Learning by Exporting: Evidence of Learning from American Manufacturing Industries.*

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Abstract

There is vast literature on the effects of exports on productivity through learning by exporting. However, the direct effect of exports on learning through skill acquisition is as important. This paper examines the link between exporting and learning activities that take place by looking at one particular form of learning: the training of workers. Using data from the United States NLSY79 survey and combining it with U.S. industry level data on exports, we examine the relationship between the training and schooling opportunities made available to workers and the total volume of exports from the specific industry in which the individual was employed across 75 manufacturing industries in the period of 1988-2000. The results show that exporting is positively and significantly associated with learning, but the estimated effect is decreasing with the individual level of skill. Consistent with learning by exporting hypothesis, the results suggest that a learning process indeed follows an increase in exporting activities and that less skilled workers (who might have more to learn in terms of productive efficiency or new techniques) are precisely the ones who experience greater learning.

Keywords: Training; Learning by Exporting.
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1 Introduction

There is ample evidence of a positive correlation between a firm's productivity and its exporting activities (Bernard and Jensen (1999)), but no consensus in the literature as to why this is the case. One leading explanation is that more productive firms self-select into exporting, as they are more likely to recuperate the sunk costs associated with selling to foreign markets and to generate profits (Clerides, Lach and Tybout (1998), Delgado, Farinas and Ruano (2002)). Another explanation is that firms learn from their exporting experiences and become more productive as the result (Blalock and Gertler (2004)). This second explanation is known as the Learning-by-Exporting hypothesis (LBE) and while its influence over economic policy has been substantial (World Bank (1998)), the support it has received from actual empirical evidence has not been as strong (Clerides et al. (1998), Keller (2004), Wagner (2007)).[1]

Up to this point, however, the empirical literature on LBE has focused almost exclusively on the causal relationship between exporting and productivity gains (Lopez (2005), Wagner (2007, 2012), Keller (2010)), but has neglected to examine how exporting affects the learning process itself. Learning, of course, is defined vaguely and may take different forms. Among other things, it may take the form of investments in specialized equipment, adjustments in management practices, or updates in the skills or techniques employed by workers. Yet, if exporting leads to increased productivity as the result of some kind of learning (as argued by LBE supporters), then one should be able to find evidence of a positive correlation between exporting and the learning-related decisions made by firms.

This paper examines evidence regarding one of those decisions: the decision to pay for the training and schooling of workers. Although not the only learning mechanism firms may employ to increase productive efficiency, on-the-job training and schooling are certainly the

[1] Later research using rich micro datasets, however, does provide evidence in support of the learning-by-exporting hypothesis (Keller 2010, Wagner 2012, and de Loecker 2013).

most important channels through which workers acquire new skills (Méndez and Sepúlveda (2012)) and are arguably a key part of the LBE process. For investments in the human capital of workers are likely to complement any kind of learning that is triggered by the firms' participation in international trade.

In order to conduct the analysis, we collect data from the National Longitudinal Survey of Youth of 1979 (NLSY79). Each year, individual NLSY79 respondents were asked whether or not "training opportunities, including tuition reimbursement" were made available to them by their employers. They were also asked about the type of industry their employer belonged to; which allowed us to merge the data with yearly, industry-level records of exporting volumes obtained from an updated version of Schott (2008). We then examine the empirical relationship between the exporting volumes of particular industries and the learning opportunities made available to workers in those industries, using a series of linear and non-linear regressions that include several firm, individual, and industry controls, as well as sets of time, industry, occupation and individual fixed effects.

The results obtained lend support to the LBE hypothesis, but suggest the relationship between exporting and learning is highly heterogenous across individuals with different skills. For individuals with low levels of education (who might be more directly involved with the actual manufacturing process and might benefit most from additional skill accumulation), we find exporting volumes are indeed positively and significantly associated with the learning opportunities made available to them. For individuals with college-level education and above, however, we find this correlation to be no different than zero and even negative at very high levels of education.

Finally, in order to account for potential simultaneity biases which may arise if the learning opportunities made available to workers were to simultaneously affect the employer's probability of becoming an exporter (a possibility raised by Blyde (2016)), we conduct a series of instrumental variable regressions using lagged exporting volumes as instruments.

The results obtained remained unaltered. Using a standard Hausman test, we cannot reject the hypothesis that exports are exogenous in the model.

