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From Innovation to Exporting or Vice Versa?

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1. INTRODUCTION

RECENT empirical research on exporting behaviour of firms has established several empirical regularities. Exporting firms are known to be superior in comparison to non-exporters in terms of productivity, capital intensity, wages and size. The productivity premium of exporting firms has received particular attention. The evidence in favour of self-selection of more productive firms into exporting is abundant, while the evidence on reverse causality, learning-by-exporting, is rather scarcer (see survey of empirical studies by Greenaway and Kneller, 2007; Wagner, 2007).

Large productivity premiums of new exporters compared to non-exporters imply that the decision to start exporting is determined by factors that affect productivity of firms before they start exporting. Empirical studies document substantial heterogeneity in firm productivity within and between industries (Bartelsman and Doms, 2000). However, theoretical models on firm dynamics do not provide a convincing explanation of what generates this heterogeneity and divergent evolution of firms, but instead typically assume that productivity is exogenous to the firm. Models of firm dynamics (Jovanovic, 1982; Hopenhayn, 1992) and their extension to international trade (Melitz, 2003) assume that productivity is assigned to a firm by luck of the draw from

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a random distribution. After making a draw, there is therefore no way for a firm to change its life path – its survival or death.

In contrast, endogenous growth theory associates productivity to decisions, such as investment in research and development (R&D) and innovation. Romer (1990) argues that technological improvements stem from intentional investment of resources by profit-maximising firms, and that a firm's innovative activity is central to its technological progress and productivity growth. There have been some attempts to model firm dynamics that allow a firm to improve its efficiency by active learning. Ericson and Pakes (1995) analyse behaviour of firms exploring profit opportunities in the world of uncertainty arising from investment in R&D types of processes and derive firm optimal policies, including entry and exit. Klepper (1996) demonstrates that product innovation dominates the early stage of the product lifecycle, while process innovation gains relevance in the later stages, after production volumes have increased and efficiency of production becomes increasingly important. Recently, Constantini and Melitz (2008) drew on this distinction by constructing a model that shows that anticipation of trade liberalisation may cause a firm to bring forward the decision to innovate in order to 'dress up' for future participation in the export market.

Over the last decade, many empirical studies, beginning with those of Wagner (1996), have observed a positive impact of innovation on exporting. More recently, some studies have also found process innovation, rather than product innovation, to positively affect productivity growth (e.g. Griffith et al., 2006). Few studies, however, have controlled for firm innovation activity in an attempt to study the productivity–exporting link in its entirety as a causal relationship. While Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) find support for the product innovation–productivity–export link in data on Spanish firms, the reverse causal direction (exporting–process innovation–productivity growth) has been investigated with less success.

In this paper we study both directions of the relationship between innovation activity and decision to export. We use Slovenian microdata combining accounting, innovation and industrial survey data, as well as data on foreign trade flows, for the period 1996–2002. This unique dataset allows us to test the prediction that a firm's inclination to innovate increases its probability of becoming an exporter, as well as the hypothesis that positive learning effects of exporting lead to additional innovations and boost productivity. We apply propensity-score matching techniques, where we classify firms according to their propensity to innovate and then match the innovating and non-innovating firms in order to compare their likelihood to start exporting (export equation). In addition, we also match exporters with non-exporters based on their propensity to export and investigate whether the two cohorts differ in their innovation efforts (innovation equation). The advantage of our approach, however, is that we explore not only the correlation between innovation and exporting status but also try to identify the direction of causality between the two. We do so by estimating the export and innovation equations to reveal whether the lagged innovation output has an impact on a firm's decision to start exporting, and whether lagged exporting status has an effect on a firm's decision to become innovative. We find no empirical support for the hypothesis that either product or process innovations increase the likelihood of becoming an exporter. However, we do find evidence that exporting increases the probability of becoming a process rather than product innovator, and that exporting leads to productivity improvements. Both of these effects are limited to a sample of medium and large first-time exporters. These findings suggest that participation in trade may positively affect firm efficiency by stimulating process innovations which makes a case in favour of the learning-by-exporting hypothesis.

The paper is organised as follows. After an overview of related research in the next section, we describe in Section 3 the datasets we use, as well as basic descriptive statistics on exporting and innovation activity of Slovenian firms. Section 4 presents results of the basic correlations between innovation and exporting using a matching approach to control for other relevant firm characteristics. Section 5 presents the results of tests of causality direction between innovation and exporting, together with some robustness checks. In the last section we draw our main conclusions.

2. RELATED RESEARCH

Extensive empirical work (see survey by Caves, 1998) has documented significant firm turnover, and pioneering theoretical work by Jovanovic (1982) and Hopenhayn (1992) has related firm size (in terms of employment and sales) and survival on the one hand and productivity on the other. More recently, Bernard and Jensen (1995, 1999) documented substantial differences between exporting and non-exporting firms, resulting in a new generation of trade models that share the key features of firm dynamics in addition to firm heterogeneity in terms of productivity. Melitz (2003), Bernard et al. (2003), and Melitz and Ottaviano (2005) built models that relate the observed heterogeneity in foreign market participation to heterogeneity in firm productivity.

Though consistent, the cross-country evidence on self-selection in exporting and high persistence of exporting status (Roberts and Tybout, 1997; Bernard and Jensen, 1999; Greenaway and Kneller, 2004; Wagner et al., 2007) falls short of a convincing explanation for why some firms are initially 'more productive' and how foreign trade participation feeds back into firms' productivity. There must be a causal link between a firm's innovation effort and its overall productivity, which triggers the decision to start exporting, and conversely there must be a causal link leading from a firm's exporting performance to further improvements in productivity. The problem is that there is still no convincing theory explaining the forward direction of the causality link (firm innovation–productivity–export), and so far no conclusive evidence has been found for the reverse direction of the causal link (learning-by-exporting).

