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Export and firms' performance in North Macedonia: self selection or learning by doing?

Abstract

Export is an important contributor to growth with numerous direct and indirect macroeconomic benefits. Moreover, firms engaged in exporting activity tend to have superior characteristics compared to their non-exporting peers. The paper is focused on identifying reasons behind this superiority of exporters by testing two hypothesis – self-selection and learning by doing hypothesis. The analysis is done on a sample of over 1,900 manufacturing firms annually, for the period 2013-2017. In line with previous empirical research, we found evidence in favor of the self-selection hypothesis. This means that more successful and more productive firms become exporters as a result of their performance i.e. they self-select themselves in the international market. In addition, our results suggest that, complementary to the self-selection process, there are some evidence of the validity of learning by doing hypothesis.

JEL Classification Numbers: D24, D22, F14
Keywords: self selection, learning by doing, export, matching

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Contents

1. Introduction

Export is an important contributor to growth. This is especially true in the case of small, open transitional economies whose core growth model is export oriented. Besides clearly identified direct effects on growth, exports also has many positive indirect effects through transfer of know-how and technology from international markets into the domestic economy. There is also a general consensus that exporting firms have superior characteristics compared to firms producing only for domestic markets. Exporting firms grow faster, are more successful and more productive compared to their non-exporting peers. Most of the empirical work on the importance of export for growth is based on macro-level data; however, characteristics of exporting firms, as well as measures that policy makers undertake to stimulate export are essentially microeconomic. Therefore, microeconometric research would shed additional light on the characteristics of exporting firms and their behavior, as well as valuable insights for policymakers that might be used in the process of designing export oriented measures and growth strategies as well.

In this paper we try to identify the reasons behind exporters' superior features. Following the empirical literature on this topic, we focus on testing two alternative, but not mutually exclusive, hypotheses on why exporters can be expected to perform better than non-exporters. The first one is the self selection hypothesis which predicts that more successful and more productive firms self-select into foreign markets. Namely, exporting is connected with additional costs (such as transportation costs, distribution or marketing costs, personnel with skills to manage foreign networks, or production costs in modifying current domestic products for foreign consumption) and therefore, only the outperforming firms will become exporters. In other words, exporters are more successful compared to other firms even before starting to export. The second hypothesis emphasizes the importance of learning by doing. Export starters become more productive once they start to export because they have easer access to information flows, knowledge flows, more favorable access to resources etc. Put differently, exporters' performance improves because of exporting.

Empirical analysis is based on firm level database constructed from the financial accounts that firms submit to the Central Register of the Republic of North Macedonia and from the National Bank's internal database on external trade. In line with other papers we are concentrated only on manufacturing firms that have more than five employees. The sample used in the analysis covers the period 2013-2017.

North Macedonia is small and open economy with export being the most important growth driver in the last five year (2013-2017). In the same period, according to aggregate national accounts data, export was growing with an average real growth rate of 9.7%. Having in mind the vital role that exports has for Macedonian economy, on one hand and the fact that exporting firm features and export-oriented policies are essentially microeconomic, as already underlined in opening paragraph of this section, we believe that a research focused on explain the superior characteristics of exporting firms by using microdata is a significant contribution to the research nexus on Macedonian economy and a valuable input in planning future growth strategies and policies. Moreover, the literature investigating export-performance nexus by using firm-level micro data in the case of small and open transition economies is rather limited. Hence, this paper adds to the empirical literature on the direction of causality between trade and firm's level performance by studying the experience in one small and open transition country – North Macedonia.

The remainder of this paper is organized as follows. The next section gives an overview of the literature review on this topic. Discussion on the database main features is presented in section 3. In section 4 we discuss some stylized facts and describe exporters' characteristics. The econometric analysis and discussion of the results is presented in section 5. First, we estimate and elaborate on the existence of the exporters' premia. Next, we continue by testing the self-selection and learning by doing hypothesis. When testing the latter one has to take into an account the existence of the so-called average treatment effect on the treated (ATT) bias by using adequate econometric methods such as propensity matching methods. Finally, in the last section the main findings are summarized.

2. Literature review

The literature investigating the relationship between export and performance by using firm-level micro data is quite extensive. One of the first papers on this subject is the one published by Bernard and Jensen in 1995. Paper presents very detailed descriptive analysis on characteristics of exporting firms versus non-exporting firms in manufacturing sectors. More specifically they analyze the difference between exporters and non-exporters in manufacturing in various dimensions of firms' performance and conclude that exporters do outperform non exporters. Exporters are larger, more productive, more capital intensive and pay higher wages. In addition, they examined whether being an exporter is a guarantee for being successful in the future and their results show no clear evidence that current exporting status is good predictor of future success.

Since Bernard and Jensen seminal paper the literature analyzing the relationship between exports and firm's level performance has expanded and it is still growing. In essence, majority of the empirical literature is testing two alternative, but not mutually exclusive, hypothesis. The first hypothesis is self-selection hypothesis which predicts that more successful and more productive firms self-select into foreign markets. The reasons behind this type of firms' behavior are connected with the existence of costs associated with selling abroad (such as transportation, distribution, marketing, personnel with skills to manage foreign networks etc.) that are difficult to be absorbed by the less productive firms. Therefore, differences between exporters and non-exporters might be linked to ex-ante differences in their performance. The second hypothesis emphasizes the importance of learning by doing. Export starters become more productive once they start to export because they have easer access to information flows, knowledge flows, more favorable access to resources and might experience positive impact from economies of scale. In other words, differences between exporters and non-exporters might be explained by ex-post differences in firms' performance.

Wagner (2007; 2011) provides comprehensive and systematic overview of the empirical literature that investigates the relationship between export and performance, as well as on the methods and models used in specific research studies. Generally, regardless on the empirical method used, most of the empirical studies find evidence in favor of the self-selection hypothesis. Alvarez and Lopez (2004), Arnold and Hussinger (2005), Clerides et al. (1998) are only some examples. Evidence on the learning-by-exporting hypothesis, on the other hand is more mixed. In fact, most of the earlier studies failed to find any support in favor of this hypothesis (Bernard and Jensen, 1999; Bernard and Wagner, 1997; Clerides et al., 1998 etc.) which was, partially, explained by the fact that they didn't control properly for the self-selection behavior of the exporting firms that induced endogeneity bias in the model. In this sense, most recent studies recognize that selection into exporting is not a random process and used methods, such as difference in difference estimators and matching techniques to control for this non-randomness. Greenaway and Kneller (2007) show that productivity growth of new exporters in UK is higher compared to that of non-exporters one to two years after entry. Similar results are found for Slovenia (De Loecker, 2007) and for Italy (Serti and Tomasi, 2009). Manez et al. (2010) on a sample of Spanish firms show that new exporters have extra-productivity growth in the first year and this effect lasts in the following one (for the large firms) to two (for small firms) years.

Second generation studies in this area extended the research agenda by controlling for the export destination of exporters. For example, Pisu (2008), using a comprehensive dataset on Belgian manufacturing firms from 1998 to 2005, finds that exporters selling their products to more developed economies have superior ex-ante productivity performance compared to non-exporters and firms that export to less developed countries. Silva et al. (2010) report similar results for Portugal – "there is significant degree of heterogeneity according to the destination of exports: the most productive starters are able to export to more demanding markets while the least productive ones seem fit to begin exporting to less exigent destinations". Positive relationship between ex-ante productivity and development level of the export destination country is also documented for Italy (Serti and Tomasi, 2009).

