Exports and Labor Skills: The Role of Training

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ABSTRACT

An increasing number of analyses show that firms that are engaged in international trade have superior labor capabilities than their counterparts serving only the domestic market. One way to improve labor skills is by training current employees. There is, however, no empirical evidence showing how the exports of a firm respond to training programs. Using firm level data from Chile this study examines the impact of training employees on the firm's export status. Based on a matching difference-in-differences estimator the results show that training employees can substantially increase the probability of becoming an exporter. Additional results provide details on how the effects differ by labor type, by the intensity of the labor training and whether there are cumulative effects over time. The analysis also sheds light on factors that complement training. All these issues are important to assess under what conditions labor training programs might work best with respect to trade outcomes.

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Key words: exports, training, skills

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1 Introduction

A growing body of empirical analyses shows that firms that are engaged in international trade tend to have superior capabilities relative to their counterparts serving only the domestic market. These superior capabilities are typically expressed in higher productivity levels (i.e. Bernard and Jensen, 1999; Pavcnik, 2002; Alvarez and Lopez, 2005; Trefler, 2004; Fernandes, 2007; Lileeva and Trefler, 2010; Topalova and Khandelwal, 2011; De Locker, 2011; Eslava et al., 2013).

Some studies have looked specifically at how labor capabilities differ between exporters and non-exporters and usually find higher skill levels in the first group (Verhoogen, 2008; Brambilla, Lederman and Porto, 2012, 2015). This could be because foreign consumers value quality and skills are required to improve quality, as in Verhoogen (2008) or because the process of exporting per se requires certain skills that are not important to sell similar goods in the domestic market, as in Matsuyama (2007).

Further evidence on the importance of skills in export outcomes has been found, for example, in studies that examine the role of the firm's managers. For instance, Giordano and Opromolla (2014) find that the export experience that managers acquired in previous firms substantially impacts the export performance of their current firms. Bloom, Manova, Sun, Van Reenen and Yu (2016) find that firms with better managerial practices exhibit better export outcomes.

One potential way to improve labor skills in a firm is by training the current employees. A handful of studies have examined the impact of training on productivity and wages but not on exports. For instance, Dearden, Reed and Van Reenen (2006) find that an increase in the proportion of workers in an industry who receive training leads to an increase in the industry's value added per worker and in the average wages. Using firm level data Konings and Vanormelingen (2015) find that trained workers exhibit a productivity premium and a wage premium of 23% and 12%, respectively. Flores-Lima, González-Velosa and Rosas-Shady (2014) find a positive association between the share of trained workers and the firm's total factor productivity. These findings are suggestive of the potential effects of training on the exports of the firm. To our knowledge, however, there are not empirical analyses showing directly how exports respond to training programs. This paper seeks to fill this gap in the literature.

We employ firm level data from Chile to examine the impact of labor training on the firm's export status. The empirical analysis relies on a matching difference-in-differences estimator that compares the before and after change in export status of firms that trained employees with that of matched firms that did not train employees. The results show that training employees increases the probability of becoming an exporter in about 9 percentage points. This implies that training at least double the average rate of entry into export markets. The results also show the existence of cumulative effects. That is, firms that promote training in more than one year are more likely to become exporters than firms that foster training only one year. We find that intensity matters in terms of the amount of resources invested in training. That is, the larger the amount spent on training as a percentage of the firm's total sales, the larger the effects. We find no statistical difference with respect training by labor type. In particular, we find no difference in the results between the firms that trained proportionally more production workers relative to those that trained proportionally more non-production workers. Nevertheless, we found that the impact increases with the level of education for both types of employees. Finally, the results suggest the existence of complementary effects. In particular, we consider the existence of specialized software available in the firm as a proxy of assets that complement the level of human capital. The results show that the effects of training are larger when these complementary assets are present in the firm.

The evidence in this study provides insights about the conditions in which labor training programs are more likely to work to foster trade outcomes, particularly the entry into export markets.

