Chapter 8

Export Intensity, Markup and Productivity: Micro-evidence from the Korean Manufacturing

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CHAPTER 8

Export intensity, Markup and Productivity: Micro-evidence from the Korean Manufacturing

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Taking recent new developments in trade literature on firm heterogeneity into account, this paper extensively investigates the relationship among export intensity, markup and productivity. We employ a new empirical framework à la De Loecker and Warzynski (2010) to measure plant-level markup and productivity of the Korean manufacturing sector for the periods of 1992-2002. Then using these measures and the generalized propensity score methodology, we reconsider the related empirical evidence provided in the existing literature.

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, we find productivity- (as well as markup-) premia of exporters relative to non-exporters, but also a substantial degree of heterogeneity among exporters with different export intensities. Generally, the dose-responses both of TFP level and of markup level along export intensity suggest an inverted U-shaped relationship.

In addition, our estimation results still suggest that exporting activity generally provides a better opportunity for productivity improvement, but not all exporters benefit from exports. Importantly, our analytic results do not support for the hypothesis that the higher export intensity induces higher productivity growth among exporters.

Finally, we find that the rankings of TFP level among plants tend to be preserved over time, but this is not the case for markup dynamics. Specifically, markup gaps between exporters and non-exporters are shown to be gradually reduced over time and the rankings of markup level substantially change over the 3-year span.

Keywords: Export intensity, markup, productivity, pro-competition effect

JEL classification: F1, L1, L6

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1. 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 productive, more capital-intensive, and pay higher wages. And it is now widely recognized that the productivity premium of exporters vis-à-vis non-exporters can be attributed largely to the fact that more productive firms only self-select into exporting activities. Meantime, the empirical evidence on the causal link from participation in export markets to plant-level productivity growth has been inconclusive so far.

A relatively unexploited but recurring issue in the literature is the relationship between firm-specific pricing behavior and exports. Different firm characteristics and competitive environments as well as the presence of trade costs would induce exporters to employ a distinct pricing strategy compared to non-exporters. For example, 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 could 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. Likewise, an endogenous distribution of markups across firms would depend largely on productivity differentials, trade costs and the relative toughness of market competition between foreign and domestic markets.

There are some reasons why the export-markups nexus has been understudied in the literature so far. From a theoretical point of view, new models of international economics put firm heterogeneity at the core of the analysis, but most of these models assume either a perfectly competitive or a Dixit-Stiglitz market structure. Under such assumption, all firms in an industry have the same degree of markups. Consequently, these studies are unable to explain differences in pricing behavior, or more precisely markup heterogeneity, across firms.

Only recently, a number of papers propose a more realistic model by relaxing assumptions on market structure and thus provide a theoretical basis to investigate the relationship between markup heterogeneity and export. For example, under the monopolistically competitive framework with firm heterogeneity, Notably, Melitz & Ottaviano (2008)'s model predicts that markups are positively related to firm productivity as well as to export intensity. Their model also indicates that all surviving firms are worse off in terms of price markups after trade liberalization, due to pro-competitive effects, while trade does not affect the rankings of firms ordered by profitability.

On the other hand, the fact that establishment-level prices are typically unobserved has posed a serious limitation in empirical research on the export-markup nexus across firms. 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.

Recently, De Loecker & Warzynski (2010) and Martin (2010) propose a new empirical framework to measure firm-specific markup and productivity on the insight of Hall (1986).[1] For example, De Loecker & Warzynski (2010) identify 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 relationship among markup, productivity and exporting activities, using the Korean manufacturing plant-level data for the periods of 1992-2002. Here we estimate firm-specific markup and productivity by adopting De Loecker & Warzynski (2010)'s procedure.

As for exports, our research focus is on export intensity rather than export status. Most of the current studies investigate the relationship between a firm's export status and the productivity growth, by measuring firms' export status as a binary treatment

[1] 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).

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, it is also an important issue to understand underlying mechanisms of apparent heterogeneity in market conduct and performance among exporters.

In order to investigate productivity and markup differentials not only between exporters and non-exporters but also among exporters, we adopt the Generalized Propensity Score (GPS hereafter) methodology developed by Hirano & Imbens (2004). This GSP method is a generalization of the binary treatment propensity method, and allows for continuous treatment like export intensity, of which the latter is measured by the export-shipment ratios.[2] Using the GSP method, we examine distributional attributes of productivity and markups at each level of export intensity.

The main research questions posited in our analyses are threefold: First of all, in order to understand the underlying mechanism of firms' decision to serve foreign markets, we examine what kinds of firms' attributes induce their export decision and determine their relative exposure to foreign markets.

Second, we explicitly investigate whether the empirical findings on the export-productivity nexus so far are also applicable to the relationship between export behavior and markups. Do markups differ dramatically between exporters and non-exporters and if so to what extend? More importantly, does there exist any systematic relationship between export intensity and markup level among exporters?

Third, we also examine the impact of export intensity on productivity and markup dynamics. In the current literature, export intensity is often related to learning-by-exporting. If learning by exporting does exist, then the higher export intensity would induce higher productivity growth, which in turn could increase markup. At the same time, export intensity also reflects competitive environment differentials between foreign and domestic markets. Hence, if firms participating in international markets are exposed to more intense competition, exposure to pro-competitive environments

[2] Unfortunately the Korean plant-level manufacturing data do not contain total sales information. Therefore, we employ export-shipments ratio as a proxy for export intensity, rather than export-sales ratio.

may worsen firms' profitability but induce a higher incentive to improve productivity. Consequently, depending on the relative importance of pro-competition effect vis-à-vis the extent of learning-by-exporting, firm-level productivity and markup dynamics may possibly differ.

The rest of this paper is organized as follows. The next section provides a brief literature survey on the related studies. In Section 3, we present our empirical strategy including estimation of TFP and markup. Section 4 provides our empirical results and the final section concludes and provides some policy implications.

2. 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. For example, documenting the characteristics of U.S. export manufacturers, Bernard & Jensen (1995) confirm that exporting plants are larger, more capital intensive, more productive, and pay higher wages and salaries 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 exporting causes productivity growth through some form of learning-by-exporting. 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 work of Bernard & Jensen (1999) on U.S. firms and the work of Clerides, Lach and Tybout (2001) on firms in Mexico, Colombia and Morroco find no differential growth in firm productivity among exporters versus non-exporters (Bernard *et al*., 2007).[3]

Fryges & Wagner (2007) recently suggest several reasons why the evidence from previous studies could be in favor of self-selection hypothesis. First of all, for a forward-looking firm, the decision to enter into export markets may induce a strong incentive to improve productivity prior to starting exporting activities. This can explain a certain extent of the ex-ante productivity differences between exporters and non-exporters.

