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Productivity, Markups and Export Intensity: Evidence from Korean Manufacturing*

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This paper empirically investigates the impacts of export intensity on plant-level productivity growth and markups by assessing Korean manufacturing data between 1992 and 2002. Our Generalized Propensity Score estimation results suggest an inverted U-shaped relationship between export intensity and productivity growth, which is consistent with Fryges and Wagner (2007). At the same time, we also find a similar pattern in the export intensity-markup nexus. Our results generally imply that increasing export intensity up to a certain threshold provides a better opportunity for exporters to improve productivity and charge higher markups than non-exporters, but a plant whose export intensity is beyond this threshold may not fully benefit from exporting activity as excessive exposure to foreign markets causes higher market uncertainties and internationalization costs.

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I. Introduction

A growing body of empirical work in international economics has documented the superior performance characteristics of exporters relative to non-exporters. Exporters tend to be larger, more capital-intensive, paying higher wages and most importantly more productive. The finding that exporters are more productive than

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non-exporters has sparked intensive empirical studies that examine whether more productive firms self-select into export markets or whether exporting causes productivity growth.[1]

A relatively unexploited but recurring issue in the literature is the relationship between exports and firm-specific markups. Different competitive environment between domestic and foreign markets would induce exporters to employ a different pricing strategy compared to non-exporters (for example, see De Loecker and Warzynski; 2012).

There are a number of reasons why the export-markup nexus has been understudied in the literature so far. From a theoretical point of view, international trade models put firm heterogeneity at the core of the analysis, but most of these models usually assume either a perfectly competitive or a Dixit-Stiglitz market structure (for example Melitz, 2003), with no implications for markup heterogeneity. Consequently, these studies are unable to provide a testable hypothesis on firm-specific pricing behavior.

Only recently, a number of papers propose more realistic models by relaxing assumptions on market structure and thus provide a theoretical basis to investigate the relationship between exports and markup heterogeneity. Most notably, under the monopolistically competitive framework with firm heterogeneity, Melitz and Ottaviano (2008)'s model predicts that plant-specific markups are positively related to productivity as well as to export intensity.

On the other hand, from an empirical point of view, very detailed micro-level data on prices, quantities sold and characteristics of products are often needed in accurately estimating firm-level markups, but researchers hardly have access to those data. In particular, unobservable establishment-level prices have posed a serious limitation in empirical research on the export-markup linkage.

Recently, De Loecker and Warzynski (2012) introduce a new empirical framework to measure firm-specific markup and productivity on the insight of Hall (1986) and the control function approach of Olley and Pakes (1996).[2] They identify plant-specific markups as the difference between a firm's variable input cost share and revenue share, where the cost share is not observed in the data but under optimality conditions has to equal the output elasticity of the relevant input.

Taking these new developments in the literature into account, our paper empirically investigates the patterns of plant-level productivity and markups by assessing Korean manufacturing data for the period between 1992 and 2002. Here we estimate plant-specific markups and productivity by adopting the aforementioned De Loecker and Warzynski (2012)'s procedure.

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[1] See Wagner (2007) and De Loecker (2010) for excellent surveys on this topic.

[2] Robert Hall published a series of papers suggesting a simple way to estimate (industry) markups based on an underlying model of firm behavior (Hall, 1986, 1988, 1990).

Another distinct feature of this paper is our research focus on export intensity rather than export status. Most of the current studies investigate the relationship between a firm's export status and productivity growth, by measuring firms' export status as a binary treatment variable and comparing the performance of exporters relative to non-exporters. Such practices may overlook the important fact that not all exporters have the same level of engagement in export markets. Some firms may devote considerable resources to their export activities, but others do not. Therefore, there may exist some differences in market performance among exporters with varying degrees of export intensity.

In this context, this paper employs the Generalized Propensity Score (GPS hereafter) methodology developed by Hirano and Imbens (2004). The GPS method is a generalization of the binary treatment propensity method in a sense that it can control for possible self-selection problem in its estimation, and allows us to examine the relationship between export intensity and productivity/markups under conditions in which export intensity can take any continuous value from zero to one.

The main research question in this paper is how export intensity affects plants' productivity and markup dynamics. While our estimation results are largely in line with those from the existing literature, we provide a number of new insights into the literature. Our results generally suggest that increasing export intensity up to a certain threshold provides a better opportunity for exporters to improve productivity and charge higher markups than non-exporters, but plants that export beyond this threshold may not fully benefit from foreign engagement as excessive exposure to foreign markets causes high internationalization costs and market uncertainties.

The rest of this paper is organized as follows. The next section provides a brief literature survey on the related studies. In Section III, we present our empirical strategy including estimation of TFP and markups. Section VI provides our empirical results and the final section concludes.

II. Literature Survey

This paper is motivated by the two strands of the previous research. The first is the international trade literature on the interaction between trade and the distribution of the firm-level productivity. Since the mid-1990s, an extensive body of empirical work demonstrates that firms engaging in international trade differ substantially from those that solely serve the domestic market. Documenting the characteristics of U.S. export manufacturers, Bernard and Jensen (1995) confirm that exporting plants are larger, more capital intensive, more productive, and paying higher wages than plants that do not export.

These findings raise important research questions about the sources of such systematic differences between exporters and non-exporters. In fact, two alternative hypotheses are proposed and extensively tested since then; "self-selection hypothesis" suggesting that higher-productivity firms self-select into export markets, and "learning-by-exporting hypothesis" that firms can improve their productivity as a consequence of their participation in export markets. The empirical studies largely confirm that high productivity precedes entry into export markets. On the other hand, most studies find little or no evidence of learning-by-exporting. For example, the works by Bernard and Jensen (1999) on U.S. firms, Clerides et al. (1998) on firms in Mexico, Colombia and Morroco and Aw et al (2000) on firms in Korea and Taiwan find no differential growth in firm productivity among exporters versus non-exporters (Bernard et al., 2007).[3]

Recently, by adopting the GPS methodology, Fryges and Wagner (2007) test the relationship between export intensity, instead of export status, and productivity in German manufacturing sector. They find the existence of a causal effect of firms' export activities on labor productivity growth. However, exporting improves labor productivity only within a sub-interval of the range of firms' export-shipment ratios.