This paper complements a small body of literature that documents the effects of exporting on the decisions firms make in order to learn and become more productive. Bastos, Silva and Proenca (2016), for example, study firm-level data from Brazil and find that export participation tends to increase the share of workers who receive job training in the technical upgrading category. Bustos (2011), in turn, studied the impact of regional trade agreements on Argentinean firms and showed that firms facing higher reductions in tariffs increased investment in technologies faster. While yet others like Brambilla, Lederman and Porto (2012) use Argentine data and find that firms that export to high-income countries use workers with greater skills than firms that do not export at all. The paper also complements a set of recent papers that show firms become more productive after they enter the export market (De Loecker (2007, 2013), Wagner (2012)).

Other related studies have studied how employer-provided training is affected by the extent of foreign competition in domestic markets. Both, Li (2010) and Kosteas (2017), used NLSY79 data, as we do here, and find foreign competition is negatively correlated with training provision and overall training enrollment, respectively. Their results are consistent with the ones we report in this paper, for the extent of foreign competition in domestic markets tends to be lower for those industries with high exporting volumes. To our knowledge, however, there are no other empirical papers available in the literature that directly examine the link between exports and training provision in specific.

The remainder of the paper is organized as follows. The next section presents the data sources and data construction methodology. Section 3 presents the empirical analysis and results. Robustness checks are discussed in section 4. Finally, section 5 concludes.

2 The Data

The necessary data to conduct the study was obtained from the National Longitudinal Survey of Youth (NLSY79). The NLSY79 follows individuals who were 14 to 22 years old in 1979, with annual interviews until 1994, and bi-annual interviews from 1996 onward. For each survey year, individual NLSY79 respondents were asked whether or not ”training opportunities, including tuition reimbursement” were made available to them by their employers. This is the main variable of interest we intend to study. We refer to this variable as the workers' “learning opportunities”, or “learning opportunities available”. Unfortunately, the NLSY79 does not collect any information regarding the employers exporting activity, so we are unable to conduct any firm-level analysis.

Survey respondents in the NLSY79 were also asked to report the industry in which they were employed, as well as the start and end dates of their employment. We use the industries' three-digit codes to merge the NLSY data with industry-level information regarding the industry's total volume of exports, total factor productivity, capital per worker, and non-production worker wage share, for each year. Data on exporting volumes was obtained from an updated version of Schott (2008) available on Peter Schott's website which has data on 4-digit US exports in SIC87 industrial classification for the years of 1972-2005. Using a concordance from NBER-CES Manufacturing Industry Database (Becker, Gray and Marvakov, 2016), SIC87 industries are concorded to SIC72. Furthermore, SIC72 codes are manually matched with 3-digit NLSY79 codes based on documentation from the US Census Bureau. Data on total factor productivity (TFP), capital per worker, and non-production wage share, was obtained from the NBER Manufacturing Industry Database (Becker, Gray and Marvakov, 2016) and similarly matched with the 3-digit NLSY79 codes.

In addition, we collected information on the individual's age, sex, job tenure, race, and education (measured as the highest grade completed), as well as information on the

Table 1: Summary Statistics

	Mean	S.D.	Min	Max	Obsvs
Learning opportunities	0.53	0.50	0.00	1.00	11402
Exports	1.02	1.56	0.00	9.67	11402
Imports	1.50	2.62	0.00	16.78	11402
Education	12.61	2.28	0.00	20.00	11402
Age	32.07	4.26	24.00	43.00	11402
Tenure	4.15	4.56	0.00	27.60	11402
White	0.57	0.49	0.00	1.00	11402
Male	0.66	0.47	0.00	1.00	11402
Firm Size	1.14	5.91	0.00	100.00	11402
TFP	0.97	0.26	0.03	4.04	11402
Capital per worker	0.09	0.11	0.01	1.05	11402
Non-prod wage share	0.40	0.14	0.19	0.80	11402

size of the firm that provides employment. Given that exporting data is available mostly for manufacturing industries, however, we utilized a sub-sample of the NLSY79 consisting of only on those respondents who were employed in manufacturing. Furthermore, because the occupational classification methodology changed after the year 2000 (from Census 1970 codes to Census 2000 codes), we decided to only include employment spells that started on, or before, the year 2000.

