Causal link between exporting and innovation activity: Evidence from Slovenian firms

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Abstract

In this paper we investigate the causal relationship between firms' innovation and exporting activity by using detailed firm-level data on innovation activity, financial variables and information on trade for Slovenian firms in 1996-2002. We employ the bivariate probit regression on a system of innovation and exporting equations as well as matching procedures to tease out the direction of causality between exporting status and innovation activity. Our results suggest a strong positive relationship between exporting and innovation activity in both directions, while results on the impacts of lagged export (or innovation) status on the probability to start innovating (or exporting) are less conclusive. In other words, whereby innovating status increases the probability of exporting it does not increase the probability of becoming a first time exporter, and vice versa. The results remain unaltered also after allowing for discrimination between product and process innovation.

JEL classification: D24, F14, F21

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1 Introduction

Empirical research has shown unanimously that exporting firms are larger and "better" than non-exporters in terms of productivity. In the last decade, enormous research activity has been devoted to explain why exporters are "better". Main research issue has focused on whether it is a self-selection process of initially better performing firms into exports or do firms become "better" through a process of learning-by-exporting. The most comprehensive study so far by Wagner et al (2007), covering 14 countries and using a common methodology, has shown that firms that become exporters are initially more productive than non-exporting firms and exporting does not boost their productivity substantially.

This opens a set of new questions. The first question refers to the primary issue of firm dynamics - why are some firms initially "better" than the other ones. What determines firm's innate ability of being comparatively more productive? Are more productive firms "better" because they are in control of a superior technology enabling them to produce their products more efficiently? Or are they "better" because they are in control of a proprietary knowledge allowing them to produce "better" products? In either case, the firms that are to become exporters should distinguish themselves by a set of superior characteristics leading to higher absorption and/or innovative capacity and allowing them to either invent or adapt to new, more efficient production techniques or to invent new products which are more attractive to consumers. Theoretical literature as well as some empirical studies point towards the Vernon (1966) product life cycle theory where product innovation should impact on the firm's productivity level and therefore be indirectely linked to the later decision of a firm to start exporting. Klepper (1996) demonstrates that product innovation dominates the early stage of the product lifecycle, while process innovation becomes important in the later stages after production volumes have increased and efficiency of production becomes increasingly important. Becker and Egger (2007) using the set of German firms, and Cassiman and Martinez-Ros (2007) and Cassiman and Golovko (2007) using a set of Spanish data find that product innovation rather than process innovation impacts firm productivity, which in turn leads firms to select into the export market.

The second question draws on the issue raised by Aw et al (2005). They argue that numerous studies that failed to find significant effects from learning-by-exporting may have omitted a potentially important element of the process of productivity change: the investments made by firms to absorb and assimilate knowledge and expertise that they may gain from foreign contacts. In other words, exporting activity may have helped firms to become more innovative in the process which may impact productivity growth in the long run.

In this paper we address these questions by focusing on the causal relationship between firms' innovation and exporting activity. Are firms that will become exporters in the future more innovative initially? Or is it exporting experience that makes them more inclined towards innovation activities? There is not much evidence so far in the literature on the exact direction of causality between innovation and exporting activity. Most of the papers find significant correlation between firms' exporting and innovation activity (Wagner (1996), Wakelin (1997, 1998), Ebling and Janz (1999), Roper nad Love (2002), Damijan et al (2007), etc.). Some recent papers (Aw et al (2005), Becker and Egger (2007), Cassiman and Martinez-Ros (2007), Cassiman and Golovko (2007) and Girma et al (2007)) do address this issue but do not unanimously show the exact direction of causality between innovation and exporting activity.

We follow a similar approach to Aw et al (2005) and Girma et al (2007) to establish the link between exporting and innovative activity. Our strategy, however, differs in two important ways. First, while Aw et al (2005) and Girma et al (2007) use information on whether the firm has invested in R&D or worker training as a proxy for the stock of knowledge, we are able to gauge the stock of knowledge from its actual output. We dispose with information on the actual outcome of the innovation process (actual product and/or process innovations undertaken) by the firm. We make use of the firm level accounting data for Slovenian firms in the period 1996-2002, which we combine with the firm level information on firms' foreign trade flows and innovation activity in the same period. This unique dataset allows us a more precise test of both the prediction that firm's ability to innovate enhances its probability of becoming an exporter as well as the postulate that positive learning effects of exporting will manifest themselves in improved firm ability to innovate. We employ bivariate probit regression approach to test a model of a firm's decisions to become an exporter and/or to innovate a product or process. We also use a matching approach after propensity score to account whether positive correlation between exporting and innovation activity is robust to estimation methods. We match exporters with non-exporters based on their propensity to export and investigate whether the two cohorts differ in terms of their innovative effort. In addition, we also match innovating and non-innovating firms (based on the propensity to innovate) in order to compare their exporting status and exporting intensity. Second, our additional novelty is that we aim at exploring not only the correlation between innovation and exporting status but try to tease out also the direction of causality between the two. In order to reveal the causality link between exporting and innovation activity (and the direction of it) we alter accordingly our exporting and innovation equations to reveal whether the lagged exporting status has an effect on firms starting to innovate and whether the lagged innovation output has an impact on firms starting to export.

The paper is organized as follows. After presenting the empirical background in the next Section, in Section 3 we present the datasets used and basic descriptive statistics on exporting and innovation activity of Slovenian firms. In Section 4 we discuss methodological issues related to the use of bivariate probit regressions on a model of simultaneous equations. Section 5 presents results of the basic bivariate probit and matching regressions as well as from altered exporting and innovation equations. Last Section concludes.