The second strand of research that motivates our paper is the recently emerging empirical literature on the relationship between international trade and firms' markups. Most notably, Melitz and Ottaviano (2008) propose a monopolistically competitive model of trade with firm heterogeneity where aggregate productivity and average markups respond both to the size of domestic market and to the extent of its integration through trade. Their model predicts that markups are positively related to firm productivity. Exporters, having an apparent productivity advantage, could sustain higher price cost margins than non-exporters, unless they pass all of the efficiency differentials to consumers in the form of lower prices. Furthermore, since exporting activity incurs trade costs, firms should charge higher markups on foreign markets than on domestic markets in order to recover their additional frictional trade costs.

On the other hand, the markup premium that a firm sets on its export markets also depends on its relative efficiency compared to foreign competitors. If competitive environment is tougher in foreign markets than domestic counterparts, exporters should charge lower markups in order to remain competitive relative to the more efficient foreign competitors. Hence, markup differentials between exporters and non-exporters could be an interesting empirical question, which highly depend on productivity differentials across firms, trade costs and the relative toughness of market competition between foreign and domestic markets. Other things being equal, exporters' higher productivity and/or the bigger size of trade

[3] Another important topic related to these works is whether FDI-doing firms exhibit higher performance. This issue was investigated by Grossman et al (2006), Wagner (2005), Yeaple (2005), Ekholm et al. (2004) and Lee (2010), for example. We thank an anonymous referee who points out this issue.

costs would widen markup differentials between exporters and non-exporters, while tougher competitive condition in foreign markets would narrow them down.

Using Slovenian firm-level data for the periods of 1994-2000, De Loecker and Warzynski (2012) find that exporters charge higher markups on average and firms' markups increase upon export entry. In a similar vein, Görg and Warzynski (2003) find that exporters have higher markups than non-exporters for differentiated goods, while no significant differences are found for the case of homogeneous goods between two types of firms. Finally, Lourdes and Rodríguez (2010) suggest that non-exporters have smaller margins than persistent exporters, but larger export ratio is negatively associated with margins for persistent exporters, largely due to higher competitive pressure in international markets.

In terms of methodology, our paper is similar to Fryges and Wagner (2007) who also uses the GPS methodology in order to examine the relationship between export intensity and productivity in German manufacturing sector. However, our approach is different from Fryges and Wagner (2007) in the following two important ways. First, Fryges and Wagner (2007) use labor productivity in their analyses, due to data constraints, without taking into account the possibility that their productivity measures may be contaminated due to firm-specific markups. As De Loecker and Warzynski (2012) point out, productivity changes could be under-estimated if the markup effects are ignored in estimation. Second, in our paper we analyze not only total factor productivity but also markup dynamics, which gives us richer empirical findings to understand the relationship between exporting intensity, productivity and markups.

II. Data and Empirical Strategy

1. Data

Our analysis draws upon the annual data of the Survey of Mining and Manufacturing from 1992 and 2002, which is conducted by the Statistics Korea.[4] This survey includes every Korean establishment with five or more employees in the mining and manufacturing sectors. First, we define export intensity of an establishment to be the value of exports divided by the value of total shipment. Next, we construct several plant-specific variables (total factor productivity, markups, size, age, wage, skill intensity, capital intensity and R&D dummy) in the following way.

A common practice in the existing literature to estimate plant-level total factor

[4] We are grateful to the Statistics Korea and the Korea Statistics Promotion Institute for allowing us access to the data used in this paper in a secure data center. All results have been reviewed to ensure that no confidential information is disclosed.

productivity is based on output measure calculated as revenue or value-added divided by a common industry-level deflator, due to the fact that plant-specific output prices are typically unobserved. Consequently, within-industry price differences are embodied in output and productivity measures. Then if these prices reflect mostly market power variation rather than production efficiency differences, high "productivity" firms may not be necessarily technologically efficient.[5] To resolve this problem, our paper employs De Loecker and Warzynski (2012)'s methodology in estimating plant-specific TFP and markups, which will be explained in the next subsection in a greater detail.

The size of a plant is defined as the log of the number of employees and the wage variable as the log of the plant's yearly wage bill (deflated by CPI) divided by the number of employees. The ratio of non-production workers to total employees is used as a proxy for skill intensity. The capital intensity is measured as the log of the plant's real capital stock over the number of employees. Plant's age is measured as (current year - established year + 1) and R&D dummy takes the value of one if a plant's R&D expenditure is positive number and zero otherwise. We also include the Herfindahl-Hirschman Index (HHI hereafter) in estimation, which measures the degree of competition at KSIC (Korea Standard Industry Classification) 4-digit level industries. It is defined by the sum of the squares of the market share of each plant.[6]

Finally, in order to properly investigate the dynamic impacts of export intensity on TFP and markups for 1 to 3-year changes from the base year, we confined our analysis to a sample of plants with at least four consecutive years of observations in our sample period.

2. Estimation of TFP and Markups

Consider the cost minimization problem for a plant i at time t with value-added production technology, $Q_{it} = f(L_{it}, K_{it})$ where L_{it} and K_{it} denote labor, which is the only variable input, and capital. Assume that $Q_{it}(\cdot)$ is continuous and twice differentiable for each of its arguments. Let w_{it} and r_{it} be plant-specific input prices for labor and capital, respectively. Then, the first-order condition for cost minimization indicates that

[5] Foster et al. (2008) argue that "*because physical productivity is inversely correlated with price while revenue productivity is positively correlated with price, previous work linking productivity to survival confounded the separate and opposing effects of technical efficiency and demand on survival, understating the true impacts of both*."