Regarding the innovation effort–productivity–export link, existing theoretical papers explaining firm dynamics (Jovanovic, 1982; Hopenhayn, 1992) and its application to international trade (Melitz, 2003) lack a convincing explanation of what 'produces' a firm's pre-trade productivity. They assign firm productivity by a random draw from a common distribution and neglect the endogenous relationship between a firm's innate ability to create a product and the *ex post* productivity enabling it to enter a market. Novel findings in this respect are reported by Bernard et al. (2007), who relate a firm's performance to its ability to create products. In a related paper, Bernard et al. (2006) go a step further by assuming firm productivity in a given product to be a combination of firm-level 'ability' and firm-product-level 'expertise'. While they still rely on the assumption that both the firm-level 'ability' and firm-product-level 'expertise' are exogenous, their contribution lies in emphasising the importance of a firm's ability to innovate new products. Ericson and Pakes (1995) analyse firm optimal policies arising from investment in R&D, including entry and exit. The work of Constantini and Melitz (2008) is the first example of a model of industry dynamics that includes endogenous innovation and export decisions. They show that anticipation of trade liberalisation may lead firms to bring forward the decision to innovate, in order to be ready for future participation in the export market. Similarly, Atkeson and Burstein (2007) model the interdependence between the choices of exporting and investing in R&D on the one hand and firm productivity on the other. In addition, Aw et al. (2008) and Lileeva and Trefler (2007) find evidence from microdata that exporting is correlated with firm investment in R&D and innovation. Aw et al. (2009) find that both R&D and exporting have a positive direct effect on the firm's future productivity which reinforces the selection effect. They find that the productivity effect of R&D is larger, but due to higher cost it is undertaken by fewer firms than exporting.

Investment in product innovation may therefore be the key to explaining a firm's productivity and decision to enter a market. While a number of empirical studies find a positive impact of innovation on exporting (Wagner, 1996; Wakelin, 1997, 1998; Ebling and Janz, 1999; Aw et al., 2005, 2009; Girma et al., 2008), a direct link leading from innovation via higher productivity to the exporting decision has yet to be demonstrated empirically. An early paper by Vernon (1966) develops a product lifecycle theory where product innovation should have an impact on firm productivity, and therefore should be indirectly linked to the 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. A recent study by Foster et al. (2005) provides some evidence in favour of this by showing that firm-specific demand variations, rather than technical efficiency, are the essential determinants of firm survival, and they positively affect firm productivity. This finding implies that a firm's product innovation due to positive demand shocks may explain a large portion of a firm's higher pre-trade productivity level and its consequent decision to start exporting. A recent study of small Spanish firms by Cassiman and Golovko (2007) finds that controlling for product innovation causes the differences in productivity among exporting and non-exporting firms to disappear. In a related paper, Cassiman and Martinez-Ros (2007) find for a sample of Spanish firms that engaging in product innovation significantly increases the probability to start exporting. Similarly, Becker and Egger (2010) find after controlling for the endogeneity of innovation that product innovation at German firms plays an important role in increasing the propensity to export, while they find no such evidence for process innovation. These results therefore suggest that the productivity–export causal link may well be explained by a firm's (product) innovation activity.

Regarding the other direction of the causal link (exporting–reverse productivity improvements), most studies conducted so far have failed to find conclusive evidence in support of the positive impact of exporting on productivity growth. Some exceptions to it are studies on Slovenian exporters (Damijan and Kostevc, 2006; De Loecker, 2007) showing some learning effects for Slovenian exporters in terms of productivity increases. Aw et al. (2005) argue that numerous studies that failed to find evidence of learning-by-exporting may have neglected a potentially important element of the process of productivity change: the investments made by firms to absorb and assimilate knowledge and expertise from foreign contacts. In other words, exporting activity may have helped firms to become more innovative in their process, which may impact productivity growth in the long run. Recently, some studies have supported the idea that innovation contributes significantly to a firm's productivity growth (Huergo and Jaumandreu, 2004; Harrison et al., 2005; Griffith et al., 2006; Parisi et al., 2006; Hall et al., 2007). This work demonstrates that process innovation, rather than product innovation, drives firm productivity growth. Process innovations have labour displacement effects and are therefore expected to result in significant productivity growth, while, because of the demand effect, product innovations are likely to cause employment growth, but not significant productivity growth. Salomon and Shaver (2005) find some evidence in favour of learning-by-exporting using data on Spanish manufacturing firms. They find that past exporting status increases the propensity of firms to innovate.

3. DATA DESCRIPTION

a. Data Sources

Our empirical analysis is based on firm-level data from Community Innovation Surveys (CIS1, CIS2, CIS3) and firm accounting data (AJPES) for the period 1996–2002. CIS is an EU-wide effort to assess innovation activity and its effects on firm performance. In Slovenia, Community Innovation Surveys have been conducted every even year since 1996 by the Slovenian Statistical Office (SORS). The surveys are carried out on a pre-selected sample of manufacturing and non-manufacturing firms with no additional conditions put on actual R&D activity or firm size. Most importantly, the data gathered by the innovation surveys include, *inter alia*, information on product and process innovation of firms during the preceding two years, as well as data on the determinants of innovation such as number of employees and R&D expenditure. We utilise CIS data on product and process innovation, which indicate whether the firm has managed to product or process innovate in the past two years since the last survey.[1] 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 export flows. All value data were deflated using NACE two-digit industry producer price indices, while the capital stock variable was deflated using the consumer price index.[2]

Table 1 compares the sample of firms chosen for the Community Innovation Surveys and all firms in Slovenia. The sample of surveyed firms represents roughly 10 per cent of the total number of firms. Average total factor productivity (TFP) and Kolmogorov–Smirnov stochastic dominance tests show that surveyed firms are more productive than all firms in the economy.[3]

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[1] The actual questions posed in CIS3 were:
(product innovations) 'During the three year period [...], did your enterprise introduce any technologically new or significantly improved products (goods or services) which were new to your firm?'
(process innovations) 'During the three year period [...], did your enterprise introduce any new or significantly improved processes for producing or supplying products (goods or services) which were new to your firm?'
To both of these questions the respondents answered with 'yes' or 'no'.

