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Learning-by-exporting and Plant Characteristics: Evidence from Korean Plant-level Data*

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This paper re-examines learning-by-exporting hypothesis employing two alternative measures of plant-level total factor productivity (TFP), utilizing propensity score matching technique. This paper also tries to identify conditions under which the learning-by-exporting may or may not take place, utilizing information on various plant or industry characteristics. We confirm large and robust learning-by-export effect for Korean manufacturing. We also find evidence that the degree of learning-by-exporting effects depends on various plant characteristics. Learning-by-exporting effects tend to be more pronounced for plants with high export propensity and for small plants. In addition, it is found that immediate productivity gain after exporting is larger for plants with high skill intensity, but that longer term gain seems larger for plants with low skill intensity.

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1. INTRODUCTION

One of the most frequently asked question in trade and growth literature is whether and how international trade or openness of trading regime promotes productivity growth of countries. Although numerous studies, both theoretical and empirical, have been conducted on this issue, there seems to be no clear consensus yet. Recently, a growing number of studies have started to utilize firm or plant level data and re-examined this issue, particularly focusing on exporting as a channel of international technology diffusion or knowledge spillover. One empirical regularity emerging from these studies is that exporters are more productive than non-exporters. The positive correlation between exporting and productivity in cross-sectional context, however, provides little useful information on the direction of causality. On one hand, this could reflect self-selection into export market: only productive firms can expect to recoup the sunk entry cost of entering into the export market and join the export market. In this case, the causality runs from productivity to exporting. On the other hand, it is also plausible that the positive correlation between exporting and productivity reflects learning-by-exporting effect: firms that become exporters could gain new knowledge and expertise after entering export market and improve their productivity relative to average player in the same industry. The self-selection hypothesis is supported by most studies, but the evidence on learning-by-exporting seems less clear-cut (Tybout, 2000).

Whether or not the learning-by-exporting effect exists has an important implication on the formulation of appropriate policy stance toward “openness”. As discussed by Bernard and Jensen (1999a), if the gains do accrue to firms once they become exporters, then the appropriate policy interventions would be those that reduce barriers to entering foreign markets including macroeconomic trade policies to promote openness to trade[1)] and microeconomic policies to reduce entry costs, such as export assistance,

[1)] De and Lee (2009) shows that reduction in transportation costs is relatively more important than tariff reduction in Korea in order to stimulate trade.

information programs, joint marketing efforts, and trade credits. On the other hand, if there are no post-entry rewards from exporting, these policies designed to increase the numbers of exporters are more likely to end up wasting resources.[2)]

There are two objectives of this paper. The first objective is to re-examine learning-by-exporting hypothesis employing two alternative measures of plant-level total factor productivity (TFP), utilizing the plant level panel data on Korean manufacturing sector (Survey of Mining and Manufacturing, SMM henceforth) from 1990 to 1998. Our first measure of plant TFP follows the chained-multilateral index number approach as developed in Good (1985) and Good, Naridi, and Sickles (1997). Our second measure of plant TFP is estimated following the approach by Levinshon and Petrin (2003).[3)] We employ propensity score matching technique to address the selection bias arising from endogenous export market participation.

The second goal of this paper is to clarify the conditions, if at all, under which the learning-by-exporting may or may not take place, utilizing information on some plant or industry characteristics. As plant characteristics, we consider export propensity, skill intensity, plant size, and R&D intensity. Most existing studies utilized information only on whether a plant exports or not and focused on the existence of learning-by-exporting effect. However, it is plausible that the degree of learning-by-exporting could be related to, for example, how important exporting activity is to the plant involved, in as much as learning-by-exporting arises through interactions with foreign buyers which requires costly resources. Thus, we examine whether plants with higher export propensity enjoys more benefits of learning-by-exporting. Meanwhile, if knowledge spillovers from exporting activities require domestic "absorptive capacity", then we could expect that plants with higher absorptive capacity will exhibit stronger learning-by-exporting. We use the skill-intensity of plants as a proxy for

[2)] See Bernard and Jensen (1999a) for detailed discussion.
[3)] Detailed explanation of the measurement of plant TFP will be discussed below.

the domestic absorptive capacity.[4] We also examine whether plant size matters in learning-by-exporting spillovers. There seems to be no a priori reason to expect larger learning-by-exporting effects for smaller or larger exporters.[5] While one can argue that large firms are generally more structured and better suited to facilitate absorption and use new knowledge obtained through exporting activities, it is also possible to argue that knowledge might be easier to disseminate in a small firm due to its flexibility and simplicity of organizational structure and its decision making process.

In addition, we examine whether the destination of exports matter in learning-by-exporting a là Loecker (2007). He shows that the degree of learning-by-exporting depends on destination of exports, using information on the plant-level export destination in Slovenian manufacturing. The analysis is based on the presumption that learning-by-exporting effect will be stronger for plants that start exporting to more advanced countries. In case of Korea, however, the plant level information about the export destination is not available. So, we examine instead whether plants in industries with higher share of exports to advanced countries tend to exhibit stronger learning-by-exporting.

Examining these issues in the Korean case is particularly important in several respects. Above all, as well recognized, Korea is one of the few success countries that have narrowed the income gap with advanced countries by adopting an outward-oriented development strategy.[6] So, examining and clarifying the openness-productivity nexus in the Korean case could provide valuable lessons on other developing countries that hope to catch-up with advanced countries. Furthermore, Korea is a country with large exposure to foreign trade that still needs to make a transition toward a

[4] R&D intensity might also be considered as another measure of absorptive capacity. However, whether the measured R&D intensity can be reasonably considered as an adequate measure of absorptive capacity is somewhat doubtful in practice. As will be seen later, R&D expenditure is zero for most small and medium-sized plants, and is positive for a small set of plants that are typically large. It is doubtful whether most small and medium-sized plants with zero R&D expenditure have zero absorptive capacity. This problem do not exists for skill intensity measure of this paper.

[5] Albonorez and Ercolani (2007) makes this point.

[6] See Krueger (1997), for example.

fully developed country. Thus, in so far as learning-by-exporting, if it exists, reflects trade-related uni-directional knowledge spillovers from advanced to less-advanced countries, Korea is the appropriate place to examine these issues.

There are some empirical studies that scrutinize the causal relationship between exporting and productivity. Most studies report that exporters are more productive than non-exporters before they start to export, suggesting that cross-sectional correlation between exporting and productivity partly reflects a self-selection effect. For example, Clerides, Lach, and Tybout (1998) find very little evidence that previous exposure to exporting activities improves performance, using the plant-level panel data from Colombia, Mexico, and Morocco. Similar results are reported by Aw, Chung, and Roberts (2000) and Aw, Chen, and Roberts (2001) for Taiwan, Bernard and Jensen (1999b) for U.S. By contrast, the evidence on a learning effect is mixed. Earlier research such as Bernard and Jensen (1999b) find little evidence in favor of learning. They report that new entrants into the export market experience some productivity improvement at around the time of entry, they are skeptical about the existence of strong learning-by-exporting effect. However, several recent studies utilizing more refined empirical technique to deal with self-selection problem provide some empirical evidence in favor of learning-by-exporting. See Girma, Greenaway, and Kneller (2002) for UK, Van Biesebroeck (2005) for Sub-Saharan African Countries, De Loecker (2007) for Slovenia, and Albonorez and Ercolani (2007) for Argentina, and Aw, Robert, Xu (2009) for Taiwan.