The study is related to two different literatures. By presenting new evidence on the specific role of training on export status, the analysis contributes to a growing literature that shows the importance of skill acquisition to the exports of the firm (Brambilla et al., 2012, 2015; Verhoogen, 2008; Matsuyama, 2007; Giordano and Opromolla, 2014; Bloom, Manova, Sun, Van Reenen and Yu, 2016). The study also relates to the group of analyses that estimate the impact of training programs on various firm-level outcomes like productivity and wages (Konings and Vanormelingen, 2015; Flores-Lima, González-Velosa and Rosas-Shady, 2014) and extends it to incorporate the impact on exports.

The rest of the paper is divided as follows. Section 2 introduces the empirical methodology that we employ. This section also describes the dataset and provides a first look at its most salient features. Section 3 discusses the results while section 4 concludes.

2 Empirical methodology and data description

We employ a matching difference-in-differences estimator to examine the effect of training on export status, that is, whether the firm exports any good. The matching consists of pairing each firm that train employees with the more similar members of the group of firms that do not train employees while training is determined by a series of observable characteristics. Below we briefly review the literature on the determinants of training to guide the selection of these characteristics.

Matching assumes that export status is independent of labor training conditional on the observable variables. In other words, after controlling for observed firm-level characteristics correlating with labor training there should be no systemic difference in export status between the firms that trained employees and the firms that did not train. But this assumption can be restrictive if there are data limitations. Hence, matching can be combined with a difference-in-differences method to account for time-invariant differences that could exist even after conditioning on observables. The matching difference-in-differences estimator compares the before and after change in export status of firms that trained employees with that of matched firms that did not train employees. This is the estimator that we employ. More formally:

$$DD = \{E[Y_1^T - Y_0^T | T = 1, P(X)] - E[Y_1^C - Y_0^C | T = 0, P(X)]\} \quad (1)$$

where Y_0^T and Y_1^T represent the export status in periods 0 and 1 respectively of the firms that trained employees, Y_0^C and Y_1^C represent the export status in periods 0 and 1 respectively of the firms that did not train employees and $P(X)$ is a propensity score which is a function of the observed covariates X. The propensity score is used to match the firms that trained and did not train employees based on the observables. In the next section we show results with alternative matching methods that do not require calculating the propensity score. We now discuss the group of variables that should be included in the X vector.

The Determinants of Training

The literature on the determinants of labor training is broad. Some studies have focused on modeling certain aspects of the investment in training while others have examined empirically the role of potential driving forces that can be observed. Reviewing this literature in detail is beyond the scope of this paper.[1] Instead, we identify here some of the factors that seem to be common in many of the studies.

At the firm level, training differences have been observed across sectors (Bassanini et al., 2005). Our dataset does not provide an industry classification at high levels of disaggregation. Nevertheless, firms are classified according to broad economic categories: agriculture- agroindustry, mining and manufactures. We use these broad categories to control for differences in training across sectors.

Firm size seems to matter. In general, larger firms tend to provide more training than the medium-size firms and those tend to provide more training than the small firms (Bassanini et al., 2005; Steffes and Warnke, 2014). We control for size using the number of employees in the firm.

[1] Arulampalam et al. (2004); Bassanini et al. (2005); Asplund (2005) and Hansson (2008) provide extensive reviews of this literature.

The education of the workers is another potential driving factor. In general, the literature finds that formal schooling is positively associated with training. For instance, high-skilled employees participate more often in training across European countries (Brunello, 2001; Arulampalam et al., 2004). The positive association between formal schooling and training seems to hold across different occupations (Oosterbeek, 1998; Pischke, 2001; Bassanini et al., 2005) It could be argued that the educational level matters because firms might prefer to provide training to the most able employees, for example because they are faster learners (Knonings and Vanormelingen, 2015). In our analysis we control for the educational level of the employee for all the occupations.

We mentioned above the existence of a positive association between management and exports, and in particular between the previous experience of managers in other firms and the export performance of their current firms (Giordano and Opromolla, 2014). It is possible that the experience of the manager exerts an influence on the level of training, for example, because the manager deems that training is critical for the export performance of the company. We observe the manager's experience in terms of the numbers of years that the individual has been in the current activity (including the number of years in other companies). We include this variable to control for differences in management experience. We also include the manager's educational level.

