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Learning-to-Export Effect as a Response to Export Opportunities: Micro-Evidence from Korean Manufacturing

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Abstract: *This paper aims to investigate whether empirical evidence supports the learning-to-export hypothesis, which has received little attention in the previous literature. By taking full advantage of plant–product level data from the Republic of Korea during 1990–1998, we find some evidence for the learning-to-export effect, especially for innovated product varieties with delayed exporters: their productivity, together with research and development and investment activity, was superior to their matched sample. On the other hand, this learning-to-export effect was not significantly pronounced for the industries protected by import tariffs. Thus, our empirical findings suggest that it would be desirable to implement some policy tools to promote the learning-to-export effect, while tariff protection cannot be justifiable for that purpose.*

Keywords: Learning-to-export; difference-in-difference; matching

JEL Classification: F13; F14

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1. Introduction

One of the most widely accepted stylised facts in the field of international trade is that exporters tend to outperform non-exporters in many respects. Since Bernard and Jensen (1995), substantial empirical literature has documented these findings for a large number of countries. In explaining this observed phenomenon, two alternative (but not mutually exclusive) hypotheses have been proposed in the literature.[1] The first one is the *self-selection hypothesis,* which states that exporting is a consequence of a firm's productive capacity. Entry into the export market is profitable, but firms must incur irreversible entry costs in order to enter. Thus, only firms with sufficient productive capacity self-select into the export market. Such interaction between export market entry cost and firm productivity is an essential component of the heterogeneous firm theory developed by Melitz (2003) and others such as Bernard et al. (2003) and Bernard, Jensen, and Schott (2006).

The other explanation is the *learning-by-exporting hypothesis,* which maintains that a firm's productive capacity is a consequence of entering the export market. Once a firm enters the export market, it grows faster as a result of fiercer yet more informative international competition and greater access to advanced technology. Under this hypothesis, firm productivity grows *after* the entry into the export market.

As emphasised in Bernard and Jensen (1999), understanding how plants perform before and after exporting is of great importance in selecting appropriate policies. For example, if there are no post-entry rewards from exporting (i.e. no learning-by-exporting effect), then policies designed to increase the number of exporters may be wasting resources. On the other hand, if gains accrue to firms once they become exporters, then reducing the entry cost into foreign markets would be an appropriate policy stance. Many empirical studies have found that pre-entry differences present substantial evidence in favour of the self-selection hypothesis, but evidence regarding the learning-by-exporting hypothesis is mixed (Wagner 2012).[2]

[1] See Greenaway and Kneller (2007) and Wagner (2012) for an extensive literature review on this issue.

[2] A growing body of studies has found some evidence for the learning-by-exporting hypothesis in developing countries: Girma, Greenaway, and Kneller (2002) for the United Kingdom; Van Biesebroeck (2005) for sub-Saharan African countries; De Loecker (2007) for Slovenia; Albornoz and Ercolani (2007) for Argentina; Aw, Roberts, and Xu (2011) for Taiwan; Ma, Tang, and Zhang (2014) for China; and Hahn (2005; 2012) for the Republic of Korea.

Yet another plausible argument can explain the pre-entry differences between exporters and non-exporters, although the literature has paid little attention to it. This argument is referred to as the learning-to-export or conscious self-selection hypothesis in López (2004); Alvarez and López (2005); Greenaway and Kneller (2007); and Eliasson, Hansson, and Lindvert (2012).

The main idea of this hypothesis is related to the timing of learning, arguing that learning takes place not when export sales begin but when the export decision is made. The export decision is usually made before export market entry. Once this decision is made, firms make conscious efforts to enhance their performance and improve the quality of their products to become exporters, thereby increasing their productivity endogenously.

If this effect is found to be empirically important, then it can contribute to the existing literature from at least two standpoints. First, it may explain (at least some of) the reasons why firm productivity increases before export market entry. In contrast with previous heterogeneous firm theories where each firm's productivity is assumed to be drawn from an exogenous distribution, productivity change can be understood as an endogenously determined process under the learning-to-export mechanism. Second, it can shed light on related policy issues as well. If firms enhance innovative and productive activity with the purpose of entering export markets, then rewarding exporting ex post may increase such activities at current non-exporters and successfully increase economic growth (Bernard and Jensen, 1999).

Thus, the main objective of this paper is to investigate whether empirical evidence supports the learning-to-export hypothesis by using manufacturing data from the Republic of Korea (henceforth, Korea) during 1990–1998. However, identifying the learning-to-export effect is not an easy task owing to the unobservable nature of the time at which the decision to start to export is made, as mentioned in López (2004) and Greenaway and Kneller (2007). Recent empirical works investigating the learning-to-export effect, such as Eliasson, Hansson, and Lindvert (2012), rely on the assumption that the decision to start to export is made several years before participating in actual exports.

As we will discuss in the next section, however, our rich plant–product matched data set with yearly information on domestic and export market sales allow us to make another plausible assumption about the timing of the export decision. The main idea is that we focus our analyses on the plants which innovate and introduce a new product variety only for the domestic market in its innovation year.[3] In other words, when a new product variety is introduced for the domestic market, it will open a new opportunity for the plant to export this variety in the international market. Therefore, at the time of the new product variety introduction, plants can decide whether to export this product variety later by improving its productivity. If this is the case, we should observe plants' conscious efforts to improve the quality of their product variety to become an exporter.