[2] A major share of physical capital on firms' balance sheets are physical structures. During the period of our analysis the prices of commercial property grew in line with the consumer price index.

[3] Total factor productivity is constructed as a residual from the production function in which value added is regressed against labour and capital inputs and industry and time dummies.

TABLE 1
Comparison in Total Factor Productivity per Employee of Sample and Population Data, 1996–2002

	Number of Firms		*Diff. in TFP Means*	*Mean(pop) > Mean(sample)*		*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:
TFP means are calculated from residuals of regression of log of value added on log of labour, log of physical capital and industry dummies.

Source: SORS and AJPES; authors' calculations.

In addition, surveyed firms are also larger both in terms of sales and employment as well as more capital intensive than the population average.[4] The sample of firms chosen to participate in the Community Innovation Surveys is therefore not representative of the population of Slovenian firms and this has to be taken into consideration when interpreting the results.

b. Descriptive Statistics

Given the small size of the domestic market, it is not surprising that roughly 85 per cent of Slovenian manufacturing firms export (Damijan and Kostevc, 2006). A large proportion of Slovenian exports is destined for the highly competitive EU-15 markets (Damijan et al., 2009), and this increases the scope for benefits from either positive spillovers in the exporting markets or by raising the productivity of exporting firms (learning-by-exporting). Damijan and Kostevc (2006) and De Loecker (2007) analyse Slovenian manufacturing firms and find productivity improvements in the year that firms start exporting. This shift may be related to capacity utilisation, but it may also reflect spillovers and learning effects. The latter may reflect the introduction of more efficient technologies or increased investment in R&D, and hence improved innovation activity of exporting firms. Alternatively, product innovation may stimulate exports, especially when exports to highly competitive markets are considered. The causal link between exporting and innovation may therefore work in both directions as innovation activity may affect future exporting status and, conversely, exporting may boost a firm's innovative activity.

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

TABLE 2
Comparison of Firm Characteristics between Exporters and Non-exporters and Innovators and Non-innovators in 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	1,181	394

Notes:
Median values of variables are reported. Value added per employee, physical capital per employee and sales are given in euros (constant 1994 prices).

Source: SORS and AJPES; authors' calculations.

The characteristics of firms in the sample with respect to both exporting and innovating status are described in Table 2. In line with existing literature, exporters are more productive, larger and more capital intensive than non-exporters. Differences between innovators and non-innovators are more subtle: the former are only marginally more productive when export status is controlled for. Furthermore, innovators are not found to be substantially more capital intensive[5] and in the case of non-exporters they are similar in size to 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 are found to be far larger than non-exporters or non-innovating exporters both in terms of sales and employment.

Table 3 presents an overview of the probabilities of being an exporter/non-exporter or innovator/non-innovator. A firm is classified as an innovator if it is reported to have made process or product innovations in the two years leading up to the survey. The results shown in the top panel of the table reveal that an innovating firm is more likely to export by almost 40 percentage points.[6]

Thus, innovating activity may be a determinant of exporting status or, at the very least, innovation and exporting are driven by the same determinants. The bottom panel of Table 3 shows that exporters are far more likely to innovate than non-exporters. Depending on the year and survey in question, exporters

[5] In fact, among exporting firms, non-innovators are found to be more capital-intensive than innovators.
[6] In 2002 the probability of being an exporter is somewhat larger (72.4 per cent).

TABLE 3
Share of Exporters (Innovators) Depending on Innovative Activity (Exports) by Firms, 1996–2002

Year	*Product Innovators*	*Process Innovators*	*Non-innovators*
	Share of Exporters (%)	*Share of Exporters (%)*	*Share of Exporters (%)*
1996	87.2	97.4	49.9
1998	77.6	86.9	50.5
2000	87.1	88.2	54.4
2002	87.4	87.0	72.4

Year	*Exporters*		*Non-exporters*	
	Share of Prod. Innov. (%)	*Share of Proc. Innov. (%)*	*Share of Prod. Innov. (%)*	*Share of Proc. Innov. (%)*
1996	28.6	15.5	5.3	0.5
1998	26.4	22.9	9.9	4.5
2000	22.8	20.4	8.6	7.0
2002	21.5	17.2	9.4	7.8

Source: SORS and AJPES; authors' calculations.

are 2–5 times more likely to innovate than non-exporting firms. Another striking feature of the data is the relatively low percentage of innovating firms among the total population of firms. Of the firms surveyed, the average percentage that have innovated is only 20 per cent, compared to 65 per cent of German enterprises or 53 per cent of Austrian firms.[7]

c. *Exploring the Link between Exporting and Innovation Activity*

The evidence discussed so far indicates that differences in productivity between non-exporters and exporters may be explained by firms' past decisions to innovate or not. The descriptive statistics confirm the notion that innovators are more likely than non-innovators to be exporters, and that exporters are 2–3 times more likely than non-exporters to be innovators. Although we still lack a convincing theory, some empirical findings, including the above descriptive statistics, point to an endogenous link connecting innovation, productivity and exporting. Future exporters may have made decisions in the past about investing in R&D and may have undertaken innovation activities, which served to expand their productivity levels and enabled them to become exporters.