Training might be influenced by other firms, for example within a supply chain. Being part of a production network, for instance, has been associated with knowledge spillovers and learning. Evidence of successful cases of learning within the chain can be found in many sectors, such as apparel (Gereffi, 1999), motorcycles (Fujita, 2011) or the computer industry (Kawakami, 2011). In some cases this learning has occurred through training courses offered directly by a company to its suppliers (Caffaggi et al., 2012). We have information on whether the firm is a supplier of a company that itself is an exporter. We use this information to capture the role of linkages behind training.

Related to this, many companies commit to hold quality certifications for various reasons, for instance because it is required by their buyers. Holding a quality certification typically means meeting certain standards in various areas including standards in management and human resources. For example, in the ISO 9001 certification, firms are required to determine training needs, provide training to meet the needs and maintain training records. Holding a quality certification has indeed been found to be positively related to the provision of training (Flores-Lima, González-Velosa and Rosas-Shady, 2014). In our analysis we include a variable that indicates whether the firm holds a quality certification.

Also related to the previous two factors is the role of foreign capital. Many multinational companies have their own standards that apply to their affiliates in other countries. These standards might differ from those followed by domestic firms and they might deal on issues related to skills and labor training. In the analysis, we include a variable that indicates whether the firm is part of a multinational company.

In Chile, there is a battery of government programs designed to assist the firms in various aspects, like support for workers capacitation through tax incentives. Other programs include assistance for export promotion by co-financing the costs of trade mission fairs or support for innovation projects via matching grants. We can include a variable that controls for whether the firm received government support. Note, however, that we do not observe whether the support was linked specifically to training activities.

Finally, we also control for differences in the productivity level of the firm. It has been argued, for example, that a firm can experience a positive productivity shock (generated for example by an introduction of a new technology) and this can chance the decisions regarding the training efforts (Zwick, 2006). While we cannot estimate total factor productivity directly we can measure labor productivity.

Admittedly, there might be other factors that could also drive labor training. For example, a number of papers have examined the role of gender in training participation. While some studies have found positive training rates for women compared to men (Bassanini et al., 2005) others have found similar training rates (Albert et al., 2010). Unfortunately, our dataset does not provide information about labor training by gender. Accordingly, it is possible that this as well as other factors might impact training participation in a way that we cannot control explicitly. To the extent that these factors remain relatively constant over time, their effects should be captured by the difference-in-differences approach that we described above.

It is worth noting that addressing the relationship between labor training and exports is likely to encounter problems of endogeneity. That is, firms that provide training to their employees might be able to spur their exports but firms that already serve foreign markets might also be incentivized to continue or increase the provision of training. In order to alleviate the endogeneity problem we focus on the export status of the firm. That is, we start from the group of firms that do not export any good and evaluate whether training makes them start exporting at some point in the future. Focusing on the export status is likely to be reduced considerably the endogeneity problem.

Data Description

We use firm-level data from Chile. In particular, we employ the *Encuesta Longitudinal a Empresas*, conducted by the Chilean statistics agency, the *Instituto Nacional de Estadísticas* (INE) and the Ministry of Economy. This is a survey of Chilean firms covering all the sectors of the economy with detailed information on firm characteristics, such as sales, employment, and investment. The sample design is probabilistic and stratified by sector and size using sales. The sample is statistically representative at the national level by economic sector. In our analysis we exclude the service sector because of our focus on exports.

The survey has been conducted in three years, 2007, 2009 and 2013. We constructed two panels. One panel is based on the firms that appeared in both years 2007 and 2009. The second panel includes the firms that appeared in both years 2009 and 2013. For each panel we follow the same procedure: we consider only the firms that did not export the first year of the panel. From this sample we match the firms that provided training that year with those that did not provide training. Then we observe which firms had positive exports the second year of the panel. This is the essence of our matching difference-in-difference approach. Note that we estimate the impact of training on export status separately for each panel. We also present estimates when we pool both panels.

In principle, we could have merged the three surveys to examine more elaborated schemes. For instance, we could have examined the effect of training on the export status of the firm during the second year of the panel and then compare this effect with the impact on the third year. Unfortunately, when we construct the panel to include the firms that appear in the three years of the survey and also impose the condition that the firms have to be non-exporters the first year of the panel we end up with a sample that is too small for a meaningful analysis.

