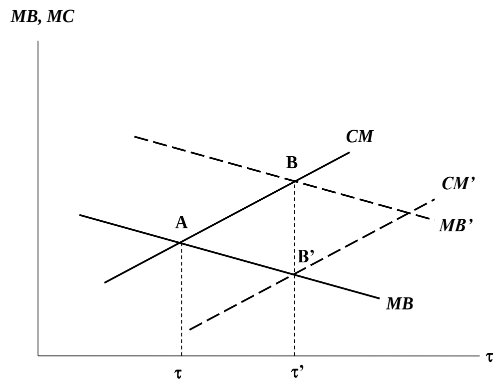

Table 1 – Variables description

Abbreviations	**Variables**
trdum	dummy variable: training firm = 1
trshare	share of workers in training by firm
locprovsett	% of manager with tertiary degree by Province and economic sector
man_col	dummy variable: manager with tertiary degree = 1
feshare	share of female employment by firm
share_finpubb_prov	number of training firm in which training activities was (almost) entirely funded by external contributions on the total number of firms, by Province
impshare	% of white collars by firm
dimissioni	% of voluntary quits on dependent employment by firm
opshare	% of blue collars by firm
mfe	average share of female employment by Province
mimp	average share of white collars by Province
mop	average share of blue collars by Province
mff	% of family firms by Province
mip	% of firms that introduced product and service innovation by Province
mpi	% of firms that introduced process innovation by Province
size	Firm size (if number of employees <15: 1; if number of employees between 1 and 50: 2; if number of employees between 50 and 250: 3; if number of employees greater than 250: 4)
__sett3	sector of economic activity (12), Ateco 2007
__area	geographical macroarea (4)
occ_kmq_2009	Employment density (number of employees by square Km by Province) (hundreds)
cinema_99	Cinemas per 100,000 inhabitants by Province (1999)
sportelli_2009	Bank branches per 100 sq km by Province (2009)
imp_dep_2009	Average value of loans and deposits for 100 bank branches by Province (2009)
aereoportT2_2009	Tonnes of cargo loaded and unloaded by 1,000 square meters of airport runways (2009)
aereoportiKm_2006	Average distance (km) of airports from the city center (2006)
corsi_lau_2008	Second level tertiary degree courses per 100,000 inhabitants aged> 20 years (2008)
master1_2007	first level university Masters per 100,000 inhabitants aged> 20 years (2007)
percuniv2004	% of tertiary graduates in the population aged 15-64 by Province (2004)

Table 2 – Descriptive statistics

stats	trdum	trshare	locprovsett	man_col	feshare	share_finpubb_prov	impshare
N	19830	19830	24459	24235	20345	24459	20345
mean	0.362935	0.214308	0.278132	0.278028	0.406657	0.039249	0.395719
sd	0.480858	0.349604	0.201276	0.448036	0.341084	0.017051	0.357219
min	0	0	0	0	0	0	0
max	1	1	1	1	1	0.103448	1
stats	**dimissioni**	**opshare**	**mfe**	**mimp**	**mop**	**mff**	**mip**
N	11031	20345	24459	24459	24459	24459	24459
mean	0.123692	0.561696	0.405395	0.393254	0.564522	0.865359	0.341619
sd	0.38549	0.375429	0.053956	0.078919	0.093265	0.06747	0.067846
min	0	0	0.248223	0.181972	0.352488	0.674238	0.142857
max	22	1	0.498494	0.544406	0.795585	0.98718	0.509259
stats	**mpi**	**size**	**__sett3**	**__area**	**occ_kmq_2009**	**cinema_99**	**sportelli_2009**
N	24459	24459	24459	24459	24311	22543	22715
mean	0.285972	1.443927	6.419641	2.391635	1.814099	9.593971	19.34869
sd	0.060825	0.782449	3.381287	1.156697	2.323193	3.34274	18.78366
min	0.152778	1	2	1	0.100807	1.72	1.4
max	0.445783	4	13	4	8.707099	16.37	130.87
stats	**imp_dep_2009**	**aereoportT2_2009**	**aereoportiKm_2006**	**corsi_lau_2008**	**master1_2007**	**percuniv2004**	
N	22715	13787	13787	22715	16882	24311	
mean	6079.883	69.57047	9.954486	5.683788	3.049822	0.041093	
sd	2818.225	138.3343	7.692218	5.344129	2.757414	0.01188	
min	2463.74	0	0	0	0.21	0.019473	
max	22697.18	624.15	37	32.66	13.13	0.093101	

Table 3 (with dimissioni)

VARIABLES	(IVTobit) Trshare	(GMMPois) trshare	(Probit) trdum
Locprovsett	-4.531**	-9.389***	-4.879*
	(0.0157)	(0.000914)	(0.0518)
man_col	0.154**	0.292***	0.199**
	(0.0120)	(0.00960)	(0.0142)
Feshare	-0.133**	-0.213	-0.237**
	(0.0223)	(0.181)	(0.0105)
share_finpubb_prov	2.737	10.120	3.043
	(0.317)	(0.164)	(0.457)
Impshare	-0.463***	-0.892***	-0.827***
	(0.00127)	(0.00273)	(9.36e-0)
Dimissioni	-0.253***	-0.535*	-0.353**
	(0.00969)	(0.0778)	(0.0167)
Opshare	-0.661***	-1.316***	-1.130***
	(7.11e-05)	(2.29e-05)	(1.45e-07)
Constant	5.361**	14.287*	7.430*
Observations	7037	7037	7037

p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 (without dimissioni)

VARIABLES	(IVTobit) trshare	(GMMPois) trshare	(Probit) Trdum
locprovsett	-4.410**	-9.114***	-4.806**
	(0.0115)	(0.00793)	(0.0219)
man_col	0.162***	0.352**	0.209***
	(0.00598)	(0.0104)	(0.00260)
feshare	-0.169***	-0.395***	-0.267***
	(0.00160)	(0.00461)	(0.000247)
share_finpubb_prov	2.111	14.570	2.612
	(0.333)	(0.143)	(0.376)
impshare	-0.452***	-0.839***	-0.847***
	(0.000463)	(0.000644)	(2.98e-07)
opshare	-0.633***	-1.071***	-1.134***
	(2.05e-05)	(3.23e-05)	(0)
Constant	5.000*	(0.268)	7.430**
Observations	7037	7037	7037

p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1