Related previous studies on Korea include Aw, Chung, and Roberts (2000), Hahn (2005), and Hahn (2010). Aw, Chung, and Roberts (2000), using plant-level panel data on Korean manufacturing for three years spaced at five-year intervals, does not find evidence in favor of either self-selection or learning-by-exporting. It differs from similar studies on other countries in that even the self-selection hypothesis is not supported. Aw, Chung, and Roberts (2000) argue that Korean government’s investment subsidies tied to exporting activity rendered plant productivity a less useful guide on the decision to export. By contrast, following the methodologies of Bernard and Jensen (1999a, 1999b), Hahn (2005) finds some supporting evidence for both selection and learning in Korean manufacturing sector, using annual plant-level panel data from 1990 to 1998. However, Hahn (2005) suffers from the same technical difficulties as Bernard and Jensen (1999a, 1999b) in that the uncontrolled self-selection problem in export market participation may have contaminated the result. Hahn (2010) finds that exporting increases plant TFP and promotes new product introduction in Korean manufacuturing, employing propensity score matching technique to deal with selection bias. In contrast with Hahn (2010), this paper re-examines learning-by-exporting hypothesis by estimating plant TFP following Levinsohn and Petrin (2003), and tries to identify a broader set of plant or industry characteristics that might be complementary or necessary for learning-by-exporting effect to materialize.[7)]

The organization of this paper is as follows. The following section explains the data set and the calculation of plant total factor productivity. Section 3 briefly discusses the estimation strategy to overcome the difficulties arising from self-selection in decision making for export market participation and to obtain a better estimate for the effects of learning-by-exporting. Section 4 discusses our main empirical results and the final section concludes.

2. DATA AND PLANT TOTAL FACTOR PRODUCTIVITY

2.1. Data

This paper utilizes the unpublished plant-level census data underlying the *Survey of Mining and Manufacturing* in Korea. The data set covers all plants with five or more employees in 580 manufacturing industries at KSIC

[7)] Hahn (2010) estimates plant TFP following chained-multilateral index number approach.

(Korean Standard Industrial Classification) five-digit level. It is an unbalanced panel data with about 69,000 to 97,000 plants for each year from 1990 to 1998. For each year, the amount of exports as well as other variables related to production structure of plants, such as production, shipments, the number of production and non-production workers and the tangible fixed investments, are available. The exports in this data set include direct exports and shipments to other exporters and wholesalers, but do not include shipments for further manufacture.

2.2. Plant Total Factor Productivity

In this paper, we estimate plant TFP in two ways. Firstly, we measure plant TFP following the chained-multilateral index number approach as developed in Good (1985) and Good, Nadiri, and Sickles (1999). This procedure uses a separate reference point for each cross-section of observations and then chain-links the reference points together over time. The reference point for a given time period is constructed as a hypothetical firm with input shares that equal the arithmetic mean input shares and input levels that equal the geometric mean of the inputs over all cross-section observations. Thus, output, inputs, and productivity level of each firm in each year is measured relative to the hypothetical firm at the base time period. This approach allows us to make transitive comparisons of productivity levels among observations in panel data set.[8)]

Specifically, the productivity index for firm *i* at time *t* in our study is measured in the following way.

[8)] Good, Nadiri, and Sickles (1999) summarize the usefulness of chaining multilateral productivity indices. While the chaining approach of Tornqvist-Theil index, the discrete Divisia, is useful in time series applications where input shares might change over time, it has severe limitations in cross-section or panel data framework where there is no obvious way of sequencing the observations. To the contrary, the hypothetical firm approach allows us to make transitive comparisons among cross-section data, while it has an undesirable property of sample dependency. The desirable properties of both chaining approach and the hypothetical firm approach can be incorporated into a single index by chained-multilateral index number approach.

$$\ln TFP_{it} = (\ln Y_{it} - \overline{\ln Y_t}) + \sum_{\tau=2}^{t} (\overline{\ln Y_\tau} - \overline{\ln Y_{\tau-1}})$$
$$- [\sum_{n=1}^{N} \frac{1}{2} (S_{nit} + \overline{S_{nt}})(\ln X_{nit} - \overline{\ln X_{nt}}) \tag{1}$$
$$+ \sum_{\tau=2}^{t} \sum_{n=1}^{N} \frac{1}{2} (\overline{S_{n\tau}} + \overline{S_{n\tau-1}})(\overline{\ln X_{n\tau}} - \overline{\ln X_{n\tau-1}})],$$

where Y, X, S, and TFP denote output, input, input share, *TFP* level, respectively, and symbols with an upper bar are corresponding measures for the hypothetical firm. The subscripts τ and n are indices for time and inputs, respectively. The year 1990 is chosen as the base year.

As a measure of output, we use the gross output (production) of each plant in the Survey deflated by the producer price index at disaggregated level. The capital stock used in this paper is the average of the beginning and end of the year book value of capital stock in the Survey deflated by the capital goods deflator. As for labor input, we use the quality-adjusted number of workers, which includes paid employees,[9)] working proprietors and unpaid family workers. We allowed for the quality differential between production workers and all other types of workers. The labor quality index of the latter was calculated as the ratio of non-production workers' and production workers' average wage at each plant, averaged again over the entire plants in a given year. The sum of "major production cost" and "other production cost" reported in the Survey was taken as the measure of intermediate input. Major production cost covers costs arising from materials, parts, fuel, electricity, water, manufactured goods outsourced and maintenance. Other production cost covers expenditures on outsourced services such as advertising, transportation, communication and insurance. The estimated intermediate input was deflated by the intermediate input price index.

We assumed constant returns to scale production technology so that the sum of factor elasticities equals to one. Labor and intermediate input

[9)] Paid employees is the sum of production and non-production workers.

elasticities for each plant are measured as average factor cost shares within the same plant-size class in the five-digit industry in a given year. Here, plants are grouped into three size classes according to the number of employees; 5-50, 51-300, and over 300. Thus, the factor elasticities of plants are allowed to vary across industries and plant size classes and over time.

The second measure of plant TFP is obtained as the residual from the estimation of production function, following Levinsohn and Petrin (2003). It is a well known problem in estimation of production function that the correlation between unobservable productivity shocks and input levels leads to biased estimates of the production function parameters and, hence, to biased estimate of plant TFP. Levinsohn and Petrin (2003) suggests a way of solving this simultaneity problem which uses intermediate inputs as a proxy for these unobservable productivity shocks. In this paper, we utilize the procedure written in STATA language as explained by Petrin, Poi, and Levinsohn (2004).[10] We use gross output production function, and output and inputs are measured in the same way as in the case for the first approach.[11]

2.3. Definition of Exporters

Following convention in the literature, we define an exporter in a given year as a plant reporting positive amount of exports. Accordingly, non-exporters in a given year are those plants with zero exports. With this definition of exporters, it is possible to classify all plants into five sub-groups: Always, Never, Starters, Stoppers, and Other.[12] "Always" is a

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10) Levinsohn and Petrin (2003) argues that their methodology has an advantage over Olley and Pakes (1996) in that their methodology can avoid the "zero investment" problem: truncation of all the zero investment firms which are likely to exist frequently in the presence of pronounced adjustment costs to investment.