2 Related research

Literature on the link between exporting and innovative activity can clearly be divided into two strains. On one hand, there are a number of studies exploring either the effects of innovation on exporting propensity or exporting status on the propensity to innovate, on the other hand, there are only a handful of analyses that examine both sides of the exporting-innovation link by searching for the direction of causality in the innovation-exporting relationship. In an early paper, using data on manufacturing firms in the German state Lower Saxony, Wagner (1996) finds a positive impact of innovation on exports. Wakelin (1997, 1998), for a sample of British manufacturing firms, finds a positive impact of firms' innovation activity on the probability of exporting as well as on the propensity to export. Similarly, for a sample of German services firms, Ebling and Janz (1999) find export activities of firms being mainly driven by their innovation activities. Using samples of British and German manufacturing plants, find that innovation has a strong and systematic effect on the probability and propensity to export. While, the scale of plants' innovation activity is positively related to export probability in both countries, in German plants innovation activity is also related positively to export propensity. Damijan et al (2007) find for Slovenian firms that exporting is an important determinant of firms innovation activity. Firms that export a higher share of their sales are more likely to introduce product or process innovation in the subsequent period. Becker and Egger (2007) explore the role of innovation on export propensity of German firms. Their results indicate that, controlling for the endogeneity of innovation, product innovation plays an important role in fostering the propensity to export, while no such evidence is found for process innovation. Those findings are echoed by Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) on a sample of Spanish manufacturing firms. Whereby most of the empirical work on the link between innovation and exporting focuses on the effects of innovation on exporting, Salomon and Shaver (2005) offer a rare look at the impact of exporting status on innovation activity. Using data on Spanish manufacturing firms they find evidence of learning-by-exporting as exporting status is found to enhance the propensity of firms to innovate.

Literature on the direction of causality between exporting and innovation is a more recent phenomenon. Aw et al (2005), by using Taiwanese data, estimate a model of a firm's decisions to participate in the export sector and/or make investments in research and development and/or worker training and then study how participation in these activities impacts firm's future productivity growth. They find that, on average, firms that export and invest in R&D (and/or worker training) have significantly higher future productivity than firms that only export. In addition, firms that export but do not invest in R&D and/or worker training have significantly higher future productivity than firms that do not participate in either activity. Girma et al (2007) investigate the two-way relationship between R&D and export activity in the British and Irish firms. They study whether R&D stimulates exports and, conversely, whether export activity leads to increasing innovative activity in terms of R&D. They find that previous exporting experience enhances the innovative capability of Irish firms, but no such effects are found for British firms.

3 Data description

3.1 Data Source

Our empirical analysis of the relationship between innovative activity and exporting is based on firm-level data from Community Innovation Surveys (CIS1, CIS2, CIS3) and firm financial data (AJPES) for the period 1996-2002. CIS represent an EU wide effort to assess innovation activity and its effects on firm performance. In Slovenia community innovation surveys are conducted every even year since 1996 by the Slovenian Statistical office (SORS). The surveys are carried out on a stratified sample of manufacturing and non-manufacturing firms with no additional conditions put on actual R&D activity or size of these firms. Crucially, the data gathered by the innovation surveys include, amongst other, information on product and process innovations undertaken by a firm in the past two years as well as data on the determinants of innovation (employment and expenditure of research and development, etc.). In order to obtain additional insight into the causes and consequences of innovation, we merged CIS data with firm accounting data from annual financial statements as well as with data on firm exports flows. All value data was deflated using Nace 2-digit industry producer price indices, while the capital stock variable was deflated using the consumer price index.

3.2 Descriptive statistics

Given the relatively small size of their domestic market, it is not surprising that around 85% of Slovene manufacturing firms are exporters (Damijan and Kostevc. 2006). Furthermore, Damijan et al (2007) show that the majority of Slovene exports are destined for the highly-competitive EU-15 markets. The fact that Slovenian firms' exports are oriented primarily towards the highly demanding exporting markets maximizes the scope for positive effects of exporting. Faced with more advanced markets exporters may benefit either from positive spillovers in the exporting markets or by raising the productivity of exporting firms (learning-by-exporting). Damijan and Kostevc (2006) found no evidence of positive effects of exporting on firm productivity growth for Slovene manufacturing establishments, but the effects of exporting on other firm characteristics were not studied. Namely, spillovers and learning effects could manifest themselves in increased investment into R&D, and hence in improved innovation activity of exporters. On the other hand, innovation could stimulate exports especially when exports into highly competitive marketplaces are considered. The causal link between exporting and innovation may therefore work in both directions as exports may affect innovative activity and it, in turn, innovation activity could impact the exporting status.

The characteristics of the firms in the sample with respect to both exporting and innovating status are described in Table 1. By splitting the sample into four cohorts of firms depending on whether they have innovated and exported in the preiod 2001-2002, we observe the difference in characteristics between them. The first difference between the groups of firms is generated by the export status as exporters (in line with the relevant literature) are revealed to be more productive, larger and more capital intensive compared with non exporters. Differences between innovators and non-innovators are more subtle as innovators are found to be only slightly more productive than non-innovators once the export status is controlled for. Furthermore, innovators are not found to be substantially more capital intensive[1] and in the case of non-exporters they are of similar size as non-innovators. Expenditure on research and development per employee at first seems to indicate that non-exporting firms invest more in research, but, given the size difference, it is clear that the median exporting innovator invests substantially more in absolute terms. Finally, innovating exporters though are found to be far larger than non-exporters or non-innovating exporters both in terms of sales and employment.