In addition, most of the current studies investigate the relationship between a firm's export status and the productivity growth, using the firms' export status as a binary treatment variable and comparing the performance of exporters and 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. Hence the scope for productivity improvement through learning-by-exporting may differ, depending on export intensity.[4]

Recently, Fryges and Wagner (2007) test the relationship between export intensity and productivity, by adopting the GPS methodology developed by Hirano & Imbens (2004). They find that, while there is a causal effect of firms' export activities on labor productivity growth, exporting improves labor productivity growth only within a sub-interval of the range of firms' export-shipment ratios.

The second strand of research that motivates this paper is the recently emerging empirical literature on the relationship between trade and firms' markups. Most notably, Melitz & 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. That is, more efficient producers have a cost advantage over their competitors, set higher markups and have higher levels of measured productivity.

[3] For an excellent survey of the empirical findings on learning-by-exporting, see De Loecker (2010) and Wagner (2007).

[4] Using measures of export intensity rather than export status, Fernandes & Isgut (2007) find strong evidence of learning-by-exporting for young Colombian manufacturing plants between 1981 and 1991.

Melitz & Ottaviano (2008) also suggest that markups are positively related to firm export intensity and markups are higher on the export market than on domestic markets. According to their model, the presence of trade costs leads firms to charge higher markups on foreign markets than on domestic markets in order to recover their additional frictional trade cost.

Theoretically, however, the markup premium that a firm sets on its export markets, would depend on its relative efficiency compared to foreign competitors. Exporters could charge lower markups in order to remain competitive relative to more efficient foreign competitors. Likewise, if foreign demand elasticity is bigger than domestic ones, non-exporting firms would have higher price-cost margins than exporters. Last not the least, if firms that extend their export activities face additional variable costs, for example due to the increasing geographic distance and differences in culture and peculiarities of the individual foreign market, this may adversely affect productivity as well as markups. Hence, unlike Melitz & Ottaviano (2008)'s prediction, it may be at least theoretically plausible that firms with less exposure to foreign markets charge higher markups.

Finally, Melitz & Ottaviano (2008)'s model indicates that all surviving firms are worse off in terms of price markups after trade liberalization, due to pro-competitive effects, while trade does not affect the rankings of firms ordered by profitability.

Using Slovenian firm-level data for the periods of 1994-2000, De Loecker & Warzynski (2010) find that exporters charge higher markups on average and firms' markups increase upon export entry. Fryges & Wagner (2010), adopting a continuous treatment approach, also provides evidence of the profitability premium of exporters compared to non-exporters from the German enterprise-level data. In addition, they find that exporting improves the profitability almost over the whole range of the export-shipment ratios.

In a similar vein, Görg & 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 for both types of firms. Finally, Lourdes & 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.

Among the aforementioned papers, De Loecker & Warzynski (2010) and Fryges & Wagner (2007, 2010) are the most closely-linked ones to our current research. As mentioned earlier, unlike De Loecker & Warzynski (2010), we focus on the relationships between export intensity and firm's performance measures such as productivity and markups.

Our research is similar in spirit to Fryges & Wagner (2007, 2010) that each study examines the potential relationships either between markups and export activities or between productivity and export activities. However, our paper is different from Fryges & Wagner (2007, 2010) in the following ways. First, Fryges & Wagner (2007) use labor productivity in their analysis, due to data constraints, without considering the possibility that their productivity measures may be contaminated due to firm-specific markups. As Martin (2008) shows, productivity changes could be under-estimated if the market power effects are ignored in estimation. Second, Fryges & Wagner (2010) calculate the rate of profits from the cost structure surveys but we instead estimate markups controlled for unobserved productivity shock.

Third, Fryges & Wagner (2007, 2010) examine the productivity-export nexus and the profitability-export nexus independently in separate papers, without taking the linkage between productivity and profitability into account. On the other hand, our paper estimates and compares productivity and markups dynamics together at each level of export intensity.

3. Empirical Strategy

3.1. Estimation of Productivity and Markups

A common practice in the existing literature to estimate plant-level total factor 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. Furthermore, if this is indeed the case, then the empirical literature on the export-productivity nexus possible documents the importance of selection on profits, but not necessarily productivity (Foster *et al*., 2008).[5]

Recently, empirical models to estimate TFP and markups in the absence of establishment-level prices are proposed by a number of papers, including De Loecker & Warzynski (2010) and Martin (2010). These studies rely on Hall (1986, 1988)'s methodology that provides an estimate for the industry-markup jointly with a productivity index by introducing the demand side into the structural model of the production process.[6]

Consider the cost minimization problem for a firm 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 firm-specific input prices for labor and capital, respectively. Then, the first-order condition indicates that

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

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 firm i at time t. Then we can rearrange Equation (2) into the following;

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

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

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[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] At the same time, however, while Hall (1987, 1988) mainly considers industry-level productivity dynamics and concentrates on separating the markups from the degree of returns to scale, the recent studies focus on establishment-level productivity and markups.

thus we only need to estimate θ_{it}^{L} to get the markup measure price for a firm i at time t.

De Loecker & Warzynski (2010) 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 firm's productivity and ε_{it} is a white noise.

The estimation procedure of Equation (4) applied by De Loecker & Warzynski (2010), 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 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 & 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.

[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 (2010) for more details.

3.2.Generalized Propensity Score (GPS) Approach

In order to investigate the potential relationship among markups, productivity and export intensity, we will utilize the generalized propensity score (GPS) methodology recently developed by Hirano & Imbens (2004). Much of the work on propensity score analysis regarding the causal effect of firms' export on productivity used export status as a binary treatment variable for each firm (e.g., De Loecker [2007] with Slovenian data and Wagner [2002] with German data). While the binary export status variable contains its own valuable information, it cannot incorporate the degree or extent of export intensity in empirical analysis.

By extending standard propensity score analysis from Rosenbaum & Rubin (1983) with binary treatment variable, Imai & van Dick (2004) and Hirano & Imbens (2004) proposed the GPS methodology which allows for the case where the treatment variable (export intensity variable in our analysis) may take on a continuum of values. Fryges & Wagner (2007) applied this GPS methodology in order to investigate the relationship between firms' export activities and productivity using German manufacturing data set.[8] However, unlike Fryges & Wagner (2007) where firm's productivity was measured by labor productivity (total sales per employee), we will use total factor productivity (which is preferred to labor productivity measure) and in addition firm's markup variable will be analyzed as firms' performance variable in our analyses.

