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ABSTRACT

Neodualism in the Italian business firms: training, organizational capabilities and productivity distributions

What has been the dynamics of productivity in the Italian business firms in the aftermath of the crisis? And what has been the impact of training efforts upon such dynamics? In this work we address these questions exploring a unique Italian microlevel dataset which links information on the amount and the nature of training and the balance-sheet data.

First, we document what we call a neo-dualist tendency with a leader-laggard dynamics entailing a widening support of the productivity distributions. Second, we analyze the relationship between productivities and training intensities by means of quantile regression analysis, also controlling for additive fixed effects by means of Canay (2011) technique. There is indeed some relationship in the whole sample which however gets weaker when disaggregating by sector and by size. Moreover, hardly any dynamic relationship appears, either between initial training intensities and subsequent productivity changes, nor between changes in both variables. Our results do not imply of course that training is not important, but that its effectiveness must be shaped by other firm-specific characteristics, plausibly associated with idiosyncratic organizational capabilities.

KEYWORDS: productivity, firm-level heterogeneity, training, organizational capabilities.

JEL CODES: M53, O12, D22

1. Introduction

A stagnant productivity of the Italian economy is a well-known phenomenon already since the beginning of the early 2000. However the malaise appears to be a more widespread pattern, affecting most OECD countries: Syverson (2017) documents that US labour-productivity growth more than halved from 2.8% in 1995-2004 to 1.3% in 2005 – 2015. A similar pattern characterizes 29 out of 30 countries analyzed in the same study, with an average decline of 1.2 percentage points. The Italian picture is even more disappointing with a slowdown that is older and deeper, with a striking large support of the distribution of productivity levels across firms, no matter the degree of sectoral disaggregation (see Dosi et al., 2012).[1]
Over the period 1995-2015 Italian labour productivity, measured in terms of value added per work hour, grew at a rate of 0.3% compared to a EU average of 1.6% (ISTAT, 2017). Together, the width of inter-firm distributions has grown with few high performing firms (in terms of productivity and sales) together with a population of (nearly) stagnant ones. This led to the suggestion that a form of neo-dualism (Dosi et al., 2012) has emerged, characterized by the coexistence of a "modern"/dynamic subset of firms and a population of "backward" ones, well identified in development theory, but destined according to the latter, to shrink along the development process.

It is not the place here to discuss the sources of the productivity slowdown in general. They are possibly quite diverse ranging from supply side explanations such as lags in the diffusion of the latest wave of new technologies and lack of adaptation of worker skills, to demand side ones including wage stagnation and lack of investment (Mishel and Biven, 2017). Here, in the interpretation of the Italian case, we restrict ourselves to the supply side ones. Even in this domain there are two alternative narratives with two underlying models. A first one has its roots in some sort of 'production function paradigm' whereby performances – in our case productivities – can be ultimately drawn back to the levels and dynamics of inputs. An alternative interpretation rests on the idea that performances are driven by *highly idiosyncratic organizational capabilities, nested in the procedural knowledge of organizations*, in turn making use of highly *complementary inputs.*

Of course, in the *production function view* the dynamics of any one well-detected input into the production function should yield unequivocal effects on productivity (basically assuming orthogonality with the other inputs). Conversely, in the *capability view* one should detect, lacking further detailed information on organizational and technological changes, much more blurred effects, if any.

Training, in this respect is an excellent case to the point, in so far as it is captured by formalized and paid for activities. The role of training is indeed crucial also for the interpretation of the relationship between individual skills and collective organizational routines and capabilities. Are the latter simply the sum of the former? Or conversely, collective procedual knowledge bears only indirect links with individual abilities? At the extreme, is '*it is firms, not people that work in firms, that know how to make gasoline, automobiles and computers*' (Winter, 1997) or are firms abilities additive in individual skills? Of course, the answers to the latter questions bear also major normative implications including the relative balance between individual training/retraining policies so emphazised e.g. under the flex-security agenda for labour markets as distinct from more discretionary and complex industrial policies.

[1] Such Italian patterns are also discussed in Calligaris et al. (2016), Codogno (2009), Daveri and Jona-Lasinio (2008).

This paper addresses the latter set of questions, albeit indirectly, looking at the relationship at firm-level between *formal* training activities, on the one hand, and the dynamics of labour productivity, on the other. We start by further documenting the evidence on neo-dualism in the distribution of productivities in the Italian business sector, exacerbated rather than curbed by the post-2008 crisis. Together, we explore the link between training activities and productivity.
In order to refine the understanding of the training-productivity relationship across the productivity distribution we rely on quantile regression analysis and we refine the firm-level analysis adding sectoral and size dimensions. We employ a quintile regression estimation strategy (Koenker and Bassett, 1978) robust to the presence of intra-cluster correlation (Parente and Santos-Silva, 2016). Finally the use of Canay (2011) technique allows to explicitly control for additive fixed effects.
The paper is organized as follows: Section 2 documents the relevance of the neo-dualist hypothesis for Italy in the aftermath of the crisis, Section 3 discusses the link between training and productivity, both empirically and theoretically, Section 4 presents some descriptive evidence on labour productivity and training costs dynamics, Section 5 specifies the econometric analysis performed for the whole sample, for manufacturing and non manufacturing firms, for small and large ones. Our conclusion are presented in Section 6.

2 Widespread, growing heterogeneity and the Italian neodualist hypothesis

Heterogeneity across firms is an extremely robust phenomenon irrespectively of the levels of disaggregation, the country, the window of observation (Bartelsman and Dooms, 2000; Dosi, 2007; Syverson, 2011). However, such degrees of heterogeneity seem to *have increased* in the new millennium and more after the 2008 crisis, contrary to the common mantra on the healthy cleansing role of recessions (Foster et al. 2016). Some alarm bells already went out before. For example, Dosi et al. (2012), who, observing nearly the universe of Italian manufacturing firms above twenty employees in the period 1989-2004, suggested a *neo-dualist hypothesis* whereby a laggard-leader type of pattern was *increasingly* characterizing the Italian production structure. The findings there included (i) widening heterogeneity in productivity distributions driven by the *left tail*, (ii) and a high persistence in the relative positioning along the productivity ladder.
A more recent study, focusing on the Italian automotive industry in the 2007-2011 period, confirmed the neo-dualist hypothesis: the automotive sector appears to be characterized by a l*eader/laggard firm divide* exacerbated during the crisis (Manello et al. 2015).
The growing intra-sectoral divergence is not only an Italian phenomenon. Rather it features, in milder forms, in many OECD economies. Therefore, Berlingieri et al. (2017) have recently documented a surge in the productivity dispersion in 16 OECD countries, from the mid-1990s to 2012, especially in the service sectors and especially concerning the bottom-part of the distributions (50-10 percentiles). In a similar vein, Barth et al. (2016) show an increase in productivity dispersion in the US economy, in both the service and the manufacturing sectors.[2]
Here, we are well short of answering any question about either the determinants of the persistent heterogeneity in productivity, or its recent increase. More modestly, we address the questions of whether

[2] Conversely, to our knowledge, patterns of convergence at the firm-level are currently characterizing some emerging economies such as China (Yu et al., 2015), where a process of internal creative restructuring has seen state-owned and public-private enterprises as the leading firms in triggering productivity growth.

and to what degrees, in the Italian case, formal training of the workforce (i) correlates with the relative efficiencies of firms at different levels and types of disaggregation; (ii) contributes to productivity growth, and, relatedly, (iii) dampens or amplify the neo-dualistic tendency.