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

Cassiman and Golovko (2007) and Cassiman and Martinez-Ros (2007) find for a set of Spanish firms that product innovations are crucial drivers of exporting in small non-exporting firms. Subsequently, exporting may lead to further innovations and enabling further improvements in productivity. The studies of Parisi et al. (2006) and Hall et al. (2007), both of which use Italian microdata but do not discriminate between exporting and non-exporting firms, demonstrate that process innovations lead to significant productivity growth through labour displacements. Hence, the causal link should run from innovation to exporting and back to additional innovation. The present study explores this causal chain, while emphasising the difference between product and process innovations.

To provide more rigorous empirical support for the observed relationship between exporting status and innovation, we examine the effects of lagged export status (lagged innovation status) on current innovation status (current exporting status) while controlling for other pertinent firm characteristics. In contrast to Aw et al. (2005) and Girma et al. (2008), who use a bivariate probit approach to test this relationship, we employ matching estimation techniques as they offer a more direct as well as more intuitive insight into the relationship between the exporting and innovation status of individual firms.

We start by matching innovating and non-innovating firms according to their propensity to innovate and then test for the average treatment effects of lagged innovation status on the propensity to export. We employ the following propensity score specification for the probability to innovate:[8]

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

where $Inov_{t-2}$ denotes the lagged innovation status, while X_{t-2} denotes all other lagged explanatory variables (productivity as measured by value added per employee, employment, capital intensity, investment in research and development, importing status, foreign ownership indicator). Based on the propensity score, we match innovating and non-innovating firms in period $t-2$ and test the effects of lagged 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:

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

where Exp_{t-2} is the lagged exporting status. The inclusion of the lagged dependent variable as a regressor introduces a potential bias in the estimation. Specifically, the coefficient on the lagged dependent variable is likely to be

[8] Here we implicitly assume that both the propensity to innovate as well as the propensity to export do not change markedly over time, which we base on the observed high persistence of both innovation activity and exporting status.

downward biased. Bernard and Jensen (2004) suggest using instrumental variables and estimating the model in first differences to obtain the correct estimate of the coefficient. But, since we are only interested in obtaining the predicted probabilities of innovation and exporting, we follow Roberts and Tybout (1997) and employ random effects probit as a robustness check in the propensity score estimation. Results based on matching, though, reveal no qualitative difference between the two approaches and only minor quantitative differences.[9]

Based on the propensity score from the predicted probability to export (2) we use matching within two-digit NACE industry codes to match exporting and non-exporting firms at time t – 2 and then observe the average treatment effects of lagged exporting status on current (t) innovation activity (innovation equation). Propensity score estimation of (1) and (2) satisfies the balancing property, which ensures that within each block of data the regressors do not differ substantially between the treatment and control groups. Table 4 presents estimates of average treatment effects (ATT) that are pooled across all industries. In this instance different types of matching were done industry-by-industry, but the treatment effects were pooled across all industries so that they could be compared with the estimates presented above. We compare estimates of three different types of matching: nearest neighbour matching, kernel matching and radius matching. Since Abadie and Imbens (2008) suggest that bootstrapped standard errors may not be valid in the case of nearest neighbour matching,[10] we also

TABLE 4
Pooled Average Treatment Effects (Across Industries) of Lagged Innovation (Export Status) on Current Export Status (Current Innovation)

	Export Equation			*Innovation Equation*		
	ATT	*SE*[a]	*Obs.*[b]	*ATT*	*SE*[a]	*Obs.*[b]
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).
*, ** and *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Source: SORS and AJPES; authors' calculations.

[9] Average treatment effects using random effects probit propensity scores are somewhat smaller than those using the fixed effects probit.
[10] Abadie and Imbens (2008) show that due to the extreme non-smoothness of nearest neighbour matching, the standard conditions for bootstrap are not satisfied, leading the bootstrap variance to diverge from the actual variance. Thus, the bootstrapped standard errors underestimate the actual standard errors and this can be corrected by sub-sampling.

present sub-sampling-based standard errors for average treatment effects in the case of nearest neighbour matching.

The results in Table 4 confirm a high and robust correlation between lagged exporting status and current innovation (innovation equation), whereas none of the types of matching supports the link between lagged innovative activity and current exporting status (export equation). However, these results present average treatment effects pooled over all industries, so it is interesting to look at the results for individual industries. We also estimate the correlation between exporting status and innovative activity on an industry-by-industry (NACE rev. 2 two-digit industries) basis[11] and find that there is in fact a strong correlation between lagged exporting status and current innovation in the majority of industries while we only find mixed support for the correlation between lagged innovation activity and current innovation status. These results, however, only confirm the existence of a strong correlation between exporting and innovation status, but give no indication of the actual direction of causality.

In order to test whether the balancing property is satisfied in our different specifications, providing better balancing of the regressors, we determine the reduction of median absolute standardised bias brought about by the use of matching[12] (Becker and Egger, 2010). As suggested by Rosenbaum and Rubin (1985) the remaining bias should not exceed 20 per cent. The lowest median bias between treated and matched control units is achieved with nearest neighbour matching and amounts to 11.8 per cent, while with kernel and radius matching the median bias amounts to 12.1 per cent and 23 per cent, respectively. The remaining bias after the matching procedure therefore falls within the guideline values with the exception of radius matching where the bias is marginally outside those bounds. Overall the three matching procedures reduce the bias by approximately 60 per cent. Furthermore, a comparison of pseudo-R^2 of the propensity score estimation before and after matching reveals a significant reduction in the explanatory power of these estimates in all specifications and size classes. For instance, when the effect of exporting status on the probability to start innovating is examined the pseudo-R^2 before matching amounts to 0.226, while after matching the explanatory power of the same regression falls to only 0.037. This indicates that in the matched sample of treated and control units there is no longer any systematic difference in observables between the two cohorts of units, leading us to conclude that our matching procedure satisfies the balancing property and the conditional independence assumption is not violated.