The basic logic of the GPS methodology is as follows.[9] Let N denote the size of our random sample (i.e., number of firms). For each firm i, we observe Xi (pre-treatment covariates that may affect the level of treatment), Ti (the level of treatment received, i.e., firm's export intensity) and Yi(t) (the value of the outcome associated with treatment, i.e., TFP or markups). Yi(t) is referred to as the unit-level dose-response function (potential outcome corresponding to the level of the treatment received) and the average dose-response function, $\mu(t) = E[Y_i(t)]$, is of our interest to be estimated.

[8] Another application can be found in Du & Girma (2009) which investigated the causal effects of foreign acquisition on domestic and export market dynamics with GPS methodology using Chinese firm-level data.

[9] See Hirano and Imbens (2004) for more details.

We can define the generalized propensity score (GPS), $R = r(T, X)$, where $r(t, x) = f_{T|X}(t|x)$ is the conditional density of the treatment given the pre-treatment covariates. If suitably specified, the GPS has a balancing property similar to that of the standard propensity score for the binary case:[10] that is, within strata with the same value of r(t, X) the probability that T=t does not depend on the value of X.[11]

Combining this balancing property with the weak unconfoundedness assumption, Hirano & Imbens (2004) proved that for every level of treatment t,[12]

$$f_T\{t|r(t, X), Y(t)\} = f_T\{t|r(t, X)\} \tag{9}$$

which implies that assignment to treatment T is unconfounded given the GPS and that the conditional density of the treatment level at t can be calculated using the GPS at the corresponding level of the treatment.[13]

Hirano & Imbens (2004) finally proved that with weak unconfoundedness assumption, the GPS can be used to eliminate any biases associated with differences in the covariates because it can be shown that

$$\beta(t, r) = E[Y(t)|r(t, X) = r] = E[Y(t)|T = t, R = r] \tag{10}$$
$$\mu(t) = E[\beta(t, r(t, X)] = E[Y(t)] \tag{11}$$

where equation (11) is the average dose-response function we are interested in.

In practice, estimating the average dose-response function consists of the following three steps. First we estimate the GPS, the conditional distribution of the treatment variable given the pre-treatment covariates: $E[T_i|X_i]$. In our case, Ti takes many zeros in our sample and thus natural choice of the estimation method would be the fraction logit model developed by Papke and Wooldridge (1996). In the second stage with the estimated GPS ($\widehat{R}_i$) from above, we estimate the regression equation (10) by using quadratic approximation following Hirano & Imbens (2004).

$$E\left[Y_i\middle|T_i, \widehat{R}_i\right] = \alpha_0 + \alpha_1 T_1 + \alpha_2 T_i^2 + \alpha_3 \widehat{R}_i + \alpha_4 \widehat{R}_i^2 + \alpha_5 T_i \widehat{R}_i \tag{12}$$

This is estimated with OLS.

In the final stage with estimated coefficient from equation (12), we estimate the average potential outcome at treatment level t (equation (11)) as

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[10] Note that with the GPS we are considering the case where $T_i \in [t_0, t_1]$ (i.e., when the treatment can take ay value between t_0 and t_1). If $T_i \in \{0,1\}$, (i.e., when the treatment is binary), we get back to the case of Rosenbaum and Rubin (1983)'s traditional propensity score.

[11] That is, we have $X \perp I(T = t) \mid r(t, X)$where $I(\cdot)$ is the indicator function.

[12] The weak unconfoundedness assumption can be written as $Y(t) \perp T \mid X$ for all *t*.

[13] Roughly speaking, equation (1) implies that $Y(t) \perp T \mid r(t, X)$. Thus theorem is referred to as weak unconfoundedness given generalized propensity score.

$$E[\widehat{Y(t)}] = \frac{1}{N}\sum_{i=1}^{N}\{\hat{\alpha}_0 + \hat{\alpha}_1 \cdot t + \hat{\alpha}_2 \cdot t^2 + \hat{\alpha}_3 \cdot \hat{r}(t, X_i) + \hat{\alpha}_4 \cdot \hat{r}(t, X_i)^2 + \hat{\alpha}_5 \cdot t \cdot \hat{r}(t, X_i)\} \quad (13)$$

This will be done for every level of the treatment we are interested in to obtain an estimate of the entire dose-response function.

4. Empirical Results

4.1. Data and Descriptive Statistics

Our plant-level micro-data come from the “Survey of Mining and Manufacturing” conducted by the KNSO (Korea National Statistical Office). This Survey covers all establishments with five or more employees in the mining and manufacturing sectors and contains necessary information to construct the variables used in this paper at plant-level, such as value-added, labor, capital stocks, intermediate input usage and many other plant-specific characteristics.

We construct three groups of variables that will be used in our empirical analyses: (1) treatment variable, (2) outcome variables and (3) pre-treatment variables. First, the treatment variable is export intensity which is defined by export value divided by total shipment. Second, the outcome variables are TFP (after taking natural logarithm) and markup as estimated by the methodology described in section III. The data needed to estimate these two outcome variables are directly taken from the Survey mentioned above.

Third, the pre-treatment variables include plant’s size, age, wage, non-production workers’ share, capital-labor ratio and R&D dummy. Plant’s size is measured as the natural logarithm of the number of total employment and plant’s age as (current year - established year + 1) divided by one hundred. Wage is the natural logarithm of yearly wage bill divided by the number of total employment. The share of non-production workers is the number of non-production workers divided by total employment. The capital-labor ratio is measured as the natural logarithm of capital stock over total employment. R&D dummy takes the value of one if firm’s R&D expenditure is positive number and zero otherwise. In addition to these plant-specific pre-treatment variables, we also constructed Herfindahl-Hirschman Index (HHI) at KSIC (Korea

Standard Industry Classification) 4-digit level.[14] HHI measures the degree of competition in each industry and is defined as the sum of the squares of the market share of each plant.[15]

After we constructed our variables as mentioned above for the time period of 1990~2002, we included plants with at least four consecutive years of observations in our sample period. In our empirical analyses using dose-response function below, we would like to analyze the dynamic impacts of export intensity on TFP and markup up to the next three years from the base year. Since one of our interests is to investigate how these dynamic impacts change over time, we excluded plants with less than four consecutive years of observations.