New empirical literature in this area is focused on implementation of new approaches for testing the traditional hypothesis, as well as expanding the sectoral dimension of the database by including services. The standard methodological approach used is combination of the OLS method together with matching methods to test for the post-entry effects of export on performance. However, most recent research shows that this approach does not deal with firms' heterogeneity in the most adequate way. More precisely, problems arise because of presence of firms with extreme values (outliers), different productivity premia over the productivity distribution when unobserved heterogeneity matters etc. Specific methods and approaches are proposed. For example, when dealing with outliers, instead of trimming and winsorizing, one might use methods like Least Absolute Deviations regression, Huber M estimator, fully robust MM estimator etc. New method for quantile regression in a linear fixed effects models has been developed for samples with unobserved heterogeneity and different productivity premia over the productivity distribution. Given the increasing importance of the service sector the number of studies investigating causal effect between export and firms' performance in services, alongside the manufacturing sector, is growing. Good review of the most important studies in this area is given in Wagner (2011).

From what is presented so far it can be concluded that most of the research is focused on single countries. The reasons behind this is twofold – 1) the access to firm level micro data might be complicated and costly and 2) it is very difficult to ensure comparability between firm level data from different countries. There are two big multi-country datasets with data on export, trade and productivity. CompNet platform contains competitiveness indicators such as employment, trade, productivity, mark-ups, financial constraints and more. A group of 18 countries is included in the platform and moments of distributions of the calculated competitiveness indicators are presented for each country. Exporter Dynamic Database managed by the World Bank provides data on the basic characteristics of the exporting firms, concentration and diversification and their dynamics in terms of entry, exit and survival for around 70 countries over the period 1997-2014.

Though very popular in the global research network, research of the export-performance relationship using firm level datasets is rarely done for countries from the region. As to the knowledge of the author analysis with this subject is conducted only for Slovenia and Croatia. Damijan, Polanec and Prasnikar (2004) on sample of Slovenian firms over the period 1997-2002 are investigating the relationship between exporting and productivity using firm-level data over the period, with special focus on the impact of the exporting destination on firms' productivity. Controlling for the exporting destination they found out that exporters can gain significant improvements in productivity but only when serving advanced markets. De Loecker (2007) tests for post-entry productivity gains for the Slovenian firms by using matching method on a similar sample of firms and concludes that all firms experience post-entry productivity gains, but the additional gains are smaller for firms that export to low-income countries. Valdec and Zrnc (2015) tested the self-selection and learning by exporting hypothesis by using firm-level dataset covering the Croatian manufacturing sector over the period 2002-2012. They found evidence in favor of both hypothesis depending on the model specification and variables transformation.

3. Data

The analysis in this paper is conducted using an initial sample of manufacturing firms that submitted financial accounts (balance sheet and income statement) to the Central Register of the Republic of North Macedonia in the period 2013-2017. This dataset is complemented by the information gathered from the National Bank's internal database on export activity. In total, the sample is relatively small for this type of studies - around 9,532 observations in total (around 1,900 firms each year)[2]. In our study the sample consists of all manufacturing firms that employ 5 and more persons. Structure of the sample is presented in Table 1. Firms in our sample are only 26% of the total number of firms in manufacturing in 2016 [3] (ranging from 5% to 60% in some subsectors); however their share in manufacturing sector's total value added and total employment is rather significant (74.4% in the total value added, and 82% in total employment). The picture is similar when looking at individual manufacturing subsectors.

In Table 1 we also present classification by degree of technological intensity following Eurostat classification of manufacturing sectors by technological intensity on high-technology, medium-high-technology, medium-low-technology and low-technology manufacturing sectors. However, as the data on employment and value added by manufacturing sectors provided from the Statistical Office is incomplete we were not able to calculate and to present sample shares of firms by degree of technological intensity in employment and value added. In the remaining of the paper, as well as in the econometric analysis we use this classification to construct the sectoral dummy variable. The reason for using more aggregated classification to control for the sectoral effect is connected with the small number of firms in some 2-digit sectors.

[2] For comparison, Alvarez and Lopez worked with 35,000 observations (5,000 firms per year in the period 1990-1996), Cirera et al. (2015) with over 260,000 observations (over 29,000 firms per year in the period 2000-2008), Arnold and Hussinger with 19,341 observations (2149 firms per year in the period 1992-2008), Valdec and Zrnc with 80,256 observations (around 7,300 firms per year in the period 2002-2012), Serti and Tomasi (2007) with 178,734 observations (around 20,000 firms per year in the period 1989-1997).

[3] Data for 2016 is presented because this is the last year from the sample on which we had final data. Data for 2017 was still preliminary at the moment when we were working on the analysis. Alternatively, one can use average for the period but, having in mind the relatively short time dimension of the sample, results will be very similar.

Table 1. Sample coverage by manufacturing subsectors in 2016

		number of firms in the sample	% in number of firms of whole population	% in value added of whole population	% in employment of whole population
MANUFACTURING		1931	25.9	74.4	81.9
10	Manufacture of food products	397	25.5	86.9	77.5
11	Manufacture of beverages	45	47.9		
12	Manufacture of tobacco products	7	53.8	77.0	47.7
13	Manufacture of textiles	47	24.1		
14	Manufacture of wearing apparel	389	42.5	90.1	91.6
15	Manufacture of leather and related products	76	51.4	83.8	94.4
16	Manufacture of wood and of products of wood	83	19.8	71.8	60.0
17	Manufacture of paper and paper products	53	25.2	80.2	79.4
18	Printing and reproduction of recorded media	97	23.8	78.5	75.0
19	Manufacture of coke and refined petroleum products	2	25.0		
20	Manufacture of chemicals and chemical products	22	23.7		
21	Manufacture of basic pharmaceutical product and pharmaceutical preparations	6	54.5		
22	Manufacture of rubber and plastic products	118	26.2	86.4	75.2
23	Manufacture of other non-metallic mineral products	83	26.9		
24	Manufacture of basic metals	21	38.9	89.4	
25	Manufacture of fabricated metal products, except machinery and equipment	189	23.1	79.1	69.4
26	Manufacture of computer, electronic and optical products	15	25.9		
27	Manufacture of electrical equipment	39	35.5		
28	Manufacture of machinery and equipment n.e.c.	40	26.8		
29	Manufacture of motor vehicles, trailers and semi-trailers	14	37.8		
30	Manufacture of other transport equipment	3	60.0		
31	Manufacture of furniture	138	21.8	89.5	72.7
32	Other manufacturing	24	5.0	49.0	24.5
33	Repair and installation of machinery and equipment	23	8.3	68.6	52.3
21,26	high-technology	21	30.4		
20,27,28,29,30	medium-high-technology	118	29.9		
19,22,23,24,25,33	medium-low-technology	436	22.7		
10,11,12,13,14,15,16,17,18,31,32	low-technology	1356	26.7		

Source: State Statistical Office, Central Registry and author's calculations.

Firm-level data is often distorted by outliers (or extreme value) due to reporting errors or idiosyncratic events. Outliers may have large influence on the mean value of the variables and, if this is the case, results will be driven by small number of firms with extremely high or low values, thus leading to incorrect conclusions. Wagner (2011) discusses this issue and summarizes techniques and methods to deal with this problem. In our paper the outlier cleaning was applied to ratios. In this way, the probability of penalizing a firm that has high capital, labor costs or productivity just because it is big or successful is minimized. More specifically, we were looking at the labor and capital ratio of individual firms and if these ratios were more than five interquartile ranges above or below the median of that sector in a specific year than that firm is eliminated from the sample.