11) The production function estimation following Levinsohn and Petrin (2003) is carried out for the whole manufacturing sample. In spite of the various differences in methodology, these two measures of plant TFP are highly correlated; the cross-sectional correlation coefficient are between 0.81 and 0.83 during the sample period.

12) We eliminated plants that switch in and out of the dataset more than twice during the

group of plants that were exporters in the year that they first appear in the data set and never changed their exporting status. Similarly, “Never” is a group of plants that were non-exporters in the year that they first appear in the data set and never switched to exporters. “Starters” includes all plants that were non-exporters in the year that they first appear, but switched to exporters in some later year and remained as exporters thereafter. “Stoppers” consists of all plants that were exporters in the year that they first appear, and then switched to non-exporters, never switching back to exporters thereafter. All other plants that switched their exporting status more than twice during the sample period are grouped as “Other”.

2.4. A Preliminary Analysis: Performance of Exporters and Non-exporters

Table 1 shows the number of exporting plants and average exports as percentage of shipments, or export intensity, for each year during the sample period. Exporting plants accounted for between 11.0 and 15.3% of all manufacturing plants. The share of exporting plants rose slightly between 1990 and 1992, but since then steadily declined until 1996. However, with the outbreak of the financial crisis in 1997, the share of exporting plants rose somewhat noticeably to reach 14.8% in 1998. The rise in the share of exporting plants can be attributed mostly to the closure of non-exporting plants, rather than increase in the number of exporting plants. Note that the increases in the number of exporters in 1997 and 1998 were modest, which are broadly consistent with the severe contraction of domestic demand and huge depreciation of Korean Won associated with the crisis.

Consistent with the high export propensity of the Korean economy, the share of exports in shipments at plant level is quite high. During the sample period, the unweighted mean export intensity is between 43.6 and 54.8%, declining from 1990 to 1996 but rising with the onset of the crisis in 1997.

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sample period. Thus, we keep only those plants that do not have a split in time series observations. This procedure eliminates about 10% of the sample in terms of number of plants.

Table 1 Number of Exporters and Export Intensity

Year	Total Number of Plants (%)	Non-exporters (%)	Exporters (%)	Exports/Shipments Ratio (%)	
				Unweighted	Weighted
1990	68,690 (100)	58,392 (85.0)	10,298 (15.0)	54.8	37.3
1991	72,213 (100)	61,189 (84.7)	11,024 (15.3)	54.3	37.3
1992	74,679 (100)	63,241 (84.7)	11,438 (15.3)	51.7	36.3
1993	88,864 (100)	77,514 (87.2)	11,350 (12.8)	49.9	36.0
1994	91,372 (100)	80,319 (87.9)	11,053 (12.1)	47.2	35.9
1995	96,202 (100)	85,138 (88.5)	11,064 (11.5)	44.8	37.2
1996	97,141 (100)	86,502 (89.0)	10,639 (11.0)	43.6	35.3
1997	92,138 (100)	80,963 (87.9)	11,175 (12.1)	44.2	38.0
1998	79,544 (100)	67,767 (85.2)	11,777 (14.8)	44.7	48.7

Source: Hahn (2005).

The average export intensity weighted by shipment shows a similar pattern, with generally lower figures than the unweighted average, suggesting that smaller exporting plants have a higher export intensity.

It is a well-established fact that exporters are better than non-exporters by various performance standards. Table 2 compares various plant attributes between exporters and non-exporters for three selected years. First, exporters are on average much larger in the number of workers and shipments than non-exporters. The differential in shipments is more substantial than that in the number of workers. So, the average labor productivity of exporters

Table 2 Performance Characteristics of Exporters vs. Non-exporters

	1990		1994		1998	
	Exporters	Non-exporters	Exporters	Non-exporters	Exporters	Non-exporters
Employment (person)	153.6	24.5	119.4	20.0	95.1	17.8
Shipments (million won)	11,505.5	957.0	17,637.1	1,260.3	25,896.8	1,773.8
Production per Worker (million won)	50.5	26.8	92.4	47.0	155.0	74.2
Value-added per Worker (million won)	16.5	11.3	31.0	20.4	51.3	29.6
TFP	0.005	−0.046	0.183	0.138	0.329	0.209
Capital per Worker (million won)	16.8	11.9	36.0	21.9	64.6	36.7
Non-production Worker/Total Employment (%)	24.9	17.1	27.5	17.5	29.6	19.2
Average Wage (million won)	5.7	5.1	10.3	9.2	13.7	11.5
Average Production Wage (million won)	5.5	5.1	10.0	9.2	13.1	11.4
Average Non-production Wage (million won)	6.8	5.3	11.6	9.4	15.6	12.4
R&D/Shipments (%)	-	-	1.2	0.6	1.4	0.6

Source: Hahn (2005). In this table, plant TFP is measured following chained-multilateral index number approach. Qualitatively similar results are obtained when plant TFP is measured following Levinsohn and Petrin (2003).

measured by either production per worker or value added per worker is higher than that of non-exporters. Compared with the cases of value added, the differential in production per worker between exporters and non-exporters is more pronounced. This might reflect a more intermediate-intensive production structure of exporters relative to non-exporters. Although exporters show both higher capital-labor ratio and a higher share of non-production workers in employment than non-exporters, they do not fully account for the differences in labor productivity. As a consequence, total factor productivity levels of exporting plants are, on average, higher than those plants that produce for the domestic market only. Some differences in the total factor productivity may be attributed to the differences in R&D intensity. Note that, controlling for the size of shipments, exporters spent about twice as much on R&D as non-exporters. From a worker's point of view, exporters had more desirable attributes than non-exporters. That is, the average wage of exporters is higher than that of non-exporters. Although both a production worker's wage and a non-production worker's wage are higher in exporters than in non-exporters, the differential in the non-production worker's wage is more pronounced.

3. EMPIRICAL STRATEGY: PROPENSITY SCORE MATCHING

It is now well-recognized in the literature that the decision to become an exporter is not a random event but a result of deliberate choice, requiring special efforts to correctly identify the true effect of becoming an exporter on its productivity (Loecker, 2007; Albonorez and Ercolani, 2007). The participation decision in the export market is likely to be correlated with the stochastic disturbance terms in the data generating process for a firm's productivity, so that the traditional simple mean difference test on productivity differences between exporters and non-exporters does not provide the correct answer. The matching method has been gaining popularity among applied researchers since it is viewed as a promising analytical tool with which we can cope with statistical problems stemming from an endogenous participation decision.

The underlying motivation for the matching method is to reproduce the treatment group (exporters) out of the non-treated (non-exporters), so that we can reproduce the experiment conditions in a non-experimental setting. Matched samples enable us to construct a group of pseudo-observations containing the missing information on the treated outcomes had they not been treated by paring each participant with members of the non-treated group. The crucial assumption is that, conditional on some observable characteristics of the participants, the potential outcome in the absence of the treatment is independent of the participation status.

$$y_i^0 \perp d_i \mid X_i , \tag{2}$$

where y_i^0 is the potential outcome in the absence of the treatment, d_i is the dummy to indicate participation, and X_i is the vector of conditioning variables. The basic idea of matching is to construct a sample analog of a counter factual control group by identifying the members of a non-participating group that possess conditioning variables as close to those of treatment group as possible. In practice, it is very difficult to construct a control group that satisfies the condition in (2), especially when the dimension of the conditioning vector X_i is high.