Table 1 shows simple correlations among these variables. First we can confirm that the export-premia found in the previous literature do exist in our sample plants as well. The export dummy variable is positively correlated with all other variables: that is, exporters are more productive, charging higher markup and at the same time they are older, paying higher wage, having higher share of non-production workers, having higher capital-labor ratio and more likely to implement R&D activities. The export intensity, our treatment variable, also exhibits the similar patterns of export-premia just like the export dummy variable. However, in all cases the correlations between the export intensity and other variables are lower than those between the export dummy and other variables.

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[14] With KSIC 4-digit level, the number of industries in our sample is 214.

[15] HHI can range from 0 to 1, moving from a huge number of very small plants to a single monopolistic producer.

Table 1: Correlation among Key Variables

	Export intensity	Export dummy	lnTFP	Markup	Age	Size	Wage	Non-production worker 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				
Non-production worker 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

In Table 2, we divide exporters by 10 categories according to their level of export intensity and provide mean values of our key variables for each group. While exporters' TFP levels are higher than that of non-exporters in all export intensity level, there seems to be no systematically monotonic relationship between export intensity and exporter's TFP level. Interestingly, the exporters with export intensity level of 0~10% have on average the highest mean value of TFP level, which is a similar level to those with 50~60%.

On the other hand, we can find a positive relationship between export intensity and markup: the higher the level of export intensity, the higher the level of markup. This positive and almost quasi-monotonic relation between markup and export intensity seems to be consistent with Melitz & Ottaviano (2008)'s theoretical prediction: markups are positively related to firm's export intensity.

Table 2: Summary Statistics by Export Intensity (Plants Surviving at Least for 4 years)

Export intensity	Obs.	ln(export)	ln(tfp)	Markup	Age	Size	Wage	NP worker share	K/L ratio	R&D dummy	HHI
0%	95,290	-	3.00	1.73	0.08	2.62	2.15	0.32	2.54	0.05	0.0464
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

Interestingly, among exporters, those with relatively lower levels of export intensity are older, paying higher wages, having a higher share of non-production workers, having higher capital-labor ratio and more likely to implement R&D activities, relative to those with higher export intensity. On the other hand, firm size, which is proxied by employment size, does not show a systematic relationship with export intensity. Finally, the extent of competitive pressure in domestic markets tends to be higher for exporters with lower export intensity.

Table 3. to Table 4. contain Markov transition matrices of export intensity for 3 years forward. As shown in the tables, 58% of non-exporters existed at year t remains as non-exporters one year later, while only around 3% of them becomes exporters at year t+1. This tendency remains about the same for 2- and 3-year span forward.

On the other hand, as for exporters, around 20% of them at year t exits out of export markets and serve only for domestic market at year t+1. The probability for switching to non-exporters is higher for exporters with relatively lower export intensity. For example, for 3-year span from t to t+3, more than one-fourth of exporters with export intensity level of 0~25% at year t becomes non-exporters at t+3, while only less than 20% of those that sell more than a half of their products to foreign markets switches their status to non-exporters.

Table 3: Markov Transition Matrix of Export Status and Intensities (one-year interval)

t=0 \ t = 1		Non-exporter	Exporter				Non-Existence	Total
			0~25%	25~50%	50~75%	75~100%		
Non-exporter		331,905 (58.2)	9,895 (1.7)	3,103 (0.5)	1,840 (0.3)	3,056 (0.5)	220,450 (38.7)	570,249 (100.0)
Exporter	0~25%	8,645 (26.9)	12,442 (38.7)	1,764 (5.5)	469 (1.5)	315 (1.0)	8,490 (26.4)	32,125 (100.0)
	25~50%	2,754 (21.4)	1,566 (12.2)	3,305 (25.7)	1,106 (8.6)	421 (3.3)	3,714 (28.9)	12,866 (100.0)
	50~75%	1,593 (17.9)	420 (4.7)	1,056 (11.9)	2,218 (24.9)	855 (9.6)	2,773 (31.1)	8,915 (100.0)
	75~100%	3,176 (18.8)	335 (2.0)	408 (2.4)	944 (5.6)	5,492 (32.5)	6,555 (38.8)	16,910 (100.0)
Non-existence/Exiter		245,565 (14.3)	9,104 (0.5)	4,011 (0.2)	2,738 (0.2)	6,715 (0.4)	1,449,862 (84.4)	1,717,995 (100.0)
Total		593,638 (25.2)	33,762 (1.4)	13,647 (0.6)	9,315 (0.4)	16,854 (0.7)	1,691,844 (71.7)	2,359,060 (100.0)

Note: Exporters are divided into four categories according to export intensities. The probabilities of status change from t to t+1 are in the parentheses.

Table 4. Markov Transition Matrix of Export Status and Intensities (two-year interval)

t=0 \ t = 2		Non-exporter	Exporter 0~25%	Exporter 25~50%	Exporter 50~75%	Exporter 75~100%	Non-Existence	Total
Non-exporter		231,660 (45.9)	9,528 (1.9)	2,895 (0.6)	1,696 (0.3)	2,632 (0.5)	256,705 (50.8)	505,116 (100.0)
Exporter	0~25%	7,547 (26.9)	8,460 (30.2)	1,663 (5.9)	543 (1.9)	318 (1.1)	9,504 (33.9)	28,035 (100.0)
	25~50%	2,327 (21.1)	1,265 (11.5)	2,013 (18.3)	907 (8.2)	401 (3.6)	4,092 (37.2)	11,005 (100.0)
	50~75%	1,486 (19.4)	385 (5.0)	736 (9.6)	1,318 (17.2)	751 (9.8)	3,000 (39.1)	7,676 (100.0)
	75~100%	2,605 (17.6)	306 (2.1)	393 (2.7)	738 (5.0)	3,493 (23.6)	7,289 (49.2)	14,824 (100.0)
Non-existence/Exiter		294,408 (18.9)	10,937 (0.7)	4,772 (0.3)	3,260 (0.2)	7,247 (0.5)	1,235,874 (79.4)	1,556,498 (100.0)
Total		540,033 (25.4)	30,881 (1.5)	12,472 (0.6)	8,462 (0.4)	14,842 (0.7)	1,516,464 (71.4)	2,123,154 (100.0)

Note: Exporters are divided into four categories according to export intensities. The probabilities of status change from t to t+2 are in the parentheses.