Once the service sector is excluded, the number of firms for the years 2007, 2009 and 2013 are 2385, 1905 and 1674, respectively. The number of firms that appeared in both years 2007 and 2009 is 645, while the number of firms that appeared in both years 2009 and 2013 is 873.

One potential concern is that the firms that appear in both years of each panel are mostly large establishments because they might be the ones that are consistently surveyed. If this is the case, we might have a sample that is biased. Table 1 shows the distributions of the firms according to size.[2] Panel A compares years 2007 and 2009 while Panel B compares years 2009 and 2013. The first two columns of Panel A show the distributions for the years 2007 and 2009 while the third column shows the distribution for the firms that appear in both years. Finally, the fourth column shows the distribution of the firms that appear in both years and that did not export in 2007. It can be seen that the distributions in 2007 and 2009 differ slightly. In particular, the micro firms were overrepresented in 2007, a situation that was corrected in 2009. Note that the distribution of the merge is very similar to the distribution in 2009. This indicates that the sample where we draw the firms for our analysis is not biased towards the large firms. Finally, the fourth column shows the distribution of the sample that we employ. Clearly, this sample is not biased towards the large firms either; if anything there is a slight bias towards the small firms. This bias, however,

[2] The size categories are developed by INE according to sales

is expected because in this sample we are restricted to firms that did not export any good in 2007. Panel B of Table 1 presents the comparison for the second panel, that is, for years 2009 and 2013. Once again the results show that the sample is not biased towards the large firms.

Before moving to the empirical estimation, we conclude this section by taking a first look of the most salient features of the dataset. Table 2 provides some summary statistics for both panels. The top part of the table presents the statistics for the first panel. In 2007, for example, 39.2% of the firms provided training to their employees. Regarding the export status, in 2009, 5.9% of the firms become exporters.

The table also presents the covariates of vector X by training status. The results in general support the intuition described above: firms that provided training tend to be larger. In particular, firms that provided training have on average 221 employees while the firms that did not provide training have 15 employees. Having foreign direct investment and holding quality certifications also appear to be positively related to training. Firms in the treatment group (those that provided training) have on average a 5.6% share of foreign capital versus 0.3% in the control group (firms that did not provide training). 57.2% of the firms that provided training hold a quality certification versus 15.7% in the control group.

On average, 65.8% of non-production workers completed technical education or a higher degree in the group of firms that provided training. This share is 34.1% in the control group. Similarly, 63.5% of production workers completed secondary education among the firms that provided training versus 56.7% in the control group. The experience of the manager does not seem to differ between the treated and the control groups, with roughly 24 years of experience on average for both samples. The education of the manager is measured with a categorical variable that goes from 1 (no education) to 8 (graduate school completed). On average, the firms that trained employees have more educated managers. Regarding public programs, 33.5% of the firms in the treatment group received government support compared only 5.9% in the control group. Finally, the firms that trained workers exhibit 0.3 log points higher labor productivity than the firms that did not train workers. The last row of the top panel shows the export status in 2009 for the treatment and control groups. While 11.6% of the firms that provided training in 2007 became exporters in 2009, this share is 2.2% for the control group.

Panel B of table 2 reports summary statistics for the second panel. In general, the results are similar to those in Panel A. The next section presents the treatment effect estimations that formally test the effect of training on export status.

3 Estimation Results

Table 3 shows results of the difference-in-differences estimation when we employ 3 alternative methods: the propensity-score matching (PSM), the nearest-neighbor matching (NNM) and the inverse-probability weighting estimator (IPW). In all the cases the table shows the average treatment effect on firms that provided training. The estimates suggest that, on average, training employees has an impact on the export status of the firm. The effects are positive and significant for both panels and across the alternative methods. The last two rows in Table 3 shows an overidentification test for covariate balance corresponding to the IPW estimator. We cannot reject the null hypothesis of covariance balance. In other words, after controlling for observable characteristics, it is as if non-exporters had been randomly assigned to control and treatment groups.