3. On the links between training and productivity

Let us start by asking what role we should expect formal training to play vis-a'-vis firm-level productivity. In the theory domain the relationship between training and productivity has been investigated mainly by means of a "training-augmented" production function, wherein labour productivity is enhanced by individual training usually measured in terms of the proportion of trained workers (Dearden et al., 2006). Training is therefore considered as a potential channel enhancer of human capital with impacts on the *mean* of the productivity distribution across firms. Recent contributions by e.g. Konings and Vanormelingen (2015) provide a more refined proxy for training, using training costs born by firms and not simply the proportion of trained workers. Their analysis tends to confirm the finding in Dearden et al. (2006): the effects of training on productivity are significant and positive, although they are higher for non-manufacturing firms.

But, why should firms engage in paying the training for their employees? And to what extent, the provided training is worker- or firm- specific? According to the standard wisdom in human capital theory (see among others Becker, 1994; Mincer, 1983) wage flexibility is the necessary condition for firms to invest in some forms of *general* training activity: in fact, if general training is performed, being the knowledge embodied in the individual human capital, in case of quitting or separation, the worker might transfer her knowledge to other firms. The direct consequence is that if general training is provided at all this would happen at lower, and possibly more variable wages: that is, the cost of the training is transferred on workers. As the returns on general training are quite uncertain, firms are likely to invest in firm-specific training programs being the benefits more appropriable: in this case the burden of the training program is shared on both parties. However, the predictions of the standard theory of human capital happen to be too restrictive and empirically unsupported. That led to the emergence of the "new training theory" (Acemoglu and Pischke, 1999) which, allowing for imperfect competitive labour market, contemplate the possibility of firms investing in general training, under the *necessary* condition that post-training productivity grows more than wages (Bassanini et al, 2005). That is, the gains of productivity derived from training are prevalently appropriated by the firm.

To sum up, both theories are built on the notions that (i) the abilities generated by the training activity are transferable from firm to firm, and this hampers firms to invest in general training; (ii) such abilities are embodied in the human capital of the individual worker; (iii) training exerts a widespread positive effect on firm productivity, independently from the firm specific characteristics; (iv) the origin of training, whether internally or externally financed is not relevant.

But, what if the firm is the locus of knowledge rather than the individuals? What if the transmission from training to productivity does not occur by increasing individual worker skills via formal training program but rather through informal training activities such as coaching? And what if the training occurs mainly tacitly and therefore underreported in terms of costs? In fact, from the perspective of the theory of the firm as *problem-solving entities,* the knowledge basis, more than resting on individual know-how, lies into specific organizational arrangements prescribing *who send which signal to whom, and who does what and in which consequence* (Dosi and Marengo, 2015). Organizational capabilities are slowly accumulated and exhibit a high degree of persistence in their ``goodness'' or ``badness''. Indeed, in this view idiosyncratic capabilities are a strong candidate able to account the remarkable degrees of heterogeneity across firms characteristics and performance. However, organizational capabilities are very hard to measure. And even more so the contribution of training activities to their enhancement. Indeed, training might just show-up *within taxonomies* of interrelated firm characteristics. And, in this case not much should show-up by means of statistical investigation of any generalized training-productivity link.

4. The data and the general evidence

Our empirical analysis is based on *Rilevazione su Imprese e Lavoro* (RIL), a survey conducted by National Institute for the Analysis of Public Policies (INAPP), in 2010 and 2015 on a representative sample of partnerships and limited liability firms operating in the non-agricultural private sector (see INAPP, 2017; Damiani et al. 2018)[3].

The RIL survey collects a rich set of information about personnel organization, industrial relations, the employment composition (use of fixed-term contracts, the educational and age structure of the workforce) and firms productive characteristics (such as innovation, export activities, etc). In particular, for our purpose here, the survey provides unique information on the total amount of training costs and who paid for it.

In order to link information concerning training variables to indicators of firm performance, a sub-sample of the RIL dataset was merged with balance-sheet information from the AIDA archives The AIDA data provides information on our dependent variables, that is the value added per employee as well as an important control, i.e. the (log of) physical capital per employee.[4]

As for sample selection, we excluded firms with fewer than five employees to retain only those productive units characterized by a minimum level of organizational structure. After excluding also firms with missing information for the key variables, the final RIL-AIDA sample was a panel of over 3500 firms observed in both 2010 and 2014.

4.1 Productivity distributions and training intensities

The striking evidence to begin with regards the apparent *non-cleansing* effects of the crisis. Table 1 displays the dynamics of the distribution of labour productivity over the period 2010-2014, distinguishing between manufacturing and non manufacturing firms. Overall, labor productivity decreases or stagnates during the period. On average, manufacturing firms experienced a less marked decrease in productivity, as compared to non manufacturing ones (-4% against -21%). Differences emerge both with reference to the sector of

[3] The RIL Survey sample is stratified by size, sector, geographic area and the legal form of firms. Inclusion depends on firm size, measured by the total number of employees. This choice has required the construction of a 'direct estimator' to take into account the different probabilities of inclusion of firms belonging to specific strata. In particular, the direct estimator is defined for each sample unit (firm) as the inverse of the probability of inclusion in the sample. By using this estimator, the RIL sample reproduces all active firms for each stratum and, simultaneously, the total number of employees in a given stratum (size, sector, and other characteristics). For more details on RIL questionnaire, sample design and methodological issues see: http://www.inapp.org/it/ril.

[4] The longitudinal RIL-AIDA merged sample was then restricted to those limited liability companies that disclose detailed accounts in accordance with the scheme of the 4th Directive CEE. In addition, we excluded firms with less than five employees. After excluding also firms with missing information for the key variables, the final sample used to perform the empirical analysis is a panel of approximately 3000 firms for 2010 and 2014.

activity and to the location of the firms along the quintile distributions: while high-productivity manufacturing firms (companies located above the 75th quantile) show a slightly positive growth, non manufacturing ones, irrespectively of the location, display a negative growth. The evidence supports the neo-dualist hypothesis: low-productivity firms (located at the bottom decile) *which however survived*, experienced the most severe losses in productivity (-37% against the -16% average of the whole sample), with negative growth five time higher for low-productivity firms in the non-manufacturing sector as compared to manufacturing.

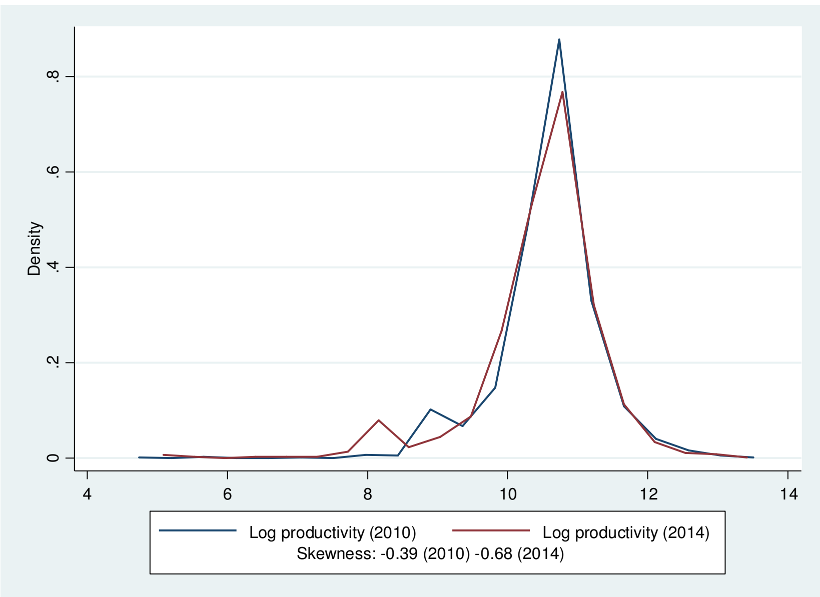
Both the longitudinal (Table 1) and the cross-sectional analysis (not reported here) corroborate such dynamics. Note however that the degree of heterogeneity across quantiles is higher in the longitudinal sample, showing at a glance how the *within* process of capabilities "de-cumulation" prevails with respect to the survival/entry of low-productivity firms in explaining the process of productivity decline.