In total, we put together a data set covering 3,364 individuals employed across 75 US manufacturing industries during the period of 1988-2000. Table 1 main variable of interest is a binary variable equal to one when workers reported having "learning opportunities" available and zero otherwise. As shown in table 1, about 53% of workers on average report having learning opportunities across all years and industries. The overall standard deviation of the learning opportunities variable was estimated to equal 0.5, while a standard deviation across individuals was 0.28 and a standard deviation between individuals was 0.43.

The variable "Exports", in turn, represents the total volume of exports at the industry level (measured in dollars but rescaled by 10^{-10}). The variables "White" and "Male" are dummy variables that take a value of one when the individual is white or male, respectively. The variable "Firm size" is the number of employees employed by the individual's employer (measured in thousands of employees). The variable "Education" is the highest grade completed by the individual at the time of the survey. The variable "Tenure" is the number of years the individual has been employed in his current job.

The variables "TFP", "Capital per worker", and "Non-production wage share" are industry level controls that vary by industry and year. Specifically, the variable "TFP" is a 5-factor total factor productivity index (benchmark year 1987), the variable "Capital per worker" is the total real capital stock divided by the number of workers, and the variable "Non-production worker wage share" is the share of non-production worker wages in total payroll. The variable "Imports" which will be used in the robustness section, represents the total volume of imports at the industry level (measured in dollars but rescaled by 10^{-10}).

With this data at hand, we then conduct a series of econometric estimations in which a binary variable equal to one when workers reported having learning opportunities available was used as the main dependent variable and the total exporting volume of the industry in which the individual is employed was used as the main independent variable. We turn to that next.

3 Empirical Analysis

In order to examine the basic premise of LBE regarding the effect of exporting volumes on learning, we estimate the following specification:

$$Learning_{i,j,t} = \beta_0 + \beta_1 Exports_{i,j,t} + \beta_2 \vec{X}_{i,j,t} + \theta_i + \mu_j + \nu_t + \epsilon_{i,j,t} \tag{1}$$

Where the term $Learning_{i,j,t}$ is a dichotomous variable taking the value of 1 whenever worker i employed in industry j at time t reported having training or schooling opportunities available and zero otherwise; the term $Exports_{i,j,t}$ represents the total exporting volume of the industry j in which the individual i was employed at time t; and $\vec{X}_{i,j,t}$ is a vector of industry and individual controls. We assume an error structure with an individual-specific component θ_i, an industry-specific component μ_j, a time-specific component ν_t, and an independently distributed error $\epsilon_{i,j,t}$.

The vector of explanatory variables $\vec{X}$ includes individual controls for age, tenure, race, sex, and education. It is important to include these variables in order to avoid potential estimation biases due to omitted controls. Age, race, tenure, and sex, are all likely to shape the individuals' willingness and capacity to learn new skills along the life cycle, but they might also help determine the choice they make to pursue a job in a particular industry. This vector $\vec{X}$ also includes the variable firm size, which measures the number of employees that work in the same firm the individual is currently employed. We expect firm size to be positively correlated with training opportunities since the provision of training is likely to be characterized by sunk costs. Thus, given that larger firms are more likely to export as well, failing to control for firm size would likely introduce biases in the estimations.

In addition, following Kosteas (2017), the vector of explanatory variables $\vec{X}$ also includes several industry-specific variables controlling for the industry's total factor productivity (TFP), capital per worker, non-production wage share, and total value of imports in some instances. It is important to control for these industry-specific variables as firms in a more productive industry can offer more learning opportunities and indeed export more, firms in industries with higher share of capital might have a stronger need for the acquisition of new skills, and firms in industries in which more non-production workers are employed might need to offer more learning opportunities.

A first set of results obtained from several estimations of equation 1 are reported in table 2. In this table, columns 1-2 show basic OLS results that do not control for individual heterogeneity, while columns 3-4 control for individual heterogeneity using fixed effects, and columns 5-6 using random effects. In most cases, one is able to reject the hypothesis that the individual error component was uncorrelated with the dependent variable. Yet, we decided to present the results from both fixed effects and random effects estimations, for comparison purposes. In all of these sets of regressions, we ran estimations without industry fixed effects (columns 1,3 and 5) and with industry fixed effects (columns 2, 4 and 6). A set of year-specific dummies was included in all cases. Standard errors are clustered at the industry level in all cases.