The variables included in the analysis are the following: sales, value added, number of employees, wage bill, capital, export, total factor productivity (TFP) and labor productivity (LP). All variables are directly extracted/constructed from the Central Register database. The only exception is the information on the exporting status of the firms based on trade statatics data produced by the State Statical Office. Following Berthou et al. (2015), we consider a firm to be an exporter (dummy variable equal to one) if its exporting value in one year period is higher than 1,000 euros.

Following López-García, Puente, & Gómez (2007), value added was constructed as difference between the value of production and intermediary consumption. The value of production equals sales revenues plus inventory changes. Intermediary consumption by definition includes purchases, changes in input stocks, insurance and renting expenses and taxes. To get the real values, nominal value added was deflated using the implicit gross value added deflator for manufacturing from the National Accounts. In fact all nominal variables used in the analysis are expressed in real terms by deflating them with the manufacturing deflator.

LP is calculated as units of value added per worker. TFP is calculated as a residual from Cobb-Douglas type of production function:

$$Y = AL^{\alpha}K^{\beta} \tag{1}$$

$$logY = logA + \alpha \mathrm{logL} + \beta \mathrm{logK} \tag{2}$$

$$logA = logY - \alpha \mathrm{logL} - \beta \mathrm{logK} \tag{3}$$

A is the total factor productivity, Y stands for the value added, labor input (L) is the total number of employees as reported by the firms in their income statements and the capital input (K) is equal to the net book value of fixed assets. The production function parameters α and β are estimated using the Ackerberg, Caves and Frazer – ACF (2006). This method is one of the control function approaches that are trying to overcome the endogeneity problem connected with the existence of positive correlation between the observable input levels and the unobservable productivity shocks. After estimating the production function we apply the estimated coefficients on labor and capital (α was estimated to be 0.841, whereas β was estimated to be 0.167) to our data for the whole period (equation 3) in order to obtain measure for the TFP, with implicitly assuming stability of the production function parameters over the whole sample period[4].

4. Descriptive analysis

North Macedonia is small and open economy with external trade constituting around 124% of GDP in 2017 and export of goods and services share standing at around 55% in the same year (nominal terms). Moreover, export is an individual expenditure component with highest positive contribution to real growth in the last five years (Figure 1). However, given high degree of import dependence of the economy, higher export leads higher imports, as well. Albeit, in recent years one can notice smaller share of the negative net-export to GDP, expressed in nominal terms (Figure 2).

[4] The usual approach is to derive the TFP directly from the estimated equations. However, by following this approach we would lose about half of the time dimension (given that in our sample T=5).

Figure 1. Real GDP growth and its components

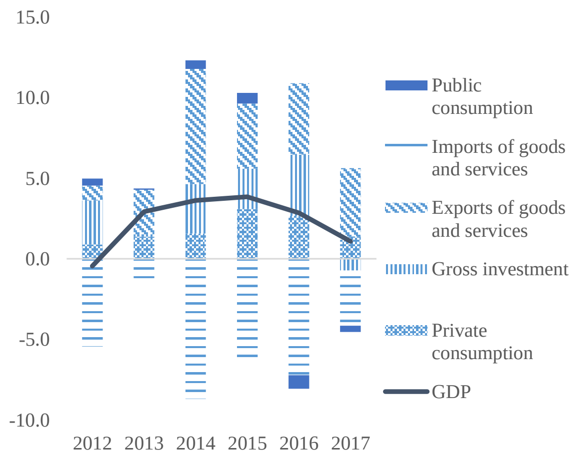
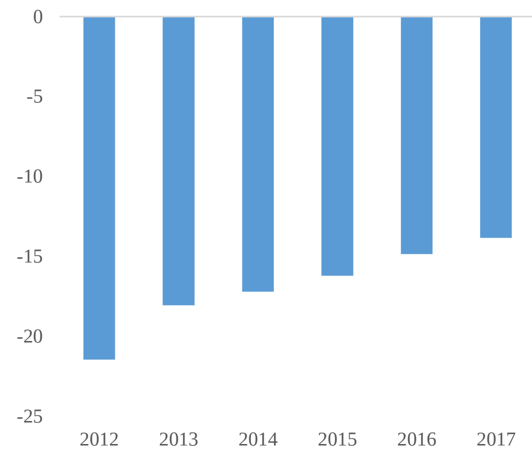


Figure 2. Net-exports, % of GDP (nominal terms)



Source: NBRNM and author's calculations.

This positive trend is, in large part, connected with the entrance of new, export oriented companies in the free economic zones that started to operate around 2009. The impact of these new companies on exports and foreign trade in general is quite significant. According to the analysis done by Ramadani et al. (2017) in 2016 SEZ companies' share in total export was around 47% (only 2% in 2009). Moreover, even though their production is import dependent, the net-effect on total trade is positive, as import increases at a lower pace compared to export. In turn, we also witnessed qualitative change in the structure of total exports as these companies are operating in technologically more intense sectors that are less sensitive to changes in commodity prices.

Turning to microdata, less than one third of the firms in our sample are exporters (average share of 27% for the whole sample period). However, the share of exporters in the key performance indicators is relatively high. Table 2 provides a summary statistics regarding the share of exporters in total value added, sales, wages, employees and capital endowment in the sample. As can be seen, for the period 2013-2017, on average, exporters account for around 60% of total employment, 67% of wages, 76% of value added, 80% of the capital and 84% of sales. Moreover, we see an increase in the share in the period under analysis (small decline only in 2016). Situation is very similar in EU countries – though not dominant in the number of firms exporters have significant share in core macroeconomic variables in EU countries, as well (Berthou et al., 2015).

Table 2. Share of exporters in key-macroeconomic performance

	share of exporters (in %)					
	number of firms	value added	sales	wages	employees	capital
2013	25.9	73.7	83.0	65.6	58.0	81.6
2014	26.1	74.8	83.8	64.6	56.3	78.6
2015	27.3	77.0	85.6	66.6	59.2	79.4
2016	27.4	74.0	79.7	66.5	59.6	80.2
2017	28.5	79.7	87.6	70.2	64.1	82.6
average for the period	27.0	75.9	83.9	66.7	59.5	80.5

Source: Central Registry and author's calculations.

Sectoral analysis reveal that share of exporters differs across different manufacturing subsectors (Table 3). The largest share of exporting firms in our sample are found in tobacco sector, pharmaceutical industry and manufacture of motor vehicles. Majority of the companies in the latter sector are foreign owned and are operating in the free economic zones. Regardless of the sectoral share of exporters, exporting firms account for significant portion of the value added, sales, employment and capital in almost all manufacturing sectors. In addition, these superior characteristics of exporters are not dependent on firms' size. Namely, exporting firms of all sizes have better output performance and employ more factors compared to non-exporters (Table 4).