Another interesting issue that is worthwhile analysing is the effectiveness of trade protection policies regarding the learning-to-export effect. This is because amongst the three different hypotheses between productivity and exports, learning to export is more closely related to the trade protection argument and can provide justification for such policies. For example, with the existence of the self-selection mechanism where intra-firm productivity is exogenously determined, trade protection cannot play any role in changing intra-firm productivity. At the same time, the learning-by-exporting effect implies that productivity increases only after international market participation and thus trade protection cannot be justified as well. As described in Slaughter (2004), dynamic arguments for infant industry protection tell us that trade protection can buy protected industries the time they require to learn before participating in the international market and to correct inefficiencies. Thus, for infant industry protection to be justified, we should observe the profound effect of learning to export in the protected industries. Therefore, in our empirical analyses we will also investigate this possibility as much as our data allow us to do so.

The rest of this paper is organised as follows. In the next section, we explain our data sets and some definitions regarding product varieties. In section 3, we present our empirical methodologies and their main results to investigate the existence of the learning-to-export effect. In section 4, we will investigate whether

[3] Thus, we exclude plants which introduce a new product variety in the domestic and export market simultaneously in our main empirical analyses. These plants may already have high productivity enough to pay the entry cost and therefore have little incentive for learning to export.

those learning-to-export effects arise disproportionately between protected and unprotected industries. Section 5 will provide some additional empirical results regarding the conscious efforts of firms to learn to export. The final section summarises the results and concludes the paper.

2. Data and Definitions Regarding Product Variety

2.1. Data

This study utilises three data sets. The first one is the unpublished plant-level data underlying Statistics Korea's Mining and Manufacturing Census for 1990–1998. It is an unbalanced panel data set and covers all plants with five or more employees in the mining and manufacturing sector. The data set has information on various plant characteristics such as production, shipments, production and non-production workers, tangible fixed assets, and research and development (R&D) expenditure.

The second data set is an unpublished plant–product level data set for the same period, which can be matched with the plant-level data set through the plant identification number. A product is identified by an 8-digit product code which is constructed by combining the 5-digit Korean Standard Industrial Classification (KSIC) code to which the product belongs and the 3-digit code based on Statistics Korea's internal product classification scheme. The product code is consistent over time during the period of analysis. For each plant–product observation, the values of total shipments (domestic plus export shipments) and export shipments are available. The plant–product data set covers 70%–80% of plants in the plant-level data set.[4] The coverage ratio is much higher for total and export shipments. Yearly total shipments and exports from the plant–product data set account for more than 84.1% of shipments and virtually all (99.9%) of the exports in the plant-level data set. Using the information on the plant–product level total and export shipments, we can identify which plant introduces a new product variety for the first time and amongst them which plant begins exporting the same product variety later or not. This is crucial information in our analyses, as discussed below.

[4] Only those plants which are included in the plant-product data set are included in the sample.

The last data set we use in our analyses is the yearly import tariff data from the Korea Customs Service at the 10-digit level Harmonized System (HS) code for 1991–1998. This provides data on the value of the applied tariffs and imports for each HS category, and the import tariff rate can be directly calculated by dividing the value of the applied tariff by the value of the import. These tariff data with the HS code system have been converted into 4-digit level International Standard Industrial Classification (ISIC) and in turn into KSIC. The trend of Korea's import tariffs during 1991–1998 is reported in Table 1. As can be seen, the mean value of import tariffs across industries was reduced until 1994 and has stabilised since then.

Table 1: Republic of Korea's Import Tariffs, 1991~1998

Year	Mean	Standard deviation
1991	0.106	0.061
1992	0.096	0.066
1993	0.083	0.065
1994	0.076	0.068
1995	0.080	0.082
1996	0.078	0.065
1997	0.079	0.060
1998	0.078	0.059
1991~1998	0.084	0.067

Note: The table reports the means and standard deviations of import tariffs across 128 industries according to the 4-digit level of the International Standard Industrial Classification (ISIC).
Source: Authors' calculation.

2.2. Definitions Regarding Product Variety

Before proceeding to explain our empirical strategies in more detail, we first provide some explanation about the structure of the plant–product level data set and definitions that we will use in our empirical study.

A *product* is defined at the 8-digit product code which can be produced by multiple plants. We define *product variety* or *variety* as a product produced by a certain plant. *Innovated product variety* is defined from the viewpoint of plants for 1992–1998. Specifically, an innovated product variety is a product variety which was not produced by a plant during 1990–1991 and began to be produced by that plant for the first time during 1992–1998. All the other product varieties are *existing* or *non-innovated* product varieties. The product variety innovation year is the first year of producing the innovated product variety, so that each innovated product variety has a unique product variety innovation year. We can define the new export (product) variety and new variety export year in an analogous way. A new export product variety is a product variety which was not exported by a plant during 1990–1991 and began to be exported by that plant for the first time during 1992–1998. The new variety export year is the first year of exporting the new export variety.