Table 1: Comparison of firm characteristics between exporters and non-exporters and innovators and non-innovators for 2002

	non-exporters		exporters	
	non-innovators	innovators	non-innovators	innovators
Value added per employee	19,627	19,707	21,257	21,293
Capital per employee	48,156	48,781	68,843	65,998
R&D expenditure per employee	0	2,692	0	1,603
Size (sales)	1,158,203	1,180,575	2,843,517	7,612,973
Size (employment)	18	19, 5	28	112
Number of firms	692	96	1181	394

Note: All variables in median values except number of firms. Value added per employee, capital per employee and sales in Euro (1994 prices).

Source: SORS and AJPES; authors' calculations

[1] Among exporting firms non-innovators are even found to be more capital intensive than non-innovators.

Tables 2 and 3 focus on the link between exporting and innovation by providing an overview of the joint probabilities of being an exporter (non-exporter) and/or innovator (non-innovator). The results shown in Table 2 are very revealing. Innovating firms' probability of being exporters (probability of being an exporter conditional on being an innovator) is some 40 percentage points higher than that of non-innovating firms. In other words, where there is an almost 90% likelihood of being an exporter if the firm is also an innovator, that probability drops to about 50% for non-innovators[2]. These characteristics indicate that innovating activity may be a determinant of exporting status or, at the very least, that innovation and exporting are intrinsically linked.

Table 2: Share of exporters depending on innovative activity by years

year	innovators share of exporters	non-innovators share of exporters
1996	87,4%	49,9%
1998	79,6%	50,5%
2000	87,0%	54,4%
2002	86,5%	72,4%

Source: SORS and AJPES; authors' calculations

Table 3 offers an alternative perspective to the one in Table 2 as instead of looking at the probability of being an exporter (given the innovator status) it reveals the likelihood of a firm being an innovator conditional on the exporting status. Again the results are telling. Exporters are far more likely to innovate than non-exporters. Depending on the year (and Survey) in question exporters are between two and five times more likely to innovate than non-exporting firms. Another striking feature of the data is the relatively low share of innovating firms in the total number of firms. The average share of firms that have innovated of those surveyed was only about 20%, compared with 65% of German enterprises or 53% of Austrian firms.[3]

Table 3: Share of innovators depending on export status

year	exporters share of innovators	non-exporters share of innovators
1996	28,1%	5,3%
1998	29,8%	9,9%
2000	26,5%	10,1%
2002	23,4%	11,1%

Source: SORS and AJPES; authors' calculations

[2] In year 2002 the probability of being an exporter is somewhat larger at 72,4%.

[3] The average share of innovating firms in manufacturing and services for the 27 EU countries was 42% (Fourth Community Innovation Survey, 2007, http://europa.eu/rapid/pressReleasesAction.do?reference=STAT/07/27&format=HTML&aged=0&language).

Although the positive link between innovative activity and exporting status appears prevalent in the data, the direction of the relationship (causality) is not evident from the above statistics. Furthermore, there may be an omitted variable such as firm size, capital intensity and foreign ownership that is positively correlated both with innovative activity as well as exporting status and may be causing a spurious relationship.

Table 4: Comparison in total factor productivity per employee of sample and population data

	number of firms		difference in means	mean (pop.) > > mean (sam.)		K-S stochastic dominance test	
	sample	population		t-stat.	P-value	D-stat	P-value
pooled	9,148	105,560	−300.561	−13.83	0.000	0.099	0.000
1996	1,743	25,243	−89.165	−1.50	0.068	0.049	0.001
1998	2,219	26,649	−584.078	−7.99	0.000	0.102	0.000
2000	2,601	27,653	−404.945	−8.90	0.000	0.173	0.000
2002	2,585	26,015	−533.742	−8.66	0.000	0.203	0.000

Note: Difference in TFP means in Euros (1994 prices)

Source: SORS and AJPES; authors' calculations

Finally, Table 4 illustrates the representability of the sample of firms chosen for the Community Innovation Surveys. The firms chosen to participate in the survey represent about 10 percent of the population with the inclusion rate being slightly larger in the later years. As is clearly evident from Table 4, the firms that were surveyed turn out to be more productive than the average in terms of total factor productivity[4] (TFP). In each of the survey years, there is a significant negative difference in average TFP between sample firms and the total population. Stochastic dominance tests confirm that the cumulative distribution function of the sample firms dominates that of the total population in terms of TFP. In addition, sample firms are revealed to be larger in terms of sales and employment as well as more capital intensive than the population average.[5] The sanple of firms chosen to participate in the Community Innovation Surveys is therefore not representative of the population of Slovene firms and that has to be taken into consideration in the interpretation of results.

4 Methodology

Our approach to establishing the link between exporting status and innovative activity is similar to Aw et al (2005) and Girma et al (2007). But, where these studies interdependently model the decision to export with the decision to enagage in research and

[4] We generate total factor productivity as a production function residual.