[6] With KSIC 4-digit level, the number of industries in our sample is 214. HHI can range from 0 to 1, moving from a huge number of very small plants to a single monopolistic producer.

$$\frac{\partial Q_{it}(\cdot)}{\partial L_{it}} = \frac{w_{it}}{\lambda_{it}} \tag{1}$$

where λ_{it} measures the marginal cost of production. By multiplying both sides of Equation (1) by L_{it} / Q_{it} and rearranging it, we get

$$\frac{\partial Q_{it}}{\partial L_{it}} \frac{L_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{w_{it} L_{it}}{Q_{it}} \tag{2}$$

Now define the markup, μ_{it} as $\mu_{it} \equiv P_{it} / \lambda_{it}$. where P_{it} denotes output price for a plant i at time t. Then we can rearrange Equation (2) into the following;

$$\mu_{it} = \frac{\partial Q_{it}}{\partial L_{it}} \frac{L_{it}}{Q_{it}} / \frac{w_{it} L_{it}}{P_{it} Q_{it}} = \frac{\theta_{it}^L}{\alpha_{it}^L} \tag{3}$$

where θ_{it}^L denotes the output elasticity of labor input and α_{it}^L is the expenditure share on labor input in total shipment. The latter can be directly obtained from the data and thus we only need to estimate θ_{it}^L to get the markup measure for a plant i at time t.

De Loecker and Warzynski (2012) consider the following estimation equation based on a translog production function;

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \psi_{it} + \varepsilon_{it} \tag{4}$$

where lower cases denote the natural logarithm of each variable, ψ_{it} is an index for plant's productivity and ε_{it} is a white noise.

The estimation procedure of Equation (4) applied by De Loecker and Warzynski (2012), which is adopted in this paper, consists of two steps and follows the control function approach of Ackerberg et al. (2006).[7] In the first stage, the following equation is estimated semi-parametrically to obtain estimates of expected output ($\hat{\phi}_{it}$) and an estimate for ε_{it}.

$$q_{it} = \phi_{it}(l_{it}, k_{it}, m_{it}) + \varepsilon_{it} \tag{5}$$

Our functional form of the expected output from the first stage estimation is

[7] Ackerberg et al. (2006) extend the semi-parametric estimator of Olley and Pakes (1996) to solve the multi-collinearity and identification issues with the labor variable. While further discussions on these issues are beyond the scope of this paper, the interested readers can find them in Van Beveren (2012). for more details.

given by

$$\phi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_{it}(m_{it}, k_{it}) \tag{6}$$

where $\psi_{it} = h_t(m_{it}, k_{it})$ à la Levinsohn and Petrin (2003) is introduced to proxy for productivity in the production function estimation. Using the first stage estimation, we can calculate

$$\psi_{it} = \hat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{lk} l_{it} k_{it} \tag{7}$$

for any value of $\beta = (\beta_l, \beta_{ll}, \beta_{lk}, \beta_k, \beta_{kk})$.

In the second stage, given the assumption that productivity follows a first order Markov process, i.e. $\psi_{it} = g_t(\psi_{it-1}) + \xi_{it}$, we non-parametrically regress $\psi_{it}(\beta)$ on $\psi_{it-1}(\beta)$ to get the residual ξ_{it}. And finally, based on moment conditions, the estimates of production functions are obtained using standard GMM estimation, which derives our estimated total factor productivity.

In addition, the estimated output elasticity of labor input can be given by

$$\hat{\theta}_{it}^L = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it} \tag{8}$$

Then, we can plug Equation (8) into (3) to get the plant-level estimates of markup.

3. The GPS Methodology

In order to investigate productivity and markup dynamics at varying degrees of export intensity, we utilize the GPS methodology recently developed by Hirano and Imbens (2004).[8] The GPS methodology is a generalization of the propensity score method (PSM) for binary treatments and allows for the continuous treatment of factors such as export intensity. Therefore, the GPS methodology will control for the possible self-selection problem in its estimation just like the propensity score method for binary export dummy variable.

Hirano and Imbens (2004) demonstrate that the relationship between the treatment level (export intensity, T_i) and the potential outcomes (performance characteristics, Y_i) can be evaluated by conditioning on the GPS, which is defined as the conditional density of the treatment given certain pre-treatment variables (X_i). If the pre-treatment variables satisfy the balancing property, then conditioning on the GPS will remove the bias associated with the differences in the

[8] See Hirano and Imbens (2004) for more technical descriptions of this methodology.

pre-treatment variables.

In practice, we first estimate the GPS by applying the fractional logit model devised by Papke and Wooldridge (1996) because our treatment variable (export intensity) can assume any value from zero to one. For each plant i, given the level of export intensity T_i, the pre-treatment covariates X_i and the estimated coefficients from the fractional logit model $\hat{\beta}$, the estimated GPS is computed as follows:

$$\hat{R}_i = \left[\frac{e^{X_i\hat{\beta}}}{1+e^{X_i\hat{\beta}}}\right]^{T_i}\left[1-\frac{e^{X_i\hat{\beta}}}{1+e^{X_i\hat{\beta}}}\right]^{1-T_i} \tag{9}$$

Conditional on the estimated GPS above and the level of export intensity, we estimate the expected value of performance characteristics (TFP growth and markups in our case) using the quadratic approximation, in accordance with the methods of Hirano and Imbens (2004):

$$E[Y_i \mid T_i, \hat{R}_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 \hat{R}_i + \alpha_4 \hat{R}_i^2 + \alpha_5 T_i \hat{R}_i \tag{10}$$