One advantage of the NNM estimator is that it allows us to present estimates not only for each panel separately but also for the pool of both panels. Pooling both panels essentially allows us to have a larger sample to estimate the treatment effect. By controlling an exact matching by year, the NNM guarantees that even though we are pooling both panels the matching between treatment and control groups takes place within firms of the same year.[3] The results are presented in Table 4 with alternative number of matches per observation. In all the cases, the estimates suggest that training employees has a positive and significant impact on the export status of the firm. For instance, the result for the pool panel in the last row of the table suggests that training employees increases the export entry rate by 9.5 percentage points. This is a significant effect. Note, for example, that the average export entry rate for the control group in 2013 is 6.9% (Table 2); therefore, the effect implies an increase of 1.4 times in the export entry rate as a result of the labor training.

Beyond the average effects

The results in Tables 3 and 4 indicate that labor training has a significant impact on the probability that a firm becomes an exporter. However, it would be interesting to know not only the extent to which training impacts export status but also whether there are heterogeneous effects across different dimensions. For instance, it could be important to examine whether the effects differ across labor types or whether training is complementary to other factors. Providing more nuances beyond the average effects could be especially informative for policy design.

[3] That is, the treatment group of 2007 is matched with the control group of 2007, while the treatment group of 2009 is matched with the control group of 2009

In Table 5 we analyze the potential existence of cumulative effects. In all the estimations that we have presented so far the comparison has been between the firms that provided training during the first year of the panel, irrespective of whether training was provided during the second year, with the firms that never provided training (control group). The treatment group, however, can be separated into two groups: the firms that provided training only the first year of the panel and the firms that provided training in both years. We can match each of these treatment groups separately with the same control group and estimate two different effects. The results are shown in Table 5 for the case when we use the pool panel. Training appears to have a positive effect on the export entry rate in both cases; however, the results are only significant in the case where firms provide training in both years. This suggests that training is likely to be more effective when it is viewed as a continuous process rather than as a one-time event.

In Table 6 we explore the role of the intensity in training. We explore two alternative measures of intensity. One measure is based on the number of employees trained and the other one is based on the amount of resources devoted to training. Rows 1 and 2 present the results related to the first measure. In particular, we calculate the share of employees that were trained in all the firms that provided training. Then we separate these firms into two groups based on whether the share of the firm is above or below the median share. Row 1 presents the result when we compare with the control group the group of firms that exhibit shares above the median. Row 2 presents the result when we compare the group of firms with shares below the median. The treatment effect is very similar in both cases. In rows 3 and 4 we explore our second measure of intensity in training based on expenditures. Specifically, we separate the groups based on the share of expenditures in training relative to total sales. According to the results, the group of firms with shares above the median exhibits an effect that is twice as high relative to the group with shares below the median.

In Table 7 we explore whether training by occupation type makes any different. We can separate employees and their training in two groups: production and non-production employees. Most firms that train employees report training both types; therefore, we examine this issue in the following way. First, for each firm, we calculate the share of production workers that are trained as the ratio of production workers trained to the total number of production workers in the firm. Similarly, we calculate the share of non-production workers that are trained as the ratio of non-production workers trained to the total number of non-production workers in the firm. Then, for each firm, we calculate whether the share of production workers trained is larger or smaller than the share of non-production employees. Table 7 presents the results. In row 1 we show the results when we compare with the control group the group of firms that exhibit the share of trained production workers larger than that of non-production employees. Row 2 presents the case when the share of non-production workers is larger. The results are very similar between the two groups, suggesting that training is important in both types of occupations.

Table 8 analyses whether the effects of training are heterogeneous with respect to educational levels. Ideally, we would like to observe the level of education of the employees that received training versus those that did not receive training. However, we only observe the overall level of education of all the employees of the firm, by occupational type. Based on this, we can separate the firms that provided training into two groups: those with an overall level of education that is above the median (among all the firms that provided training) and those with an overall level of education that is below the median. We do this separately for the non-production employees and for the production employees. Row 1 of table 8 shows the result for the group of firms that exhibit non-production employees with educational levels above the median. Row 2 presents the case when the educational levels of the non-production employees are below the median. The impact of training seems to be larger for the group of firms with more educated non-production employees. Rows 3 and 4 repeat the exercise when we separate the treatment group according to the median value of the production worker's education. Once again, the impact of training on export status is found to be larger among the group of firms that have more educated production workers. The results indicate that the impact of training on export status increases with the level of education of the employee.