[5] For the sake of brevity we do not show these results.

development, our data is richer and allows us to test the theoretical propositions more directly. We dispose with information on the actual outcome of the innovation process (actual product and/or process innovations undertaken) by the firm, which allows us a more precise test of both the prediction that positive effects of exporting will manifest themselves in improved firm ability to innovate as well as the postulate that improved ability to innovate would foster greater probability of becoming an exporter. Aw et al (2005) and Girma et al (2007) use information on whether the firm has invested in R&D or worker training as a proxy for the stock of knowledge, while we are able to gauge the stock of knowledge from its actual output. Specifically, we estimate the probability that a firm is exporting at time t as a function of a number of firm characteristics:

$$Prob(Exp_t = 1) = f(Exp_{t-2}, Inov_{t-2}, X_{t-2}) \tag{1}$$

$$Prob(Inov_t = 1) = f(Inov_{t-2}, Exp_{t-2}, X_{t-2}) \tag{2}$$

where Exp_t is an indicator variable for export status (assuming value 1 if a firm is exporter and 0 otherwise), $Inov_t$ is an indicator of innovation[6] (taking on value 1 if a firm has innovated in the between two consecutive innovation surveys and 0 otherwise) while Exp_{t-2} and $Inov_{t-2}$ are the respective lagged variables. X_{t-2} represents a set of other lagged firm characteristics which determine the decision to export and decision to innovate.

Lagged indicator of innovation is the variable of interest in equation 1.[7] The regression coefficient of that variable will indicate whether innovating firms are more or less likely to be also exporters. The inclusion of additional explanatory variables is waranted by the relevant literature on the determinants of exports (Wagner, 2007). We include the lagged exporting status, which is used in related literature to account for the sunk cost of entry into the export markets (Roberts and Tybout, 1997). Amongst other determinants of exporting status (as suggested in the relevant literature) we also include firm productivity measured in terms of (logged) value added per employee, which accounts for the common empirical finding that more productive firms self-select into exporting. Size measured by logged number of employees appears as a determinant of both innovation as well as exporting status (Love and Roper, 2002; Barrios et al., 2003; Damijan and Kostevc, 2006). We base the inclusion of capital to labor ratio in logarithms and logged investment in R&D on the proposition that firms with higher capital to labor ratios and more investment in R&D are likelier to be able to compete in highly competitive mature markets. Finally, we follow Girma et al (2007) and approximate foreign penetration with the share of R&D

[6] We do not discriminate between product and process innovations here, but come back to this important distinction below.

[7] In line with Barrios et al (2003) and Girma et al (2007).

expenditures of foreign owned firms in total R&D expenditures of the sector.[8] We have also estimated specifications where labor productivity and capital intensity were replaced by total factor productivity per employee, but that did not alter the significance or even the magnitude of the remaining variables of interest.

In equation 2 we follow the spirit of Aw et al. (2005) and Girma et al (2007) and assume that the determinants of innovation activity are the same as those included in the determination of exporting status. The explanatory variable of particular interest is the lagged export status, the coefficient on which should indicate whether exporters are more or less likely to innovate than non-exporters. This would indicate that there is the possibility of learning-by-exporting manifesting itself through increased innovative activity.[9] Again, compared with both Aw et al. (2005) and Girma et al (2007), the interpretation of our results would be different as we employ the actual indicator of innovation as the dependent variable and not R&D or worker training dummies. A positive coefficient on lagged exporting status would imply that exporting leads to "new knowledge" and not just investment in "new knowledge".

The estimation of the two equations has to take account of the fact that they are not independent of each other. Given that both export status as well as innovative activity are highly serially correlated and that they appear both as regressors and regressants, the error terms of the two equations are likely to be correlated. The two equations therefore need to be estimated simulatenously. Following Aw et al. (2005) and Girma et al (2007) we employ bivariate probit estimation approach. Bivariate probit fits a maximum likelihood two-equation probit model to the two simultaneous equation.

5 Results

5.1 Results with bivariate probit regressions

In order to gain insight into the link between exporting status and innovation, we first present estimates of the effects of innovation on the exporting status. As noted above, by including lagged indicator variable for innovation as a determinant of exporting status, we aim to see whether being an innovator (in the recent past) increases the likelihood of exporting either due to a lowering of the price of products or because of an increase in product quality brought about by innovation. The top panel (Panel A) of Table 5 presents the estimates of the exporting equation. The first column of Panel A reports the estimates of the basic model specification. As expected, lagged exporting status is positively related to current exporting status indicating the presence of sunk costs of

[8] Again, replacing this variable with the share of innovation of foreign-owned firms in total sectoral innovation does not substantially alter the main results.

[9] Instead of the direct effects of exporting on productivity growth which were not found in Slovene manufacturing firms (Damijan, Kostevc 2006).

export market entry. This finding persists in all model specifications tested as can be seen in columns 2-6. Column 1 also shows that pre-entry productivity levels, size as well as capital intensity positively affect the probability to export. Significant positive impact of lagged productivity signals the importance of self-selection into exporting, which has been found by other studies on Slovenian exporting firms (Damijan and Kostevc, 2006). Interestingly lagged innovation is not significantly related to current exporting status which contradicts theoretical predictions. Column 2 offers estimates of a slightly broader model as we follow Girma et al (2007) and introduce an FDI penetration variable in order to control for the domestic spillovers from foreign ownership. The added variable is revealed to have an insignificant impact on the likelihood of exporting. In columns 3 and 4 we repeat the estimation of the first two columns but broaden it slightly with the inclusion of lagged R&D investment. The effect of lagged R&D investment on exporting status is is not significant, which serves to confirm the finding that lagged innovation does not effect current exporting status. Finally, columns 5 and 6 offer estimates of the preferred specification but we descriminate explicitly between product innovations (5) and process innovation (6). These results confirm the finding that innovators are not more likely to export than non-innovators.