Table 3. Share of exporters in value added, sales, wages, employment and capital in 2016, by individual subsectors

		number of exporting firms	share of exporters (in %)					
			number of firms	value added	sales	wages	employment	capital
10	Manufacture of food products	95	23.9	68.7	69.8	60.0	52.7	66.6
11	Manufacture of beverages	27	60.0	91.3	87.0	86.7	81.9	85.1
12	Manufacture of tobacco products	7	100.0	100.0	100.0	100.0	100.0	100.0
13	Manufacture of textiles	23	48.9	89.4	93.0	86.7	85.0	94.9
14	Manufacture of wearing apparel	101	26.0	46.0	61.2	42.7	41.0	59.4
15	Manufacture of leather and related products	26	34.2	45.4	64.7	41.0	38.1	85.3
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	14	16.9	45.7	38.4	36.7	32.2	37.2
17	Manufacture of paper and paper products	13	24.5	64.7	60.2	56.8	48.5	70.5
18	Printing and reproduction of recorded media	14	14.4	41.1	47.3	37.5	34.4	56.8
19	Manufacture of coke and refined petroleum products	0	0.0	0.0	0.0	0.0	0.0	0.0
20	Manufacture of chemicals and chemical products	13	59.1	86.6	87.2	81.5	73.1	88.8
21	Manufacture of basic pharmaceutical product and pharmaceutical preparations	4	66.7	98.7	99.0	99.1	97.9	96.4
22	Manufacture of rubber and plastic products	33	28.0	71.6	71.2	56.8	53.7	74.0
23	Manufacture of other non-metallic mineral products	16	19.3	82.5	75.8	72.6	51.8	75.0
24	Manufacture of basic metals	12	57.1	97.2	98.8	95.9	95.4	98.5
25	Manufacture of fabricated metal products, except machinery and equipment	44	23.3	56.8	60.5	59.2	52.8	66.5
26	Manufacture of computer, electronic and optical products	3	20.0	85.2	88.4	80.7	84.3	91.4
27	Manufacture of electrical equipment	14	35.9	85.4	92.4	81.3	81.4	88.0
28	Manufacture of machinery and equipment n.e.c.	17	42.5	69.0	71.4	71.7	66.1	72.2
29	Manufacture of motor vehicles, trailers and semi-trailers	11	78.6	99.7	99.9	99.8	99.8	99.2
30	Manufacture of other transport equipment	1	33.3	91.7	97.0	81.5	70.3	95.9
31	Manufacture of furniture	36	26.1	68.3	70.0	55.5	53.5	72.7
32	Other manufacturing	4	16.7	20.5	25.7	26.2	24.8	40.7
33	Repair and installation of machinery and equipment	2	8.7	13.9	16.8	14.1	14.5	24.1
21,26	high-technology	7	33.3	95.1	95.1	94.3	91.9	95.3
20,27,28,29,30	medium-high-technology	56	47.5	93.0	95.1	93.2	93.2	93.3
19,22,23,24,25,33	medium-low-technology	107	24.5	75.8	80.8	69.2	64.0	83.7
10,11,12,13,14,15,16,17,18,31,32	low-technology	360	26.5	65.1	71.5	55.0	49.7	72.3

Source: Central Registry and author's calculations.

Table 4. Comparison of exporters and non-exporters (average over the sample period)

Non-exporters						
	capital	wages	sales	employees	value added	TFP
1-49 employees	11	2	19	15	14.6	10.1
50-249 employees	49	16	79	102	16.6	10.2
250 and more	72	58	169	369	17.9	10.3
Total	16	4	27	27	15	10

Exporters						
	capital	wages	sales	employees	value added	TFP
1-49 employees	43	4	76	22	15.7	10.6
50-249 employees	146	21	241	106	17.1	10.4
250 and more	998	138	2670	606	18.9	10.5
Total	172	23	386	108	16.5	10.5

Note: Capital, wages and sales are expressed in million of denars, employees in number of workers, whereas value added and TFP are in log levels. Source: Central Registry and author's calculations.

5. Empirical analysis and results

In this section we test for the statistical significance of the superior characteristics of exporters by calculating the export premium. Next we proceed by formally checking the validity of the self-selection hypothesis (in section 5.2) and learning by exporting hypothesis (in section 5.3) using micro data on Macedonian manufacturing firms from 2013 until 2017.

5.1 Export premium

Exporter premium is being defined as existence of statistically significant difference in the performance of exporters vs the performance of non-exporters. Following Bernard and Jensen (1999) we estimate the following regression:

$$\ln X_i = \alpha + \beta Export_i + \gamma Control_i + \varepsilon_i \tag{4}$$

X_i represents a measure of firms' performance such as TFP, LP, wage, capital and sales; export is a dummy variable for the current export status (1 if the firm exports in year t, 0 else); Control is a vector of control variables (sector dummies, firm size and year dummies), ε_i is the random error term.

We estimate this regressions by using pooled OLS (i represents the index of the firm); we also tried fixed effects estimation but the results were very similar. The exporter premia is equal to 100*(exp(β)-1) and shows the average percentage difference between exporters and non-exporters after controlling for size, sectors and time.

Table 5. Exporter premium estimates

	TFP	LP	wage	capital	sales
estimated cofficient	0.338***	0.576***	0.187***	1.732***	1.344***
	(0.029)	(0.032)	(0.017)	(0.085)	(0.049)
transformed coefficient	40.2	77.9	20.6	465.2	283.2
N	9511	9513	9516	9530	9529
r2	0.08	0.16	0.13	0.32	0.52

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. The transformed coefficient was calculated as 100(exp(β)-1) and this shows the exact percentage differential between exporters and non-exporters controlling for size, sectors and time. Robust standard errors in brackets bellow estimates. Source: Author's calculations.

The estimated equations are presented in Appendix 1. Table 5 summarizes the estimated coefficients on the export dummy variable which are all highly significant and reveal existence of sizable difference in performance between exporters and non-exporters. This is consistent with previous empirical research in this field (Bernard and Jansen, 1999; Clerides et al., 1998; Serti and Tomasi, 2007; Valdec and Zrnc, 2015). With regards to productivity, exporters have higher labor productivity by 78%, as well as higher TFP by 40.2%. Firms that sell on international markets pay 20.6% higher wages as compared to non-exporters. The difference is largest when looking at sales and capital.

Estimates of the export premium documents statistically significant differences in the performance between exporters and non-exporters; however the direction of causality of the positive export-performance relationship is still unknown. In other words we don't know whether more successful (and productive) firms become exporters or exporters improve their performance (and productivity) by exporting. To investigate this question in the next sections we formally test the self-selection and learning by doing hypothesis.

5.2 Self selection hypothesis

Firms that are more efficient and more productive self-select into the export market. As previously denoted, exporting is connected with additional costs (such as transportation costs, distribution or marketing costs, personnel with skills to manage foreign networks, or production costs in modifying current domestic products for foreign consumption) and therefore, only the outperforming firms will become exporters. To test this hypothesis, one should compare the performance of entrants (export starters) to non-exporters in the years before entry. If self-selection hypothesis holds than the difference in performance between export starters and never-exporters in the period before entering the international market should be statistically significant.

The first step in formally testing this hypothesis is re-definition of the sample. Namely, in order to test the self-selection hypothesis we need data only on export starters and never-exporters. Different authors have different definitions for export starters and the choice is usually determined by the sample size. An export starter, according to Bernard and Wagner (1997), is a firm that exports for the first time after at least three years in the sample. Valdec and Zrnc (2015) define export starter as a firm that exports for the first time and continues to export for three consecutive years. For Serti and Tomasi (2007) export starters are firms that do not export for at least two years, start exporting in year t and keep on exporting in the following period. Berthou et al. (2015) use less data restrictive definition for export starters – export starter is a firm that exports in t and t+1, but didn't export in t-1. Having in mind that our sample has only five years of data we decided to follow Berthou et al. (2015) definition.

After redefining the sample we can evaluate the self-selection hypothesis. To that end, we estimate the model proposed by Bernard and Jensen (1999) and also employed by Serti and Tomasi (2007):

$$\ln(X)_{i,t-1} = \alpha_B + \beta_B Starter_{it} + \gamma_B Controls_{it} + \vartheta_{it} \qquad (5)$$

where Starter is a dummy variable taking on value one if the firm starts to export in time t and zero if the firm never exported. As previously, X represents a measure of firms' performance (TFP, LP, wages, capital and sales in our case) in the period $t-1$; controls is a vector of control variables (sector dummies, firm size and year dummies), ϑ_i is the random error term. The main results are presented in Table 6, whereas the estimated equations in total are presented in Appendix 2.