Table 5. Markov Transition Matrix of Export Status and Intensities (three-year interval)

t=0 \ t = 3		Non-exporter	Exporter 0~25%	Exporter 25~50%	Exporter 50~75%	Exporter 75~100%	Non-Existence	Total
Non-exporter		164,484 (37.8)	7,174 (1.7)	2,049 (0.5)	1,122 (0.3)	1,758 (0.4)	259,071 (59.5)	435,658 (100.0)
Exporter	0~25%	6,909 (26.5)	6,741 (25.9)	1,446 (5.6)	427 (1.6)	245 (0.9)	10,306 (39.5)	26,074 (100.0)
	25~50%	2,088 (20.0)	1,135 (10.9)	1,560 (15.0)	814 (7.8)	322 (3.1)	4,513 (43.3)	10,432 (100.0)
	50~75%	1,257 (16.9)	378 (5.1)	704 (9.5)	1,056 (14.2)	631 (8.5)	3,398 (45.8)	7,424 (100.0)
	75~100%	2,276 (15.5)	273 (1.9)	384 (2.6)	705 (4.8)	2,837 (19.3)	8,232 (56.0)	14,707 (100.0)
Non-existence/Exiter		306,370 (22.0)	12,009 (0.9)	5,162 (0.4)	3,518 (0.3)	7,235 (0.5)	1,058,659 (76.0)	1,392,953 (100.0)
Total		483,384 (25.6)	27,710 (1.5)	11,305 (0.6)	7,642 (0.4)	13,028 (0.7)	1,344,179 (71.2)	1,887,248 (100.0)

Note: Exporters are divided into four categories according to export intensities. The probabilities of status change from t to t+3 are in the parentheses.

4.2. Determinants of Export Intensity

As aforementioned, we estimate generalized propensity score by using fractional logit model where export intensity is regressed on one year lag values of pre-treatment variables (TFP, markup, age, size, wages, non-production worker share, capital-labor ratio, R&D dummies and HHI), year dummies and industry dummies. Basing on this estimation results, we can figure out what kinds of firms' attributes induce their export decision and determine their relative exposure to foreign markets. The estimation results are shown in Table 6.

Table 6: Fractional Logit Regression Results

	Dependent Variable: Export Intensity$_t$
$\ln TFP_{t-1}$	1.011***
	(0.092)
Markup $_{t-1}$	-0.041
	(0.038)
Age_{t-1}	2.639***
	(0.396)
$(Age_{t-1})^2$	-7.769***
	(0.947)
$Size_{t-1}$	0.442***
	(0.019)
$Wage_{t-1}$	-0.110
	(0.088)
NP share$_{t-1}$	-0.046**
	(0.019)
K/L ratio$_{t-1}$	0.076***
	(0.015)
R&D dummy$_{t-1}$	0.038
	(0.033)
HHI_{t-1}	1.097**
	(0.484)
$(HHI_{t-1})^2$	-2.971**
	(1.216)
Constant	-6.115***
	(0.328)
Observations	71,979
Log-likelihood	-13,607

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

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. This relationship does not hold for markups as the estimated coefficient for markup level is statistically insignificant. The estimation results also suggest that relatively younger plants tend to have higher export intensity, while interestingly exporters belonging to more concentrated industries sell a bigger portion of their products to international markets.[18]

4.3.TFP and Markup Differentials

Table 7 shows TFP and markup differentials between exporters and non-exporters. We can see that the mean value of exporters' TFP (after taking log) level (3.51) is higher than that of non-exporters (3.00) and the same is true with the median value (3.42 vs. 2.96). At the same time the mean value of exporters' markup level (1.84) is also higher than that of non-exporters (1.73).

Table 7: TFP and Markup: Exporters vs. Non-exporters

Outcome variable	Export status	Obs.	Mean	Standard deviation	p10	p25	p50	p75	p90
lnTFP	Non-exporter	95,290	3.00	0.29	2.66	2.80	2.96	3.15	3.37
	Exporter	23,246	3.51	0.46	3.01	3.18	3.42	3.76	4.15
	Total	118,536	3.10	0.39	2.69	2.84	3.03	3.27	3.60
Markup	Non-exporter	95,289	1.73	1.23	0.91	1.15	1.49	1.95	2.59
	Exporter	23,246	1.84	1.03	1.02	1.27	1.63	2.13	2.82
	Total	118,535	1.75	1.19	0.93	1.17	1.52	1.98	2.64

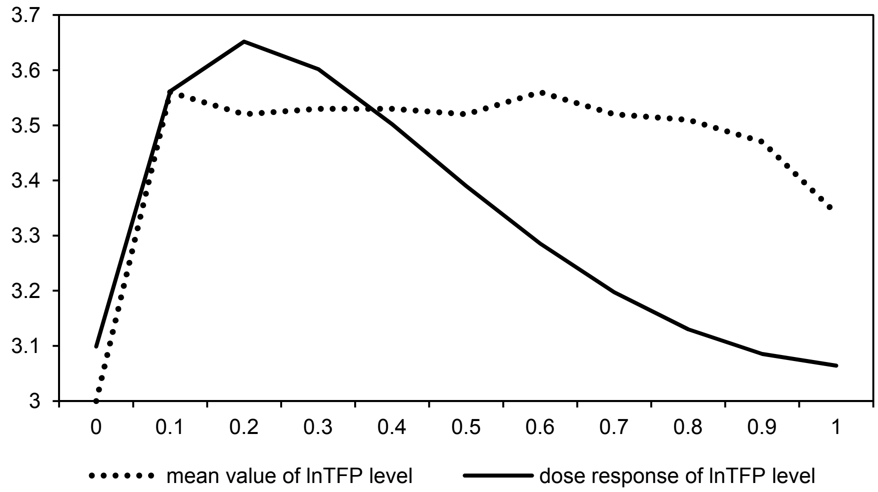
As shown in Table 2, while exporters' TFP levels are higher than that of non-exporters in all export intensity level, there seems to be no systematically monotonic relationship between export intensity and exporter's TFP level, which is depicted as a

[18] 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 tow variables.

dotted line in Figure 1. In addition, as aforementioned, there exists a positive and almost quasi-monotonic relation between markup and export intensity (Figure 2).