Table 5: Results of bivariate probit regressions of equations 1 and 2

Panel A: Export decision

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged innovation	0.129	0.054	0.096	−0.093	0.191	−0.041
	(0.088)	(0.112)	(0.213)	(0.291)	(0.231)	(0.219)
Lagged export status	1.876***	2.281***	2.128***	2.443***	2.421***	2.401***
	(0.072)	(0.104)	(0.156)	(0.242)	(0.241)	(0.236)
Lagged productivity	0.126*	0.145	−0.076	−0.067	−0.108	−0.050
	(0.066)	(0.092)	(0.144)	(0.173)	(0.193)	(0.186)
Lagged employment	0.214***	0.166***	0.321**	0.130*	0.177**	0.145*
	(0.035)	(0.042)	(0.071)	(0.077)	(0.084)	(0.082)
Lagged capital intensity	0.144***	−0.108**	0.067	−0.092*	−0.029	−0.064
	(0.042)	(0.052)	(0.085)	(0.129)	(0.129)	0.134
Lagged R&D Investment			0.004	0.025	0.009	0.026
			(0.025)	(0.030)	(0.024)	0.022
FDI penetration in sector		0.151		0.114	−0.097	−0.079
		0.183		0.303	(0.306)	(0.311)
Sector dummies	*yes*	*no*	*yes*	*no*	*no*	*no*
Time dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Note: standard errors robust for clustering at firm level in parentheses.

(1) - (4) Both product and process innovation considered, (5) only product innovation is considered and (6) only process innovation considered

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Panel B: Innovation decision

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged innovation	1.226***	1.396***	0.631***	0.891***	0.912***	0.463***
	(0.064)	(0.091)	(0.134)	(0.196)	(0.166)	(0.132)
Lagged export status	0.223***	0.332***	−0.053	0.536**	0.478**	0.254
	(0.079)	(0.099)	(0.149)	(0.211)	(0.210)	(0.212)
Lagged productivity	0.167***	0.171**	0.199**	0.072	0.092	0.208*
	(0.062)	(0.080)	(0.098)	(0.135)	(0.134)	(0.120)
Lagged employment	0.224***	0.256***	0.178***	0.130**	0.134**	0.228***
	(0.026)	(0.035)	(0.039)	(0.056)	(0.053)	(0.052)
Lagged capital intensity	0.069*	−0.057	0.124*	0.049	−0.042	0.053
	(0.041)	(0.049)	(0.069)	(0.083)	(0.087)	(0.073)
Lagged R&D Investment			0.077	0.051***	0.057***	0.049***
			(0.014)	(0.020)	(0.017)	(0.014)
FDI penetration in sector		0.793***		0.708**	0.564	0.651***
		(0.168)		(0.219)	(0.206)	(0.204)
Sector dummies	*yes*	*no*	*yes*	*no*	*no*	*no*
Time dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	3812	1551	1428	602	623	623
Log pseudolikelihood	−2423.9	−1098.7	−918.8	−393.7	−410.3	−446.4
ρ	0.125	0.139	0.118	0.275	0.423	0.197
Prob $\rho = 0$	0.058	0.078	0.092	0.063	0.007	0.132

Note: standard errors robust for clustering at the firm level in parentheses.

(1) - (4) Both product and process innovation considered, (5) only product innovation is considered and (6) only process innovation considered

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

In the bottom panel of Table 5 we present bivariate probit estimates of the innovation equation of the equation system (equations 1 and 2). As was the case above, lagged dependent variable (lagged innovation status) has a positive significant effect on the probability to innovate. Importantly, lagged export status has a significant positive impact in all but two specifications. Only in the third column, where R&D investment is introduced and in column 6, where only process innovation is considered are the effects of lagged exporting insignificant. This provides provisional evidence of the existence of learning-by-exporting.

Lagged productivity also matters for the probability to innovate in most specifications, while the effect of lagged capital intensity is not robust to changes in specification. In line with predictions, the probability to innovate is positively linked with the size of the firms, which indicates the importance of scale in research activity. Given that no definitive answer on the direction of causality in the exporting - innovation link could be established with bivariate probit estimation, we propose to determine the direction of the relationship by using matching econometric techniques.

5.2 Robustness check using matching approach

In order to investigate the above results further as well as to provide a robustness check, we first match innovating and non-innovating firms according to their probability to innovate and then test for the average treatment effects of lagged innovation status on the propensity to export (exporting equation). We employ the following propensity score specification for the probability to innovate

$$Prob(Inov_t = 1) = f(Inov_{t-2}, X_{t-2}) \tag{3}$$

where, again, $Inov_{t-2}$ represents the lagged innovation status, while X_{t-2} are other lagged explanatory variables (productivity, employment, capital intensity, investment in research and development, foreign ownership indicator). Based on the propensity score, we match innovating and non-innovating firms in period $t-2$ and test the effects of innovation on the current (t) exporting status. Second, we also match exporting and non-exporting firms based on the probability to export and then test for the average treatment effects of exporting status on innovative activity. We use the following specification to estimate the probability of being an exporter

$$Prob(Exp_t = 1) = f(Exp_{t-2}, X_{t-2}) \tag{4}$$

Based on the propensity score from the predicted probability to export (4), we use nearest neighbour matching by NACE 2-digit industry to match exporting and non-exporting firms at time $t-2$ and then observe the average treatment effects of lagged exporting status on current innovation (t) activity (innovation equation). Table 6 presents estimates of average treatment effect that are pooled across all industries. In this instance different types of matching were done on industry by industry basis, but the treatment effects were pooled across all industries so that they can be compared with the estimates presented above. We compare estimates of three different types of matching, namely, nearest neighbour matching, kernel matching and radius matching. As Abadie and Imbens (2006) suggest that bootsrapped standard errors may not be valid in the case of nearest neighbour matching[10], we also present sub-sampling based standard errors for average treatment effects in the case of nearest neighbour matching. The industry-specific average treatment effects for both the exporting and innovation equation are presented in Table 7. With some notable exceptions, we can see that in majority of industries the above conclusions are confirmed. Average treatment effects (ATT) of the export equation reveal that innovators are more likely to be also exporters,[11] while, similarly, the innovation equation, by and large, confirms that lagged exporting status has a significant impact on innovation.[12]