After obtaining the coefficient estimates for Equation (10) by OLS, the average potential value of performance characteristics associated with any specific level of export intensity $t \in [0,1]$ can be calculated as follows:

$$E[\hat{Y}(t)] = \frac{1}{N}\sum_{i=1}^{N}\left\{\hat{\alpha}_0 + \hat{\alpha}_1 \cdot t + \hat{\alpha}_2 \cdot t^2 + \hat{\alpha}_3 \cdot \hat{r}(t,X_i) + \hat{\alpha}_4 \cdot \hat{r}(t,X_i)^2 + \hat{\alpha}_5 \cdot t \cdot \hat{r}(t,X_i)\right\} \tag{11}$$

where N is the number of plants in our sample. By repeating this calculation for each level of export intensity, we can obtain an estimate of the dose response function (the relationship between export intensity and the GPS-adjusted performance characteristics).[9]

III. Empirical Results

1. Descriptive Statistics

Table 1 shows simple correlations among the variables included in estimation. As expected, the export dummy variable is positively correlated with all other variables.

[9] In accordance with Hirano and Imbens (2004), the confidence intervals of the dose response functions are estimated by a bootstrapping procedure with 1,000 repetitions.

The export intensity, our treatment variable, also exhibits the similar patterns of export-premia just like the export dummy variable. However, it is noteworthy to mention that in all cases the correlations between the export intensity and other plant's characteristics variables are unanimously weaker than those between the export dummy and these characteristics variables. Given the observation that the difference in the correlations solely stems from exporters, we can see that there would exist a certain extent of heterogeneity in characteristics among exporting plants.

[Table 1] Correlation among key variables

	Export intensity	Export dummy	lnTFP	Markup	Age	Size	Wage	NPW share	K/L ratio	R&D dummy	HHI
Export intensity	1.000										
Export dummy	0.694	1.000									
lnTFP	0.314	0.522	1.000								
Markup	0.035	0.037	0.117	1.000							
Age	0.126	0.235	0.323	-0.068	1.000						
Size	0.317	0.510	0.671	-0.013	0.324	1.000					
Wage	0.136	0.259	0.529	-0.566	0.246	0.307	1.000				
NPW share	0.037	0.122	0.266	0.013	0.090	0.167	0.187	1.000			
K/L ratio	0.129	0.255	0.524	0.092	0.245	0.218	0.414	0.167	1.000		
R&D dummy	0.177	0.335	0.364	0.027	0.150	0.356	0.194	0.137	0.187	1.000	
HHI	0.068	0.093	0.101	0.072	0.026	0.096	0.030	0.034	0.032	0.068	1.000

Note: NPW share means non-production worker share.

To see this more clearly, we first calculate the mean values of various plants' characteristics of non-exporters (export dummy = 0) and exporters (export dummy = 1) which are presented in the first two rows of Table 2. We can see that on average exporters are more productive than non-exporters. This implies that our data are consistent with other previous empirical studies on the well-known exporter premium.[10]

[10] Using different data set from this paper, Lee (2010) also showed that there does exist exporter premium in Korean manufacturing sector.

[Table 2] Summary statistics by export dummy and intensity (plants surviving at least for 4 years)

Export Dummy	Export intensity	Obs.	Ln (export)	Ln (tfp)	Markup	Age	Size	Wage	NPW share	K/L ratio	R&D dummy	HHI
0	0%	95,290	-	3.00	1.73	0.08	2.62	2.15	0.32	2.54	0.05	0.0464
1		23,246	6.55	3.51	1.84	0.13	3.97	2.47	0.54	3.36	0.30	0.0629
	0-10%	7,553	4.81	3.56	1.80	0.14	4.06	2.52	0.67	3.50	0.34	0.0616
	10-20%	3,045	6.44	3.52	1.80	0.13	3.97	2.50	0.57	3.45	0.31	0.0621
	20-30%	2,124	7.01	3.53	1.83	0.13	4.01	2.49	0.55	3.45	0.34	0.0626
	30-40%	1,769	7.38	3.53	1.83	0.13	4.03	2.49	0.51	3.43	0.30	0.0604
	40-50%	1,583	7.57	3.52	1.90	0.13	3.96	2.49	0.49	3.46	0.29	0.0662
	50-60%	1,196	7.96	3.56	1.91	0.13	4.12	2.48	0.47	3.42	0.30	0.0678
	60-70%	1,168	7.99	3.52	1.93	0.13	4.05	2.47	0.44	3.33	0.30	0.0686
	70-80%	1,043	8.10	3.51	1.86	0.12	4.02	2.45	0.45	3.32	0.28	0.0655
	80-90%	1,004	8.08	3.47	1.85	0.12	3.98	2.41	0.40	3.13	0.28	0.0632
	90-100%	2,761	7.59	3.34	1.89	0.11	3.54	2.28	0.36	2.82	0.15	0.0613
Total		118,536	6.55	3.10	1.75	0.09	2.88	2.22	0.36	2.70	0.10	0.0497

In addition, we also find that exporters tend to charge higher markups than non-exporters. The sources of higher markups for exporters may due to their productivity premium or to additional frictional trade costs incurred to exporters, as suggested in Melitz and Ottaviano (2008).

In the next ten-rows in Table 2, on the other hand, we document the mean values of various plants' characteristics of exporters by dividing them into 10 categories according to their level of export intensity. As shown in the table, there seems to be no monotonic relationship between export intensity and other characteristics variables. However, we can see that exporters with relatively lower export intensity tend to be more productive, older, paying higher wages, more capital-intensive and more likely to engage in R&D activity.

For instance, exporters at an export-shipment ratio of around 0∼10% have on average the highest TFP level, which is a similar level to those with 50∼60%. On the other hand, exporters who sell the majority of their output, notably more than 80%, to foreign markets reveal the lowest TFP level among exporters. Similarly, the exporters with export intensity of more than 80% are relatively younger, smaller in size, paying lower wages, less capital-intensive and less skill-intensive than other exporting plants.