Table 6. Self-selection into exporting: levels

	TFP	**LP**	**wages**	**capital**	**sales**
Estimated coefficients	0.064	0.238*	0.074	1.068***	0.538***
	(0.099)	(0.100)	(0.051)	(0.208)	(0.124)
transformed coefficients (%)	6.6	26.9	7.7	191.0	71.2
number of observations	3723	3724	3726	3731	3731
r2	0.05	0.08	0.09	0.11	0.24

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. The transformed coefficient was calculated as 100(exp(β)-1) and this shows the exact percentage differential between exporters and non-exporters controlling for size, sectors and time. Robust standard errors in brackets bellow estimates. Source: Author's calculations.

Generally, we can confirm the existence of statistically significant difference between starters and never-exporters in the period before exporters entered the international market. Firms that will start to export in the next period are more productive and have higher capital and sales as compared to never exporters. On average, in the period before starting to export, future exporters have 27% higher labor productivity than that of never-exporters. Again, as in the case with the export premia, the difference between the two groups of firms is largest in capital and sales – future exporters have 191% higher capital and 71% higher sales compared to never exporters. The difference in pre-entry performance is not significant for TFP and wages. In addition, it is interested to see whether in the years before entry new exporters started to make changes in their organization to achieve higher efficiency. This hypothesis can be tested by estimating model similar to the previous case, but instead of using level of performance indicator as dependent variable, one has to use change in the performance indicator in the periods before exporting (Serti and Tomasi, 2007):

$$\ln(X)_{i,t-s} - \ln(X)_{i,t-p} = \alpha_B + \beta_B Starter_{it} + \gamma_B Controls_{it} + \vartheta_{it} \quad (6)$$

As can be seen from the results reported in Table 7 we cannot see any statistically significant difference between new exporters and never-exporters. The coefficients of all performance related variables are never significant meaning that during the pre-entry period starters' and never-exporters' efficiency dynamics were not statistically different, on average. This result is generally in line with Serti and Tomasi (2007) results for Italian manufacturing firms.

Table 7. Self-selection into exporting: growth rates

	TFP	LP	wages	capital	sales
Estimated coefficients	-0.030	-0.037	0.005	-0.053	-0.042
	(0.082)	(0.080)	(0.033)	(0.056)	(0.093)
transformed coefficients (%)	-2.94	-3.66	0.54	-5.13	-4.14
number of observations	2168	2168	2168	2175	2175
r2	0.01	0.01	0.04	0.02	0.07

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. The transformed coefficient was calculated as 100(exp(β)-1) and this shows the exact percentage differential between exporters and non-exporters controlling for size, sectors and time. Robust standard errors in brackets bellow estimates. Source: Author's calculations.

5.3 Learning by exporting

In this section we are interested in testing the learning by exporting hypothesis which suggests that firm's productivity increases after entry on the foreign market. In other words, we want to test whether exporting activity increases productivity and performance which, in essence, is equivalent to estimating the average effect of the exporting activity on exporters. In the evaluation literature this effect is known as the average treatment effect on the treated (ATT). However, evaluation of the "true" ATT with standard econometric techniques is problematic because of the existence of the so-called ATT bias. This section is organized in two parts. First, we give the intuition behind the ATT bias and briefly summarize the basic characteristics about the Propensity Score Matching (PSM) method, which is one of the methods designed to control for the ATT bias, and then, in the second part, we test learning by exporting hypothesis for North Macedonia, estimate ATT and comment on the results.

5.3.1 Propensity score matching method

The main pillars of the PSM methodology are individuals, treatment and potential outcomes. In our case individuals are the firms, treatment is exporting and outcomes is firms' performance (measured by productivity, wages, capital, sales etc.). The treatment indicator D_i is a dummy variable that takes value 1 if the firm started to export (received the treatment) and value 0 otherwise. Each firm in the sample has two outcomes – $Y_{it}(D_i = 1)$, if it was exposed to the treatment, which in our case is starting to export, and $Y_{it}(D_i = 0)$ if not. The treatment effect for individual i can be written as:

$$\tau_i = Y_i(1) - Y_i(0) \tag{7}$$

The evaluation problem arises because for each individual we observe only one outcome. However, in order to calculate the treatment effect in addition to actual outcome, one needs to know the unobserved, counterfactual outcome. Therefore, estimating the individual treatment effect τ_i is not possible; instead one has to concentrate on average treatment effects on the treated (ATT). The unobserved ATT is the average expected effect of the treatment on those observations who were actually treated.

$$ATT = E(\tau|D = 1) = E(Y(1)|D = 1) - E(Y(0)|D = 1) \tag{8}$$

From the data we can only compute $E(Y(1)|D = 1)$; the counterfactual mean of $E(Y(0)|D = 1)$ is not observed. Using the mean outcome of untreated individuals is not good option because components which determine the treatment decision usually determine the outcome as well. Thus, the outcomes between the treated and not-treated individuals will differ even in the absence of the treatment leading to the so-called ATT selection bias $B(ATT)$.

$$B(ATT) = E(Y(0)|D = 1) - E(Y(0)|D = 0) \tag{9}$$

If the group of export starters was randomly selected from the population than all characteristics between the treated and the control group would be the same and the bias will be equal to zero. However, as we saw in the previous section, this is not the case with export starters meaning that export starters and never exporters may differ in non-ignorable characteristics, other than treatment intake.

There are special techniques developed to overcome the ATT bias. One of the methods that can overcome this problem and that is widely used to investigate empirical questions of this type is the so-called propensity score matching (PSM) method. PSM method is popular approach for estimating causal treatment effects and is used in many different fields of study. In the area of exporting and productivity Wagner(2002), Girma et al. (2003, 2004), Serti and Tomasi (2007) and Haidar (2012) are only some of the empirical papers that used matching techniques to examine the causal relationship between export and productivity.

An extensive overview about the practical implementation of the PSM method is given in Caliendo and Kopeinig (2008). Here we will just try to explain the basic intuition behind the method and the interpretation of the results. The basic idea behind the PSM method is to find in a large group of non-participants (in our case group of never-exporters) individuals similar to participants (export-starters) in all relevant pre-treatment characteristics. The first step in the method is to calculate the propensity score (PS). PS is the probability of participating in the programme given the observed characteristics (Rosenbaum and Rubin, 1983). In our case, PS is the probability of exporting dependent on all observed, firm specific characteristics. To that end we estimate the following logit model (equation 10):

$$P\left(ExpDum_{i,t} = 1\right) = F(X_{i,t-k}, Control_{i,t-k}) \tag{10}$$

,where $ExpDum_{i,t}$ is a dummy variable which is equal to one if the firm i is an export-starter in time t, k is the number of lags, F is the cumulative distribution function of the logistic distribution, $X_{i,t-k}$ are different firm level characteristics that influence the probability of exporting in time t-k and $Control_{i,t-k}$ are control variables that include size, time and sector dummy variables. In the next step, a non-exporting firm j, which is closest in terms of its propensity score to firm i, is selected as a match. In practice, there are several matching estimators – nearest neighbor (NN), caliper and radius, stratification and interval, kernel and local linear and weighting. In our analysis we used the NN matching which is the most straightforward matching estimator. NN chooses the matching partner that is closest in terms of the estimated propensity score to the treated individual.