Finally, we explore the role of complementary capital to training. In particular, we would like to assess whether the effects of training can be leveraged with other types of capital available in the firm. That is, whether training is more fruitful if there are other assets that potentiate its effects. We can conjecture, for example, that training can induce larger effects when it is matched with adequate machinery or suitable technology. To analyze this issue, we consider the existence of specialized software available in the firm as a proxy of assets that complement the level of human capital. More specifically, we separate the firms that train employees into two groups: those that have specialized software and those that do not. Table 9 presents the results. The evidence provides support to the existence of complementary capital to training. When compared to the control group, the effect of training among firms with specialized software is more than three times higher relative to the firms without specialized software. In fact, the impact for the firms without specialized software is not statistically significant.

4 Concluding Remarks

A growing body of analyses in international trade shows that firms that sell their products in foreign markets tend to have superior labor capabilities than firms that target only the domestic market. This evidence tend to support trade models in which skills are important either to the process of exporting per se or to meet the quality valuation of consumers in other countries. Firms typically engage in training to improve labor skills. In this study we examine directly how the exports of a firm respond to training programs.

Using a matching difference-in-differences estimator we compare the before and after change in export status of firms that trained employees with that of matched firms that did not train employees. We find that training employees has a significant impact on the probability that a firm becomes an exporter. The evidence suggests that the average export entry rate of a firm can double as the result of training.

Our analysis goes beyond the average effects and presents also estimations that provide interesting insights on the conditions in which labor training programs are more likely to foster the entry into foreign markets. For example, training is likely to be more effective when it is viewed as a continuous process rather than as a one-time event. The intensity of training also matters. For instance, the larger the share of expenditures on training the larger seems to be the impacts. Another important factor is the role of education. The effect of training increases with the level of education of the employees suggesting that training and formal education are complements. Finally, the results suggest that the impact of training can be leveraged with other assets available in the firm like adequate machinery or suitable technology/ software.

While this study focuses on the impact of training on the export status of the firm, there is potentially a much broader research agenda that could examine the influence of training on other export margins of the firm.

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Table 1: Size distributions

Panel A	2007	2009	Merge	Merge & non-exporters in 2007
Micro	38%	13%	9%	10%
Small	30%	37%	35%	45%
Medium	15%	22%	22%	25%
Large	17%	28%	33%	19%
Number of Firms	2385	1905	645	469

Panel B	2009	2013	Merge	Merge & non-exporters in 2013
Micro	13%	8%	7%	9%
Small	37%	28%	27%	37%
Medium	22%	17%	22%	26%
Large	28%	48%	44%	28%
Number of Firms	1905	1905	873	604

Table 2: Summary Statistics

Panel A (2007 vs 2009)		
Firms with employees that received training in 2007	39.2%	
Firms with positive exports in 2009	5.9%	

	Training = 0	Training = 1
Firm characteristics in 2007:		
Employment	15	221
Foreign share	0.3%	5.6%
Certification	15.7%	57.2%
Education of non-production employees	34.1%	65.8%
Education of production employees	56.7%	63.5%
Experience of manager	24.2	24.5
Education of manager	4.7	6.3
Government support	5.9%	33.5%
Labor productivity	9.9	10.2
Firms with positive exports in 2009	2.2%	11.6%

Panel B (2009 vs 2013)		
Firms with employees that received training in 2009	34.1%	
Firms with positive exports in 2013	11.9%	

	Training = 0	Training = 1
Firm characteristics in 2009:		
Employment	26	468
Foreign share	0.5%	11.2%
Certification	16.7%	62.9%
Education of non-production employees	30.2%	49.4%
Education of production employees	51.5%	61.5%
Experience of manager	24.2	21.5
Education of manager	5.0	6.4
Government support	6.4%	36.6%
Labor productivity	9.9	10.1
Firms with positive exports in 2013	6.9%	21.5%

Note: Employment refers to the number of total employees of the firm; Foreign share refers to the share of foreign capital; Certification refers to whether the firm holds a quality certification; Education of non-production employees is measured as the percentage of non-production employees with technical education or higher completed; Education of production employees is measured as the percentage of production employees with secondary education completed; Experience of the manager is measured in number of years; Education of the manager is measure as a categorical variable that goes from 1 (no education) to 8 (graduate school completed); Government support refers to whether the firm participated in a government assistance program, and Labor productivity is the log of the labor productivity of the firm