Rosenbaum and Rubin (1983) propose a clever way to overcome the curse of dimensionality in the traditional matching method. Suppose that the conditional probability of firm *i*'s becoming an exporter can be specified as a function of observable characteristics of the firm before the participation;

$$p(X_i) = \Pr\left[d_i = 1 \mid X_i \right] = E(d_i \mid X_i) \tag{3}$$

Rosenbaum and Rubin (1983) call the probability function in (3) propensity score and show that if the conditional independence assumption in

(2) is satisfied it is also valid for $p(X_i)$ that

$$y_i^0 \perp d_i \;\middle|\; p(X_i). \tag{4}$$

We have replaced the multi-dimensional vector with a one-dimensional variable containing the same information contents so that the highly complicated matching problem in (2) is reduced to a simple single dimensional one in (4).

One can define the average treatment effect on the treated (*ATT*) as;

$$\begin{aligned} ATT &= E\left[y_i^1 - y_i^0 \middle| d_i = 1\right] = E\left[E\left[y_i^1 - y_i^0 \middle| d_i = 1,\ p(X_i)\right]\right] \\ &= E\left[E\left[y_i^1 \middle| d_i = 1,\ p(X_i)\right] - E\left[y_i^0 \middle| d_i = 1,\ p(X_i)\right]\right], \end{aligned} \tag{5}$$

where y_i^0 is the potential outcome that would have been observable had participating firm i decided not to participate in an export market and y_i^1 is the observable outcome for participating firm i. Note that *ATT* is not the measure for the effect of exporting on all firms but on firms that start to export.

Since y_i^0 is not observable, the definition (5) is not operational. Given that the unconfoundedness condition under propensity score (4) is satisfied and the propensity score (3) is known, the following definition is equivalent to (5).

$$\begin{aligned} ATT &= E\left[y_i^1 - y_i^0 \middle| d_i = 1\right] \\ &= E\left[E\left[y_i^1 \middle| d_i = 1,\ p(X_i)\right] - E\left[y_i^0 \middle| d_i = 0,\ p(X_i)\right]\right]. \end{aligned} \tag{6}$$

Since both y_i^0 and y_i^1 are observable in (6), one can construct an estimator for *ATT* by constructing its sample analog.

As the first step, we estimate the probability function in (3) with the following probit specification.

$$p\left(X_i : \beta,\ \sigma\right) = 1 - \int_{-\infty}^{\beta' X_i} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz. \tag{7}$$

Log of total factor productivity, log of the number of workers employed (a proxy for plant size), log of capital per worker (a proxy for capital intensity), 9 yearly dummies, and 10 industry dummies are included in the conditioning vector X_i. We use the values of these variables at one year before the firm starts to export in order to account for the time difference between decision to participate and actual participation. Plant TFP variable is included following the prediction of recent heterogeneous firm trade theories, such as Melitz (2003): High productivity firms self-select into exporting which requires sunk entry costs. We also include plant size as a measure of plant performance; in view of the firm dynamics models such as Jovanovic (1982) and Hopenhayn (1992), firms with high-productivity draws grows larger. We include plant size to additionally control for plant productivity,[13)] which is also a convention in the literature. Capital intensity is included along the lines of comparative advantage theories of trade. In our probit estimation results for the full sample, all variables — plant TFP, size, capital intensity — are highly significant with expected signs.[14)]

Based on estimated version of (7), one can calculate propensity score for all observations, participants and non-participants. Let T be the set of treated (exporting) units and C the set of control (non-exporting) units, respectively, and denote by $C(i)$ the set of control units matched to the treated unit i with an estimated value of propensity score of P_i. Also, denote the number of controls matched with a treated unit $i \in T$ by N_i^C and define the weight $w_{ij} = 1 / N_i^C$ if $j \in C(i)$ and $w_{ij} = 0$ otherwise. Then, the propensity score matching estimator for the average treatment

13) Plant size could also matter if plants (or firms) have to finance upfront investment to enter export market under financial market imperfection. In this case, plant size can be considered as a rough proxy for the degree of asymmetric information.

14) We do not report the probit estimation results to draw the attention of the readers to the main argument of the paper. The results of probit analysis are available from the authors upon request.

effect on the treated at time t is given by;

$$ATT_t^* = \frac{1}{N^T}\sum_{i\in T}\left(y_{i,\,t}^T - \sum_{j\in C(i)} w_{ij} y_{j,\,t}^C \right), \tag{8}$$

where $y_{i,\,t}^T$ is the observed value on firm i in the treatment group at time t and $y_{j,\,t}^0$ the observed value on firm j in the matched control group for firm i at time t. Moreover, one can easily show that the variance of the estimator in (8) is given by;

$$\mathrm{Var}(ATT_t^*) = \frac{1}{N^T}\mathrm{Var}(y_{i,\,t}^T) + \frac{1}{(N^T)^2}\sum_{i\in T}\sum_{j\in C(i)} (w_{ij})^2 \mathrm{Var}(y_{j,\,t}^C). \tag{9}$$

An asymptotically consistent estimator for (9) can be estimated by replacing two variance terms for the treatment and control groups with corresponding sample analogs.

We use two different versions of the propensity score matching procedure written in STATA language; **attn.ado** explained in Becker and Ichino (2002) (BI, hereafter) and **psmatch2.ado** provided by Leuven and Sianesi (2003) (LS, hereafter).[15)]

Among various matching methods available to form the set $C(i)$ for each member i in treatment group, we use the nearest-neighbor matching for both procedures given as

$$C(i) = \min_{j\in C}\left\| p_i - p_j \right\|. \tag{10}$$

Note that in case of the nearest-neighbor matching the set $C(i)$ is a singleton set for all i.

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15) BI algorithm divides the entire sample into several blocks (groups) to ensure the equality of the mean propensity score between treated and controls in each block. This procedure is known to an effective way of examining confoundedness property. For more discussion, see Becker and Ichino (2002).

In order to allow for the possibility that the effect of learning by exporting works at different intensities depending on a firm's characteristics and industry, we divide the entire sample into several categories according to plant or industry characteristics, such as the export intensity of plants, skill intensity of plants, plant size measured by the number of workers, R&D intensity of plants, and export destination of industries. We measure the average treatment effect of the treated for each sub-sample.

4. EMPIRICAL RESULTS: LEARNING-BY-EXPORTING EFFECTS

4.1. Starter vs Non-exporter

Table 3 reports the estimated productivity gain from participating in an export market when heterogeneity in treatment effect is not taken into account.[16] The estimated coefficients indicate percentage productivity differentials between plants that start exporting and their domestic counterparts *s* years after entering the export market. We report results from the two different versions of propensity score matching procedure, BI and LS.

First and foremost, all estimated coefficients are positive and highly significant, suggesting the existence of a learning-by-exporting effect, regardless of measure of plant TFP. Although the learning-by-exporting effect was estimated to be higher when Levinsohn-Petrin plant TFP is employed, the qualitative results were quite similar across the two methodologies. These results confirm the findings of Hahn (2010). This

[16] We could have employed difference-in-differences (DID) technique after the selection of the control group through propensity score matching a la Heckman, Ichimura, and Todd (1997). The authors thank an anonymous referee for pointing out the point. One reason we did not pursue the path is that the average difference between the control and the treated is enough to convey the information on the policy intervention since the assignment to either the control or the treated can be regarded as quasi-random process and changes in variables that can affect the productivity level other than export market participation could be regarded as random events.