PSM method is valid only if certain conditions are satisfied. The first one refers to the so-called "common support" range. Namely for the results to be valid one must ensure that there is overlap in the range of the propensity scores across treatment and comparison groups. In other words, this assumption assures that individuals with same characteristics have a positive probability to be treated. The second condition is the fulfillment of the balancing property which states that observations with the same propensity score must have the same distributions of the observable (and unobservable) characteristics independently of treatment status (equation 11). In other words, for a given propensity score, exposure to treatment is random and, therefore treated and control units should be, on average, observationally identical.

$$D \perp X \quad \Big| \quad p(X) \tag{11}$$

After ATT are estimated and common support condition and balancing property are fulfilled, additional complication is the calculation of the standard errors. Namely, the estimated variance of the treatment effects should also include the variance due to the estimation of the propensity score, the imputation of the common support and the order in which treated individuals are matched. There are two alternative methods for correcting this problem. If the propensity score is estimated and the sample is matched separately, then standard errors can be adjusted by using bootstrapping (Lechner, 2002). For matched data, however, bootstrapping gives unreliable estimates. In addition Abadie and Imbens (2008) show that due to the extreme non-smoothness of nearest neighbors matching, the standard conditions for bootstrapped standard errors are not satisfied, leading the bootstrap variance to diverge from the actual variance. In this case it is recommendable to calculate Abadie-Imbens (AI) robust standard errors which are calculated by taking into account the fact that the propensity score is estimated.

5.3.2 Testing learning by exporting hypothesis

In this section we implement PSM method to test learning by exporting hypothesis. We use the same subsample as in the previous section that consisted only of export starters and never-exporters. Export starters are defined as before - export starter is a firm that exports in t and t+1, but doesn't export in t-1. When this assumption is applied the sample reduces to only three years - 2014, 2015 and 2016. The first step, as explained previously, is estimation of the propensity score which is equal to the probability of becoming an exporter. The logit model[5] is presented in equation 12:

$$\Pr(Start_{it}) = \Phi\{TFP_{i,t-1}; LP_{i,t-1}; Employment_{i,t-1}; Capital_{i,t-1}; Sales_{i,t-1}; Wages_{i,t-1}; Time; Sectors; Size\} \tag{12}$$

,where $\Phi\{\}$ is the cumulative distribution function of the logistic distribution. The choice of the variables follows closely Serti and Tomasi (2007). More specifically, it is assumed that propensity score is well described by productivity (LP and TFP), employment, capital, sales and wages. In addition, we included time dummies, sectoral dummies and size dummy variables to control for firms' size. All variables are lagged by one period in order to avoid possible endogeneity. If included contemporaneously then there is possibility that explanatory variables are affected by the treatment, thus creating endogeneity problems. Serti and Tomasi (2007) were matching on variables up to 3 lags, whereas Valdec and Zrnc (2015) were using only two lags. The relatively small time dimension of our sample restricted the choice of lags to be used when estimating the propensity score and therefore, we used only one lag of all explanatory variables, with the exception of control dummies. As stated previously matching of the treated and control individuals is done by using the NN matching method.

After matching the data we checked whether the balancing property holds by using Becker and Ichino (2002) balancing test[6]. This test splits the sample into a number of equally spaced intervals of the propensity score and then, within each interval, it tests whether the mean of each characteristic between treated and control individuals differ or not. The test verified that the balancing property is satisfied. In addition, we performed t-test for equality of the means between treatment and control individuals after matching. As shown in Table 8, no significant difference remained after matching was completed i.e. the hypothesis of equality of means for all relevant variables cannot be rejected at the conventional significance levels. This conclusion is also confirmed by looking at the box-plot presented in Appendix 3.

Table 8. Assessing the matching quality – means of treated and controlled observations after matching

	Means	**Employment**	**Capital**	**TFP**	**LP**	**Wages**	**Sales**
	treated	3.2	16.0	10.3	12.4	11.6	16.9
Outcome TFP	control	3.2	15.9	10.2	12.4	11.5	16.9
	p-value	0.98	0.85	0.70	0.66	0.14	0.97
Outcome LP	control	3.1	15.9	10.2	12.3	11.5	16.8
	p-value	0.85	0.86	0.53	0.53	0.12	0.59
Outcome wages	control	3.2	16.0	10.1	12.2	11.6	16.9
	p-value	0.74	0.96	0.14	0.13	0.63	0.90
Outcome capital	control	3.2	15.9	10.1	12.3	11.5	16.9
	p-value	0.93	0.97	0.33	0.32	0.37	0.91
Outcome sales	control	3.2	15.8	10.1	12.2	11.5	16.9
	p-value	0.96	0.57	0.23	0.17	0.51	0.83

Note: Total number of observations is 3,717 individuals. From this 77 firms are treated. Source: author's calculations.

[5] We choose logit model instead of probit because it ensures balancing property to hold. However, results were very similar in the case probit model is used.

[6] To estimate the propensity score and check the balancing property we used pscore command in Stata written by Becker and Ichino; the matching and t-test for equality of the means are performed by using command psmatch2 written by Leuven and Sianesi; the ATTs, AI robust standard errors and balancing box plots are calculated by using Stata build-in command teffects.

In Table 9 we present the estimated ATT together with AI robust standard errors. As outcome variables we used different measures of firms' performance (TFP, LP, wages, capital, sales). Moreover, we calculated ATT for the current period and one period ahead (one year after starting to export), for the level of the outcome variables, as well as for the growth rates. The latter actually tests whether exporters tend to grow faster than never-exporters. Valdec and Zrnc (2015) calculated ATTs for the current period and two years ahead; however our time dimension is rather small (only three years) and employing two leads in the ATTs calculation would cause significant decrease of the sample size.

Table 9. ATT estimates

Outcome variable		**levels**		**growth rates**	
		t	**t+1**	**t/t-1**	**t+1/t**
TFP	ATT	0.080	0.111	0.026	0.059
	AI std. error	0.088	0.095	0.111	0.079
LP	ATT	**0.241****	0.154	0.157	0.064
	AI std. error	**0.097**	0.109	0.106	0.080
Wage	ATT	**0.100***	0.057	0.066	0.020
	AI std. error	**0.060**	0.056	0.060	0.034
Capital	ATT	0.211	**0.363*****	**0.201*****	**0.151*****
	AI std. error	0.159	**0.126**	**0.056**	**0.048**
Sales	ATT	**0.256*****	**0.450*****	**0.215*****	**0.216*****
	AI std. error	**0.095**	**0.107**	**0.072**	**0.038**

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. AI standard errors refer to Abadie-Imbens robust standard errors. Source: author's calculations.

First two columns of Table 9 show the estimated average effects in levels. Results suggest that, after controlling for firm specific characteristics, there are positive statistically significant learning by exporting effects for Macedonian exporters. This is valid for almost all performance indicators. Namely, exporters, as a result of the learning effects acquired during exporting activities, have higher labor productivity, sales, pay higher wages, and have higher capital (only in period t+1) in comparison to never exporters. The difference between these two groups of firms is largest for sales and capital and smallest for wages. However, we didn't find evidence that export improves TFP. Valdec and Zrnc (2015) found similar results for Croatian manufacturing firms. They estimated positive and statistically significant average effects for labor productivity, sales and wages with higher sales being the most distinguishing characteristic of export starters, even just a few years after starting to export. This is similar to Macedonian case where sales remain significant one year after starting to export. As TFP is concerned this variable is also not significant in the Croatian case.