Table 1: Descriptive statistics on labor productivity distribution by macro-sector

	2010		2014		Var. 10-14	2010		2014		Var. 10-14	2010		2014		Var. 10-14
	Whole sample					**Manufacturing**					**Services**				
	Logs	*Abs value*	*Logs*	*Abs values*		*Logs*	*Abs values*	*Logs*	*Abs values*		*Logs*	*Abs values*	*Logs*	*Abs values*	
Mean	10,69	43915	10,51	36680	-16%	10,74	46166	10,7	44356	-4%	10,67	43045	10,43	33860	-21%
p10	10,09	24101	9,63	15214	-37%	10,19	26635	10,04	22925	-14%	10,05	23156	9,21	9997	-57%
p25	10,41	33190	10,3	29733	-10%	10,46	34892	10,45	34544	-1%	10,37	31888	10,21	27174	-15%
p50	10,68	43478	10,64	41773	-4%	10,73	45707	10,71	44802	-2%	10,66	42617	10,61	40538	-5%
p75	10,98	58689	10,95	56954	-3%	10,99	59278	11,01	60476	2%	10,97	58105	10,91	54721	-6%
p90	11,33	83283	11,33	83283	0%	11,32	82454	11,35	84965	3%	11,34	84120	11,33	83283	-1%

Source: RIL-AIDA 2010-2015 longitudinal sample. Note: Values in thousands of euro at constant prices. Sampling weights applied. Absolute values at constant prices.

Figure 1. Kernel density - log productivity (2010 and 2014)



In order to document the increasing heterogeneity across firms, we present in Figure 1 the Kernel density distribution of (log) productivity for the two periods for the whole sample. The figure confirms that the left tail of the distribution drives the heterogeneity, highlighted by the negative skewness coefficient going from -0.39 to -0.68 in the period. Table 1b shows the second and the third moment of the productivity distribution divided by sub-sectors.

The sectors that mostly contributed to the increasing negative skewness are in the Finance/Insurance/Real Estate (FIRE) and in the retail trade/hotel/restaurant sectors. Conversely, circumstantial evidence on *some* cleansing selection appears in some subsectors of manufacturing, such as mechanical and chemical industries. How do such distributions and their dynamics relate to training efforts of whatever form, in so far as it accounted as some explicit training cost?

Table 1b: Descriptive statistics on labor productivity-standard deviations and skweness by macrosectr

	2010		2014	
	Std. Dev	Skewness	Std. Dev	Skewness
macro-sector				
Mining, water and gas	0.78	0.16	0.79	0.08
Food, tobacco, paper and printing	0.59	-0.15	0.63	-0.48
Chemical industry	0.52	-0.32	0.54	-0.08
Mechanical industry and other manuf.	0.56	-1.09	0.52	-0.55
Construction	0.62	-2.05	0.67	-1.56
Retail trade, hotel and restaurants	0.69	-0.04	0.69	-0.51
Transport services	0.61	-0.04	0.81	-0.06
FIRE (Finance/Insurance/Real Estate)	0.81	-0.31	0.82	-0.77
Social and other services	0.7	-0.65	0.67	-0.67

Source: RIL-AIDA 2010-2014 longitudinal sample.
Note: Values in thousands of euro at constant prices. Sampling weights applied.

4.2 Training

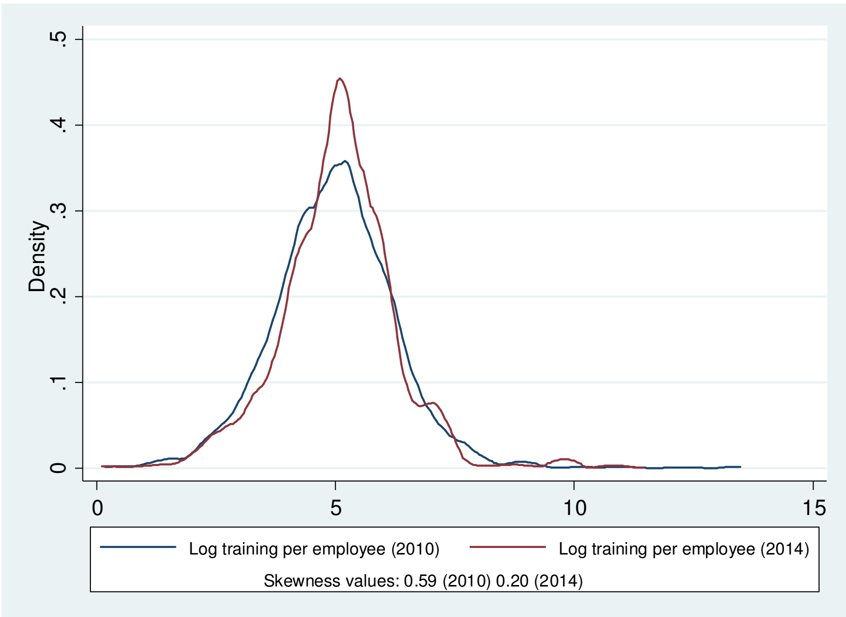
Let us consider the training cost distribution within the subsample of firms that invest in training activities (Table 2) disaggregated by macro sector of activity and by quintile. Figure 2 presents the kernel distribution of the (log) training costs. Unlike log-labour productivity, the distribution is right-skewed although less so in 2014 compared to 2010: that is among those firms which undertake training activities, firms investing in more than the median are more frequent than those investing less. The reduction of the skewness, from 0.59 to 0.20, is mainly attributable to firms located under the median which increased their training expenditures.

Table 2: Descriptive statistics on training costs distribution (subsample of firms with positive training)

	2010		2014		Var 10-14	2010		2014		Var 10-14	2010		2014		Var 10-14
	Whole sample					**Manufacturing**					**Services**				
	Logs	*Abs values*	*Logs*	*Abs values*		*Logs*	*Abs values*	*Logs*	*Abs value*		*Logs*	*Abs values*	*Logs*	*Abs value*	
Mean	4,63	103	4,88	132	28%	4,63	103	4,66	106	3%	4,64	104	5,0	148	42%
p10	2,63	14	3,31	27	92%	3,01	20	3,02	20	0%	2,46	12	3,48	32	166%
p25	4,0	55	4,26	71	29%	3,93	51	4,0	55	7%	4,04	57	4,39	81	42%
p50	4,9	134	5,04	154	14%	4,66	106	4,83	125	17%	5,01	150	5,17	176	17%
p75	5,66	287	5,74	311	8%	5,6	270	5,42	226	-16%	5,78	324	5,79	327	1%
p90	6,37	584	6,27	528	-10%	6,25	518	6,1	446	-14%	6,44	626	6,38	590	-6%

Source: RIL-AIDA 2010-2015 longitudinal sample.
Note: Values in thousands of euro at constant prices. Sampling weights applied. Absolute values at constant prices.