Combining the definitions of innovated product variety and exported product variety (and product variety innovation year and new variety export year), we can categorise all the product varieties into five different product types as summarised in Table 2. First, the innovated product varieties can be categorised into the first three types: innovated product varieties with simultaneous export (IN_SE), with delayed export (IN_DE), and without export (IN_NE). Second, the non-innovated product variety can be categorised into the next two types: non-innovated product variety with export (NI_E) and without export (NI_NE).

Table 2: Classification of Product Variety Types

Product variety type	Description
IN_SE	Innovated product variety with simultaneous export (innovation year = export year)
IN_DE	Innovated product variety with delayed export (innovation year < export year)
IN_NE	Innovated product variety without export
NI_E	Non-innovated product variety with export
NI_NE	Non-innovated product variety without export

Source: Authors' calculation.

As shown in Table 3, the total number of product varieties is 402,312, amongst which the IN_NE type of product variety takes the highest share of 58.5%, followed by NI_NE (29.7%), IN_SE (8.8%), IN_DE (1.9%), and NI_E (1.1%). The basic statistics of major variables for each product type are summarised in Table 4. For example, the initial value of total factor productivity (TFP) is the highest in the case of simultaneous exporters, while those of the other two innovated variety types are more or less the same. The initial TFP level is lowest in the case of non-innovated product variety producers (NI_E and NI_NE).

Table 3: Number of Product Varieties According to Types

Product variety type	Frequency	Share (%)	Cumulative share (%)
IN_SE	35,363	8.8	8.8
IN_DE	7,729	1.9	10.7
IN_NE	235,195	58.5	69.2
NI_E	4,531	1.1	70.3
NI_NE	119,494	29.7	100.0
Total	**402,312**	**100.0**	**-**

Source: Authors' calculation.

From the standpoint of our empirical interest, the plants with the IN_DE type of product variety are most likely to have the learning-to-export effect. Because they introduce a newly innovated product variety first and then export it later with a delay, they are most likely to make conscious efforts to increase their productivity during these two time periods to become an exporter. Table 5 shows the number of years from innovation to export participation amongst the IN_DE type of product varieties. It takes only 1 year for the innovated variety to become an exported variety for around 53.1% of the IN_DE type of variety, 2 years for 23.7% of the IN_DE type of variety, and so on. Those years could be thought of as the periods when the learning-to-export effect is mostly pronounced if it exists.

In the case of the other two types of innovated product varieties (IN_SE and IN_NE), the learning-to-export effect may not be profound compared with the delayed exporters. For simultaneous exporters (IN_SE), the fact that they can innovate and export a specific product variety at the same time may imply that they are already capable of paying the fixed cost to participate in the export market, and thus have little need to learn to export. In the case of innovators without exports (IN_NE), some of them may have the intention to become an exporter and make the necessary efforts to improve their productivity yet fail to export while others may not even have such an intention.

Table 4: Summary Statistics of Variables According to Product Variety Types

Major variables	Product variety type	Observation	Mean	Standard deviation	Minimum	Maximum
TFP (log of Levinsohn and Petrin's total factor productivity)	IN_SE	35,146	2.56	1.01	-1.66	7.39
	IN_DE	7,686	2.35	0.94	-1.05	5.90
	IN_NE	234,000	2.37	0.88	-2.63	7.39
	NI_E	4,503	2.30	0.97	-1.52	6.11
	NI_NE	119,000	2.28	0.94	-1.80	6.62
Size (log of number of worker)	IN_SE	35,363	3.60	1.48	0.69	10.33
	IN_DE	7,729	3.35	1.32	0.69	10.33
	IN_NE	235,000	2.54	0.88	0.69	10.33
	NI_E	4,531	3.75	1.37	1.61	10.33
	NI_NE	119,000	3.06	1.22	1.39	10.33
Age (log of plants' age)	IN_SE	31,650	1.84	1.05	0.00	4.71
	IN_DE	6,763	1.77	1.05	0.00	4.65
	IN_NE	197,000	1.49	0.96	0.00	4.72
	NI_E	4,302	2.03	0.99	0.00	4.50
	NI_NE	110,000	1.77	0.99	0.00	4.66
K/L (log of capital–labour ratio)	IN_SE	35,340	2.55	1.35	-5.02	10.44
	IN_DE	7,725	2.65	1.32	-3.24	7.44
	IN_NE	235,000	2.25	1.29	-5.02	10.44
	NI_E	4,528	2.57	1.21	-1.82	7.10
	NI_NE	119,000	2.19	1.23	-3.07	10.23
R&D (dummy)	IN_SE	35,363	0.09	0.29	0.00	1.00
	IN_DE	7,729	0.08	0.27	0.00	1.00
	IN_NE	235,000	0.05	0.21	0.00	1.00
	NI_E	4,531	0.02	0.13	0.00	1.00
	NI_NE	119,000	0.01	0.09	0.00	1.00

R&D = research and development, TFP = total factor productivity.

Notes: Innovated varieties are categorised into IN_SE (simultaneous exporter), IN_DE (delayed exporter), and IN_NE (non-exporter). Non-innovated varieties are categorised into NI_E (non-innovated exporter) and NI_NE (non-innovated non-exporter). All basic statistics are calculated at the first year of each product variety. TFP is measured by the Levinsohn and Petrin (2003) method. Size is the natural logarithm of the number of employees. Age is the log value of a plant's age. K/L is the ratio of capital to the number of workers in the log. R&D is a dummy variable which takes the value of 1 if the value of R&D is positive and the value of 0 otherwise.