Table 6: Pooled (across industries) average treatment effects of lagged export status (lagged innovation) on current innovation (current export status)

	export equation			innovation equation		
	ATT	SE^a	obs.	ATT	SE	obs.
nearest neighbour matching	0.006	0.034	314 (36)	0.288***	0.109	437 (17)
nearest neighbour matching^c	0.006	0.041	314 (36)	0.288***	0.111	437 (17)
kernel matching	0.015	0.026	314 (155)	0.268***	0.111	437 (29)
radius matching (r = 0.2)	0.027	0.056	43 (77)	0.254***	0.080	336 (45)

Notes: ^{a} bootstrapped standard errors (100 repetitions)

^{b} number of treatment observations, number of control observations in parentheses.

^{c} sub-sampling based standard errors (100 draws of sub-samples of size 234 and 337, respectively for the export and innovation equations)

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Table 7: Industry average treatment effects of lagged export status (lagged innovation) on current innovation (current export status)

[10] Abadie and Imbens (2006) show that due to the extreme non-smoothness of nearest neighbour matching, the standard conditions for bootstrap are not satisfied, leading the bootsrap variance to diverge from the actual variance. The bootstrapped standard errors underestimate the actual standard errors and this can be corrected with subsampling.

[11] This result is confirmed in 12 out of the 20 industries tested. Additional 4 industries exhibit positive but not significant average treatment effects, while the remaining 4 are negative and non-significant.

[12] Of the 14 industries tested, 10 exhibit positive and significant average treatment effects, while of the remaining four two are negative and non-significant, one is negative signficant and one positive non-significant.

industry	export equation			innovation equation		
NACE 2-digit	ATT	SE[a]	obs.[b]	ATT	SE[a]	obs.[b]
15	0.004	0.253	101 (150)	−0.207	0.246	284 (191)
17	0.085***	0.020	51 (99)	0.511***	0.099	253 (29)
18	−0.065	0.174	16 (124)	0.267***	0.106	197 (35)
19	0.124***	0.051	11 (39)	0.630***	0.204	79 (10)
20	0.149*	0.098	30 (144)	−0.212*	0.121	267 (43)
21	0.088**	0.038	12 (54)			
22	−0.023	0.290	12 (126)	−0.252	0.298	177 (60)
24	−0.002	0.044	68 (55)	0.637***	0.109	231 (9)
25	0.095***	0.019	41 (102)			
26	−0.056	0.163	33 (106)	0.502**	0.220	240 (45)
27	0.142***	0.037	22 (44)			
28	0.082***	0.014	81 (268)	0.361***	0.068	571 (93)
29	0.057	0.115	124 (160)	0.575***	0.208	509 (40)
30	0.447	0.352	8 (21)	0.250	0.361	26 (18)
31	0.141***	0.030	56 (53)			
32	0.079*	0.042	44 (25)	0.616***	0.118	128 (12)
33	0.798***	0.302	38 (53)	0.589***	0.130	158 (20)
34	0.094***	0.026	29 (51)			
36	0.079***	0.022	42 (145)	0.394***	0.101	313 (50)
37	0.051	0.042	3 (14)			

Notes: [a] bootstrapped standard errors (100 repetitions)

[b] number of treatment observations, number of control observations in parentheses.

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

5.3 Searching for causality using matching approach

5.3.1 Not discriminating between the type of inovations

Above bivariate probit and matching results confirm high correlation between firms' exporting and innovation activity, but neither of them accounts for the causality between the two. Furthermore, given that both the export status and innovation activity appear to be highly serially correlated, the above relationship between exporting status and innovative activity may also be purely spurious. Therefore, we alter our empirical tests to check for the causality between both variables. In order to test whether exporting status induce firms to start to innovate we redefine the innovation equation

$$Prob(Inov_t = 1 | Inov_{t-2} = 0) = f(Exp_{t-2}) \tag{5}$$

In this case we are testing a dynamic version of those presented in Table 5. By, again, matching exporters with non-exporters at period $t-2$,[13] we test whether previously non-innovating exporting firms are likelier to become innovators in period (t) than non-exporting non-innovators[14].

In addition, we analogously alter the exporting equation to test for probability that lagged innovation activity enables firms to start exporting in the future

$$Prob(Exp_t = 1 | Exp_{t-2} = 0) = f(Inov_{t-2}) \tag{6}$$

Estimates of the average treatment effects of lagged exporting status on the change in innovation activity (innovation equation) and of lagged innovative activity on the change in exporting (exporting equation) obtained with nearest neighbour matching are presented in Table 8. These results, similarly as those presented in Table 6, rely on industry-by-industry matching whereby the average treatment effects are pooled across industries. In contrast to the effects of innovation and exporting status on level variables (exporting and innovation, respectively), the impact on changes in exporting and innovation status are far less conclusive. Most of the obtained coefficients by industries are not significant. In fact, in the exporting equation we find a significant impact only in 5 out of 20 industries, whereby in four industries a negative impact of lagged innovation on the change in export status is found. A positive impact is found in food industry only. In the innovation equation, only one industry shows significant (negative) impact of lagged exporting status on the change in innovation activity. Based on these results one can hardly make any conclusions about the causality link between exporting and innovation activity.