[11] These results are not presented here, but are available upon request from the authors.
[12] We calculate the median absolute standardised bias in the observables included in the selection specification between the treated firms and all control observations compared with the treated and matched control units.

4. SEARCHING FOR CAUSALITY

a. Methodology and Descriptive Statistics

In this section we study both directions of the causal link between innovation and exporting. On one hand, we examine whether past innovation activity affects the switches from non-exporting to exporting. In the reverse direction, we examine whether past exporting status affects the switch from non-innovation to innovation. These switches can be effectively observed by examining the probabilities of firms to change states.

Table 5 shows that only 2.8 per cent of firms (1.5 per cent + 1.3 per cent) that were product innovators in period $t-2$ switched from non-exporters to exporters in period t, whereas 4.7 per cent of firms that were not product innovators became exporters. Similarly, only 2.6 per cent of process innovators in $t-2$ became first-time exporters in period t, whereas 4.6 per cent of firms that did not do process innovations started to export. Allowing for simultaneous decisions both to innovate and to start exporting, and thereby also including innovators in period t, only 8.7 per cent and 8.9 per cent of all switchers into exporting can be attributed to product or process innovators, respectively. These results confirm previous conclusions of negligible impact of innovation activity on export status.

TABLE 5
Transitional Probabilities of Successful Innovation Conditional on Becoming an Exporter

	$Exp_t = 1 \mid Exp_{t-2} = 0$			
	0		*1*	
	$product_t = 0$	$product_t = 1$	$product_t = 0$	$product_t = 1$
$product_{t-2} = 0$	8,158 (86.4%)	849 (9.0%)	421 (4.5%)	16 (0.2%)
$product_{t-2} = 1$	294 (34.6%)	532 (62.6%)	13 (1.5%)	11 (1.3%)
	$Exp_t = 1 \mid Exp_{t-2} = 0$			
	0		*1*	
	$process_t = 0$	$process_t = 1$	$process_t = 0$	$process_t = 1$
$process_{t-2} = 0$	8,540 (88.4%)	678 (7.0%)	429 (4.4%)	16 (0.2%)
$process_{t-2} = 1$	255 (40.4%)	360 (57.0%)	11 (1.8%)	5 (0.8%)

Source: SORS and AJPES; authors' calculations.

On the other hand, the evidence of transition from exporting to innovation is more convincing. Table 6 shows that 4.8 per cent and 5.8 per cent of past exporters became first-time product and process innovators, respectively, during the present period. Moreover, when allowing for simultaneous decisions to start exporting and to start innovating, 85 per cent and 89 per cent of first-time product and process innovators, respectively, were exporters in the past or in the present period. This indicates that among Slovenian firms, the probability that exporting will induce innovations is larger than the probability that innovations will lead a firm to export.

To estimate the importance of innovation for the decision to start exporting, and conversely the importance of exporting for the decision to start innovating, we alter our exporting and innovation equations. The exporting equation now restricts the data sample to non-exporting firms in period $t - 2$:

$$\text{Prob}(Exp_t = 1|Exp_{t-2} = 0) = f(Inov_{t-2}), \tag{3}$$

whereas the innovation equation restricts the sample to non-innovating firms in period $t - 2$:

$$\text{Prob}(Inov_t = 1 \,|\, Inov_{t-2} = 0) = f(Exp_{t-2}). \tag{4}$$

TABLE 6
Transitional Probabilities of Exporting Conditional on Becoming a Product or Process Innovator

	product inov$_t$|*product inov*$_{t-2}$ = 0			
	0		*1*	
	$Exp_t = 0$	$Exp_t = 1$	$Exp_t = 0$	$Exp_t = 1$
$Exp_{t-2} = 0$	1,458 (67.7%)	633 (29.4%)	46 (2.2%)	16 (0.7%)
$Exp_{t-2} = 1$	276 (5.5%)	4,492 (89.7%)	5 (0.0%)	239 (4.8%)
	process inov$_t$|*process inov*$_{t-2}$ = 0			
	0		*1*	
	$Exp_t = 0$	$Exp_t = 1$	$Exp_t = 0$	$Exp_t = 1$
$Exp_{t-2} = 0$	1,467 (68.1%)	633 (29.4%)	37 (1.8%)	16 (0.7%)
$Exp_{t-2} = 1$	275 (5.5%)	4,447 (88.7%)	6 (0.1%)	284 (5.7%)

Source: SORS and AJPES; authors' calculations.

We use the exporting equation (3) to match innovators with non-innovators in period $t - 2$,[13] and then, using the average treatment effects approach, we test whether previously non-exporting innovating firms are likelier to become exporters in period t than non-innovating non-exporters. Analogously, we estimate the innovation equation (4) and match exporters with non-exporters in period $t - 2$, to test whether previously non-innovating exporting firms are more likely than non-exporting non-innovators to become innovators in period t.

b. Results

Tables 7 and 8 present estimates of the average treatment effects of lagged innovative activity on the change in exporting (exporting equation) and of

TABLE 7
Pooled Average Treatment Effects of Lagged Innovation (Lagged Export Status) on the Change in Export Status (Innovation)

	Product Innovation					
	Pr[Exp_t]			Pr[$Inov_t^{prod}$]		
	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)
	Process Innovation					
	Pr[Exp_t]			Pr[$Inov_t^{proc}$]		
	ATT	*SE*[a]	*Obs.*[b]	*ATT*	*SE*[a]	*Obs.*[b]
Nearest neighbour matching	−0.001	0.016	245 (168)	0.016*	0.008	437 (33)
Nearest neighbour matching[c]	−0.001	0.017	245 (168)	0.016*	0.009	437 (33)
Kernel matching	−0.030*	0.020	245 (168)	0.016*	0.010	437 (33)
Radius matching (r = 0.2)	−0.032**	0.013	245 (756)	0.046***	0.008	326 (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).
*, ** and *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Source: SORS and AJPES; authors' calculations.