Source: Authors' calculation.

Table 5: Years from Innovation to Export Participation Amongst Innovated Product Varieties with Delayed Export (IN_DE)

Years from innovation to export participation	Frequency	Share (%)	Cumulative share (%)
1 year	4,103	53.1	53.1
2 years	1,834	23.7	76.8
3 years	898	11.6	88.4
4 years	484	6.3	94.7
5 years	306	4.0	98.7
6 years	104	1.4	100.0
Total	**7,729**	**100.0**	**-**

Source: Authors' calculation.

3. Main Empirical Analyses

3.1. Methodology

As mentioned above, the most difficult part of our empirical investigation comes from the fact that the actual time of the decision to export is unobservable. Thus, we will take two different approaches in our empirical implementation, which depends on our assumptions on the timing of the decision to become an exporter.

The first approach assumes that the decision to become an exporter is directly related to the actual export participation time, which is the approach taken in most of the other papers studying learning to export (e.g. López, 2004; Greenaway and Kneller, 2007; and Eliasson, Hansson, and Lindvert, 2012). Put differently, given the observed export participation year, this approach assumes that the decision to become an exporter is made some years before the export participation year and investigates whether there is a learning-to-export effect between the decision year and the export year. To estimate the learning-to-export effect in the first approach, we compare the performance outcome (TFP) of plants with innovated product variety with delayed export (IN_DE) with plants with innovated product variety without export (IN_NE).[5]

[5] We can also compare other pairs of product variety types, e.g. IN_SE and IN_NE. Although this is not our major interest, it is reported in our empirical results for comparison.

The second approach assumes that the decision to become an exporter is directly related to the actual innovation time at which plants have a new opportunity to become an exporter. Because this approach requires not only export participation year data but also new innovation year data for each variety, we can take full advantage of our plant–product level data to investigate this issue. Under this approach, given the observed product variety innovation year, we assume that the decision to become an exporter is made at the product variety innovation year and investigate whether there are learning-to-export effects after this year. In this approach, we compare the performance outcome (TFP) of the innovated product variety with delayed export (IN_DE) with non-innovated product variety without export (NI_NE).

In either approach, the decision to become an exporter can be correlated with the data-generating process for the plant TFP. In this case, propensity score matching is a popular way to reduce the estimation bias associated with an endogenous participation decision. This can be done by comparing the outcome variable of the treated group (actual exporters amongst plants with innovated products) with that of the control group (non-exporters with innovated products or non-exporters without innovation), which is as similar to the treated group as possible. However, as explained by Heckman, Ichimura, and Todd (1997), when there is a selectivity of export decision based on unmeasured characteristics, or if there are time-invariant level differences in outcome variables between the treated and control groups, then the difference-in-difference propensity score matching (DID PSM) estimator is a more appropriate econometric methodology. In this paper, we use a DID PSM estimator to estimate the effect of the export decision on TFP to measure the learning-to-export effect.

3.2. Empirical Results

Approach 1: Export Decision with Observed Export Participation

To apply the DID PSM method, we first start by estimating the following probit model.

$$P(X_i) = Pr(d_i = 1|X_i) = E(d_i|X_i) \quad (1)$$

where $P(X_i)$ is the probability of becoming an exporter for plant *i* conditional on the vector of pre-exporting characteristics X_i, and d_i is the dummy indicating export market participation. As pre-exporting characteristics, we include the variables that are considered to be important in other previous studies such as the log of plant TFP, the log of the number of employees as a proxy for plant size, the log of plant age, the log of the plant's capital–labour ratio, and a dummy variable indicating whether the plant is engaged in R&D.

Table 6: Probability of Exporting Participation: Probit Model

Variables	(1) IN_DE vs. IN_NE	(2) IN_SE vs. IN_NE
TFP_{t-3}	0.023**	0.061***
	(0.010)	(0.006)
$Size_{t-3}$	0.163***	0.268***
	(0.006)	(0.003)
Age_{t-3}	-0.037***	-0.018***
	(0.007)	(0.005)
K/L_{t-3}	0.034***	0.036***
	(0.006)	(0.004)
$R\&D_{t-3}$	0.089***	0.045***
	(0.018)	(0.013)
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
No. of obs.	366,816	375,246
Log likelihood	-22,007.3	-48,367.1

No. = number, obs. = observations, R&D = research and development, TFP = total factor productivity.

Notes: TFP is measured by the Levinsohn and Petrin (2003) method. Size is the natural logarithm of the number of employees. Age is the log value of the plant's age. K/L is the ratio of capital to the number of workers in the log. R&D is a dummy variable which takes the value of 1 if the value of R&D is positive and the value of 0 otherwise. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculation.

All these explanatory variables are lagged by 3 years, so the plant characteristics in the probit model are the values 3 years before actually beginning to export. This approach allows us to examine whether there is a learning-to-export effect in the outcome variables up to 2 years before actual beginning to export.[6] The results of these probit estimations are reported in Table 6, which shows that more productive, larger, younger, more capital-intensive, and more R&D-doing plants are more likely to become exporters.