Table 3: Average treatment effects on firms that trained employees

	Panel A	Panel B
Propensity-score matching (PSM)	0.086**	0.169***
	(0.037)	(0.039)
Nearest-neighbor matching (NNM)	0.064**	0.092*
	(0.032)	(0.051)
Inverse-probability weighting (IPW)	0.064*	0.153***
	(0.036)	(0.037)
Overidentification test of covariance balance		
chi2 (13)	3.28	1.39
Prob > chi2	0.92	0.98

Note: The table report estimates of average effects of training on firms that trained employees using the difference-in-differences procedure under alternative estimators: propensity-score matching, nearest-neighbor matching and inverse-probability weighting. A one match per observation was employed in the PSM and NNM estimators.

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 4: Alternative nearest-neighbor matching specifications

	Panel A	Panel B	Pool
NNM, matches per observation (1)	0.064**	0.092*	0.096***
	(0.032)	(0.051)	(0.029)
NNM, matches per observation (2)	0.063**	0.098**	0.089***
	(0.031)	(0.045)	(0.026)
NNM, matches per observation (3)	0.071**	0.109***	0.095***
	(0.029)	(0.041)	(0.024)
NNM, matches per observation (4)	0.078***	0.116***	0.095***
	(0.028)	(0.039)	(0.023)

Note: The table report estimates of average effect of training on firms that trained employees using the difference-in-differences procedure with alternative number of matches per observation for the nearest-neighbor matching estimator

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 5: Cumulative effects

	Pool panel
1. Firms that trained only the first year of the panel	0.043
	(0.029)
2. Firms that trained both years of the panel	0.177***
	(0.030)

Note: The table report estimates of the average effect of training on firms that trained employees using the difference-in-differences procedure with the nearest-neighbor matching estimator (with 4 matches per observation). Each row report a treatment effect from comparing the treatment group described in the row with the control group consisting on firms that never provided training to employees

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 6: Intensity in training

	Pool panel
1. Share of trained employees above the median	0.089**
	(0.036)
2. Share of trained employees below the median	0.090***
	(0.027)
3. Share of expenditures in training above the median	0.154***
	(0.039)
4. Share of expenditures in training above the median	0.079***
	(0.029)

Note: The table report estimates of the average effect of training on firms that trained employees using the difference-in-differences procedure with the nearest-neighbor matching estimator (with 4 matches per observation). Each row report a treatment effect from comparing the treatment group described in the row with the control group consisting on firms that never provided training to employees

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 7: Training by occupational type

	Pool panel
1. Share of trained production workers larger than share of trained non-production workers	0.091***
	(0.030)
2. Share of trained production workers smaller than share of trained non-production workers	0.089***
	(0.031)

Note: The table report estimates of the average effect of training on firms that trained employees using the difference-in-differences procedure with the nearest-neighbor matching estimator (with 4 matches per observation). Each row report a treatment effect from comparing the treatment group described in the row with the control group consisting on firms that never provided training to employees

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 8: Training and education

	Pool panel
1. Education of non-production employees above the median	0.108***
	(0.031)
2. Education of non-production employees below the median	0.076***
	(0.026)
3. Education of production employees above the median	0.109***
	(0.030)
4. Education of production employees below the median	0.082***
	(0.026)

Note: The table report estimates of the average effect of training on firms that trained employees using the difference-in-differences procedure with the nearest-neighbor matching estimator (with 4 matches per observation). Each row report a treatment effect from comparing the treatment group described in the row with the control group consisting on firms that never provided training to employees

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 9: Complementary capital

	Pool panel
1. Firms with specialized software	0.127***
	(0.030)
2. Firms without specialized software	0.034
	(0.029)

Note: The table report estimates of the average effect of training on firms that trained employees using the difference-in-differences procedure with the nearest-neighbor matching estimator (with 4 matches per observation). Each row report a treatment effect from comparing the treatment group described in the row with the control group consisting on firms that never provided training to employees

*** ; ** ; * significant at the 1%, 5% and 10% level respectively