Table 8: Pooled average treatment effects of lagged export status (lagged innovation) on the change in innovation (change in export status)

	export equation			innovation equation		
	ATT	SE^a	obs.^{b}	ATT	SE^a	obs.^{b}
nearest neighbour matching	0.003	0.016	720 (169)	−0.043	0.049	437 (33)
nearest neighbour matching^c	0.003	0.023	720 (169)	−0.043	0.054	437 (33)
kernel matching	−0.024	0.017	720 (370)	−0.050	0.038	437 (45)
radius matching (r = 0.2)	−0.020*	0.012	718 (370)	−0.017	0.044	331 (45)

[13] We continue applying the propensity score specifications (4) and (3).

[14] This specification differs from the previous one because we are looking only at firms that became innovators. We test whether exporting status is concusive to becoming an innovator instead of being an innovator, which was tested before.

Notes: ^{a} bootstrapped standard errors (100 repetitions)

^{b} number of treatment observations, number of control observations in parentheses

^{c} sub-sampling based standard errors (100 draws of sub-samples of size 580 and 337, respectively for the export and innovation equations)

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Table 9: Industry average treatment effects of lagged export status (lagged innovation) on the change in innovation (export status)

industry	export equation			innovation equation		
NACE 2-digit	ATT	SE^a	obs.^{b}	ATT	SE	obs.^{b}
15	0.093*	0.055	101 (155)	0.025	0.053	284 (198)
17	−0.007	0.005	51 (106)	−0.012	0.015	253 (29)
18	0.091	0.099	16 (127)	0.000	0.000	197 (37)
19	0.250	0.251	11 (40)	0.278	0.214	79 (10)
20	−0.009*	0.005	30 (148)	−0.533***	0.097	267 (43)
21	−0.009	0.007	12 (56)			
22	−0.156	0.146	12 (128)	−0.297	0.234	177 (61)
24	−0.031	0.156	68 (57)	0.000	0.000	231 (9)
25	−0.008	0.006	41 (106)			
26	−0.020**	0.009	33 (111)	0.046	0.056	240 (48)
27	0.000	0.000	22 (44)			
28	−0.064	0.040	81 (282)	0.027	0.028	571 (95)
29	−0.126	0.079	124 (168)	0.028	0.026	509 (42)
30	−0.103	0.278	8 (21)	0.000	0.000	26 (19)
31	−0.024*	0.013	69 (57)			
32	0.000	0.000	44 (26)	0.000	0.000	128 (12)
33	−0.014	0.011	38 (56)	0.000	0.000	158 (20)
34	−0.010	0.009	29 (52)			
36	−0.030***	0.009	42 (151)	−0.006	0.009	313 (51)
37	−0.038	0.050	3 (14)			

Notes: ^{a} bootstrapped standard errors (100 repetitions)

^{b} number of treatment observations, number of control observations in parentheses.

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

5.3.2 Robustness check: Discriminating between product and process innovations

Thus far we have neglected the distinction between product and process innovations, which could have important implications for the relationship between exporting and innovation. As demonstrated by Becker and Egger (2007), Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) product innovations are key for successful market entry, while process innovation helps maintain its market position given the maintained product characteristics. Product innovation should therefore play a more important role in the decision to start exporting and the discrimination between both types should proove crucial. In order to examine the causal relationship between becoming an exporter (starting with product innovation) and being a product innovator (being an exporter), we test for the pooled (by industries) average treatment effects of (product) innovating status on becoming an exporter for the first time and the pooled average treatment effects of exporting status on becoming a first-time product innovator.

Table 10: Pooled average treatment effects of lagged export status (lagged product innovation) on the change in product innovation (export status)

	export equation			innovation equation		
	ATT	SE^a	obs.^{b}	ATT	SE^a	obs.^{b}
nearest neighbour matching	0.015	0.014	265 (172)	−0.014	0.057	437 (33)
nearest neighbour matching^c	0.015	0.013	265 (172)	−0.014	0.046	437 (33)
kernel matching	−0.022	0.015	265 (722)	−0.020	0.038	437 (45)
radius matching (r = 0.2)	−0.024*	0.013	265 (722)	0.013	0.030	331 (45)

Notes: ^{a} bootstrapped standard errors (100 repetitions)

^{b} number of treatment observations, number of control observations in parentheses

^{c} sub-sampling based standard errors (100 draws of sub-samples of size 206 and 337, respectively for the export and innovation equations)

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Table 10 reveals that even if only product innovations are considered, innovators are no likelier to become exporters than non-innovators (export equation). Furthermore, we find no evidence that exporting status enchances the probability of a firm to become a product innovator. As product innovations were considered likelier to increase the probability to export, this can serve as definitive proof of the lack of a causal relationship between changes in exporting status and changes in innovating outcomes. We obtain similar results when only process innovations are considered, but do not report the results here for the sake of brevity. In the Appendix we present estimates of the average treatment effects of specifications (6) and (5) on an industry-by-industry level and finding further support for the aggregated results presented in Table 10.