Next, based on the estimated propensity score, a set of plants with 'innovated product variety without export' is matched to each plant with 'innovated product variety with delayed export'. Let T and C denote the set of treated (IN_DE) and control (IN_NE) units and y^T and y^C be the observed outcomes of the treated and control units, respectively, while *i* and *j* are indexes for treated and control units. The subscript t_0 is some time before exporting, which is set to be 3 years before exporting. The subscript *s* is the number of years after exporting starts. Denote the set of control units matched to the treated unit *i* by C(i), the number of control units matched with $i \in$ T by N^C and the number of plants in the treated units by N^T. Then, the propensity score DID estimator at s-years after export market entry is given by

$$\hat{\alpha}^{PSMDID} = \frac{1}{N^T} \sum_{i \in T} \left(\left(y_{i,s}^T - y_{i,t_0}^T \right) - \sum_{j \in C(i)} w_{ij} \left(y_{j,s}^C - y_{j,t_0}^C \right) \right) \quad (2)$$

where $w_{ij} = 1/N_i^C$ if $j \in C(i)$ and $w_{ij} = 0$ otherwise.

The results of the DID PSM estimates are reported in Tables 7 and 8. Table 7 shows the results when plants in the IN_DE type (plants with innovated product variety with delayed export) are included as treated units and plants in the IN_NE type (plants with innovated product variety without export) as control units. While some strong evidence supports self-selection (outcome difference when actual product participation at s = 0), the DID PSM estimates 1 and 2 years before export participation are statistically insignificant, which means that there is no learning-to-export effect for IN_DE compared with IN_NE.

[6] This empirical setup using explanatory variables with 3-year lags implies that the decision to export is assumed to be made 3 years before the actual export participation.

Table 7: Estimated Effect of Product Variety Export (treated: IN_DE, control group: IN_NE)

Estimator	Learning-to-export		Self-selection	Learning-by-exporting		
	s = -2	s = -1	s = 0	s = +1	s = +2	s = +3
Cross-sectional PSM	0.029*	0.014	0.037**	0.041**	0.020	0.051
	(0.017)	(0.017)	(0.016)	(0.021)	(0.026)	(0.032)
DID PSM	0.010	0.011	0.029***	0.010	0.003	0.001
	(0.010)	(0.012)	(0.011)	(0.016)	(0.019)	(0.026)

DID = difference-in-difference, PSM = propensity score matching.
Notes: Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors' calculation.

Table 8: Estimated Effect of Product Variety Export (treated: IN_SE, control group: IN_NE)

Estimator	Learning-to-export		Self-selection	Learning-by-exporting		
	s = -2	s = -1	s = 0	s = +1	s = +2	s = +3
Cross-sectional PSM	0.032***	0.040***	0.071***	0.045***	0.033**	0.035**
	(0.010)	(0.010)	(0.011)	(0.012)	(0.015)	(0.017)
DID PSM	0.018***	0.014**	0.042***	0.038***	0.016	0.008*
	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.013)

DID = difference-in-difference, PSM = propensity score matching.
Notes: Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors' calculation.

For comparison, we repeat the same procedure when plants in the IN_SE type (plants with innovated product variety with simultaneous export) are included as treated units (Table 8). In this case, we find better performance of the IN_SE type plants over their matched IN_NE type plants at s = -1 and s = -2. However, because IN_SE plants simultaneously innovate and export at s = 0, the superior performance s = -1 and s = -2 may reflect both the learning-to-export and learning-to-innovate effects.

Now, we turn to the empirical results under our next (preferable) approach where we assume that the export decision is more directly related to the timing of new product variety innovation.

Approach 2: Export Decision with Observed Product Variety Innovation

Our second approach assumes that the decision to become an exporter is more directly related to the actual innovation time at which plants have a new opportunity to become an exporter. In this case, although the estimation procedures are almost identical, there are some differences from the first approach. First, in estimating equation (1) to obtain the propensity score, d_i is a dummy variable indicating product variety innovation (instead of export market participation). In addition, there is no lag structure in the explanatory variables in estimating equation (1) although we include the same set of explanatory variables as before.[7] Second, when we estimate the DID PSM in equation (2), t_0 is defined by the year in which the actual product variety innovation is introduced. Thus, by estimating the DID PSM at s = + 1, +2 and +3, we can estimate the learning-to-export effect after product variety innovation of IN_DE type plants compared with NI_NE (non-innovated and non-exported) type plants.

The result of the probit estimation to obtain a matched sample in NI_NE to those in IN_DE sample is reported in Table 9. As in Table 6, more productive, larger, younger, more capital-intensive, and more R&D-doing plants are more likely to become innovators.

[7] The results of these probit estimations are almost identical to Table 4 so we do not report them here.

Table 9: Probability of Innovation: Probit Model

Variables	IN_DE vs. NI_NE
TFP $_t$	0.039*** (0.006)
Size $_t$	0.123*** (0.003)
Age $_t$	-0.491*** (0.008)
K/L $_t$	0.060*** (0.005)
R&D $_t$	0.144*** (0.016)
Year dummy	Yes
Industry dummy	Yes
Number of observations	279,775
Log likelihood	-29,348.6

No. = number, obs. = observations, R&D = research and development, TFP = total factor productivity.