Figure 2. Kernel density - log training expenditure per employee (2010 and 2014)



4.3 *Training costs, productivities and firm size: conditional distributions*

Next, let us consider the distributions of training expenditures (and the source of finance thereof) conditional on the quantile of the labour productivity distribution. At a first look the share of firms undertaking training appears to grow with the productivity quantiles and so does the share of firms which back it with their own funds (Table 3). Moreover, training frequency increases from 2010 to 2014. But such regularities are not robust to disaggregation (Table 3a). In particular, in the manufacturing sector, the growth of training costs has been rather modest, and more importantly, non-monotonic along the productivity distribution.

Let us consider the distribution of training expenditures conditional on firm size, both over time and cross-sectionally (Tables 4, 4a). Overall, the expenditure of smaller firms seems to grow more, but again the property is not robust to disaggregation.

Table 3: Training investment over the productivity distribution. **Longitudinal sample**

	2010					2014				
	N.	Training incidence	Privatedly financed	Share trained	Ln (tr costs pc)	N.	Training incidence	Privatedly financed	Share trained	Ln(tr costs pc)
labor productivity										
ln (lab prod)<p10	308	0.25	0.21	0.13	1.08	138	0.33	0.30	0.22	1.44
p10< ln (lab prod)<p25	507	0.29	0.21	0.17	1.24	493	0.45	0.29	0.32	1.66
p25< ln (lab prod)<p50	988	0.37	0.25	0.19	1.53	933	0.51	0.38	0.37	1.88
p50< ln (lab prod)<p75	1214	0.44	0.31	0.23	1.82	1194	0.56	0.38	0.40	2.28
p75< ln (lab prod)<p90	881	0.46	0.31	0.27	1.99	931	0.56	0.38	0.37	2.40
ln (lab prod)>p90	664	0.46	0.36	0.25	2.20	608	0.67	0.47	0.43	3.41

Source: RIL-AIDA 2010-15 longitudinal sample.
Note: Sampling weights applied.

Table 3a: Training costs distribution (subsample of firms with positive training investment) over the productivity distribution by macrosector. **Longitudinal sample**

	Whole economy			Manufacturing			No manufacturing		
	2010	2014	Var 10-14	2010	2014	Var 10-14	2010	2014	Var 10-14
labor productivity									
ln (lab prod)<p10	4.62	5.15	0.53	4.73	4.80	0.07	4.72	5.2	0.48
p10< ln (lab prod)<p25	4.68	4.46	-0.22	4.88	4.57	-0.31	4.45	4.3	-0.15
p25< ln (lab prod)<p50	4.4	4.89	0.49	4.68	4.48	-0.2	4.18	4.95	0.77
p50< ln (lab prod)<p75	4.56	4.71	0.16	4.33	4.49	0.16	4.75	4.86	0.11
p75< ln (lab prod)<p90	4.7	4.92	0.22	4.59	4.76	0.17	4.75	5.04	0.29
ln (lab prod)>p90	5.06	5.5	0.44	4.99	4.93	-0.05	5.09	5.76	0.66

Source: RIL-AIDA 2010-14 longitudinal sample.
Note: Sampling weights applied.

Table 4: Training costs distribution (subsample of firms with positive training investment) by firm size. **Longitudinal sample**

	Whole economy			Manufacturing			No manufacturing		
	2010	2014	Var 10-14	2010	2014	Var 10-14	2010	2014	Var 10-14
firms size									
ln(n of employees)<p10	4.08	5.02	0.95	5.54	4.56	-0.99	3.69	5.15	1.47
p10< ln (n of employees)<p25	4.69	5.02	0.34	5.09	4.96	-0.13	5.54	5.15	-0.39
p25< ln (n of employees)<p50	4.74	5.22	0.49	4.64	4.54	-0.1	4.79	5.3	0.51
p50< ln (n of employees)<p75	4.7	4.72	0.02	4.52	4.65	0.13	4.8	4.82	0.02
p75< ln (n of employees)<p90	4.5	4.72	0.22	4.43	4.63	0.21	4.55	4.76	0.21
ln(n of employees)>p90	4.5	4.68	0.18	4.51	4.76	0.25	4.43	4.68	0.26

Source: RIL-AIDA 2010-14. Sampling weights applied.

Table 4a: Training costs distribution (subsample of firms with positive training investment) by firm size.
Cross sectional sample

	whole economy			Manufacturing			No manufacturing		
	2010	2014	Var 10-14	2010	2014	Var 10-14	2010	2014	Var 10-14
firms size									
ln (n of employees)<p10	4.43	4.99	0.56	5.17	4.65	-0.52	4.28	5.06	0.78
p10< ln (n of employees)<p25	4.81	4.99	0.18	4.82	5.03	0.21	4.28	5.06	0.78
p25< ln (n of employees)<p50	4.75	5.12	0.37	4.8	4.83	0.03	4.65	5.19	0.54
p50< ln (n of employees)<p75	4.61	4.8	0.2	4.45	4.79	0.34	4.82	4.8	-0.02
p75< ln (n of employees)<p90	4.59	4.78	0.2	4.35	4.63	0.28	4.58	4.91	0.33
ln (n of employees)>p90	4.51	4.64	0.13	4.55	4.72	0.17	4.49	4.65	0.16

Source: RIL-AIDA 2010-14 cross sectional sample. Sampling weights applied.

5. Training and productivity: some econometric analysis

On the grounds of this broad picture, in order to better grasp the relations between training and productivity, both cross-sectionally and in their dynamics, let us turn to some econometric estimates.
Given the distributions and dynamics of productivity and training documented above, we resort to quantile regression analysis (Koenker and Bassett, 1978) allowing for the relations under scrutiny to change along the distributions. We explore the following econometric specification (1):

$$ln\left(\frac{y}{L}\right)_{i,t} = \alpha_\theta \cdot ln\left(\frac{trcost}{L}\right)_{i,t} + \beta_\theta \cdot PFT_{i,t} + \delta_\theta \left(\frac{trcost}{L}\right)_{i,t} * PFT_{i,t} + \lambda_\theta \cdot X_{i,t} + \eta_i + \varepsilon_{i,t} \quad (1)$$

where $ln\left(\frac{y}{L}\right)_{i,t}$ is the (log) valued added per employee registered in firm i at time t; $ln\left(\frac{trcost}{L}\right)_{i,t}$ is the (log) training costs per employee; $PFT_{i,t}$ is a dummy variable that takes value 1 if training is internally financed and 0 otherwise; while $\left(\frac{trcost}{L}\right)_{i,t} * PFT_{i,t}$ is the interaction between training costs and the internally-financed dummy. The vector $X_{i,t}$ includes a relevant set of firm-level controls concerning companies characteristics (value of physical capital, age, sector of activity, size, type of corporate governance); workforce composition (gender, education, age, contractual arrangement, professions), regional (Nuts 2 classification) and sectoral-level (Ateco 2-digits classification) dummies. In addition, we include a time dummy corresponding to year 2014 to control for the crisis. The parameter η_i denotes the firms' time-invariant unobserved heterogeneity. The vector of coefficients α_θ β_θ and $\delta_\theta$is estimated at each of the following quantiles θ=0.1,0.25,0.5,0.75 and 0.9.
Two main specifications of equation (1) are estimated namely i) the basic one including the (log) training costs per employees without considering the source of financing, and ii) a second one adding the dummy variable $PFT_{i,t}$ and the interaction term $\left(\frac{trcost}{L}\right)_{i,t} * PFT_{i,t}$ capturing the effect of internally financed training. That is, the coefficient δ_θ (associated to the interaction term) can be interpreted as a 'productivity premium' summing up over the average effect of training across the distribution of productivity.