Table 3 Average Productivity Gain of Exporters

Matching Method	Plant TFP	Number of Treated	*s*=0	*s*=1	*s*=2	*s*=3
BI	Multilateral Index	5,797	0.055*** (0.008)	0.066*** (0.009)	0.075*** (0.011)	0.061*** (0.014)
	Levinsohn-Petrin	5,797	0.100*** (0.010)	0.158*** (0.012)	0.193*** (0.015)	0.185*** (0.018)
LS	Multilateral Index	5,751	0.036*** (0.008)	0.046*** (0.011)	0.068*** (0.015)	0.061*** (0.018)
	Levinsohn-Petrin	5,751	0.115*** (0.009)	0.160*** (0.014)	0.199*** (0.019)	0.190*** (0.026)

Note: Since BI procedure searches the matched sample with replacement, multiple samples in treatment group can be matched with one sample in control group. That is the reason we observe the size of treatment group is larger than control group. For further discussion, see Becker and Ichino (2002).

raises the possibility that the existence of learning-by-exporting effect might be country-dependent. In the case of Korea, exporting led to productivity improvement.

Second, productivity gain for starters begins to materialize immediately after entering the export market, and the productivity gap between the starters and non-exporters[17] widens further as time passes, although at a decelerating pace. Third, it seems that the choice of procedures in constructing the control group does not yield any material differences in the final result, not only qualitatively but also qualitatively. In the case of plant TFP based on chained multilateral index number approach, the estimated coefficients from BI procedure indicate that starters become about 5.5% more productive in the year of entry. Over the following years, productivity gain for starters fluctuates between 6.6 and 7.5 percentage points. Thus, it is suggested that entering the export market has a permanent effect on productivity level,

[17] Non-exporters correspond to the "never" group in our earlier definition.

especially during the first several years after entry. In other words, export market entry has a temporary effect on productivity growth especially during the first few years after entry.

4.2. Sub-group Estimation: Plant Characteristics

In order to allow for a differential treatment effect depending on plant characteristics, we divided our sample into three sub-groups according to various features such as an exports-production ratio, the skill intensity, plant size measured by the number of workers, and R&D-production ratio. Then we apply the matching estimators discussed in section 3 and estimate the learning-by-exporting effect separately for each sub-group. Based on BI procedure,[18)] we report the estimated productivity gains for starters in each sub-group in table 4.

First, the estimated coefficients are generally larger and more significant for plants with higher exports-production ratio. For example, in the case of Levinsohn and Petrin plant TFP for the group of low export intensity (exports-production ratio < 10%), starters become more productive, between 5.6 and 11.6% during the three years after the participation. By contrast, in the group of high export intensity with an exports-production ratio greater than 50%, productivity gains for starters are between 12.4 and 27.1% for the same time span. In the earlier section, we argued that if the estimated effect of learning-by-exporting indeed captures the beneficial consequences of learning activities associated with exporting, then the effect is likely to be stronger for plants with higher exports-output ratios; if learning-by-exporting arises from contact with foreign buyers and foreign markets, which require costly resources, then firms for whom exporting is their major activity are likely to be more heavily exposed to foreign contact and experience productivity gain. The results for sub-groups with different export intensities are very consistent with this hypothesis.

Second, the learning-by-exporting effect seems to be more pronounced for

[18)] Estimation results based on LS procedure are reported in the appendix.

Table 4 Average Productivity Gain of Starters by Firm Characteristics: BI Procedure

Firm Characteristics	Plant TFP		Number of Treated	s=0	s=1	s=2	s=3
Export Ratio	Multilateral Index Number	Low	2,166	0.058*** (0.012)	0.020 (0.014)	0.021 (0.018)	0.020 (0.021)
		Medium	1,871	0.026** (0.013)	0.091*** (0.015)	0.108*** (0.018)	0.069*** (0.023)
		High	1,741	0.067*** (0.014)	0.089*** (0.017)	0.099*** (0.019)	0.108*** (0.021)
	Levinsohn-Petrin	Low	2,166	0.056*** (0.016)	0.057*** (0.020)	0.116*** (0.023)	0.096*** (0.029)
		Medium	1,871	0.090*** (0.016)	0.196*** (0.020)	0.259*** (0.024)	0.236*** (0.031)
		High	1,741	0.124*** (0.017)	0.205*** (0.019)	0.270*** (0.022)	0.271*** (0.028)
Skill Intensity	Multilateral Index Number	Low	1,115	0.001 (0.020)	0.050** (0.024)	0.100*** (0.029)	0.120*** (0.035)
		Medium	3,389	0.041*** (0.010)	0.044*** (0.010)	0.052*** (0.013)	0.040*** (0.015)
		High	1,293	0.070*** (0.018)	0.086*** (0.021)	0.104*** (0.027)	0.072*** (0.026)
	Levinsohn-Petrin	Low	1,115	0.052*** (0.022)	0.109*** (0.028)	0.199*** (0.036)	0.231*** (0.044)
		Medium	3,389	0.131*** (0.011)	0.190*** (0.013)	0.202*** (0.016)	0.217*** (0.019)
		High	1,293	0.121*** (0.021)	0.207*** (0.026)	0.216*** (0.031)	0.183*** (0.036)
Plant Size (Number of Workers)	Multilateral Index Number	Low	1,481	0.061*** (0.016)	0.121*** (0.020)	0.188*** (0.025)	0.174*** (0.030)
		Medium	3,239	0.045*** (0.010)	0.079*** (0.011)	0.067*** (0.013)	0.079*** (0.015)
		High	1,077	0.000 (0.020)	–0.015 (0.023)	0.003 (0.028)	0.068*** (0.029)
	Levinsohn-Petrin	Low	1,481	0.135*** (0.018)	0.196*** (0.024)	0.290*** (0.028)	0.242*** (0.038)
		Medium	3,239	0.095*** (0.011)	0.156*** (0.013)	0.170*** (0.015)	0.164*** (0.017)
		High	1,077	0.131*** (0.024)	0.156*** (0.027)	0.204*** (0.033)	0.190*** (0.037)
R&D Intensity	Multilateral Index Number	None	4,806	0.058*** (0.009)	0.060*** (0.010)	0.067*** (0.012)	0.072*** (0.014)
		Low	357	0.032 (0.033)	0.073** (0.035)	0.081* (0.044)	0.040 (0.054)
		Medium	453	0.052* (0.029)	0.052 (0.037)	0.094* (0.049)	0.036 (0.044)
		High	181	0.008 (0.045)	0.004 (0.065)	0.014 (0.050)	0.148 (0.094)
	Levinsohn-Petrin	None	4,806	0.101*** (0.011)	0.161*** (0.013)	0.186*** (0.015)	0.169*** (0.018)
		Low	357	0.166*** (0.040)	0.253*** (0.044)	0.315*** (0.054)	0.214*** (0.059)
		Medium	453	0.087*** (0.036)	0.140*** (0.045)	0.268*** (0.052)	0.259*** (0.054)
		High	181	0.110* (0.056)	0.255*** (0.080)	0.205*** (0.072)	0.336*** (0.106)

plants with higher skill intensity[19] for the first two years after export market entry. Since then, however, it becomes more pronounced for plants with low skill intensity. In other words, although participation in export market has a greater immediate benefit for plants with higher skill intensity, it has a greater benefit for plants with low skill intensity over the longer run. Although we do not have a clear explanation for this result, one explanation might be that exporting has a disproportionately positive effect on skill intensity for plants with initially low skill intensity. Broadly speaking, these results suggest that domestic "absorptive capacity" matters for exporting plants to take advantage of the benefits of international knowledge spillovers immediately.[20] Nevertheless, the lack of initial absorptive capacity does not seem to prevent exporting plants to benefit from exporting over the longer term.