The results presented in table 2 lend weak support to the LBE hypothesis, but do not allow one to draw definite conclusions. As shown, the coefficient of interest is positive and significant under some specifications, but becomes insignificant (at the 10% level) when industry fixed effects are included. The relation between exports and learning, however, is likely to be highly heterogeneous across individuals with different skill levels. If the marginal productivity of human capital is decreasing and the cost associated with learning is independent of the initial human capital level, then one would expect learning opportunities to be provided mostly to individuals with low skill levels. We then considered an alternative specification in which the effects of exporting on learning are allowed to depend on the individual's skill, as measured by their educational level.

The results obtained from this alternative specification are shown in table 3. As before, this table shows linear OLS, FE and RE estimations with and without industry fixed effects, with year fixed effects included in all cases and standard errors clustered at the industry level in all cases. The results reveal a positive and significant (at the 1% level) correlation between exporting and learning in all instances; but with an estimated coefficient that decreases as the individual's level of education increases. In our preferred specification with individual and industry fixed effects (column 4), for example, a one-standard deviation increase in

Table 2: Learning by Exporting: Basic Regressions

	OLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.042***	-0.003	0.018***	0.007	0.028***	0.001
	(0.000)	(0.645)	(0.000)	(0.271)	(0.000)	(0.858)
Education	0.051***	0.049***	0.007	0.006	0.049***	0.047***
	(0.000)	(0.000)	(0.558)	(0.640)	(0.000)	(0.000)
Age	-0.001	-0.003	0.007***	0.007***	0.000	-0.001
	(0.678)	(0.277)	(0.002)	(0.005)	(0.884)	(0.746)
Tenure	0.015***	0.015***	0.004**	0.005***	0.012***	0.012***
	(0.000)	(0.000)	(0.032)	(0.008)	(0.000)	(0.000)
White	0.049***	0.043***	0.000	0.000	0.050***	0.048***
	(0.001)	(0.001)	(.)	(.)	(0.003)	(0.001)
Male	0.012	-0.006	0.000	0.000	0.018	-0.001
	(0.539)	(0.683)	(.)	(.)	(0.405)	(0.943)
Firm Size	0.005***	0.005***	0.001**	0.001*	0.003***	0.003***
	(0.003)	(0.005)	(0.040)	(0.055)	(0.000)	(0.001)
TFP	-0.035*	0.018	0.008	0.026	-0.013	0.019
	(0.093)	(0.310)	(0.541)	(0.129)	(0.384)	(0.274)
Capital per worker	0.305***	-0.212	0.005	-0.079	0.145***	-0.145
	(0.001)	(0.165)	(0.900)	(0.429)	(0.005)	(0.239)
Non-prod wage share	0.357***	0.077	0.068*	-0.148	0.275***	0.031
	(0.001)	(0.869)	(0.093)	(0.622)	(0.001)	(0.932)
Constant	-0.377***	-0.520***	0.156	0.167	-0.379***	-0.472***
	(0.000)	(0.000)	(0.266)	(0.241)	(0.000)	(0.000)
Observations	11402	11402	11402	11402	11402	11402
Industry FE	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the exporting volume is associated with a 2.3% increase in the frequency of learning at the average educational level.

In addition, it is interesting to note that the effect of exports is maximized when the level of education is approximately fifteen years, the college level, thus for individuals with college-level education and above there is no significant effect of exporting volumes on the learning opportunities. We investige this issue further in the robustness section using indicator variable for college instead of the highest grade completed to measure the level of education.

These results do not change substantially when both industry and occupational fixed effects are included into the specification. It is possible that some occupations require more training while at the same time are more conducive to exporting or provide an exporting advantage. It is therefore important to check that the results remain unaltered when these effects are allowed. Table 4 shows the corresponding estimations obtained from OLS, fixed-effects, and random-effects regressions, with and without industry fixed effects, and with both time fixed effects and occupational fixed effects included in all regressions. The results obtained are remarkably close to those obtained before.

Our findings then suggest that exporting and the extent to which learning opportunities are available for workers are indeed positively correlated. But they also suggest the effect is mainly concentrated on the individuals with lower skill levels. For simplicity, we have chosen to rely mainly on linear estimations of the relationship of interest. As shown later in the robustness section, however, the results and economic intuition remained unaltered when the estimations are conducted using non-linear methods.