6 Conclusions

In this paper we investigate the relationship between firms' innovation and exporting activity. While most of the papers study correlation between firms' exporting and innovation activity (Wagner (1996), Wakelin (1997, 1998), Ebling and Janz (1999), Roper nad Love (2002), Damijan et al (2007), Egger and Becker (2007), Cassiman and Golovko (2007), Cassiman and Martinez-Ros (2007), etc.), we focus on the causality link between the two. In doing this we apply three different empirical specifications. In the first approach, we follow Aw et al (2005) and Girma et al (2007) by applying bivariate probit regressions of the model of simultaneous exporting and innovation equations. Results show high positive correlation between exporting and innovation activity. In the second approach, we check for robustness of the above results by applying the matching after propensity score approach. We first match exporters with non-exporters based on their propensity to export and investigate whether the two cohorts differ in terms of their innovative effort. In addition, we also match innovating and non-innovating firms (based on the propensity to innovate) in order to compare their exporting status and exporting intensity. By estimating the average treatment effects on a set of matched firms on both the exporting and innovation equation, we by large confirm the above results of a positive correlation between the exporting and innovation activity. However, as both the export status and innovation activity appear to be highly serially correlated, the above relationship between exporting status and innovative activity may also be purely spurious. Hence, we alter our empirical tests to check for the causality between both variables. In the third approach we therefore test whether lagged exporting status has an effect on firms starting to innovate and whether the lagged innovation output has an impact on firms starting to export. Our results obtained by average treatment effects on a set of matched data are far less conclusive. We find that the large majority of the estimated coefficients by specific industries are not significant. Based on these estimates the direction of causality cannot be established. We can conclude that exporting status and innovative activity are higly correlated, but this in itself does not ensure a causal relationship. In other words, whereby innovating status increases the probability of exporting it does not increase the probability of becoming a first time exporter, and vice versa, exporting status increases the probability of innovating, but it does not increase the probability of becoming a first time innovator. The results remain unaltered also after allowing for discrimination between product and process innovation.

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Appendix

Table 10: Industry average treatment effects of lagged export status (lagged product innovation) on current product innovation (current export status)

industry	export equation			product innovation equation		
NACE 2-digit	ATT	SE[a]	obs.[b]	ATT	SE	obs.[b]
15	0.101*	0.059	95 (390)	0.017	0.042	284 (197)
17	−0.015***	0.005	43 (250)	0.040	0.034	253 (29)
18	0.200	0.178	39 (204)	0.067	0.073	197 (38)
19	0.221	0.289	10 (77)	0.289	0.214	79 (10)
20	−0.009	0.006	29 (248)	−0.478***	0.127	267 (43)
21	−0.003	0.075	12 (105)			
22	−0.031**	0.013	10 (187)	−0.257	0.257	177 (61)
24	−0.002	0.060	68 (167)	0.040	0.037	231 (9)
25	−0.007	0.005	38 (10)			
26	−0.091	0.065	31 (223)	0.087	0.066	240 (48)
27	0.000	0.010	17 (90)			
28	−0.007	0.007	73 (582)	0.050*	0.029	571 (95)
29	−0.026	0.033	119 (416)	0.055*	0.029	509 (42)
30	0.939	0.066	6 (2)	0.250	0.271	26 (19)
31	−0.010	0.023	65 (175)			
32	−0.042	0.072	41 (95)	−0.031	0.033	128 (12)
33	−0.018**	0.009	41 (139)	−0.019	0.019	158 (20)
34	−0.014	0.010	27 (117)			
36	−0.069	0.045	46 (324)	−0.016	0.009	313 (51)

Notes: [a] bootstrapped standard errors (100 repetitions)

[b] number of treatment observations, number of control observations in parentheses.

*, **, *** indicate statistical significance at 10%, 5% and 1% level of significance, respectively.

Source: SORS and AJPES; authors' calculations.

Table 11: Industry average treatment effects of lagged export status (lagged process innovation) on current process innovation (current export status)

industry	export equation			product innovation equation		
NACE 2-digit	ATT	SE[a]	obs.[b]	ATT	SE	obs.[b]
15	0.004	0.090	77 (407)	−0.038	0.131	284 (197)
17	−0.011	0.007	40 (249)	0.025	0.037	253 (29)
18	−0.014**	0.005	11 (236)			
19	0.221	0.243	9 (78)	−0.044	0.051	79 (10)
20	−0.015	0.050	24 (9)	0.141	0.093	267 (43)
21	−0.007	0.083	8 (109)			
22	−0.015	0.025	10 (189)	−0.458*	0.241	177 (61)
24	−0.003	0.044	55 (178)	0.040	0.045	231 (9)
25	−0.016***	0.006	28 (226)			
26	−0.083	0.082	28 (228)	−0.013	0.009	240 (48)
27	−0.013	0.009	16 (94)			
28	−0.047	0.027	66 (585)	0.030	0.026	571 (95)
29	−0.002	0.004	82 (434)	0.119***	0.040	509 (42)
30	0.442	0.355	6 (43)	0.000	0.000	26 (19)
31	−0.011	0.039	51 (183)			
32	−0.029	0.074	34 (102)	−0.029	0.036	128 (12)
33	−0.018**	0.009	28 (148)	0.036	0.057	158 (20)
34	−0.015	0.011	19 (124)			
35	−0.033	0.239	4 (16)			
36	−0.063	0.054	41 (335)	0.023	0.036	313 (51)
37	−0.016	0.019	2 (32)			