Notes: TFP is measured by the Levinsohn and Petrin (2003) method. Size is the natural logarithm of the number of employees. Age is the log value of the plant's age. K/L is the ratio of capital to the number of workers in the log. R&D is a dummy variable which takes the value of 1 if the value of R&D is positive and the value of 0 otherwise. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculation.

Table 10: Estimated Effect of Product Variety Export Decision (IN_DE vs. NI_NE): When Export Decision is Made at the Point of Product Variety Innovation

	s = +1	s = +2	s = +3
Cross-sectional PSM	0.020 (0.015)	0.011 (0.021)	0.014 (0.029)
DID PSM	0.041*** (0.008)	0.040*** (0.011)	0.039*** (0.017)
Number of treated observations	6,893	3,241	1,623

DID = difference-in-difference, PSM = propensity score matching.

Notes: Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at 10%, 5%, and 1% levels, respectively.

Source: Authors' calculation.

With a matched sample, we estimated the DID PSM as before where the treatment unit is IN_DE type varieties and the control unit is NI_NE type varieties. As shown in Table 10, the DID PSM results show a statistically significant learning-to-export effect this time. After the first, second, and third year of product variety innovation, the TFP differences between IN_DE and NI_NE are 4.1%, 4.0%, and 3.9%, respectively.

Note that when the learning-to-export effect is estimated at s = +1 (i.e. just after the innovation year), all the IN_DE samples are used in the whole procedure. However, when we estimate it at s = +2, we exclude the product varieties with 1 year of innovation–export lapse (the samples in the first line in Table 5). This is because these product varieties are already exported at s = +1. By the same reasoning, when we estimate the learning-to-export effect at s = +3, the product varieties with 1 and 2 years of innovation–export lapse (the samples in the first and second lines in Table 5) are excluded as well.

4. The Role of Industrial Protection

4.1. Parametric DID Estimation

The next question we would like to ask is whether these learning-to-export effects, if any, are dependent on the degree of import protection by tariff policy. As mentioned in section 1, amongst three different hypotheses between productivity and exports, learning to export is more closely related to the trade protection argument and can provide justification for such policies. For example, with the existence of a self-selection mechanism where intra-firm productivity is exogenously determined, trade protection cannot play any role in changing intra-firm productivity. At the same time, the learning-by-exporting effect implies that productivity increases only after international market participation and thus trade protection cannot be justified as well. As described in Slaughter (2004), dynamic arguments for infant industry protection tell us that trade protection can buy protected industries the time they require to learn before participating in the international market and to correct inefficiencies. In this section, we investigate this possibility.

However, since our DID PSM estimate in the previous section is non-parametric methodology that gives a single estimated value, it would not be appropriate to tackle this issue. To deviate this problem, we return to the usual parametric DID estimation procedure combined with matching technique. Having estimated the probit model in equation (1) and matched the sample between the treated (IN_DE type) and control units (NI_NE type), we run the following parametric DID model:

$$y_i = \alpha_0 + \alpha_1 IN\_DE_i + \alpha_2 t_i + \gamma(IN\_DE_i \times t_i) + \varepsilon_i \quad (3)$$

where y_i is an outcome variable (in our case TFP), IN_DE_i is the treatment dummy variable (1 if innovated product variety with delayed export and 0 if non-innovated variety without export), and t_i is the time dummy (0 at the time when the innovation occurs and 1 after the innovation occurs). In this specification, estimated γ represents the DID treatment effect.

The estimated result of equation (3) is shown in Table 11. The DID treatment effect is 5.2% of the TFP difference at s = +1, 4.6% at s = +2, and 5.1% at s = +3. These results are broadly consistent with the result by DID PSM in Table 10.

Table 11: Parametric DID Estimation (IN_DE vs. NI_NE) for TFP

Variables	(1) s = +1	(2) s = +2	(3) s = +3
IN_DE	0.031*** (0.008)	0.033*** (0.011)	0.028* (0.016)
Time	-0.021** (0.010)	0.026* (0.015)	0.000 (0.032)
IN_DE*Time	0.052*** (0.012)	0.046** (0.018)	0.051* (0.026)
Constant	2.369*** (0.010)	2.345*** (0.012)	2.356*** (0.017)
Year dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
Number of observations.	25,256	12,280	6,256
Adjusted R2	0.737	0.737	0.721

DID = difference-in-difference, TFP = total factor productivity.
Notes: The dependent variable is the natural logarithm of TFP measured by the Levinsohn and Petrin (2003) method. IN_DE is a dummy variable which takes the value of 1 if the product variety belongs to IN_DE and the value of 0 to the matched sample in NI_NE. Time is a dummy variable which takes the value of 0 when innovation takes place and the value of 1 after s-year where s = 1, 2, 3. Industry dummies are constructed on the 3-digit Korean Standard Industrial Classification level. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors' calculation.