Table 3: Learning by Exporting: Heterogeneous Effects

	OLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.100***	0.036**	0.108***	0.091***	0.095***	0.056***
	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.056***	0.052***	0.017	0.015	0.055***	0.051***
	(0.000)	(0.000)	(0.143)	(0.206)	(0.000)	(0.000)
Exports × Education	-0.004***	-0.003**	-0.007***	-0.006***	-0.005***	-0.004***
	(0.004)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.001	-0.003	0.007***	0.007***	0.000	-0.001
	(0.718)	(0.293)	(0.002)	(0.006)	(0.880)	(0.749)
Tenure	0.015***	0.015***	0.004**	0.005***	0.012***	0.012***
	(0.000)	(0.000)	(0.029)	(0.008)	(0.000)	(0.000)
White	0.049***	0.044***	0.000	0.000	0.051***	0.049***
	(0.001)	(0.001)	(.)	(.)	(0.003)	(0.001)
Male	0.014	-0.004	0.000	0.000	0.021	0.001
	(0.471)	(0.758)	(.)	(.)	(0.340)	(0.956)
Firm Size	0.006***	0.005***	0.001*	0.001*	0.003***	0.003***
	(0.001)	(0.003)	(0.057)	(0.073)	(0.000)	(0.001)
TFP	-0.030	0.020	0.015	0.030*	-0.007	0.021
	(0.140)	(0.253)	(0.291)	(0.066)	(0.620)	(0.177)
Capital per worker	0.302***	-0.203	0.003	-0.068	0.142***	-0.136
	(0.001)	(0.176)	(0.942)	(0.503)	(0.007)	(0.253)
Non-prod wage share	0.355***	0.076	0.064	-0.155	0.273***	0.027
	(0.001)	(0.871)	(0.110)	(0.607)	(0.001)	(0.942)
Constant	-0.446***	-0.563***	0.027	0.062	-0.452***	-0.529***
	(0.000)	(0.000)	(0.842)	(0.653)	(0.000)	(0.000)
Observations	11402	11402	11402	11402	11402	11402
IND	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Learning by Exporting: Including Occupational Fixed Effects

	OLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.080***	0.036***	0.111***	0.092***	0.089***	0.058***
	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.042***	0.038***	0.015	0.012	0.044***	0.042***
	(0.000)	(0.000)	(0.201)	(0.313)	(0.000)	(0.000)
Exports × Education	-0.004***	-0.003***	-0.007***	-0.007***	-0.005***	-0.004***
	(0.003)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.002	-0.003	0.007***	0.007***	-0.000	-0.002
	(0.413)	(0.203)	(0.001)	(0.001)	(0.879)	(0.547)
Tenure	0.014***	0.013***	0.004**	0.005**	0.011***	0.011***
	(0.000)	(0.000)	(0.033)	(0.013)	(0.000)	(0.000)
White	0.036***	0.029**	0.000	0.000	0.043***	0.040***
	(0.008)	(0.017)	(.)	(.)	(0.009)	(0.006)
Male	0.012	0.008	0.000	0.000	0.013	0.003
	(0.441)	(0.614)	(.)	(.)	(0.469)	(0.878)
Firm Size	0.005***	0.004***	0.001	0.001	0.003***	0.003***
	(0.003)	(0.005)	(0.116)	(0.125)	(0.000)	(0.001)
TFP	-0.022	0.020	0.016	0.032	-0.003	0.024
	(0.220)	(0.259)	(0.249)	(0.115)	(0.857)	(0.126)
Capital per worker	0.239***	-0.227*	0.012	-0.122	0.121**	-0.166
	(0.004)	(0.073)	(0.803)	(0.226)	(0.014)	(0.104)
Non-prod wage share	0.242**	-0.079	0.078*	-0.188	0.219***	-0.075
	(0.012)	(0.870)	(0.058)	(0.535)	(0.004)	(0.843)
Constant	-0.077	-0.132	-0.016	-0.011	-0.196**	-0.244**
	(0.413)	(0.254)	(0.908)	(0.940)	(0.037)	(0.049)
Observations	11394	11394	11394	11394	11394	11394
IND	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1 IV Estimations

It is important to note that there are potential endogeneity issues that remain to be addressed in relation to the results obtained above. One potential endogeneity issue may arise if the learning opportunities made available to workers were to simultaneously affect the employer's probability of becoming an exporter (see Blyde (2016)). One can argue that if firms invest in training and train their workers more they can potentially start exporting more as through training they can learn how to package their products for the export market, how to deal with foreign customers and other avenues. Therefore, to control for the potential reverse causality in exports, we use five year lagged exports as an instrument for exports. Lagged exports are highly correlated with exports, but they should not be correlated with the training opportunities provided to employees by the firm in later periods. Since we have data on exports from 1972, it is possible to construct five-year lagged exports. [2] If we treat exports as endogeneous, then the interaction of exports with education will also be endogeneus. The remedy to this issue is to use lagged exports as an instrument for exports and the interaction of lagged exports with the education as an instrument for the interaction of exports with the education.