On the other hand, markup levels are increasing almost monotonically as export intensity goes up, and they reach the highest mean values when export intensities are around at the 60∼70% interval. After that, markup levels decrease slightly but still remain higher levels than those for exporters who sell a small share of their output to foreign markets. As aforementioned, markup levels are determined by plant's productivity, the size of trade costs and the toughness of market competition. Our observation here implies that exporters who sell relatively a higher portion of their products to foreign markets tend to charge higher markups in order to recover their bigger frictional trade costs, even though they are not in fact more productive than other exporters.

2. Impacts of Export Intensity on TFP and Markup Dynamics

As aforementioned, this paper investigates productivity and markup dynamics at varying degrees of export intensity, by adopting the GPS methodology developed by Hirano and Imbens (2004). Our GPS estimation consists of the following three steps. We first estimate the GPS by applying the fractional logit model devised by Papke and Wooldridge (1996). Specifically, we estimate generalized propensity score by using fractional logit model in Equation (9) where export intensity is regressed on one year lag values of pre-treatment variables (TFP, age, size, wages, non-production worker share, capital-labor ratio, R&D dummies and HHI), including year dummies and industry dummies.[11]

In the second stage, given the estimated GPS in the first stage, we run an OLS regression to obtain the expected values of performance characteristics, based on the regression equation (10). In the final stage with estimated coefficient from Equation (10), we estimate the average dose response function which contains the average potential value of performance characteristics associated with any specific level of export intensity as in Equation (11).

Our fractional logit estimation results are reported in Table 3.[12] Based on these estimation results, we can figure out what kinds of plants' attributes induce their export decision and determine their relative exposure to foreign markets. Other things being equal, plants with higher productivity level, bigger size and higher capital-labor ratio tend to sell a higher portion of their products in foreign markets. The estimation results also suggest that relatively younger plants tend to have

[11] This fractional logit estimation process in GPS methodology is corresponding to the probit estimation process in usual propensity score matching technique. Both these processes resolve the possibility that plants with higher productivity self-select into export market (or exporting higher share out of their total shipments). See Hirano and Imbens (2004) for more technical details on the methodology.

[12] In estimating the fractional logit model in Table 3, we implemented various other specifications and compared their goodness-of-fit by assessing the values of AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). We found that the specification in Table 3 gives us the lowest AIC and BIC values among various models and chose this specification in calculating the dose response functions below. The results with other specifications are not reported in the paper but available upon request. We are grateful to the anonymous referee for pointing out this issue.

higher export intensity, while interestingly exporters belonging to more concentrated industries sell a bigger portion of their products to international markets.[13]

[Table 3] Fractional logit regression results

	Dependent Variable: Export Intensity
Ln(TFP)	0.928***
	(0.054)
Age	2.692***
	(0.391)
(Age)2	-7.841***
	(0.945)
Size	0.451***
	(0.017)
Wage	-0.013
	(0.041)
NP worker share	-0.046**
	(0.019)
K/L ratio	0.068***
	(0.013)
R&D dummy	0.041
	(0.033)
HHI	1.026
	(0.736)
(HHI)2	-3.025*
	(1.762)
Constant	-6.152***
	(0.327)
Observations	71,979
Log-likelihood	-13,609

Note: One-year lags are taken for all explanatory variables. Year dummies and industry dummies are not reported but included in the regression. HHI and industry dummies are calculated at KSIC 4-digit level. The robust standard errors are in the parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% level, respectively.

With these results, by repeating the procedures in Equations (10) and (11) for TFP growth/markups and for each export intensity level (by increasing the export intensity successively by five percentage point), we estimate the dose response

[13] While the estimation results suggest an inverted U-shape relationship between export intensity and the extent of market concentration, the estimated turning point of the slopes is where the Herfindahl-Hirschman index reaches at 0.2. Since the HHI for most of the plants is much lower than this turning point, we can conclude the positive relationship between two variables.

functions of outcome variables.[14]

1) The Dose Responses of TFP

In Figure 1, we depict the estimated dose response functions (solid lines), along with their 95% confidence intervals, for TFP growth rates in the periods from year t+1 to t+3, given the export-shipment ratio at t. As depicted in the figure, we find an inverted U-shaped relationship between a plant's export intensity and its TFP growth. This result is consistent with Fryges and Wagner (2007)'s empirical findings on the nexus between labor productivity growth and export intensity for the German manufacturing.