4.2. Triple Differences Estimation to Accommodate Tariff

To see whether there is any disproportionate learning-to-export effect according to protection policies, we extend equation (3) into the following triple DID estimation equation.

$$\begin{aligned} y_i = \alpha_0 + \alpha_1 IN\_DE_i + \alpha_2 t_i + \alpha_3 tariff_i \\ + \beta_1(IN\_DE_i \times t_i) + \beta_2(IN\_DE_i \times tariff_i) + \beta_3(t_i \times tariff_i) \\ + \gamma(IN\_DE_i \times t_i \times tariff_i) + \varepsilon_i \end{aligned} \qquad (4)$$

In this specification, the triple interaction term, γ, is of our interest because it represents whether the DID estimate depends on the tariff rate. This can be easily seen by taking the partial derivative of equation (4) with respect to tariffs:

$$\frac{\partial y_i}{\partial tariff_i} = \alpha_3 + \beta_2 IN\_DE_i + \beta_3 t_i + + \gamma(IN\_DE_i \times t_i) \qquad (5)$$

The right-hand side of equation (5) is identical to equation (3) and thus γ captures to what extent and to what direction the effect of tariffs on the outcome depends on the DID term (IN_DE_i x t_i).

Table 12 shows these triple differences estimation results of equation (4) above. The triple differences terms in Table 12 are all estimated to be negative and statistically significant only at s = +1. The negative sign implies that the learning-to-export effect is lower when the tariff rate is high, and this is particularly significant 1 year after the innovation year. This empirical result seems to provide some evidence against the infant industry argument: protection by the tariff rate may not justifiable to enhance the learning-to-export effect in our data.

Table 12: Triple Differences Estimation (IN_DE vs. NI_NE) for TFP

Variables	(1) s = +1	(2) s = +2	(3) s = +3
IN_DE	0.072*** (0.015)	0.042* (0.022)	0.062** (0.031)
Time	-0.027 (0.018)	0.043* (0.023)	0.047 (0.042)
Tariff	0.306** (0.128)	-0.009 (0.147)	0.393* (0.226)
IN_DE x Time	0.088*** (0.023)	0.053* (0.031)	0.072 (0.046)
IN_DE x Tariff	-0.475*** (0.157)	-0.088 (0.222)	-0.369 (0.300)

Time x tariff	0.039 (0.182)	-0.206 (0.200)	-0.559* (0.313)
IN_DE x time x tariff	-0.480** (0.235)	-0.161 (0.292)	-0.303 (0.427)
Year dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
Number of observations	24,654	11,975	6,097
Adjusted R2	0.742	0.740	0.731

TFP = total factor productivity.
Notes: IN_DE is a dummy variable which takes the value of 1 if the product variety belongs to IN_DE and the value of 0 to the matched sample in NI_NE. Time is a dummy variable which takes the value of 0 when innovation takes place and the value of 1 after s-year where s = 1, 2, 3. Industry dummies are constructed on the 3-digit Korean Standard Industrial Classification level. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors' calculation.

5. Further Discussion

The analyses in sections 3 and 4 imply that some evidence exists for the learning-to-export effect for the IN_DE type of product varieties in the sense that their productivity outcome is superior to its control group after the innovation and that tariff protection is not helpful to promote such a learning-to-export effect. Then where does this superior productivity outcome come from? López (2004) emphasised that such a learning-to-export effect can be accomplished by firms which consciously invest more in physical or knowledge capital. Thus, we investigate this possibility in this section with our data set.

Table 13 shows how three different outcome variables (capital–labour ratio, R&D dummy, and investment dummy variable) behave under DID specifications in equation (3). All procedures are the same as before, but dependent variables are replaced by other outcome variables. The DID terms (IN_DE x time) in Table 13 are estimated to be positive, and most of them are statistically significant with two exceptions (K/L ratio and investment dummy at s = +3). This means that physical capital and R&D activities are higher for IN_DE group varieties after innovation and before export participation compared with its control group. This in turn implies that higher productivity performance of IN_DE varieties is closely related to their investment in physical capital and R&D activities.

The next natural question is then whether these conscious efforts of firms are related to the tariff protection. In Table 14, we run triple differences (equation (4)) for three different outcome variables once again. As seen in the table, the coefficients on the triple difference term (IN_DE x time x tariff) are all insignificantly estimated except for the K/L ratio at s = +1. As in the case of productivity outcome, protection by import tariff cannot be justified to induce firms to investment more in physical capital and R&D activities.

Table 13: Parametric DID Estimation (IN_DE vs. NI_NE) for Other Variables Related to Conscious Efforts

Dependent variable	(1) K/L ratio			(2) R&D dummy			(3) Investment dummy		
	s = +1	s = +2	s = +3	s = +1	s = +2	s = +3	s = +1	s = +2	s = +3
IN_DE	0.072*** (0.020)	0.091*** (0.028)	0.101*** (0.038)	0.141*** (0.028)	0.167*** (0.039)	0.166*** (0.055)	0.131*** (0.023)	0.121*** (0.033)	0.156*** (0.046)
Time	-0.032 (0.021)	-0.062* (0.034)	-0.100 (0.066)	-0.186*** (0.032)	-0.158*** (0.051)	-0.297*** (0.101)	-0.063** (0.025)	-0.119*** (0.040)	0.016 (0.081)
IN_DE x Time	0.066** (0.028)	0.066* (0.039)	0.072 (0.055)	0.231*** (0.040)	0.211*** (0.056)	0.200** (0.080)	0.070** (0.032)	0.131*** (0.047)	0.011 (0.065)
Constant	2.713*** (0.023)	2.730*** (0.030)	2.705*** (0.040)	-1.394*** (0.075)	-1.444*** (0.101)	-1.615*** (0.149)	0.392*** (0.059)	0.482*** (0.081)	0.317*** (0.106)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	25,256	12,280	6,256	25,184	12,192	6,222	25,256	12,280	6,216
Adj.R^2/ Pseudo-R^2	0.197	0.191	0.186	0.083	0.075	0.083	0.027	0.034	0.033