Within this econometric framework, we start by performing quantile regression with robust and clustered standard errors controlling for heteroschedasticity and autocorrelation within firms across the distribution (Machado and Santos Silva, 2000; Parente and Santos-Silva, 2016).
As a robustness check, we rely on the simple two step procedure proposed by Canay (2011) in order to control for time-invariant firm-specific unobserved heterogeneity. Following this procedure, the estimation is carried out controlling for fixed effects under the assumption that these effects are pure location shifters across the productivity distribution. In our case, the first step is needed to estimate the unobserved fixed effect using a standard within FE estimator of equation (1). In the second step, the consistently estimated FE are used to demean the (log of) labour productivity and this transformed (adjusted) measure is taken as dependent variable to conduct a standard conditional quantile regression of equation (1).
We acknowledge that there might be selection of firms into training investment which is likely to be affected by the size and /or sectorial specialization (and or the culture of corporate governance). This avenue of selection at firm level represents potential biases for our estimates. Moreover, if employees are not randomly assigned to the training activities, the effect of the training costs on the labor productivity will be confounded by the biasedness of the characteristics which are specific of these firms and employees. On the other hand, the use of instrument is quite problematic in an econometric framework where the short time (T=2) relationship between job-related training and productivity are examined across the entire distribution (Abadie, Angrist et Imbens, 2002).[5] On these grounds, we refrain from using instruments to identify the causal effect of the training costs and address these selection issues through i) the inclusion of a wide set of observed explanatory variables, ii) controlling for firm specific time invariant unobserved heterogeneity iii) performing separate quantile regressions for the sub-samples of firms operating in manufacturing sector and with different size.

5.1 Model estimates

As described above, the analysis is carried out first by examining the relationship between labour productivity and firm-level training expenditure. Subsequently, we test a second specification of equation (1) interacting companies' training expenditure with the dummy variable assuming value 1 if training is internally financed and 0 otherwise. Both specifications – i.e. productivity vs training and productivity vs internally financed training – are tested looking at both levels and first differences. Results are presented as follows. We first report the outcome of the model pooling all firms irrespective of the sector to which they belong and their size. Next we show the results looking at manufacturing firms only. Finally, we replicate the estimations distinguishing between small (<49 employees) and medium-large firms (50 or more employees). Robustness checks are performed using the Canay (2011) technique (see next section).
Table 5 reports the results of the model in levels regressing productivity on training (first specification); together with the interaction between training and the source of financing dummy (second specification). In the first specification productivity and training efforts turn out to be positively and significantly correlated across all quantiles of the dependent variable's conditional distribution (columns 1-5). However, the picture changes when training is interacted with the source-of-financing dummy. The effects of training activities now present a more heterogeneous dynamics along the productivity distribution: while training cost is still positive and statistically significant at the lower quantiles, high-productivity firms seem to

[5] We also estimate unconditional quantile model for longitudinal data with non-additive fixed effects, i.e maintaining the non-separable disturbance terms (Powell ,2016), rather that conditional one with additive fixed effects (Canay, 2011; Koenker, 2004). This approach is computational burden and shows problems of convergence in short panel. However results are available upon request

benefit from training activities only when they are internally financed. The magnitude of the coefficient for firms located in the higher quantiles is now more than doubled. The positive and significant sign of the interaction term registered at the top of the distribution may signal that for high-performance firms training impacts positively on productivity only in case this is actually a purposeful activity undertaken with the firm own money. Conversely, companies populating the first three quantiles of the distribution display a positive correlation between productivity and training, when the latter is considered as a whole; but no significant relationships is found regarding the source of financing.

To sum up, the foregoing results are significantly affected by aggregation, both among sectors and size classes. Therefore, let us first consider the manufacturing sector alone. According to the results of the pooled quantile regression, training efforts are again positively and significantly correlated with productivity all across the dependent variable's distribution (Table 6). However, contrary to the whole sample the relation basically disappears when the source of training expenditure is taken into account. On further disaggregation within the manufacturing sector, our results, available upon request, show a weaker relation training-productivity even in industries like mechanical engineering where one would expect to find a strong one.

An additional source of heterogeneity potentially affecting the training-productivity relation might relate to the structural and organizational differences among small, medium and large firms. In what follows we report the results of the model when breaking down the sample between small firms (less than 49 employees), and medium-large ones (more than 49 employees). Table 7 reports the evidence for small firms. Concerning the overall training (first specification), it emerges a strong and positive correlation for all quantiles in line with the whole sample results. However, considering the second specification, the overall training displays a positive correlation with productivity only for firms located at the bottom of the distribution (first and second quantile); while those at the top (fourth and fifth quantiles) show a positive relationship only in case of internally financed training programs, suggesting again that training expenditures are positively related to productivity only when they are part of an intentionally pursued investment strategy.

As for the subsample of medium-large firms (Tables 8), results are in line with the whole sample model. Looking at productivity levels, a positive effect of training is found all across the distribution. However, once the source of financing is taken into consideration, overall training remains significantly correlated with productivity only for firms populating the first two quantiles; while for firms at the top of the distribution training exerts an effect on productivity only when it is internally financed.

A complementary view comes from a dynamic analysis. In fact, let us turn to the relationship between the change (from 2010 to 2014) in productivity and training. The model in equation (1) is now implemented using the first differences of both dependent and independent variables. Differently from what emerged analysing productivity levels, training expenditure now shows no correlation with the change in productivity (Table 9). This is true for both model's specifications. Only when the focus is shifted on internally financed training (columns 6-10), some positive and significant links emerge, – particularly for the upper part of the distribution. The lack of any dynamic link appears even more vividly when separating out manufacturing alone (Table 10) and between small and medium-large firms (Tables 11-12). But, what about the links between initial levels of training intensities and variations in productivities? We do not report the results here, simply because there are none: variations in productivity do not seem to bear any relation with formal training expenditures.