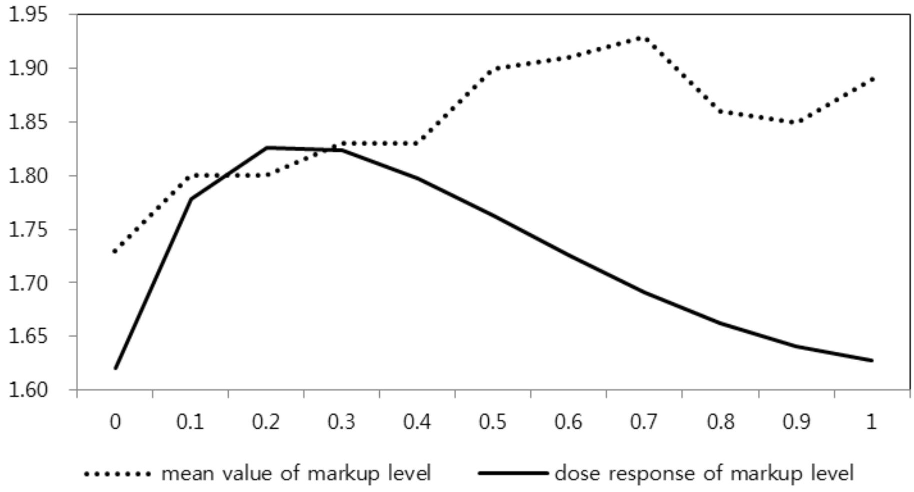
But how would TFP and markups at each level of export intensity look like once we control for other plant-specific characteristics at hands? In this purpose, we adopt here the generalized propensity score (GPS) methodology recently developed by Hirano & Imbens (2004), in order to see the causal effect of firms' export intensity on productivity and markups. After having run the aforementioned fractional logit model, we get the estimates for propensity score of each firm. With these estimates and observed export intensity, we can calculate dose-response function of outcome variables by estimating (13) in section III.[19] The dose-response functions of TFP and markup levels are drawn as solid lines in Figure 1 and 2. The dotted line (observed mean value of outcome variable) and the solid line (estimated dose-response of outcome variable) in these figures provide strikingly different implications.

Figure 1: Mean Value and Dose-Response of TFP Level



[19] In the next subsection, we will estimate the dose-response function of growth rate of TFP and markup which is the major part of our empirical work. Here we will take the level of TFP and markup as outcome variables in order to see how these variables are different after we control for other pre-treatment variables.

Figure 2: Mean Value and Dose-response of Markup level



While observed mean value of TFP level has little variation among exporters, the dose-response of TFP level reveals an inverted U-shaped relationship. The level of TFP increases until the export intensity reaches at 10~20% but above this threshold level it actually decreases, once we control for plant-specific characteristics, such as productivity level at year t-1, size, wages, capital-labor ratio and R&D activity among many others. Hence, on average, the productivity premium still hold for exporters vis-à-vis non-exporters, but the estimation results suggest substantial heterogeneity in productivity level among exporters with different export intensities.

As a matter of fact, Fryges &Wagner (2007) provide a plausible explanation for this inverted U-shaped relationship. They argue that for firms that sell a relatively small share of their total sales in the foreign market, here those with export intensity of less than 10%, learning by-exporting could be less relevant for them. Thus, it can be hypothesized that an exporter must exceed a minimum export-sales ratio before it can benefit from learning-by-exporting. Beyond this minimum intensity productivity growth is expected to increase with the firms' export intensity.

However, when a firm's export intensity exceeds a critical value, then increasing its foreign engagement incurs rising coordination and control costs for exporting activities. For example, As Gomes & Ramaswamy (1999) suggest, firms that extend their export activities often enter more distant markets. The increasing geographic distance, differences in culture and peculiarities of the individual foreign markets raise the costs of exporting, which adversely affects productivity.

One notable observation is a strong correlation between the TFP level and markup. Like TFP, the level of markups also increases as the export intensity approaches to 10~20% after which it decreases, as depicted in Figure 2. While a similar explanation as the inverted U-shape of the TFP distribution in terms of costs incurred by internationalization could be also applied to explain markup distribution, we can add some other plausible explanations; for example, if foreign markets are more competitive compared to domestic ones and/or if foreign demand elasticity is bigger than domestic counterparts, exporters with relatively higher exposure to foreign markets would charge lower markups in order to in order to remain competitive in foreign markets.

4.4. The Impacts of Export Intensity on TFP and Markup Dynamics

In the following we examine the impact of export intensity on productivity and markup changes. As aforementioned, the existing studies often relate export intensity either to learning-by-exporting or to competitive environment differentials between foreign and domestic markets. According to these studies, in the presence of learning-by-exporting, the higher export intensity could induce higher productivity growth, which in turn could increase markups. On the other hand, if firms participating in international markets are exposed to more intense competition, exposure to pro-competitive environments may worsen firms' profitability but induce a higher incentive to improve productivity. Consequently, depending on the relative importance of pro-competition effect vis-à-vis the extent of learning-by-exporting, firm-level productivity and markup dynamics may possibly differ.

To see this, we estimate here three dose-response functions that depict TFP growth rate and markup change in the periods from year t to t+3, given the export-shipment ratio in t. The dose-response functions are based on the pooled data set, using data from 1992 to 2002. Figure 3 presents the dose responses of productivity growth over 3-year span forward at each level of export intensity in t.

As depicted in the Figure, our findings indicate that over time an inverted U-shaped relationship with a peak at 0~10% of the export-shipment ratio emerges between a firm's export intensity and its TFP growth. This result is consistent with Fryges & Wagner (2007)'s empirical findings on the nexus between labor productivity and export intensity for the German manufacturing.