Third, we also examine whether the degree of learning-by-exporting is related to plant size, dividing the entire sample into three groups: a group of small plants with the number of workers less than 10, a group of medium-sized plants with the number of workers between 11 and 49, and a group of large plants with 50 or more workers. Table 4 suggests that effect of learning-by-exporting is generally larger and more significant for smaller plants. As argued by Albonorez and Ercolani (2007), there seems to be no a priori reason to expect larger learning-by-exporting effects for small exporters.[21] While one can argue that large firms are generally more structured and better suited to facilitate absorption and use new knowledge obtained through exporting activities, it is also possible to argue that knowledge might be easier to disseminate in a small firm due to its flexibility

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[19] Skill intensity is measured by the share of non-production workers out of the total of production and non-production workers.

[20] These results are consistent with the previous empirical literature that emphasizes the role of human capital in facilitating technology adoption (Welch, 1975; Bartel and Lichtenberg, 1987; Foster and Rosenzweig, 1995; Benhabib and Spiegel, 1994). These studies are empirical investigations of Nelson-Phelps hypothesis which suggests that the rate at which the gap between the technology frontier and the current level of productivity is closed depends on the level of human capital. See Benhabib and Spiegel (2005) for detailed explanation.

[21] They also find that small firms learn more from exporting activities using firm-level panel data on Argentinian manufacturing.

and simplicity of organizational structure and its decision making process. Our findings in table 4 seem to suggest that the latter effect dominates.

Finally, we examine whether plants with higher R&D investment exhibit a larger learning-by-exporting effect. To do so, we classify plants into four sub-groups: a group with no R&D investment, a low R&D group with a ratio of R&D expenditure to production less than 2%, a medium R&D group with a ratio from 2 to 10% and a high R&D group with a ratio higher than 10%. The results do not reveal a clear pattern.

4.3. Sub-group Estimation: Export Destinations as an Industry Characteristic

As far as we are aware of, little is known about industry characteristics that affect the degree of learning-by-exporting. In this subsection, we examine whether the export destination of industry as an industry characteristic affects the strength of learning-by-exporting of the plants. If the learning-by-exporting effect found in this paper captures international knowledge spillovers from advanced to less advanced countries which arise through the contact with foreign buyers in more advanced countries, then we could expect to find that the learning-by-exporting effect is stronger in industries that have larger share of their exports directed to more advanced countries.

However, we cannot expect that measured productivity gain will be stronger unambiguously in industries with a larger share of exports directed to more advanced countries for the following reasons. First of all, international knowledge spillovers might arise not only through direct contact with foreign buyers in advanced countries but also through indirect contact with foreign competitors in the markets of less advanced countries. For example, Korea’s car exporters could learn from the business practices of German car exporters in the Chinese market. Secondly, generally more intense competition in export markets can exert pressure on firms that start to export to improve their productive efficiency. Then the degree of competition in an export market could be an important factor in determining the degree of measured productivity gain. Thirdly, there should be an industry-level technology gap between the exporting country and the frontier country in order for the learning-by-exporting effect to take place. That is, there should be some "advanced knowledge" out there to learn from in the first place. If this is the case, then the direction of exports would be immaterial for an industry that is at or close to the world frontier.[22)]

Fourthly, if exporting is associated with fragmentation of production by multinational firms, then efficiency improvement coming from the fragmentation of production which, in some cases, involves exporting to lower income countries within the production network might be captured as measured productivity gain. Kimura, Hayakawa, and Matsuura (2009) provide a theoretical explanation related to this story. They show that in the case of vertical FDI, the larger the gap in capital-labor ratios between a Northern fragment and a Southern fragment, the greater the total cost reduction in international fragmentation. In this case, exporting to lower income countries within a production network might be associated with a greater learning-by-exporting effect.

Although exploring all these possibilities is out of the scope of this paper, we think that examining whether the direction of exports matters for the strength of learning-by-doing is the first step toward understanding the exact nature of the learning-by-exporting effect captured in this paper.

As a preliminary step, we first examine whether there are cross-industry differences in productivity gains from becoming exporters. To do so, we divided our sample into 10 sub-industries[23)] and repeated the matching procedure for each industry. The results are somewhat different depending on which measure of plant TFP we use as the outcome variable (table 5). When plant TFP is measured following chained multilateral index number approach, the learning-by-exporting effects are visible for about half of the

[22)] This might be one reason that learning-by-exporting effect is occasionally reported in studies of developing countries but not in developed countries, such as the U.S.

[23)] They are food, textile and apparel, wood and pulp, chemical, metal, general machinery, electronics, precision instrument, transport equipment, and others.

Table 5 Average Productivity Gain of Starters by Industry: BI Procedure

Industry	TFP	Number of Treated	*s*=0	*s*=1	*s*=2	*s*=3
Food	CMIN	286	0.059 (0.038)	0.046 (0.047)	−0.006 (0.048)	0.007 (0.048)
	L-P	286	0.173*** (0.063)	0.271*** (0.073)	0.201*** (0.084)	0.366*** (0.106)
Textile and Apparel	CMIN	1,363	0.120*** (0.018)	0.118*** (0.019)	0.126*** (0.023)	0.057** (0.027)
	L-P	1,363	0.188*** (0.018)	0.263*** (0.020)	0.329*** (0.025)	0.292** (0.029)
Wood and Pulp	CMIN	245	0.015 (0.033)	−0.031 (0.044)	−0.068 (0.043)	−0.227*** (0.060)
	L-P	245	−0.019 (0.043)	0.140*** (0.053)	0.158*** (0.067)	-0.099 (0.078)
Chemical	CMIN	702	0.044** (0.021)	0.082*** (0.027)	0.079*** (0.031)	0.112*** (0.034)
	L-P	702	0.108*** (0.029)	0.170*** (0.038)	0.187*** (0.043)	0.269*** (0.060)
Metal	CMIN	327	0.066** (0.030)	0.098*** (0.035)	0.117*** (0.042)	0.037 (0.039)
	L-P	327	0.107*** (0.044)	0.199*** (0.049)	0.291*** (0.063)	0.204*** (0.060)
General Machinery	CMIN	1,456	0.036*** (0.015)	0.022 (0.017)	0.028 (0.024)	0.047* (0.022)
	L-P	1,456	0.063*** (0.018)	0.107*** (0.024)	0.115*** (0.029)	0.158*** (0.034)
Electronics	CMIN	632	0.025 (0.025)	0.024 (0.034)	0.002 (0.038)	−0.066 (0.047)
	L-P	632	0.116*** (0.031)	0.158*** (0.053)	0.251*** (0.042)	0.205*** (0.042)
Precision Instrument	CMIN	212	−0.021 (0.046)	0.054 (0.049)	0.079 (0.064)	−0.050 (0.109)
	L-P	212	−0.008 (0.056)	0.139*** (0.051)	0.161** (0.070)	0.088 (0.100)
Transport Equipment	CMIN	248	0.013 (0.036)	0.010 (0.047)	0.089 (0.062)	0.102* (0.058)
	L-P	248	0.082* (0.050)	0.134** (0.060)	0.177** (0.077)	0.241*** (0.081)
Other	CMIN	326	0.054* (0.032)	0.091*** (0.036)	0.118*** (0.035)	0.129*** (0.052)
	L-P	326	0.106*** (0.038)	0.111*** (0.045)	0.153*** (0.056)	0.158** (0.070)