Following Valdec and Zrnc (2015) and Serti and Tomasi (2007) we also estimated average effects in differences in order to check whether Macedonian exporters grow faster in comparison to non-exporters as a result of learning effects. Results are presented in the last two columns of Table 9. As can be noticed, in comparison to results in levels, fewer ATTs are significant in this case. Similar results was found for Croatian firms (Valdec and Zrnc, 2015) and for Italian firms (Serti and Tomasi, 2007). In our case, results reveal higher sales and capital growth as a significance difference between new exporters and never-exporters (in both time periods t/t-1 and t+1/t). The post-entry effects for TFP, LP and wages were not significant.

In addition we wanted to check whether treatment effects are heterogeneous across firms depending on the size of the firm (small and large and medium sized firms) and the degree of technological complexity (high and low technology firms) of firm's main sector of activity. However, as the created subsamples were relatively small, the number of matched individuals is also small and the estimated results were counterintuitive and not stable. Results are presented in Appendix 4.

6. Conclusion

The goal of this paper was to identify the reasons behind superior features of exporters by testing the self-selection and learning by exporting hypothesis. To that end we used firm level dataset constructed from the financial accounts that firms submit to the Central Register of the Republic of North Macedonia and from the National Bank's internal database on export activity for the period 2013-2017. In line with other papers we are concentrated only on manufacturing firms that have more than five employees.

Empirical analysis confirmed that Macedonian exporters, as it was the case with other countries, do have better performance in comparison to firms that never entered the international market. Estimated export premia are all highly significant and reveal existence of sizable difference in productivity, capital, wages and sales between exporters and never-exporters. One part of this difference might be explained by the self-selection process – firms that are already performing well self-select themselves in the international market. Indeed, when testing this hypothesis results confirmed that firms with higher productivity, capital and sales will become exporters in the next period. This difference seems to be intrinsic and it is not connected with changes and re-organizations made by the firms as a preparation before entering the foreign markets.

In addition, we tested learning by exporting hypothesis which suggests that firm's performance improves after entering the foreign market. After controlling for firm specific characteristics, we found evidence of existence of positive statistically significant post-entry effects for labor productivity, wages, sales and capital. Exporters have higher labor productivity, pay higher wages and have higher capital and sales in comparison to never exporters. Moreover, we found some evidence that Macedonian exporters grow faster in comparison to non-exporters as a result of learning effects. Results suggested that exporters experienced significantly higher sales and capital growth compared to never-exporters, in current period, as well as one period ahead.

The contribution of the research is twofold. First, this is one of the few papers on Macedonian economy that explores the advantages of the microdata as an efficient way to fill "aggregate data gaps". Second, this paper adds to the empirical literature on the direction of causality between trade and firm's level of performance by studying the experience of one small and open transition country – North Macedonia. Having in mind the importance of export as the main driving growth force of Macedonian economy, deeper understanding of firms' exporting patterns and additional analysis on this topic will be useful input in compiling growth strategies and policies. Future research in this area might be focused on inclusion of more countries, in order to get broader picture for the exporting patterns in the region; inclusion of the services sector, in line with the increasing importance of the services for the economic growth; as well as, analysis on the impact of the exporting destination on firms' productivity and performance. Of course, all this suggestions are conditional on the data availability which is a general issue when conducting microdata analysis.

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Appendix 1. Estimates of export premia

	TFP	LP	Wage	Capital	Sales
export dummy	0.3380***	0.5758***	0.1874***	1.7320***	1.3435***
	(0.0285)	(0.0321)	(0.0172)	(0.0850)	(0.0491)
medum	-0.0074	-0.0636	0.0804***	1.4028***	1.3239***
	(0.0301)	(0.0350)	(0.0188)	(0.1014)	(0.0577)
large	0.0364	-0.0245	0.1617***	2.7658***	2.8451***
	(0.0765)	(0.0905)	(0.0445)	(0.2348)	(0.1300)
medium-high-technology	-0.0349	-0.0583	-0.2377*	-0.2915	-0.2766
	(0.1173)	(0.1350)	(0.0935)	(0.3699)	(0.2048)
medium-low-technology	-0.2419*	-0.2412	-0.4093***	-0.2315	-0.4216*
	(0.1067)	(0.1248)	(0.0902)	(0.3533)	(0.1956)
low-technology	-0.4499***	-0.5995***	-0.5803***	-0.9827**	-0.8824***
	(0.1043)	(0.1222)	(0.0891)	(0.3490)	(0.1928)
2014	0.0581**	0.0729***	0.1000***	0.1014***	0.0872***
	(0.0178)	(0.0181)	(0.0111)	(0.0239)	(0.0155)
2015	0.0320	0.0275	0.0753***	0.0244	0.0452*
	(0.0182)	(0.0187)	(0.0108)	(0.0331)	(0.0199)
2016	0.0206	0.0065	0.0602***	-0.0411	-0.0093
	(0.0194)	(0.0198)	(0.0114)	(0.0372)	(0.0221)
2017	0.0123	-0.0064	0.0775***	-0.0627	-0.0194
	(0.0195)	(0.0201)	(0.0110)	(0.0394)	(0.0233)
constant	10.4931***	12.5838***	11.9258***	15.0420***	16.5229***
	(0.1050)	(0.1227)	(0.0892)	(0.3480)	(0.1926)
N	9511	9513	9516	9530	9529
r2	0.0834	0.1596	0.1312	0.3209	0.5218

Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

Appendix 2. Self-selection models

Self-selection into exporting: levels

	TFP	LP	Wage	Capital	Sales
export starter	0.0641	0.2379*	0.0740	1.0683***	0.5376***
	(0.0987)	(0.1000)	(0.0511)	(0.2075)	(0.1241)
medum	0.0538	0.0006	0.1064***	1.5101***	1.4355***
	(0.0406)	(0.0456)	(0.0276)	(0.1550)	(0.0844)
large	0.1811*	0.0529	0.1076	2.2505***	2.4505***
	(0.0805)	(0.0917)	(0.0711)	(0.4844)	(0.1682)
medium-high-technology	-0.0233	-0.0305	-0.2345*	-0.2298	-0.4582
	(0.1490)	(0.1794)	(0.0963)	(0.5357)	(0.2731)
medium-low-technology	-0.3044*	-0.2829	-0.4638***	-0.0594	-0.5457*
	(0.1293)	(0.1627)	(0.0881)	(0.5034)	(0.2602)
low-technology	-0.5343***	-0.6663***	-0.6414***	-0.8299	-1.0539***
	(0.1264)	(0.1600)	(0.0861)	(0.4985)	(0.2579)
2015	0.0797***	0.0914***	0.1192***	0.1719***	0.2009***
	(0.0210)	(0.0216)	(0.0134)	(0.0342)	(0.0217)
2016	0.0809***	0.0769***	0.1035***	0.0682	0.1301***
	(0.0209)	(0.0216)	(0.0127)	(0.0432)	(0.0254)
constant	10.5680***	12.6453***	11.9735***	14.9045***	16.6777***
	(0.1253)	(0.1587)	(0.0858)	(0.4948)	(0.2557)
N	3723	3724	3726	3731	3731
r2	0.050	0.084	0.095	0.107	0.239

Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

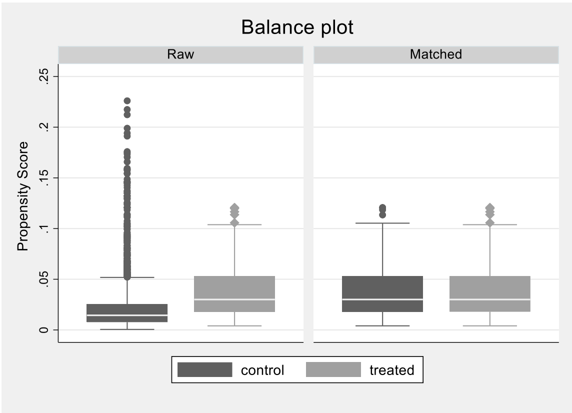
Self-selection into exporting: growth rates

	TFP	LP	Wage	Capital	Sales
export starter	-0.0299	-0.0372	0.0054	-0.0527	-0.0423
	(0.0824)	(0.0800)	(0.0332)	(0.0564)	(0.0931)
medum	0.0211	0.0219	0.0298*	0.0087	0.0272
	(0.0242)	(0.0241)	(0.0127)	(0.0282)	(0.0197)
large	0.0574*	0.0776**	0.0581*	0.1037*	0.0529
	(0.0238)	(0.0293)	(0.0268)	(0.0424)	(0.0308)
medium-high-technology	-0.0373	-0.0320	-0.1470*	0.0991	-0.0627
	(0.1595)	(0.1551)	(0.0669)	(0.1297)	(0.0908)
medium-low-technology	-0.0458	-0.0388	-0.0840*	0.0358	-0.1209*
	(0.1430)	(0.1353)	(0.0398)	(0.1113)	(0.0604)
low-technology	-0.0702	-0.0603	-0.0887*	0.0384	-0.1410*
	(0.1415)	(0.1338)	(0.0366)	(0.1101)	(0.0577)
2016	0.1004***	0.1173***	0.1245***	0.1390***	0.2011***
	(0.0289)	(0.0291)	(0.0149)	(0.0210)	(0.0164)
constant	-0.0192	-0.0392	-0.0360	-0.1662	-0.0283
	(0.1408)	(0.1331)	(0.0362)	(0.1096)	(0.0581)
N	2168	2168	2168	2175	2175
r2	0.008	0.011	0.037	0.020	0.067

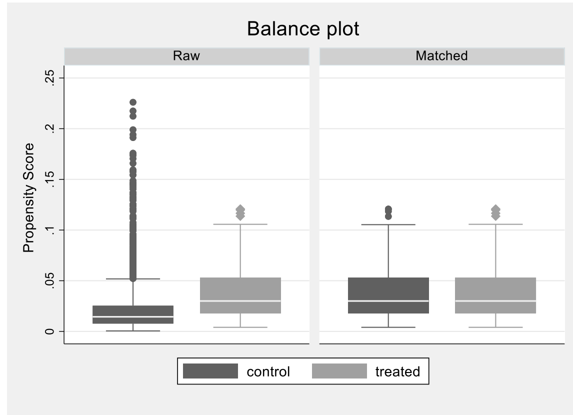
Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

Appendix 3. Balancing box plots

Outcome TFP

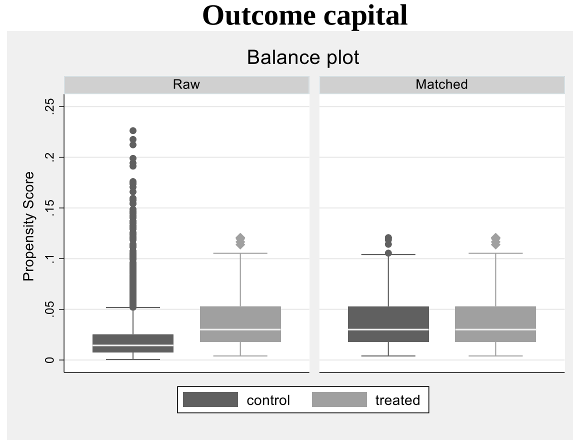


Outcome LP



Outcome wage

Outcome capital



Outcome sales

Appendix 4. Heterogeneity of the treatment effect

Heterogeneity of the treatment effect: size

Small firms

Outcome variable		levels		growth rates	
		t	t+1	t/t-1	t+1/t
TFP	ATT	0.083	-0.100	0.018	-0.026
	AI std. error	0.099	0.088	0.102	0.121
LP	ATT	0.127	**-0.146***	0.043	-0.041
	AI std. error	0.115	**0.083**	0.114	0.123
Wage	ATT	**0.118****	0.081	**0.083***	-0.047
	AI std. error	**0.054**	0.053	**0.048**	0.040
Capital	ATT	**0.546****	0.072	**0.202*****	0.039
	AI std. error	**0.223**	0.127	**0.062**	0.061
Sales	ATT	**0.442*****	**0.353*****	**0.488*****	0.125
	AI std. error	**0.075**	**0.116**	**0.114**	0.085

Medium and large firms

Outcome variable		levels		growth rates	
		t	t+1	t/t-1	t+1/t
TFP	ATT	**0.942****	**-0.426***	-0.237	0.055
	AI std. error	**0.376**	**0.245**	0.392	0.059
LP	ATT	**1.106*****	-0.371	-0.127	0.054
	AI std. error	**0.372**	0.290	0.392	0.062
Wage	ATT	**0.263****	**-0.269***	**0.265*****	**0.094****
	AI std. error	**0.110**	**0.138**	**0.097**	**0.045**
Capital	ATT	0.182	**-0.528***	**0.362*****	-0.037
	AI std. error	0.240	**0.311**	**0.119**	0.098
Sales	ATT	0.353	**-1.010*****	**0.221****	0.121
	AI std. error	0.229	**0.350**	**0.103**	0.077

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. AI standard errors refer to Abadie-Imbens robust standard errors. Source: author's calculations.

Heterogeneity of the treatment effect: degree of technological intensity

High technology firms

	Outcome variable	**levels**		**growth rates**	
		t	**t+1**	**t/t-1**	**t+1/t**
TFP	ATT	**-0.226***	**-0.192***	-0.549	0.062
	AI std. error	**0.121**	**0.110**	0.464	0.122
LP	ATT	**-0.222***	**-0.1434*****	-0.646	0.074
	AI std. error	**0.123**	**0.051**	0.546	0.123
Wage	ATT	**-0.181*****	**-0.234*****	-0.792	0.001
	AI std. error	**0.068**	**0.062**	0.526	0.052
Capital	ATT	0.537	0.724	-0.599	0.155
	AI std. error	0.546	0.621	0.516	0.113
Sales	ATT	**0.322***	0.544	-0.358	**0.197*****
	AI std. error	**0.190**	0.343	0.541	**0.062**

Low technology firms

	Outcome variable	**levels**		**growth rates**	
		t	**t+1**	**t/t-1**	**t+1/t**
TFP	ATT	0.117	0.137	0.118	-0.095
	AI std. error	0.084	0.106	0.096	0.073
LP	ATT	0.044	0.131	0.109	-0.098
	AI std. error	0.072	0.116	0.079	0.074
Wage	ATT	-0.033	0.072	0.060	-0.009
	AI std. error	0.047	0.054	0.039	0.041
Capital	ATT	**0.211****	**0.332****	**0.239*****	0.041
	AI std. error	**0.100**	**0.137**	**0.047**	0.066
Sales	ATT	**0.233****	**0.577*****	**0.266*****	**0.113****
	AI std. error	**0.102**	**0.105**	**0.054**	**0.054**

Note: *, ** and *** refer to 10%, 5%, and 1% level of statistical significance, respectively. AI standard errors refer to Abadie-Imbens robust standard errors. Source: author's calculations.