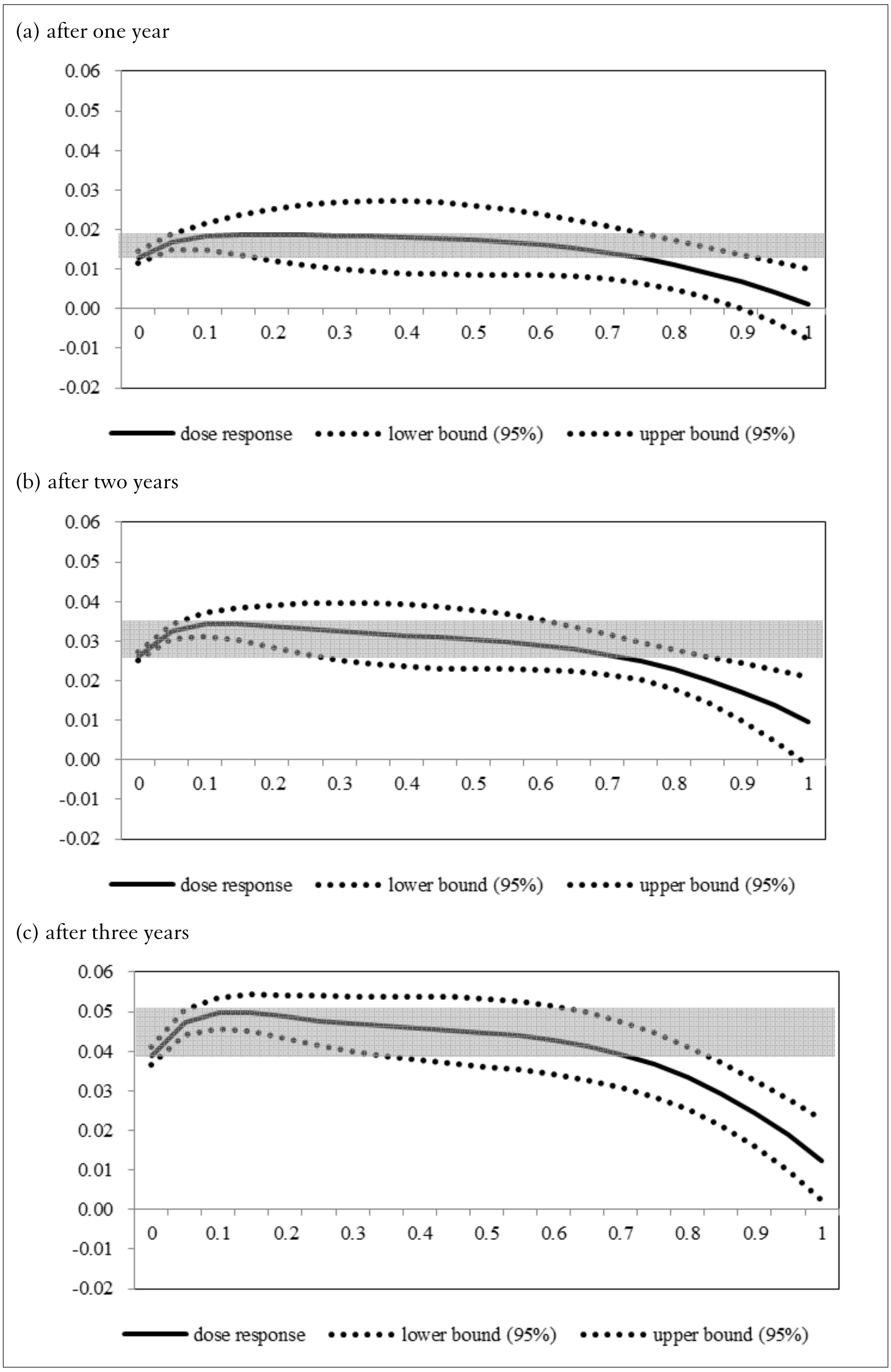
The maximum value of the TFP growth over 3-year span, depicted in the bottom graph is reached at an export-shipment ratio of around 10~15%, where the expected value of the total TFP growth rate during 3 years amounts to 4.97%.[15] This TFP growth rate is significantly larger than that of non-exporters (3.88%). This result implies that, if we eliminate plant-specific differences by conditioning on the GPS, a hypothetical switch of a plant from non-exporting to exporting 10~15% of its total shipment leads around 1.09 % point increase in the TFP growth rate. The higher TFP growth of exporters compared to non-exporters continues to hold up to the 70~75% range, but after a plant's export-shipment ratio exceeds 75%, then its productivity growth rate is shown to be even lower than non-exporters.[16]

[14] Before we calculate dose response functions, we need to check whether pre-treatment variables satisfy balancing property as explained in the previous section. Following Kluve et al. (2012), we evaluate the balancing of the covariates by regressing each covariate on the export intensity with and without conditioning on the predicted export intensity, $E[T\,|\,X_i]$. Once we condition on $E[T\,|\,X_i]$, we expect that the export intensity is not correlated with the covariate if adjustment for the GPS works in balancing the observable characteristics. The results are shown in Table A1 in the appendix which confirms that the correlation between export intensity and each covariate disappears when the predicted export intensity is conditioned for.

[15] The estimated peaks of the TFP growth distribution seems to happen at a relatively low range of export intensity. Such results come partly from our stringent control for unobserved industrial characteristics at KSIC 4-digit industry classification with a total of 214 different industries. In fact, when we re-do the estimations with less disaggregated industrial classification, KSIC 2 digit (23 sectors) and 3-digit (61 sectors), the peaks of the TFP growth distribution gradually move towards higher ranges of export intensity (for example, at around 20~30% over 3-year span). These results are not reported here but available upon request.

[16] It would be interesting to do the same exercise by focusing on Chaebol firms only because in Korea it is well known that Chaebol firms' behavior is very different from others. However, our data set does not provide firm identification code and thus it is impossible to identify Chaebol firms in our sample. One way to indirectly address this issue is to analyze only large plants in our sample (with more than 300 workers). The empirical results for this subsample (not reported in the paper but available upon request) did not change our empirical results in any materialized way. We are grateful to the anonymous referee who raised this issue.

[Figure 1] Dose responses of TFP growth (KSIC 4-digit classification applied)



Our GPS estimation results here imply that exporting activity generally provides a better opportunity for productivity improvement, but higher export intensity does not automatically guarantee higher productivity growth. These findings are somewhat puzzling, at least from theoretical views of the existing trade literature. In the literature, exporting is often related to learning-by-exporting effect and/or pro-competition effect. If these effects are substantial sources of plant-level productivity enhancement, then all the surviving firms with a higher exposure to foreign markets would experience higher productivity growth.

One plausible explanation for our results is provided by Fryges and Wagner (2007). They argue that the costs of coordination and control (i.e. internationalization costs) rise as a firm increases its foreign engagement, possibly due to the increasing export destinations/geographic distance, differences in culture and peculiarities of the individual foreign markets, etc. Therefore, an increasing exposure to foreign markets beyond a certain threshold could have a negative impact on a plant's TFP, which may exceed the benefits an exporter can gain from learning-by-exporting and/or pro-competitive effects.