Note: CMIN stands for chained multilateral index number approach and L-P stands for Levinsohn and Petrin.

industries. By contrast, when Levinsohn-Petrin plant TFP is used, we find learning-by-exporting effect for almost all industries, although the magnitude of the effect varies across industries. For industries such as textile and apparel, chemical, metal, and general machinery, and other, we find learning-by-exporting effect for both measures of plant TFP. These results seem to suggest the possible existence of some industry factors that might play a role in determining the existence or the degree of learning-by-exporting effect, although we cannot pin down the exact nature of those industry factors.

We next turn to the export destinations of industries as one possible factor explaining differential strengths of the learning-by-exporting effect estimated at the sub-group level of industries. As explained above and also in Loecker (2007), this hypothesis is based on the presumption that a learning-by-exporting effect will be stronger for plants that start exporting to more advanced countries, where the opportunities for learning new knowledge and technology are relatively abundant. Although Loecker (2007) examined this issue using plant-level information on the destination of exports, we do not have such information available for Korea. Instead, we examine whether plants in industries with a higher share of exports to advanced countries exhibit higher productivity gains.[24)]

To do so, we first matched the direction of exports dataset at SITC 5 digit level complied from UNComtrade (Rev. 3) with the Mining and Manufacturing Survey dataset at KSIC[25)] three-digit level. Then, we classified Korea's export destination countries into two groups: "lower-income" and "higher-income" countries. Here, higher-income countries are those with an average per capita GDP for the period from 1990 to 1998 larger than that of Korea. The remaining countries are lower-income countries. Next, for each of the 58 three-digit manufacturing industries, we calculated their shares of exports to lower-income and higher-income countries averaged over the same period. Then, we classified each industry into "higher-income" or "lower-income" group if its share of exports to higher-

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24) In some respect, direction of exports is more likely to be an industry characteristic rather than plant characteristic.

25) Korean Standard Industrial Classification.

Table 6 Average Productivity Gain of Starters by Export Destinations: BI procedure

Destination	TFP	Number of Treated	*t*=0	*t*=1	*t*=2	*t*=3
Higher-income	CMIN	3,165	0.051*** (0.011)	0.065*** (0.013)	0.091*** (0.015)	0.060*** (0.017)
	L-P	3,165	0.078*** (0.014)	0.141*** (0.018)	0.162*** (0.021)	0.147*** (0.025)
Lower-income	CMIN	2,602	0.059*** (0.012)	0.059*** (0.014)	0.064*** (0.016)	0.063*** (0.019)
	L-P	2,602	0.096*** (0.014)	0.173*** (0.017)	0.212*** (0.020)	0.217*** (0.024)

Note: CMIN stands for chained multilateral index number approach and L-P stands for Levinsohn and Petrin.

income countries is greater or smaller than lower-income countries, respectively.

The estimated productivity gain for starters is reported in table 6 for each sub-group. At first glance, the results are not supportive of the hypothesis that the learning-by-exporting effect is more pronounced in industries with more of their exports directed to more advanced countries. In fact, the result is the other way around in the case of Levinsohn and Petrin plant TFP: Learning-by-exporting effect in the lower-income group is stronger than that of the higher-income group, although both are highly significant. We conjecture that the result is driven by the fact that the gain from participating in export markets depends on many factors conveniently branded as the benefits of openness. We believe that those factors must be interlinked in a very complicated fashion and a simple approach like ours cannot give the definite answer to this important question.

Given the inadequate control of various factors that might be relevant for determining the degree of productivity gain or learning-by-exporting effect, the above results should not be taken as a definitive piece of evidence against the hypothesis that the learning-by-exporting effect is larger in industries with more of their exports directed to higher-income countries. We think that various industry as well as plant characteristics might also play a role here. Further analysis seems to be warranted to shed light on this issue.

5. CONCLUSION

This paper re-examined learning-by-exporting hypothesis employing two alternative measures of plant-level total factor productivity (TFP), utilizing propensity score matching technique. This paper also tried to clarify the conditions under which the learning-by-exporting may or may not take place, utilizing information on various plant or industry characteristics.

We find clear and robust evidence for a learning-by-export effect, which has been previously reported by Hahn (2010) for Korean manufacturing. We also find evidence that the degree of learning-by-exporting effects depends on various plant characteristics. Learning-by-exporting effects tend to be more pronounced for plants with high export propensity and for small plants. Immediate productivity gain after exporting is larger for plants with high skill intensity, but longer term gain seems larger for plants with low skill intensity.

Although this paper examined the learning-by-exporting effect, it should be born in mind that the measured productivity gains from exporting can arise from other channels, such as scale efficiency, competition, innovation, allocation efficiency, and so on. Clarifying the channels seems to deserve further research. Furthermore, although this paper tried to identify various plant characteristics that might play a role in determining the existence or the magnitude of learning-by-exporting effect, further studies seem necessary to clearly understand the mechanism.

APPENDIX

Table A1 Average Productivity Gain of Starters by Firm Characteristics: LS Procedure