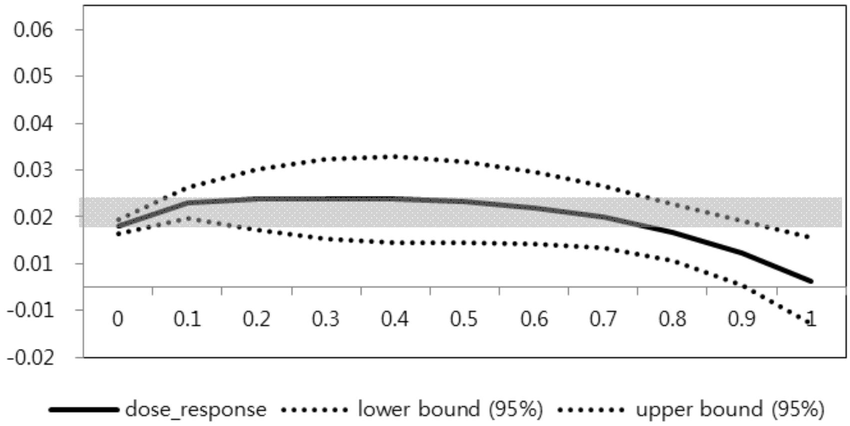
On the other hand, our results suggest that exporters with export intensity of less than 10% experience the largest productivity gains, while it is around 50% of export intensity in the case of Fryges & Wagner (2007)'s estimation. We believe that such difference in estimated peaks of the TFP growth distribution compared to Fryges and Wagner (2007) attributes largely to the extent of controlling for industry characteristics to which each firm belongs. We adopted quite a disaggregated industrial classification (KSIC 4 digit with a total of 214 different industries) in controlling unobserved industry-specific attributes. Such practice is legitimate because it allows for more stringent control for unobserved characteristics. In fact, when we re-do the estimation with less disaggregated industrial classification, the peaks of the TFP growth distribution gradually move towards around 30~40%. Figure A.1 and A.2 in appendix present estimation results when KSIC 2 digit (23 sectors) and 3-digit (61 sectors) classifications are applied, respectively.

The estimation results also show that the TFP growth rates for exporting firms with export intensity ranging from 10% to 70% are slightly higher than those for non-exporters. One the other hand, if a firm's export-shipment ratio exceeds 70%, then its productivity growth rate is lower even than non-exporters. This implies that exporting activity generally provides a better opportunity for productivity improvement, but not all exporters benefit from exports. Importantly, our GPS estimation results do not support for the hypothesis that the higher export intensity induces higher productivity growth among exporters.

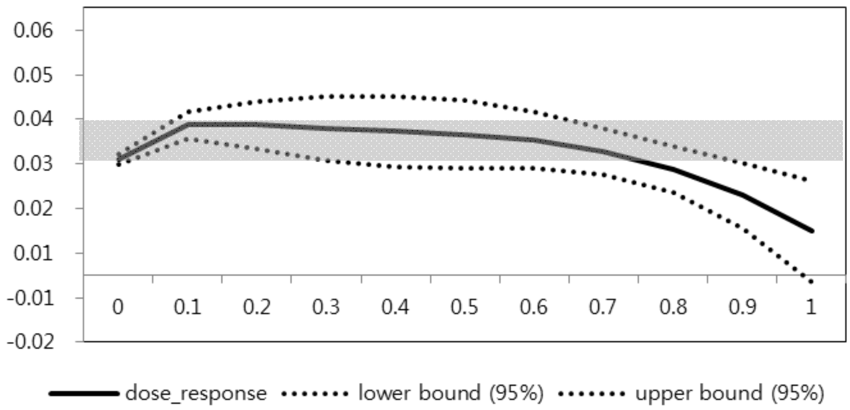
One additional interesting finding here is that generally more productive plants reveals higher productivity enhancement. As shown in Figure 2, exporters with export intensity up to 30% are most productive relative to others. These exporters are also those that experiences relative faster productivity growth. This implies that the rankings of TFP level and thus the shape of TFP distribution would be preserved over time.

Figure 3: Dose Responses of TFP Growth over 3-year Span Forward

a. TFP Growth after one year



b. TFP Growth after two years



c. TFP Growth after three years

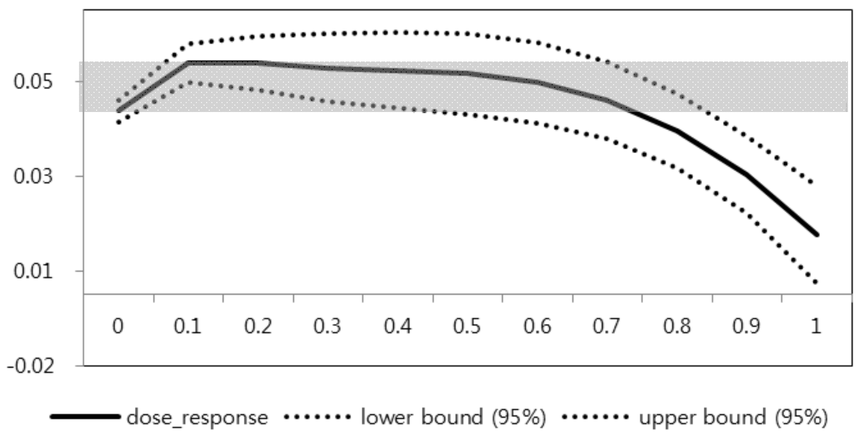


Figure 4 depicts the dose responses for the impact of the export-shipment ratio on markup changes. We can see that, regardless of export status, markups have been generally deteriorating. During the sample periods of 1992-2002, Korean firms faced a more intense competitive pressure both in domestic and foreign markets, largely due to the country's liberalization efforts as well as to accelerating globalization in the world. In addition, Korean firms also 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 decreases.[20]

Our results suggest that markup deterioration has been more severe for exporters than non-exporters. The extent of markup deterioration is the largest for exporters with export intensity of less than 20%, which are relatively more productive, have a higher capital-labor ratio and, most importantly, pay higher wages than others. And over the periods from t to t+3, non-exporters' markups has declined the least, compared to exporters at any level of export intensity.

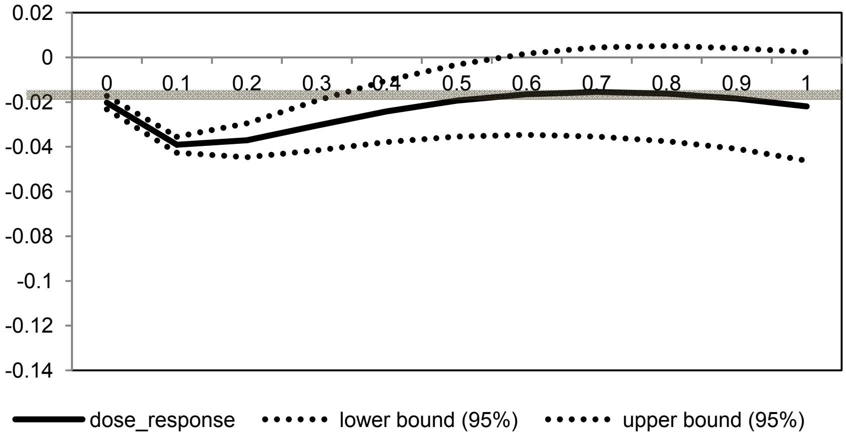
Given these observations Figure 5 depicts changes in the markup-level distribution over time given the export-shipment ratio in t, after controlling for plant-specific characteristics via the GPA method. In the figure, we normalize the markup level of non-exporters to 1 for each time period. As shown in the figure, all of exporters had higher markups than non-exporters at the reference year t, but markup gaps between exporters and non-exporters are shown to be gradually reduced over time. Furthermore, the markup levels for exporters that sell more than 80% of their products to foreign market become even lower than non-exporters after 3 years.