The results are presented in table 5 below. The results of the estimations treating exports and interaction of exports with education as endogenous are qualitatively and quantitatively very similar to the results where exports and its interaction are treated as exogenous. The first-stage F-tests (Chi-square for random effects) for all specifications of table 5 confirm that the instruments are very strong- the p-values of the tests are all 0.00 in all specifications. We also conducted the Hausman test which tests the null hypothesis that exports and the interaction of exports with the education are properly exogenous in the model. For example, in column (1) of table 5 the p-value of the Hausman endogeneity test

[2] We also tried three-year and ten-year lagged exports, and the results were similar.

is 0.6485, which shows that the data cannot reject the use of OLS in favor of instrumental variables regressions. The Hausman test shows that the same situation arises when industry fixed effects are included in column (2), as well as when individual fixed or random effects are controlled for in columns (3)-(6).

4 Robustness Analysis

In this section we present several important robustness checks. First, we present results when we use college instead of highest grade completed to examine how exporting affects learning at different skill levels in table 6. College is a dummy variable indicating whether individuals have a college degree. As expected, the coefficient on exports and college are positive, while the interaction of college with exports is negative and significant showing that the effects of exporting are more important for people without college degrees and thus the lower level of skill. These results confirm and reinforce our earlier findings.

Second, we replicate the results obtained in tables 2 and 3, but using non-linear methods instead. The results are shown in tables 7 and 8, below. More specifically, these tables present the results obtained when a logistic regression is used to estimate the effects of exporting on learning. The specification used is comparable to that used before. However, to facilitate convergence of the maximum likelihood algorithm, both the age and the firm size variables were included in logarithmic form. The results obtained with fixed-effects and random-effects regressions, after controlling for time fixed effects in all cases, are reported. Also as before, the results are shown with and without industry fixed effects.

Third, we present results where we also control for the level of imports in the regressions. Given the results of Li (2010) and Kosteas (2017), who use the effect of import competition on training provision and training participation respectively, it is interesting to see whether the results are mainly driven by exports, as in learning-by-exporting, or imports. Table 9

Table 5: Learning by Exporting: Instrumental Variables - Lagged Exports

	IV		IVFE		IVRE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.101***	0.037**	0.109***	0.093***	0.096***	0.059***
	(0.000)	(0.017)	(0.000)	(0.001)	(0.000)	(0.006)
Education	0.056***	0.053***	0.017	0.015	0.055***	0.052***
	(0.000)	(0.000)	(0.156)	(0.215)	(0.000)	(0.000)
Exports x Education	-0.005***	-0.003**	-0.007***	-0.006***	-0.005***	-0.004***
	(0.003)	(0.019)	(0.000)	(0.001)	(0.001)	(0.003)
Age	-0.001	-0.003	0.007***	0.007**	0.000	-0.001
	(0.717)	(0.285)	(0.007)	(0.011)	(0.879)	(0.763)
Tenure	0.015***	0.015***	0.004*	0.005**	0.012***	0.012***
	(0.000)	(0.000)	(0.076)	(0.031)	(0.000)	(0.000)
White	0.049***	0.044***	0.000	0.000	0.051***	0.049***
	(0.001)	(0.000)	(.)	(.)	(0.000)	(0.000)
Male	0.014	-0.004	0.000	0.000	0.021	0.001
	(0.464)	(0.758)	(.)	(.)	(0.143)	(0.946)
Firm Size	0.006***	0.005***	0.001*	0.001*	0.003***	0.003***
	(0.000)	(0.002)	(0.059)	(0.085)	(0.000)	(0.000)
TFP	-0.029	0.020	0.015	0.029	-0.006	0.021
	(0.154)	(0.253)	(0.560)	(0.353)	(0.759)	(0.437)
Capital per worker	0.302***	-0.203	0.003	-0.067	0.141***	-0.135
	(0.001)	(0.167)	(0.960)	(0.706)	(0.004)	(0.431)
Non-prod wage share	0.356***	0.078	0.064	-0.157	0.272***	0.024
	(0.001)	(0.866)	(0.316)	(0.574)	(0.000)	(0.924)
Constant	-0.449***		0.024	0.061	-0.455***	-0.530***
	(0.000)		(0.874)	(0.730)	(0.000)	(0.000)
Observations	11402	11402	11402	11402	11402	11402
IND	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Learning by Exporting: Heterogeneous Effects by College

	OLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.054***	0.007	0.024***	0.015**	0.036***	0.009
	(0.000)	(0.256)	(0.000)	(0.031)	(0.000)	(0.128)
College	0.299***	0.287***	0.195***	0.171***	0.297***	0.284***
	(0.000)	(0.000)	(0.005)	(0.008)	(0.000)	(0.000)
College × Exports	-0.050***	-0.042***	-0.041***	-0.037***	-0.043***	-0.039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.000	-0.002	0.007***	0.007***	0.001	-0.001
	(0.873)	(0.392)	(0.001)	(0.004)	(0.835)	(0.792)
Tenure	0.016***	0.015***	0.004**	0.005***	0.012***	0.012***
	(0.000)	(0.000)	(0.021)	(0.005)	(0.000)	(0.000)
White	0.053***	0.046***	0.000	0.000	0.051***	0.048***
	(0.001)	(0.001)	(.)	(.)	(0.002)	(0.001)
Male	0.014	-0.004	0.000	0.000	0.020	-0.001
	(0.506)	(0.764)	(.)	(.)	(0.393)	(0.971)
Firm Size	0.006***	0.005***	0.001*	0.001*	0.003***	0.003***
	(0.000)	(0.002)	(0.061)	(0.078)	(0.000)	(0.001)
TFP	-0.021	0.024	0.013	0.029*	-0.005	0.022
	(0.327)	(0.161)	(0.357)	(0.088)	(0.734)	(0.148)
Capital per worker	0.329***	-0.184	0.001	-0.069	0.152***	-0.132
	(0.000)	(0.212)	(0.977)	(0.500)	(0.006)	(0.254)
Non-prod wage share	0.414***	0.087	0.061	-0.146	0.309***	0.045
	(0.000)	(0.856)	(0.128)	(0.628)	(0.000)	(0.903)
Constant	0.154*	-0.005	0.213***	0.216**	0.163*	0.045
	(0.070)	(0.967)	(0.000)	(0.014)	(0.073)	(0.711)
Observations	11402	11402	11402	11402	11402	11402
IND	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Learning by Exporting: Basic Non-Linear Regressions

	FE		RE	
	(1)	(2)	(3)	(4)
Exports	0.113***	0.114	0.178***	0.040
	(0.002)	(0.123)	(0.000)	(0.530)
Education	0.236*	0.262*	0.416***	0.397***
	(0.094)	(0.070)	(0.000)	(0.000)
Age (log)	-3.082	-4.499	-0.047	-0.367
	(0.512)	(0.356)	(0.950)	(0.614)
Tenure	0.043***	0.049***	0.088***	0.089***
	(0.004)	(0.002)	(0.000)	(0.000)
White	0.000	0.000	0.613***	0.544***
	(.)	(.)	(0.000)	(0.000)
Male	0.000	0.000	0.386***	0.200*
	(.)	(.)	(0.000)	(0.072)
Firm size (log)	0.411***	0.414***	0.548***	0.546***
	(0.000)	(0.000)	(0.000)	(0.000)
TFP	0.081	0.298	-0.097	0.186
	(0.654)	(0.273)	(0.541)	(0.422)
Capital per worker	0.077	-0.744	1.256***	-1.084
	(0.869)	(0.638)	(0.001)	(0.434)
Non-prod wage share	0.545	-1.847	2.671***	0.733
	(0.233)	(0.400)	(0.000)	(0.698)
Constant			-10.035***	-10.043***
			(0.000)	(0.000)
Observations	4994	4994	11402	11395
IND	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Learning by Exporting: Heterogeneous Effects in Non-Linear Regressions