Firm Characteristics	Plant TFP		Number of Treated	s=0	s=1	s=2	s=3
Export Ratio	Multilateral Index Number	Low	77,233	0.041^{***} (0.012)	0.018^{***} (0.018)	0.019 (0.022)	0.016 (0.027)
		Medium	77,233	0.041^{***} (0.012)	0.049^{***} (0.018)	0.101^{***} (0.025)	0.039 (0.030)
		High	77,233	0.050^{***} (0.013)	0.104^{***} (0.019)	0.130^{***} (0.025)	0.096^{***} (0.034)
	Levinsohn-Petrin	Low	77,233	0.100^{***} (0.015)	0.085^{***} (0.023)	0.062^{*} (0.033)	0.077^{*} (0.040)
		Medium	77,233	0.103^{***} (0.015)	0.173^{***} (0.024)	0.248^{***} (0.031)	0.204^{***} (0.045)
		High	77,233	0.145^{***} (0.015)	0.199^{***} (0.024)	0.254^{***} (0.031)	0.243^{***} (0.045)
Skill Intensity	Multilateral Index Number	Low	30,920	0.014 (0.017)	0.045* (0.026)	0.047 (0.042)	0.144^{***} (0.047)
		Medium	38,027	0.043^{***} (0.009)	0.047^{***} (0.013)	0.043^{***} (0.017)	0.055^{***} (0.022)
		High	8,286	0.068^{***} (0.028)	0.071^{***} (0.025)	0.143^{***} (0.031)	0.096^{***} (0.039)
	Levinsohn-Petrin	Low	30,920	0.037^{**} (0.028)	0.137^{***} (0.029)	0.215^{***} (0.043)	0.319^{***} (0.063)
		Medium	38,027	0.140^{***} (0.011)	0.177^{***} (0.017)	0.180^{***} (0.022)	0.125^{***} (0.032)
		High	8,286	0.115^{***} (0.021)	0.168^{***} (0.032)	0.216^{***} (0.040)	0.192^{***} (0.053)
Plant Size (Number of Workers)	Multilateral Index Number	Low	39,869	0.063^{***} (0.015)	0.109^{***} (0.025)	0.134^{***} (0.041)	0.196^{***} (0.058)
		Medium	33,726	0.055^{***} (0.010)	0.079^{***} (0.013)	0.073^{***} (0.018)	0.082^{***} (0.022)
		High	3,638	−0.005 (0.021)	−0.047 (0.023)	−0.038 (0.032)	0.055 (0.037)
	Levinsohn-Petrin	Low	39,869	0.113^{***} (0.016)	0.189^{***} (0.028)	0.269^{***} (0.046)	0.173^{***} (0.072)
		Medium	33,726	0.114^{***} (0.011)	0.171^{***} (0.016)	0.182^{***} (0.022)	0.223^{***} (0.029)
		High	3,638	0.140^{***} (0.023)	0.097^{***} (0.029)	0.195^{***} (0.037)	0.158^{***} (0.046)
R&D Intensity	Multilateral Index Number	None	74,558	0.039^{***} (0.008)	0.067^{***} (0.011)	0.051^{***} (0.016)	0.090^{***} (0.019)
		Low	829	0.058^{*} (0.033)	−0.018 (0.039)	−0.019 (0.050)	0.111 (0.070)
		Medium	1,208	0.030 (0.030)	0.084^{**} (0.042)	0.049 (0.055)	0.055 (0.067)
		High	638	0.020 (0.051)	−0.056 (0.073)	−0.045 (0.084)	0.175 (0.154)
	Levinsohn-Petrin	None	74,558	0.118^{***} (0.010)	0.168^{***} (0.014)	0.202^{***} (0.020)	0.202 (0.027)
		Low	829	0.144^{***} (0.041)	0.153^{***} (0.056)	0.337^{***} (0.069)	0.153 (0.106)
		Medium	1,208	0.077^{**} (0.037)	0.151^{***} (0.058)	0.172^{**} (0.074)	0.172^{*} (0.089)
		High	638	0.067 (0.051)	0.094 (0.083)	0.144 (0.097)	0.583^{***} (0.212)

Table A2 Productivity Gain of Starters by Industry: LS Procedure

Industry	TFP	Number of Treated	*s*=0	*s*=1	*s*=2	*s*=3
Food	CMIN	4,962	0.059 (0.036)	0.046 (0.048)	0.021 (0.063)	0.077 (0.069)
	L-P	4,962	0.148^{***} (0.058)	0.134^{*} (0.081)	0.103 (0.106)	0.298^{***} (0.129)
Textile and Apparel	CMIN	17,543	0.115^{***} (0.016)	0.143^{***} (0.024)	0.110^{***} (0.031)	0.117^{***} (0.042)
	L-P	17,543	0.184^{***} (0.028)	0.257^{***} (0.027)	0.322^{***} (0.035)	0.288^{**} (0.057)
Wood and Pulp	CMIN	8,937	−0.001 (0.032)	0.019 (0.054)	0.022 (0.056)	−0.005 (0.085)
	L-P	8,937	0.089^{**} (0.040)	0.203^{***} (0.064)	0.086 (0.101)	-0.292^{*} (0.159)
Chemical	CMIN	6,215	0.047^{**} (0.020)	0.013 (0.031)	0.056 (0.040)	0.061 (0.041)
	L-P	6,215	0.087^{***} (0.027)	0.126^{***} (0.041)	0.120^{**} (0.057)	0.171^{**} (0.074)
Metal	CMIN	5,792	0.038 (0.030)	0.080^{*} (0.046)	0.131^{**} (0.056)	0.104^{*} (0.064)
	L-P	5,792	0.060 (0.043)	0.137^{**} (0.064)	0.194^{**} (0.081)	0.217^{**} (0.110)
General Machinery	CMIN	18,401	0.029^{**} (0.015)	0.022 (0.023)	0.009 (0.029)	0.008 (0.040)
	L-P	18,401	0.074^{***} (0.018)	0.098^{***} (0.026)	0.138^{***} (0.035)	0.066 (0.059)
Electronics	CMIN	5,597	0.024 (0.023)	−0.017 (0.037)	0.040 (0.043)	0.066 (0.045)
	L-P	5,597	0.119^{***} (0.027)	0.185^{***} (0.042)	0.146^{***} (0.053)	0.101^{*} (0.059)
Precision Instrument	CMIN	1,237	−0.000 (0.043)	0.028 (0.077)	0.052 (0.083)	0.101 (0.097)
	L-P	1,237	0.098^{**} (0.049)	0.048 (0.073)	0.247^{***} (0.091)	0.277^{**} (0.137)
Transport Equipment	CMIN	3,538	0.034 (0.036)	−0.063 (0.060)	−0.004 (0.067)	0.107 (0.077)
	L-P	3,538	0.075 (0.048)	0.147^{***} (0.063)	0.210^{***} (0.085)	0.101 (0.092)
Other	CMIN	5,011	−0.007 (0.027)	0.034 (0.041)	0.073 (0.056)	0.115^{*} (0.070)
	L-P	5,011	0.080^{***} (0.033)	0.197^{***} (0.047)	0.159^{*} (0.086)	0.289^{***} (0.084)

Note: CMIN stands for chained multilateral index number approach and L-P stands for Levinsohn and Petrin.

Table A3 Average Productivity Gain of Starters by Export Destinations: LS Procedure

Destination	TFP	Number of Treated	*t*=0	*t*=1	*t*=2	*t*=3
Higher-income	CMIN	47,165	0.036** (0.010)	0.055*** (0.016)	0.043** (0.020)	0.074*** (0.025)
	L-P	47,165	0.101*** (0.012)	0.146** (0.019)	0.191*** (0.026)	0.207*** (0.035)
Lower-income	CMIN	29,512	0.057*** (0.011)	0.045*** (0.016)	0.092*** (0.020)	0.058** (0.029)
	L-P	29,512	0.126*** (0.013)	0.163*** (0.020)	0.235*** (0.027)	0.203*** (0.039)
Other Lower-income	CMIN	15,965	0.054*** (0.016)	0.061*** (0.022)	0.103*** (0.026)	0.132*** (0.036)
	L-P	15,965	0.130*** (0.019)	0.191*** (0.026)	0.244*** (0.037)	0.236*** (0.048)
East Asia	CMIN	13,547	0.065*** (0.015)	0.059*** (0.022)	0.046* (0.028)	0.083** (0.043)
	L-P	13,547	0.097*** (0.020)	0.153** (0.029)	0.171*** (0.040)	0.163*** (0.064)

Note: CMIN stands for chained multilateral index number approach and L-P stands for Levinsohn and Petrin.

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