Table 5: Pooled quantile estimates. Whole sample

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Ln(training cost pc)	0.016***	0.015***	0.010***	0.011***	0.013***	0.018***	0.014***	0.008***	0.002	0.006
	[0.005]	[0.003]	[0.002]	[0.003]	[0.005]	[0.006]	[0.004]	[0.003]	[0.004]	[0.008]
Private financed tr						0.033	-0.040	-0.031	-0.044	-0.156***
						[0.065]	[0.037]	[0.029]	[0.038]	[0.038]
Ln(tr pc)* private financed						-0.007	0.008	0.009	0.022**	0.038***
						[0.016]	[0.008]	[0.007]	[0.009]	[0.011]
Year 2014	-0.075***	-0.059***	-0.035***	-0.030**	-0.036*	-0.076***	-0.061***	-0.036***	-0.028**	-0.038**
	[0.023]	[0.012]	[0.010]	[0.012]	[0.019]	[0.024]	[0.012]	[0.010]	[0.012]	[0.018]
Ln(n of employees)	0.045***	0.029***	0.027***	0.014**	-0.005	0.046***	0.033***	0.027***	0.018**	0.001
	[0.010]	[0.007]	[0.007]	[0.007]	[0.013]	[0.010]	[0.008]	[0.007]	[0.007]	[0.010]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	9.746***	10.280***	10.893***	11.332***	11.668***	9.715***	10.268***	10.871***	11.283***	11.737***
	[0.177]	[0.128]	[0.116]	[0.181]	[0.240]	[0.220]	[0.132]	[0.130]	[0.162]	[0.262]
Obs	7382	7382	7382	7382	7382	7378	7378	7378	7378	7378
R2	0.286	0.325	0.335	0.324	0.295	0.284	0.325	0.335	0.323	0.296

Source: RIL 2010-2014.
Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), gross workers turnover, product innovation, process innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Pooled quantile estimates. Manufacturing

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Ln(training cost pc)	0.015**	0.017***	0.013***	0.015***	0.014**	0.014	0.013**	0.007*	0.004	0.011
	[0.007]	[0.004]	[0.003]	[0.004]	[0.007]	[0.008]	[0.005]	[0.004]	[0.005]	[0.010]
Private financed tr						-0.025	-0.033	-0.023	-0.042	-0.142**
						[0.108]	[0.046]	[0.039]	[0.045]	[0.071]
Ln(tr pc)* private fin						0.009	0.014	0.013	0.026**	0.033*
						[0.024]	[0.011]	[0.009]	[0.010]	[0.019]
Year 2014	-0.043	-0.039***	-0.010	0.010	-0.002	-0.039	-0.037**	-0.004	0.008	-0.003
	[0.029]	[0.015]	[0.014]	[0.016]	[0.028]	[0.028]	[0.015]	[0.014]	[0.015]	[0.029
Ln(n of employees)	0.071***	0.054***	0.050***	0.026**	0.003	0.071***	0.056***	0.056***	0.031***	0.013
	[0.017]	[0.009]	[0.008]	[0.010]	[0.015]	[0.017]	[0.010]	[0.009]	[0.010]	[0.015]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	9.677***	9.934***	10.378***	10.746***	11.122***	9.677***	9.932***	10.390***	10.816***	11.158***
	[0.320]	[0.146]	[0.184]	[0.230]	[0.333]	[0.322]	[0.172]	[0.174]	[0.273]	[0.405]
Obs	3519	3519	3519	3519	3519	3518	3518	3518	3518	3518
R2	0.316	0.345	0.356	0.348	0.322	0.316	0.347	0.357	0.349	0.325

Source: RIL 2010-2014.

Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), net workers turnover, product innovation, proecess innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Quantile pooled estimates. Small firms with less than 50 employees

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Ln(training cost pc)	0.014***	0.013***	0.007***	0.006*	0.011**	0.015**	0.013***	0.001	-0.005	-0.005
	[0.005]	[0.003]	[0.003]	[0.003]	[0.005]	[0.006]	[0.004]	[0.003]	[0.004]	[0.008]
Private financed tr						0.024	-0.046	-0.003	-0.027	-0.143**
						[0.073]	[0.049]	[0.032]	[0.035]	[0.058]
Ln(tr pc)* private fin						-0.007	0.007	0.009	0.020**	0.045***
						[0.017]	[0.011]	[0.007]	[0.008]	[0.014]
Year 2014	-0.084***	-0.067***	-0.048***	-0.027**	-0.052**	-0.085***	-0.067***	-0.043***	-0.024*	-0.039*
	[0.023]	[0.013]	[0.011]	[0.014]	[0.022]	[0.025]	[0.013]	[0.011]	[0.013]	[0.020]
Ln(n of employees)	0.127***	0.075***	0.054***	0.02	-0.032	0.124***	0.076***	0.056***	0.022*	-0.021
	[0.021]	[0.012]	[0.012]	[0.014]	[0.020]	[0.021]	[0.013]	[0.012]	[0.013]	[0.020]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	9.481***	9.932***	10.585***	10.974***	11.450***	9.493***	9.933***	10.574***	10.944***	11.438***
	[0.221]	[0.172]	[0.144]	[0.226]	[0.236]	[0.228]	[0.164]	[0.152]	[0.244]	[0.246]
Obs	5471	5471	5471	5471	5471	5468	5468	5468	5468	5468
R2	0.24	0.285	0.299	0.285	0.261	0.238	0.284	0.299	0.284	0.261

Source: RIL 2010-2014.
Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), net workers turnover, product innovation, proecess innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Quantile pooled estimates. No small firms with more than 49 employees

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Ln(training cost pc)	0.029***	0.020***	0.017***	0.014**	0.017*	0.025**	0.017***	0.014**	0.009	0.017
	[0.009]	[0.006]	[0.005]	[0.006]	[0.010]	[0.010]	[0.006]	[0.005]	[0.007]	[0.011]
Private financed tr						-0.035	-0.018	-0.065	-0.085	-0.139*
						[0.119]	[0.075]	[0.063]	[0.076]	[0.079]
Ln(tr pc)* private fin						0.020	0.011	0.019	0.021	0.025
						[0.028]	[0.018]	[0.014]	[0.017]	[0.018]
Year 2014	-0.042	-0.015	-0.016	-0.011	-0.014	-0.027	-0.007	-0.009	-0.015	-0.003
	[0.032]	[0.019]	[0.018]	[0.022]	[0.028]	[0.032]	[0.019	[0.019	[0.027	[0.029
Ln(n of employees)	0.003	-0.001	-0.010	-0.025	-0.009	0.004	-0.001	-0.009	-0.022	-0.013
	[0.019]	[0.015]	[0.014]	[0.018]	[0.023]	[0.019]	[0.015]	[0.013]	[0.021]	[0.022]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	11.078***	11.853***	12.606***	13.246***	12.850***	11.157***	12.038***	12.709***	13.220***	12.846***
	[0.571]	[0.332]	[0.393]	[0.379]	[0.337]	[0.485]	[0.327]	[0.378]	[0.368]	[0.362]
Obs	1911	1911	1911	1911	1911	1910	1910	1910	1910	1910
R2	0.373	0.414	0.417	0.407	0.375	0.368	0.414	0.416	0.409	0.373

Source: RIL 2010-2014.

Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), net workers turnover, product innovation, proecess innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 9: First difference estimates Whole sample

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
D. ln(training cost pc)	0.005	0.000	0.002	0.004	-0.001	0.009	0.003	0.001	0.003	-0.005
	[0.005]	[0.003]	[0.002]	[0.003]	[0.005]	[0.007]	[0.004]	[0.003]	[0.003]	[0.007]
D. Private finaced tr						-0.040	-0.024	0.010	0.002	0.010
						[0.027]	[0.019]	[0.012]	[0.014]	[0.028]
D. ln(tr cost pc)*D. priv fin						0.007	0.004	0.006*	0.008*	0.016*
						[0.006]	[0.005]	[0.003]	[0.004]	[0.009]
D. ln(n of employees)	-0.460***	-0.417***	-0.385***	-0.377***	-0.408***	-0.456***	-0.411***	-0.382***	-0.376***	-0.408***
	[0.043]	[0.044]	[0.035]	[0.035]	[0.044]	[0.048]	[0.046]	[0.035]	[0.034]	[0.057]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.602***	-0.266***	-0.03	0.177***	0.402***	-0.646***	-0.287***	-0.027	0.177***	0.382***
	[0.090]	[0.066]	[0.039]	[0.047]	[0.087]	[0.113]	[0.057]	[0.039]	[0.049]	[0.086]
Obs	2964	2964	2964	2964	2964	2960	2960	2960	2960	2960
R2	0.186	0.20	0.203	0.202	0.182	0.186	0.201	0.205	0.204	0.183

Source: RIL 2010-2014.