[13] We continue applying the propensity score specifications (1) and (2).

TABLE 8
Pooled Average Treatment Effects of Lagged Process Innovation (Lagged Export Status) on the Change in Export Status (Process Innovation) for Three Size Classes

	$Pr[Exp_t]$			$Pr[Inov_t]$		
	ATT	*SE*[a]	*Obs.*[b]	*ATT*	*SE*[a]	*Obs.*[b]
Small (10<*Emp*≤50)						
Nearest neighbour matching	−0.024	0.037	95 (1,026)	0.010	0.014	1,050 (375)
Nearest neighbour matching[c]	−0.024	0.038	95 (1,026)	0.010	0.013	1,050 (375)
Kernel matching	−0.074***	0.020	95 (1,389)	0.010	0.015	1,050 (375)
Radius matching (r = 0.2)	−0.077***	0.019	44 (382)	0.046***	0.008	4,340 (766)
Medium (50<*Emp*≤200)						
Nearest neighbour matching	0.027	0.024	270 (1,177)	0.046*	0.024	1,386 (152)
Nearest neighbour matching[c]	0.027	0.021	270 (1,177)	0.046	0.032	1,386 (152)
Kernel matching	0.023	0.022	270 (1,351)	0.082*	0.049	1,386 (154)
Radius matching (r = 0.2)	0.014	0.025	105 (247)			
Large (200<*Emp*)						
Nearest neighbour matching	0.005	0.011	275 (1,532)	0.064***	0.023	1,603 (164)
Nearest neighbour matching[c]	0.005	0.011	275 (1,532)	0.064***	0.024	1,603 (164)
Kernel matching	0.011	0.012	275 (1,575)	0.057*	0.029	1,603 (164)
Radius matching (r = 0.2)	0.011	0.011	93 (88)			

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).
*, ** and *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Source: SORS and AJPES; authors' calculations.

lagged exporting status on the change in innovation activity (innovation equation) obtained with different matching techniques. Note that we distinguish between product and process innovations, and this may have important implications for the relationship between exporting and innovation. As demonstrated by several others (Cassiman and Golovko, 2007; Cassiman and Martinez-Ros, 2007; Becker and Egger, 2010), product innovations are crucial for successful market entry, while process innovations help it to maintain its market position with a product of fixed characteristics. Product innovations should therefore play a greater role in the decision to start exporting, while the decision to engage in process innovation may be triggered by successful exporting.

Table 7 (top panel) reveals that when only product innovations are considered, innovators are not more likely to become exporters than non-innovators (export equation). Only one out of four specifications (radius matching) shows a significant but negative impact of past product innovation on the decision to start exporting. On the other hand, we find no evidence that exporting status increases a firm's probability of becoming a product innovator. In contrast, the bottom panel of Table 7 provides consistent evidence across all specifications that lagged exporting status has a statistically significant positive impact on the probability that a firm will become a process innovator. Past exporting status is shown to increase the probability of engaging in process innovation in the future by approximately 1.6–4.6 per cent. Again, the exporting equation reveals no effect or a significant negative effect of lagged process innovation on the decision to export.

In Table 8 we provide results disaggregated by size classes[14] for the relationship between exporting and process innovations. Interestingly, we find consistent evidence for a causal link leading from past exporting to future process innovation between medium and large firms, but no such link among small firms. Moreover, the marginal effect of exporting on process innovation seems to increase with size. While for a subset of small firms the effect of exporting on process innovation is low and mostly insignificant, exporting by a group of medium firms increases the probability that the firms will engage in process innovation by approximately 4.6 per cent (nearest neighbour matching) to 8.2 per cent (kernel matching). In large firms this effect increases to 5.7 per cent to 6.4 per cent. These findings support a version of the learning-by-exporting hypothesis in which exporters use their exporting status to improve their knowledge of the production process, marketing activities and managerial skills that lead to improvements in TFP.

There are a few caveats worth noting. Firstly, the CIS innovation survey employs a very broad definition of innovation by including all products and processes that are new to the firm, but not necessarily new to the marketplace. As pure imitation is not excluded, this may bias our findings in that we are likelier to witness imitation stemming from export market participation than first-time exporting resulting from successful imitation. Secondly, as shown above, our sample is biased toward larger and more productive firms excluding a disproportionate share of small enterprises. Firm size and productivity are, in turn, correlated with innovation activity, leading the sample to overrepresent both exporting and innovating firms. Potentially, a more representative cohort of non-innovating and non-exporting firms may alter the perceived relationships. Thirdly, the length of our sample may be too short to fully capture the effects of either innovation and/or exporting activity. Indeed, the time from innovation to its commercial application may be both firm/industry as well as product/innovation specific. Given that we do not dispose with any information

[14] We split the sample into three standard size classes: small firms with between 10 and 50 employees, medium-sized firms with at least 51 and at most 200 employees, and large firms with more than 200 employees.

on the nature of innovation, we cannot control for innovation-specific characteristics that impact the length of the period between innovation and its adaptation for commercial use.[15] Finally, innovating firms can choose licensing or foreign direct investment in order to attempt to appropriate the rent from innovation in exporting markets instead of settling for arm's-length trade (see for instance Caves, 1974). Some successful innovators not captured in our results may hence never choose to start exporting and instead invest directly into foreign-based production facilities or license the technology abroad.

c. Robustness Check: Industrial Production Data

To check whether and how the above results obtained from innovation surveys are robust to the use of alternative measures of product and process innovation, we use data from the industrial production survey (IPS) for the period 1995–2003. This survey asks respondents to list the products they produce and sell to domestic and foreign markets. These data allow us to consider whether firms that start exporting increase the number of products they sell more quickly than do firms that do not decide to serve foreign markets.