As illustrated in Fryges and Wagner (2007), the existence of internationalization costs and their impacts on firms' performance are often discussed the international business literature, but has not been drawn much attention in the economic literature. The empirical findings in this paper suggest the necessity of more extensive research on the costs and benefits of a higher foreign exposure.

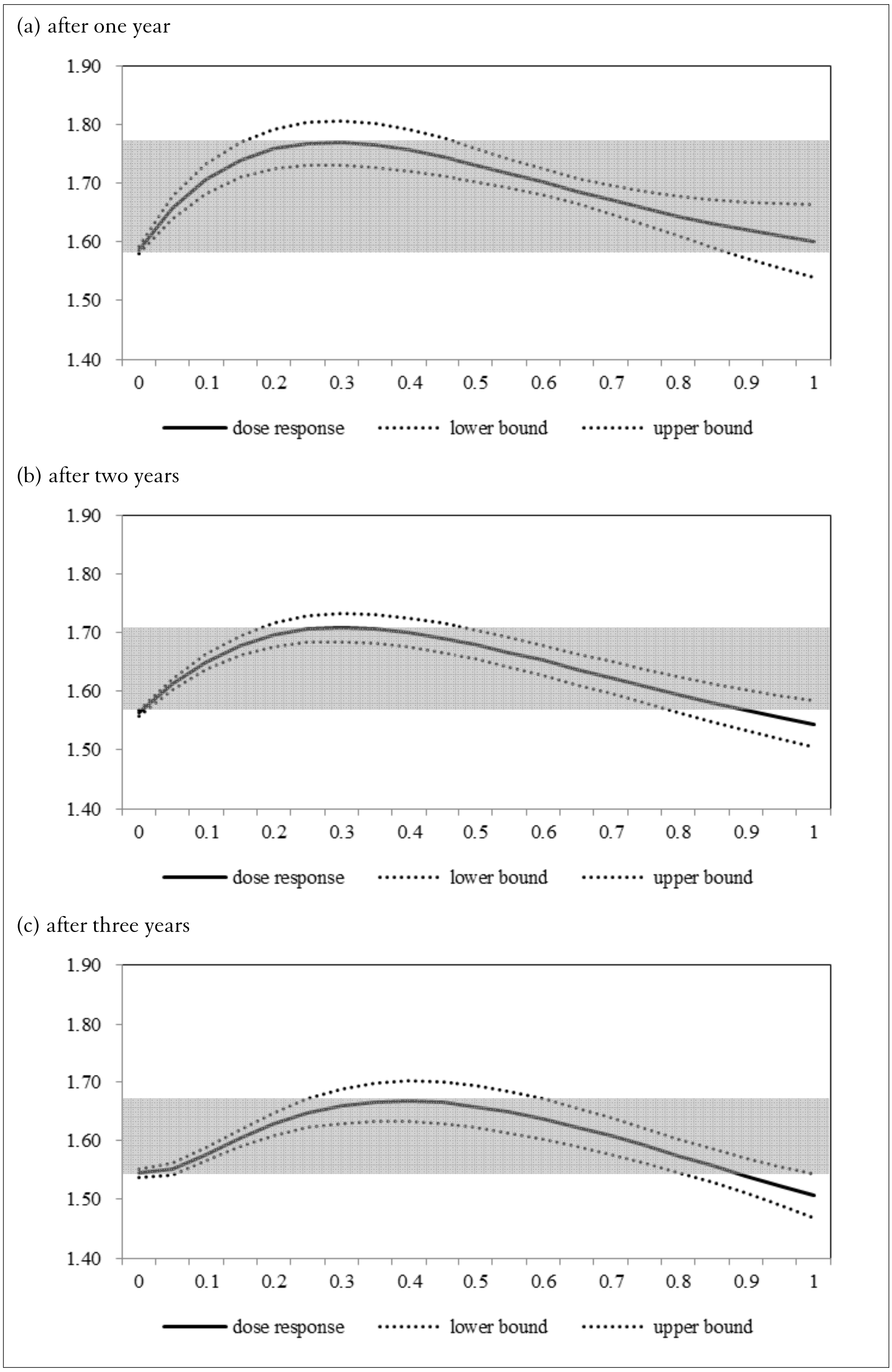
2) The Dose Responses of Markups

As for plant-level markups, our descriptive statistics presented in Table 2 indicated a quasi-positive relationship between export intensity and markup levels. On the other hand, Figure 2 depicts our estimated does response functions of markup levels in the periods from year t+1 to t+3, given the export-shipment ratio in year t. As depicted in the figure, once we control for differences in plant-specific attributes, again an inverted U-shaped relationship between export intensity and markups emerges.

Based on Melitz and Ottaviano (2008), we can interpret this inverted U-shaped relationship between export intensity and markups as follows; first of all, if competitive environment is tougher in foreign markets than domestic counterparts, exporters with higher export intensity should charge lower markups than others in order to remain competitive relative to the more efficient foreign competitors (i.e. pro-competitive effect). On the other hand, firms with higher export intensity tend to impose relatively higher markups to recover their additional trade costs (i.e. trade cost effect).