Note: Other control variables (in first difference): managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), gross workers turnover, product innovation, process innovation, R&D activities, (ln of) physical capital per employees, firms' caracteristics (age, sector of activity, size, macro-region, ecc). All regression includes fixed efffect (in levels) for nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 10: First difference estimates Manufacturing

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
D. ln(training cost pc)	0.009	0.002	0.002	-0.001	-0.002	0.002	0.002	0.000	-0.004	-0.005
	[0.009]	[0.004]	[0.004]	[0.003]	[0.005]	[0.012]	[0.005]	[0.004]	[0.003]	[0.006]
D. private finaced tr						-0.003	-0.002	0.016	0.029	0.013
						[0.052]	[0.025]	[0.018]	[0.022]	[0.034]
D. ln(tr cost pc)*D. priv fin						0.012	-0.001	0.006	0.000	0.005
						[0.011]	[0.007]	[0.005]	[0.006]	[0.011]
D. ln(n of employees)	-0.262**	-0.308***	-0.340***	-0.376***	-0.460***	-0.270***	-0.308***	-0.342***	-0.367***	-0.465***
	[0.104]	[0.066]	[0.052]	[0.042]	[0.087]	[0.084]	[0.068]	[0.065]	[0.044]	[0.087]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.732***	-0.289***	-0.009	0.229***	0.508***	-0.729***	-0.286***	0.016	0.224***	0.511***
	[0.133]	[0.074]	[0.055]	[0.047]	[0.057]	[0.151]	[0.074]	[0.053]	[0.056]	[0.062]
Obs	1424	1424	1424	1424	1424	1423	1423	1423	1423	1423
R2	0.118	0.153	0.148	0.15	0.127	0.121	0.154	0.147	0.151	0.130

Source: RIL 2010-2014.

Note: Other control variables (in first difference): managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), gross workers turnover, product innovation, process innovation, R&D activities, (ln of) physical capital per employees, firms' caracteristics (age, sector of activity, size, macro-region, ecc). All regression includes fixed efffect (in levels) for nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 11: First difference estimates Small firms with less than 50 employees

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
D. ln(training cost pc)	0.000	-0.001	0.001	0.002	-0.006	0.005	0.003	0.003	0.003	-0.008
	[0.006]	[0.004]	[0.003]	[0.003]	[0.005]	[0.009]	[0.005]	[0.004]	[0.004]	[0.010]
D. private finaced tr						-0.028	-0.029	-0.010	-0.009	-0.008
						[0.045]	[0.024]	[0.018]	[0.022]	[0.039]
D. ln(tr cost pc)*D. priv fin						0.015*	0.004	0.005	0.006	0.015*
						[0.008]	[0.006]	[0.004]	[0.005]	[0.009]
D. ln(n of employees)	-0.463***	-0.459***	-0.448***	-0.411***	-0.422***	-0.485***	-0.454***	-0.441***	-0.418***	-0.436***
	[0.064]	[0.049]	[0.042]	[0.038]	[0.061]	[0.062]	[0.043]	[0.043]	[0.040]	[0.053]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.701***	-0.333***	-0.057	0.157***	0.416***	-0.724***	-0.351***	-0.057	0.131**	0.351***
	[0.125]	[0.068]	[0.051]	[0.053]	[0.110]	[0.115]	[0.079]	[0.052]	[0.054]	[0.067]
Obs	2223	2223	2223	2223	2223	2220	2220	2220	2220	2220
R2	0.183	0.198	0.199	0.2	0.17	0.184	0.199	0.201	0.203	0.175

Source: RIL 2010-2014.

Note: Other control variables (in first difference): managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), net workers turnover, product innovation, proecess innovation, R&D activities, (ln of) physical capital per employees, firms' caracteristics (age, sector of activity, size, macro-region, ecc). All regression includes fixed efffect (in levels) for nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 12: First difference estimates No small firms with more than 49 employees

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
D. ln(training cost pc)	0.016**	0.008	0.008*	0.008	0.015*	0.012	0.008	0.006	0.004	0.007
	[0.007]	[0.007]	[0.004]	[0.006]	[0.009]	[0.008]	[0.007]	[0.005]	[0.005]	[0.007]
D. private finaced tr						0.023	0.025	0.032*	0.025	0.022
						[0.038]	[0.030]	[0.019]	[0.025]	[0.024]
D. ln(tr cost pc)*D. priv fin						0.012	0.007	0.010	0.020*	0.021
						[0.013]	[0.015]	[0.008]	[0.011]	[0.015]
D. ln(n of employees)	-0.298***	-0.322***	-0.278***	-0.267***	-0.357***	-0.336***	-0.327***	-0.284***	-0.253***	-0.319***
	[0.069]	[0.059]	[0.069]	[0.054]	[0.109]	[0.105]	[0.056]	[0.062]	[0.052]	[0.088]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.294**	-0.068	0.106	0.193*	0.548***	-0.274*	-0.064	0.109*	0.240***	0.509***
	[0.121]	[0.089]	[0.068]	[0.111]	[0.114]	[0.150]	[0.111]	[0.066]	[0.078]	[0.134]
Obs	741	741	741	741	741	740	740	740	740	740
R2	0.21	0.24	0.237	0.248	0.212	0.222	0.25	0.241	0.25	0.217

Source: RIL 2010-2014.

Note: Other control variables (in first difference): managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), net workers turnover, product innovation, proecess innovation, R&D activities, (ln of) physical capital per employees, firms' caracteristics (age, sector of activity, size, macro-region, ecc). All regression includes fixed efffect (in levels) for nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5.3 Robustness checks

The robustness of the previous findings (or lack of it) is corroborated by running quantile regression with additive fixed effects (QFE) (Canay 2011).

Table 13 reports QFE results for the whole sample. We can observe that controlling for firm-specific time invariant unobserved heterogeneity all results (for both specifications of equation (1)) are broadly confirmed, but in the first specification, the magnitude of the coefficient associated to general training is slightly decreasing across the distribution while a negative but not significant sign is found at the 90th quantile, and in the second specification, the coefficient associated to the interaction is again significant only at the middle and at the top of the distribution. Such an evidence matches also with the loss of influence exerted by the amount of training costs once netting out the source of its financing. More generally, the QFE estimates are lower in magnitude than those derived from the pooled quantiles ones across the entire distribution.

Aggregation, again, does matter. Table 14 reports the QFE estimates for the subsample of manufacturing firms. In this case, the coefficient associated to general training is positive in the middle part of the distribution, while no significant impact is detected on the tails. Similarly, the second specification shows that the interaction term is positive only between the 25th and 75th quantiles. In further estimates available upon request, we analysed separately small vs medium-large firms. Concerning the former, the relationship gets overall weaker and its significance depends to a good extent on the specific quantiles, but, interestingly, own-financed training appears as positive and significant in the upper echelons of the productivity distribution.