Participation in the IP survey in Slovenia is compulsory.[16] The survey sheets are sent out to a sample of firms reported to employ at least 20 workers in the preceding year. Once included in the survey, a firm continues to receive survey sheets even if the number of employees declines below the stated limit. Since many firms start exporting before they are first included in the survey, many new exporters are excluded from the analysis. As a result, the sample of new exporters in the IP survey is reduced to 108 firms out of 776 in the complete dataset. Table 9 compares the key characteristics of all new exporters and new exporters that were in the IPS for the period 1995–2002. The average size of all new exporters is as low as 20 employees, while the average firm size in the censored IP sample is almost 4.5 times larger. Similar size advantage applies when annual sales are used as measure of size. In other words, while micro and small firms are over-represented in the sample of firms, firms with less than 20 employees are excluded from the IP sample, leaving mostly medium first-time exporters. On the other hand, the average values for productivity and capital intensity among new exporters in the IP survey are 80 per cent and 86 per cent respectively, of the corresponding values for the entire sample of new exporters. Clearly, lower labour productivity and capital intensity in the censored sample may affect the results on differential performance of new exporters.

The last column of Table 9 shows the key statistics for the sample of surveyed firms that did not export. Comparison of firm characteristics in

[15] This may be less of an issue for process innovation than product innovation.
[16] The survey is conducted by the Slovenian Statistical Office.

TABLE 9
Firm Characteristics of New Exporters and Non-exporters, 1995–2002

Variable	*All New Exporters*	*IP Sample of New Exporters*	*IP Sample of Non-exporters*
Number of firms	776	108	238
Employment	19.66	89.78	38.03
	(165.57)	(432.42)	(47.95)
Turnover	194.84	957.51	286.85
	(2,060.34)	(5,474.22)	(468.28)
Labour productivity	3.03	2.41	2.56
	(2.75)	(1.62)	(1.64)
Capital intensity	4.4	3.89	3.26
	(8.82)	(6.42)	(5.77)
Number of products	–	3.72	3.93
	–	(3.48)	(4.36)

Notes:
Exporters in the IP sample are the sample from the whole population surveyed by SORS. Table 9 consists of average values for key firm characteristics and standard deviations in parentheses. Monetary variables are given in millions of Slovenian tolars (1994 constant prices).

Source: SORS and Slovenian Customs Office; authors' calculations.

the last two columns suggests that firms that did not start exporting were on average smaller, slightly more productive and less capital intensive.[17] On average these two sets of firms produced similar numbers of products.

d. Impact of Exporting on Number of Products and Productivity Growth

This section reports the average treatment effects (ATT) on treated firms caused by exporting regarding product and process innovation.[18] We do this by observing the effects of exporting on the number of products that a firm sells and on the firm's total factor productivity (TFP) growth. Here, an increase in a number of products provides direct evidence of product innovation at a firm, while an increase in the TFP provides direct evidence of process innovations at a firm. Note that this distinction is based on findings of Harrison et al. (2005), Griffith et al. (2006), Parisi et al. (2006) and Hall et al. (2007), showing that process innovations have labour displacement effects and are therefore expected to result in significant productivity growth, whereas because of the demand effect, product innovations are likely to cause employment growth and,

[17] Lower productivity of new exporters compared to non-exporters is specific to our censored sample. Damijan et al. (2009) show that the productivity of new exporters is higher than that of non-exporters.
[18] We only present the robustness check of the effects of lagged exporting status on innovative activity. Similarly, as is the case with the CIS sample, we also found no evidence that lagged innovation effects (product or process) affect the current exporting status in IP data. For the sake of brevity, we omit these results from the presentation.

thus, may not result in significant productivity growth. The propensity scores for the export decision are estimated by:

$$\begin{aligned}&\mathrm{Prob}(Exp_t = 1 | Exp_{t-1} = 0)\\&\quad = f(\log TFP_{t-1}, \log k_{t-1} \log \ell_{t-1}, \log NoP_{t-1}, time),\end{aligned} \tag{5}$$

where explanatory variables are lagged log of *TFP*, log of capital intensity *k*, log of employment *l*, and log of number of products *NoP*, and *time*, which denotes dummy variables for cyclical effects (annual dummies).[19] All regression coefficients with the exception of number of products are statistically significant.[20] In particular, size of firms is the most important explanatory variable. Validity of calculated treatment effects is granted by the fact that the observables underlying the estimated propensity scores are balanced.

Based on the above definition of propensity score, we match first-time exporters with non-exporters in period $t - 1$ by using either nearest neighbour matching or kernel matching, and then estimate average treatment effects of exporting on treated firms with respect to product and process innovation.

Table 10 reports changes in log of number of products using nearest neighbour and kernel matching for $t + 1$, $t + 2$ and $t + 3$ years after firms start exporting. The results suggest that firms that start exporting increase the number of products faster; however, these effects are marginally significant only one year (based on nearest neighbour matching) or two years (kernel matching) after a firm starts to export. These results confirm our findings from the innovation survey that the decision to export does not trigger significant increases in product innovation.

Similarly, Table 11 reports results for the impact of exporting on process innovations. Estimates of ATT for the change of TFP over the first three years after the start of exporting show large and statistically significant effects of the

TABLE 10
Treatment Effects of Exporting (for First-time Exporters) on the Number of Products

Time Span	*Nearest Neighbour Matching*				
	Treated	*Controls*	*ATT*	*Std. Error*	*t-Statistic*
$t + 1/t$	165	118	0.083*	0.044	1.872
$t + 2/t$	165	108	0.067	0.051	1.303
$t + 3/t$	165	98	0.051	0.056	0.907

[19] This propensity score equation includes only firms that did not export in period $t - 1$. This is different to previous specifications, which we constrained using biannual data from the innovation survey.
[20] For the sake of brevity, we do not report these results here but they are available upon request from the authors.