	FE		RE	
	(1)	(2)	(3)	(4)
Exports	0.789***	0.829***	0.720***	0.521***
	(0.000)	(0.001)	(0.000)	(0.002)
Education	0.314**	0.341**	0.461***	0.439***
	(0.030)	(0.021)	(0.000)	(0.000)
Exports × Education	-0.054***	-0.056***	-0.043***	-0.038***
	(0.002)	(0.002)	(0.000)	(0.002)
Age (log)	-3.268	-4.713	-0.058	-0.379
	(0.487)	(0.334)	(0.938)	(0.603)
Tenure	0.042***	0.049***	0.087***	0.089***
	(0.005)	(0.002)	(0.000)	(0.000)
White	0.000	0.000	0.620***	0.551***
	(.)	(.)	(0.000)	(0.000)
Male	0.000	0.000	0.406***	0.217*
	(.)	(.)	(0.000)	(0.051)
Firm size (log)	0.411***	0.415***	0.551***	0.548***
	(0.000)	(0.000)	(0.000)	(0.000)
TFP	0.104	0.317	-0.064	0.204
	(0.565)	(0.245)	(0.686)	(0.377)
Capital per worker	0.043	-0.693	1.242***	-1.043
	(0.927)	(0.662)	(0.001)	(0.452)
Non-prod wage share	0.544	-1.823	2.681***	0.730
	(0.235)	(0.406)	(0.000)	(0.699)
Constant			-10.624***	-10.549***
			(0.000)	(0.000)
Observations	4994	4994	11402	11395
IND	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

replicates our baseline results of table 3 with imports added as an additional control. It is important to note that there is a high correlation of exports with imports, but despite that the results on exports and the interaction of exports with the level of skill are still highly significant, while imports are not significant in any of the regressions. This lends additional support and validity to our results that learning-by-exporting is important.

5 Conclusion

This paper analyzed the relationship between exporting and learning-related decisions made by the firm, looking at one particular form of learning: the training provision. To our knowledge, this is the first paper to address the link between exports and training provision in particular. Using individual-level data from NLSY79 and combining it with industry-level data on exports, this paper looked at the empirical connection between the exporting volumes of particular industries and the learning opportunities made available to workers of those industries. The results we find are consistent with the learning-by-exporting hypothesis, but suggest the relationship between exporting and learning is highly heterogenous across individuals with different levels of skill.

The results remain robust after including a rich set of individual and industry controls and fixed effects, various linear and non-linear methods, as well as instrumental variables estimations to control for the potential endogeneity of exports. The results are also robust to including imports as an additional control, as suggested by papers that find a link between import competition and training.

Table 9: Learning by Exporting: Controlling For Imports

	OLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports	0.081**	0.038**	0.106***	0.093***	0.086***	0.058***
	(0.020)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.056***	0.052***	0.017	0.015	0.054***	0.051***
	(0.000)	(0.000)	(0.147)	(0.202)	(0.000)	(0.000)
Exports × Education	-0.004***	-0.003**	-0.007***	-0.006***	-0.005***	-0.004***
	(0.009)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.001	-0.003	0.007***	0.007***	0.000	-0.001
	(0.675)	(0.293)	(0.002)	(0.006)	(0.895)	(0.749)
Tenure	0.015***	0.015***	0.004**	0.005***	0.012***	0.012***
	(0.000)	(0.000)	(0.029)	(0.008)	(0.000)	(0.000)
White	0.049***	0.044***	0.000	0.000	0.051***	0.049***
	(0.002)	(0.001)	(.)	(.)	(0.003)	(0.001)
Male	0.016	-0.004	0.000	0.000	0.021	0.001
	(0.430)	(0.756)	(.)	(.)	(0.321)	(0.958)
Firm Size	0.006***	0.005***	0.001*	0.001*	0.003***	0.003***
	(0.000)	(0.003)	(0.057)	(0.074)	(0.000)	(0.001)
TFP	-0.031	0.020	0.015	0.030*	-0.007	0.021
	(0.139)	(0.245)	(0.291)	(0.060)	(0.634)	(0.171)
Capital per worker	0.303***	-0.206	0.004	-0.071	0.144***	-0.138
	(0.001)	(0.180)	(0.928)	(0.484)	(0.007)	(0.254)
Non-prod wage share	0.403***	0.079	0.069	-0.151	0.295***	0.029
	(0.000)	(0.866)	(0.126)	(0.614)	(0.000)	(0.937)
Imports	0.010	-0.002	0.001	-0.002	0.005	-0.001
	(0.299)	(0.795)	(0.694)	(0.667)	(0.489)	(0.813)
Constant	-0.455***	-0.564***	0.028	0.057	-0.457***	-0.529***
	(0.000)	(0.000)	(0.841)	(0.677)	(0.000)	(0.000)
Observations	11402	11402	11402	11402	11402	11402
IND	No	Yes	No	Yes	No	Yes

p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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