DID = difference-in-difference, R&D = research and development.
Notes: IN_DE is a dummy variable which takes the value of 1 if the product variety belongs to IN_DE and the value of 0 to the matched sample in NI_NE. Time is a dummy variable which takes the value of 0 when innovation takes place and the value of 1 after s-year where s = 1, 2, 3. Industry dummies are constructed on the 3-digit Korean Standard Industrial Classification level. Regressions of the R&D dummy and investment dummy are run by probit specification. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors' calculation.

Table 14: Triple Differences Estimation (IN_DE vs. NI_NE) for Other Variables Related to Conscious Efforts

Dependent variable	K/L ratio			R&D dummy			Investment dummy		
	s = +1	s = +2	s = +3	s = +1	s = +2	s = +3	s = +1	s = +2	s = +3
IN_DE	-0.014 (0.041)	-0.006 (0.058)	0.091 (0.079)	0.045 (0.065)	0.007 (0.088)	-0.017 (0.120)	0.177*** (0.050)	0.065 (0.067)	0.195** (0.097)
Time	-0.060 (0.043)	-0.037 (0.056)	-0.089 (0.090)	-0.178** (0.077)	-0.188* (0.097)	-0.075 (0.171)	0.019 (0.052)	-0.156** (0.068)	0.150 (0.116)
Tariff	-0.767** (0.365)	-0.687* (0.412)	-0.172 (0.564)	-1.051 (0.694)	-1.077 (0.868)	-2.168** (1.073)	0.729 (0.454)	-0.378 (0.521)	0.626 (0.806)
IN_DE x time	0.175*** (0.057)	0.123 (0.078)	0.145 (0.106)	0.224** (0.092)	0.171 (0.118)	0.092 (0.188)	0.016 (0.069)	0.186** (0.092)	-0.001 (0.135)
IN_DE x tariff	1.034** (0.442)	1.072* (0.608)	0.083 (0.794)	1.357* (0.742)	1.983** (0.973)	2.300* (1.295)	-0.524 (0.537)	0.761 (0.686)	-0.360 (0.996)
Time x tariff	0.297 (0.479)	-0.451 (0.558)	-0.329 (0.733)	-0.152 (0.933)	0.275 (1.089)	-3.165* (1.868)	-1.039* (0.576)	0.662 (0.682)	-1.543 (1.010)
IN_DE x time x tariff	-1.309** (0.627)	-0.595 (0.840)	-0.901 (1.088)	0.282 (1.080)	0.631 (1.321)	1.624 (2.246)	0.634 (0.757)	-0.832 (0.976)	0.082 (1.430)
Constant	2.772*** (0.041)	2.791*** (0.049)	2.716*** (0.067)	-1.304*** (0.109)	-1.449*** (0.153)	-1.326*** (0.207)	0.316*** (0.087)	0.489*** (0.112)	0.302** (0.151)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	24,654	11,975	6,097	24,578	11,892	6,076	24,654	11,972	6,046
Adj.R^2/ Pseudo-R^2	0.199	0.194	0.188	0.0871	0.0791	0.0855	0.0277	0.0350	0.0335

R&D = research and development.
Notes: IN_DE is a dummy variable which takes the value of 1 if the product variety belongs to IN_DE and the value of 0 to the matched sample in NI_NE. Time is a dummy variable which takes the value of 0 when innovation takes place and the value of 1 after s-year where s = 1, 2, 3. Industry dummies are constructed on the 3-digit Korean Standard Industrial Classification level. Robust standard errors are in parentheses. *, **, and *** denote that the estimated coefficients are significant at the 10%, 5%, and 1% levels, respectively.
Source: Authors’ calculation.

6. Concluding Remarks

Using Korean manufacturing data for 1990–1998, this paper aimed to investigate whether empirical evidence supports the learning-to-export hypothesis which has received little attention in the previous literature. By taking full advantage of our plant–product level data, we find some evidence for the learning-to-export effect, especially for innovated product varieties with delayed exports. Our DID estimation results combined with propensity score matching imply that between the time of innovation and export participation, innovating firms show superior productivity performance compared with their matched control groups. Moreover, other performance outcome variables such as the K/L ratio, R&D dummy, and investment dummy behave in the same manner. Thus, during the time lapse between innovation and export, productivity, K/L ratio, R&D, and investment move in the same direction: this is an indication of the learning-to-export effect. However, our triple differences estimation results show that protecting industries by using higher import tariffs is not justifiable to enhance learning-to-export effects in all the specifications with different outcome variables.

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