TABLE 10 *Continued*

Time Span	*Kernel Matching*				
	Treated	*Controls*	*ATT*	*Std. Error*	*t-Statistic*
$t + 1/t$	165	615	0.036	0.033	1.096
$t + 2/t$	165	615	0.067*	0.035	1.900
$t + 3/t$	165	615	0.018	0.051	0.354

Notes:
Standard errors for both nearest neighbour and kernel are based on bootstrapping (100 repetitions).
*, ** and *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Source: SORS and Slovenian Customs Office; authors' calculations.

TABLE 11
Treatment Effects of Exporting (for First-Time Exporters) on Total Factor Productivity

Time Span	*Nearest Neighbour Matching*				
	Treated	*Controls*	*ATT*	*Std. Error*	*t-Statistic*
$t + 1/t$	165	131	0.140***	0.042	3.352
$t + 2/t$	165	130	0.156***	0.070	2.220
$t + 3/t$	165	132	0.239***	0.067	3.562
Time Span	*Kernel Matching*				
	Treated	*Controls*	*ATT*	*Std. Error*	*t-Statistic*
$t + 1/t$	165	615	0.110***	0.035	3.145
$t + 2/t$	165	615	0.097*	0.060	1.625
$t + 3/t$	165	615	0.168***	0.046	3.670

Notes:
Standard errors for both nearest neighbour and kernel matching are based on bootstrapping (100 repetitions).
*, ** and *** indicate statistical significance at 10, 5 and 1 per cent, respectively.

Source: SORS and Slovenian Customs Office; authors' calculations.

export decision on firm productivity for a subset of medium and large firms. Based on nearest neighbour matching, we find that one year after the start of exporting, the average productivity of firms increases by 14 percentage points faster in comparison to non-exporters. In subsequent periods, the effect increases further.[21] The results based on kernel matching are lower, but they

[21] Note that these results on learning-by-exporting for Slovenian firms are more pronounced compared to the evidence reported by Damijan and Kostevc (2006) and De Loecker (2007) for the sample of all new exporters in the Slovenian manufacturing sector.

are statistically significant, leading us to conclude that exporting does lead to productivity improvements that are likely to be related to process rather than product innovations.

These results are consistent with those reported in the previous sub-section, where exporting is shown to increase the probability that medium and large first-time exporters will become future process innovators. These results are striking, since both the likelihood of engaging in process innovations after starting to export (using the innovation survey), as well as the likelihood of increasing TFP after starting to export (using the industrial production survey) are obtained from a very similar sample of medium and large first-time exporters. One can therefore conclude that for Slovenian firms, exporting leads to process rather than product innovations, and these in turn boost productivity. However, this causal relationship is not general but is likely to be limited to a group of medium and large first-time exporters.

5. CONCLUSIONS

In this paper we explore the causal relationship between innovation and export activities of firms. The majority of papers on this topic have studied only correlations between them; we attempt to establish a causal link. We argue that two causal links are possible. First, from product innovation to productivity and to decision to export may effectively explain how a firm's decision to invest in R&D and to innovate a product drives its productivity and triggers the decision to start exporting. Second, in the opposite direction, the link going from exporting to process innovation to productivity growth may be key to understanding how export activity can force a firm to engage in process innovation, which in turn improves its productivity growth in the long run. Our empirical approach is to tackle both sides of this causality link using Slovenian microdata, including financial data, innovation survey data, industrial survey data, as well as information on trade flows, for the period 1996–2002. This unique dataset allows us to test the prediction that a firm's innovation enhances its probability of becoming an exporter, and the prediction that learning effects of exporting will translate to a greater effort to innovate and thus to improvements in productivity.

We apply matching techniques to establish the direction of causality between innovation activity and exporting by testing whether lagged innovations affect the decision to start exporting, and whether past exporting affects a firm's decision to start innovating. We estimate average treatment effects on probabilities of exporting and innovating using data from innovation surveys and then use data from industrial production surveys as a robustness check.

We find no evidence that either product or process innovations increases the likelihood that a firm will become a first-time exporter. However, we find evidence that past exporting status increases the probability that medium and large firms will become process innovators. At the same time we find no impact of past exporting on product innovations. These results are supported by estimated treatment effects from the industrial production survey data. We find no impact of past exporting on the increase in number of products that firms produce, which is direct evidence that exporting firms are not faster product innovators. However, we do find a positive impact of past exporting on productivity growth among medium and large first-time exporters, which is indirect evidence of process innovations.

These findings suggest that participation in trade may improve a firm's efficiency by stimulating process innovations. It is important to note, however, that these positive effects are likely to be limited to a group of medium and large first-time exporters. Export volumes of small first-time exporters are probably too small to achieve immediate efficiency gains through process innovations. Alternatively, efficiency improvements among small exporters may also become visible if data covering a longer time period are studied.

On the other hand, our results do not confirm the implications of the Constantini and Melitz (2008) model and the findings of Aw et al. (2009) that in the case of Slovenian firms the linkage from product innovation to productivity growth drives the self-selection of more productive firms into exporting. On the contrary, we do find evidence in favour of learning-by-exporting of Slovenian firms, which was already indicated by Damijan and Kostevc (2006) and De Loecker (2007). Our results, however, demonstrate that these learning-by-exporting effects occur through the mechanism of process innovation enhancing firm technical efficiency and not through introduction of new products.

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