The QFE estimates on medium-large firms describe a quite different patterns. In the first specification, the coefficient of general training is positive and tends to increase along the distribution while own-financing is positive and significant only at the 50th and 75th quantiles. Of course, the comparisons between the foregoing estimates and the previous ones are meant to detect the importance of idiosyncratic factors which modulate the relationship, if any, between training expenditures and productivity. Indeed, they are there, they are important, and especially so in manufacturing and in medium-large firms. Putting it in another way, the links between training intensities and productivity levels appear to be significantly nested into other firm-specific characteristics plausibly associated with the technological capabilities and organizational structures of the firms.

Table 13: Quantile fixed effect estimates (Canay technique). Whole sample

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Ln(training cost pc)	0.006***	0.004***	0.003***	0.002*	-0.002	0.003	0.003***	0.002***	0.000	0.000
	[0.002]	[0.001]	[0.000]	[0.001]	[0.002]	[0.003]	[0.001]	[0.000]	[0.001]	[0.003]
Private financed tr						-0.006	-0.014	-0.035***	-0.032***	-0.064***
						[0.027]	[0.016]	[0.003]	[0.011]	[0.020]
Ln(tr pc)* private fin						0.005	0.002	0.007***	0.007***	0.010*
						[0.007]	[0.003]	[0.001]	[0.002]	[0.005]
Year 2014	-0.046***	-0.026***	-0.040***	-0.008	-0.021*	-0.045***	-0.027***	-0.040***	-0.009	-0.025**
	[0.009]	[0.006]	[0.002]	[0.006]	[0.011]	[0.010]	[0.006]	[0.002]	[0.006]	[0.011]
Ln(n of employees)	-0.341***	-0.350***	-0.356***	-0.361***	-0.368***	-0.342***	-0.351***	-0.357***	-0.361***	-0.370***
	[0.004]	[0.001]	[0.000]	[0.002]	[0.004]	[0.005]	[0.001]	[0.000]	[0.002]	[0.005]
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	10.311***	10.630***	10.694***	10.793***	11.085***	10.532***	10.832***	10.903***	10.998***	11.297***
	[0.079]	[0.032]	[0.007]	[0.033]	[0.079]	[0.070]	[0.034]	[0.007]	[0.032]	[0.086]
Obs	7382	7382	7382	7382	7382	7378	7378	7378	7378	7378

Source: RIL 2010-2014.

Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), gross workers turnover, product innovation, process innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 14: Quantile fixed effect estimates (Canay technique). Manufacturing

	First specification					Second specification				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
ln(training cost pc)	0.004	0.003**	0.003***	0.004***	-0.001	-0.003	-0.002	-0.002***	-0.001	-0.002
	[0.003]	[0.002]	[0.000]	[0.001]	[0.003]	[0.003]	[0.002]	[0.001]	[0.002]	[0.004]
private financed tr						-0.022	-0.021	-0.045***	-0.038***	-0.048
						[0.042]	[0.019]	[0.006]	[0.014]	[0.029]
ln(tr pc)* private fin						0.015	0.011***	0.016***	0.014***	0.009
						[0.010]	[0.004]	[0.001]	[0.003]	[0.008]
year 2014	-0.007	0.002	-0.004	0.019**	0.012	0.000	0.006	0.000	0.022**	0.01
	[0.017]	[0.010]	[0.003]	[0.008]	[0.012]	[0.013]	[0.011]	[0.003]	[0.009]	[0.015]
ln (n of employees)	-0.266***	-0.271***	-0.275***	-0.281***	-0.284***	-0.265***	-0.271***	-0.276***	-0.281***	-0.284***
	[0.009]	[0.003]	[0.001]	[0.003]	[0.007]	[0.008]	[0.003]	[0.001]	[0.003]	[0.008]
other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	9.948***	10.402***	10.395***	10.550***	10.701***	9.955***	10.397***	10.381***	10.516***	10.677***
	[0.141]	[0.075]	[0.015]	[0.087]	[0.154]	[0.14]	[0.073]	[0.014]	[0.074]	[0.188]
Obs	3519	3519	3519	3519	3519	3518	3518	3518	3518	3518

Source: RIL 2010-2014.

Note: Other control variables: managers' educational level, family ownership, employment composition (gender, age, education contractual arrangment,ecc), gross workers turnover, product innovation, process innovation, R&D activities, (ln of) physical capital per employees, nuts_2 regions, sector of activity and firms' age. Robust (boostrapped) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

6. Discussion and conclusions

This work investigates the joint dynamics of Italian companies' training activities, on one side; and labor productivity on the other, on the grounds of a representative panel of Italian firms observed between 2010 and 2014 – and it contributes to two distinct and relevant debates. The first one regards what elsewhere (Dosi et al., 2012) we have called Italian neo-dualism, that is an *expanding* heterogeneity in the supports of the firm-level distributions irrespectively of the level of disaggregation. In Dosi et al. 2012 we were detecting such a phenomenon in presence of the Euro-shock: the Italian entry into the Euro system, one could have expected, should have increased the selective pressure of competition thus reducing the width of the left tail in the productivity distributions. The contrary indeed happened. In this work we are able to consider another major shock, namely the 2008 crisis. Did it weed out less efficient firms? The evidence, again, suggests that it did not, further widening the degrees of heterogeneity across firms.

How does training of the workforce links with productivity levels and dynamics? This is the second contribution of this work. The overall picture suggests a positive association between training intensities and productivity levels. However, such link looses significance with disaggregation. In particular, it does not apply to the manufacturing sector as a whole and neither it does to industries such as the mechanical one within it. Our data-bank allows to distinguish the sources of financing of training itself – whether external or at least partly internal to the firm. Quantile-based analysis reveals here that training is positively associated with productivity levels in the upper quantiles of the conditional productivity distribution only when it is at least partly firm-financed.

In terms of firm sizes, the disaggregation between small (less than 50 employees) firms and medium large reveals broadly similar patterns. However, the link between training intensity and productivity holds across all quantiles of the productivity distribution, while somewhat puzzling, a positive effect of own-financed training appears only for the bottom and top quantiles.

Dynamics analysis reveals other interesting and striking properties. First, all tests of the relationships between initial training intensities and productivity changes turn out to be non-significant over all quantiles. And so do first-difference analysis. The mild exception is own-financed training, limitedly to the upper quantiles of the productivity distribution, but also that association disappears when disaggregating between manufacturing and services.

There are few important messages which come out of this study. First, the persistence and possibly widening neo-dualism in terms of productivities in the Italian production does not have its roots in different training intensities of different firms, and dynamically, the training does not contribute to reduce it. Second, when training turns out to significantly correlate with productivity, it does especially within the upper quantiles of the productivity distribution, and especially, when at least part of it is self-financed by the firm. The picture which seems to emerge is that formal training might be effective only when it comes together with an ensemble of idiosyncratic firms characteristics. In that, informal, on- the job, firm-specific forms of training, which we are unable to capture, might play a more greater role. All this is well in tune with a capability-based theory of the firm (Dosi et al., 2001, Helfat et al., 2009). And it is quite at odds with theories which see the firm as a production function – in which training is either as input as such or a factor-enhanced variable (of e.g. "human capital").

Finally, form a normative point of view, our findings further debunk the myth that active labour market policies – of which training is of course a part – are the panacea for both employment and productivity. We argue against that in Dosi et al., 2018 on the grounds of a formal model: here the Italian evidence supports this negative view at least with respect to productivity.

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