Last but not the least, plants with lower costs, i.e. more productive plants, are able to set higher markups as they do not pass all of their cost advantage to consumers in the form of lower prices. Therefore, other things being equal, plants experiencing

[Figure 2] Dose responses of markups (KSIC 4-digit classification applied)

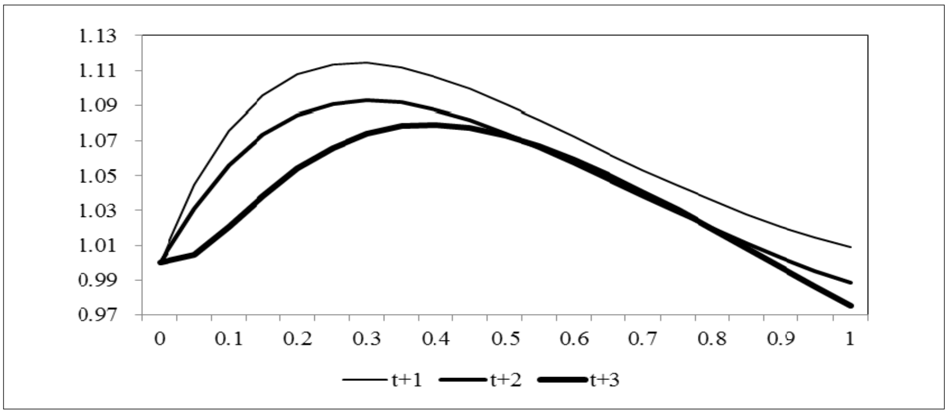


relatively higher productivity growth could have a better chance to maintain high markup levels (i.e. productivity effect). Our finding of the inverted U-shaped relationship between export intensity and markups suggests that productivity effect, rather than pro-competitive effect and trade cost effect, is a dominant force in shaping plant-specific markups.

Another important observation from Figure 2 is that plant-specific markups have been generally declining during the sample period between 1992 and 2002, regardless of export status; as we move down from Panel (a) to (c) in Figure 2 the overall markup levels go down as well.[17] As a matter of fact, Korean firms faced intense competitive pressure both in domestic and foreign markets during our sample period, largely due to the country's liberalization efforts as well as to accelerating globalization in the world economy. Furthermore, Korean firms experienced rising wages over time, with a notable exception of the Asian financial crisis period of 1998-1999. These all led to a general trend of markup deterioration.

To see this more clearly, we put the estimated markup distributions from t+1 to t+3 together in Figure 3, but normalize the markup level of non-exporters to 1 for each time period. We can see that non-exporters' markups have declined the least, compared to exporters at any level of export intensity. Markup gaps between exporters and non-exporters are shown to be gradually reduced over time and consequently markup distribution becomes more flattened out over time. Interestingly, markup deterioration over the sample period has been more severe for exporters at an export-shipment ratio of 10~20% that experience the largest productivity gains. This implies that exporters who adjust most flexibly their pricing behavior to heightened competitive pressure gain the most in terms of productivity enhancement.

[Figure 3] Markup dynamics by export intensity (markup for non-exporters=1)



[17] Bellone et al. (2008) also find a sharp decline in the average markups for French manufacturing since the early 1992.

V. Concluding Remarks

Taking recent new developments in trade literature on firm heterogeneity into account, we empirically investigate productivity and markup dynamics at varying degrees of export intensity by using plant-level Korean manufacturing data for the period between 1992 and 2002.

While our estimation results are largely in line with those from the existing literature, we also provide a number of new insights into the literature. First of all, our estimation results re-confirm the well-known exporter premium; exporters are more productive, paying higher wages, more capital-intensive and more likely engage in R&D activity than non-exporters. Furthermore, they reveal on average more conspicuous productivity improvement over time than non-exporting plants. In addition, we also find evidence that exporters tend to charge higher markups than non-exporters, as suggested in Melitz and Ottaviano (2008).

On the other hand, when we examine the impact of export intensity on subsequent productivity growth, we find an inverted U-shaped relationship between these two variables. Strikingly, subsequent productivity growth rates for exporters who sell the majority of their output to foreign markets are shown to be even lower than non-exporters. We also find a similar pattern of the relationship between export intensity and plant-level markups, after controlling for plant-specific characteristics.

Our results imply that increasing export intensity up to a certain threshold provides a better opportunity for exporters to improve productivity and charge higher markups than non-exporters, but plants that export beyond this threshold may not fully benefit from foreign engagement as excessive exposure to foreign markets causes high internationalization costs and market uncertainties.

Overall, this paper highlights the necessity to further scrutinize heterogeneity among exporters to better understand the potential benefits and costs of firms' decision on its relative exposure to foreign markets. In addition, our results suggest that considering productivity and markups dynamics together could be a fruitful way to better understand the mechanisms through which international trade affects domestic economy.

Further research on the relationship between firm-specific pricing behavior and exports is also promising. These are important and recurring issues in the literature, but it is only recently that the literature starts to provide testable theoretical bases and relevant empirical tools to investigate the relationship between markup heterogeneity and exports.

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Appendix

[Table A1] Covariate balance with and without adjustment

Covariate	Unconditional Effect of Export Intensity	Effect of Export Intensity conditional on $E(T \mid X_i)$
Ln(TFP)	0.5340***	0.0000
	(0.0078)	(0.0031)
Age	0.0440***	-0.0000
	(0.0012)	(0.0015)
$(\text{Age})^2$	0.0121***	0.0000
	(0.0005)	(0.0006)
Size	1.6115***	0.0000
	(0.0234)	(0.0088)
Wage	0.2794***	0.0000
	(0.0075)	(0.0072)
NPW share	0.1134***	0.0000
	(0.0102)	(0.0171)
K/L ratio	0.6748***	0.0000
	(0.0200)	(0.0197)
HHI	0.0011	-0.0000
	(0.0008)	(0.0008)
(HHI)2	-0.0002	-0.0000
	(0.0003)	(0.0003)
R&D Dummy	0.9942***	-0.0025
	(0.0268)	(0.0356)

Note: The second column shows the results of regressing each corresponding covariate on export intensity. The third column reports the same results conditional on the predicted export intensity, $E(T \mid X_i)$. All coefficients are estimated by OLS except for that of R&D dummy for which probit model is used. All regressions include year dummies and industry dummies at KSIC 4-digit level. The robust standard errors are in the parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% level, respectively.