Generally, as markup gaps between exporters and non-exporters tend to decline, markup distribution becomes more flattened out over time. And the peak of distribution moves from 10~20% to 30~40%. These all indicate that, unlike the TFP case, the rankings of markup level substantially change over the 3-year span.

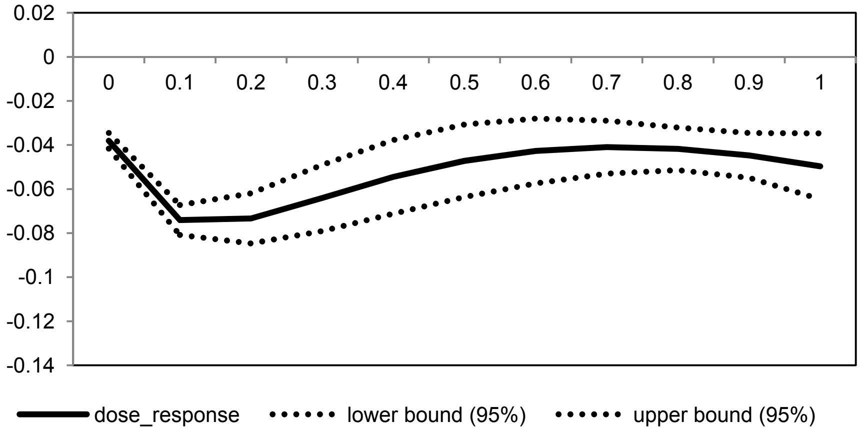
[20] Bellone *et al*. (2008) also find a sharp decline in the average markup for French manufacturing since the early 1992.

Figure 4: Dose Responses of Markup Changes over 3-year span forward

a. Markup Changes after one year



b. Markup Changes after two years



c. Markup Changes after three years

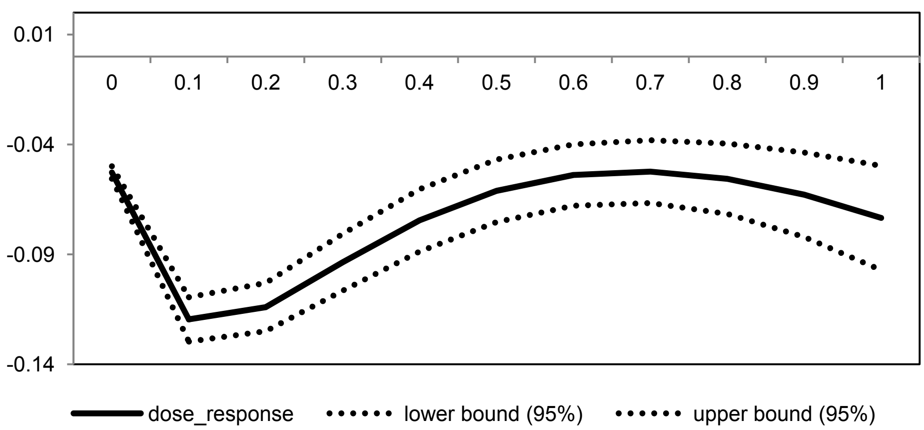
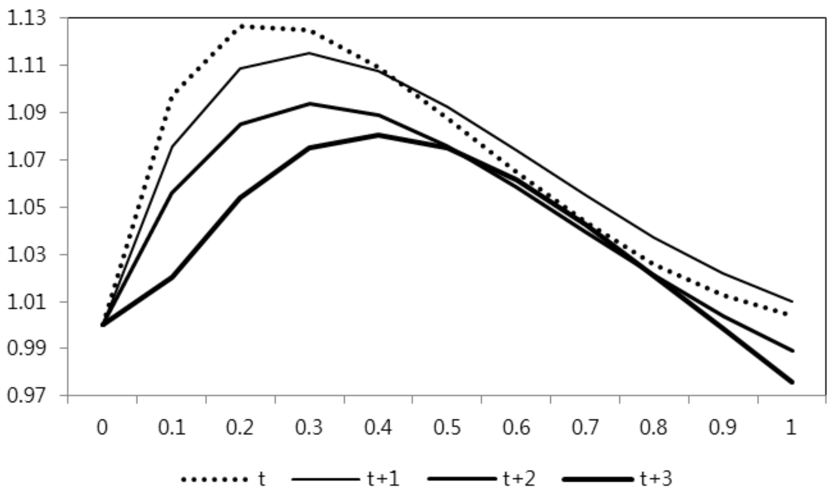


Figure 5: Markup Dynamics by Export Intensity (Markup for non-exporters=1)



5. Conclusions and Policy Implications

Taking recent new developments in trade literature on firm heterogeneity into account, this paper extensively investigates the relationship among markups, productivity and exporting intensity. We employ a new empirical framework à la De Loecker & Warzynski (2010) to measure plant-level markups and productivity of the Korean manufacturing sector for the periods of 1992-2002. Then using these measures and the GPS method, we reconsider the related empirical evidence proposed in the existing literature.

Our main findings can be summarized as follows; first of all, similar to the well-known productivity-export nexus, we find that the markup premia of exporters do exist. However, taking export intensity rather than export status into consideration, there is no monotonic relationship between export intensity and productivity (markup as well) level. Rather, the dose-responses both of TFP level and of markup level given export intensity suggest an inverted U-shaped relationship. Both TFP and markup increase until the export intensity reaches at 10~20% but above this threshold it actually decreases.

Second, this paper also finds an inverted U-shape between a firm's export intensity and its subsequent TFP growth with a peak at 0~10% of the export-shipment ratio. While our estimation results still imply that exporting activity generally provides a better opportunity for productivity improvement, but not all exporters benefit from exports. Importantly, our GPS estimation results do not support for the hypothesis that the higher export intensity induces higher productivity growth among exporters.

We can infer from our results that a usual positive relationship between export intensity and TFP growth suggested in the existing literature could stem mainly from different performances between exporters and non-exporters, but not necessarily from those among exporters. To confirm our inference here, we run fixed-effect model estimations for the whole sample and for exporters only, respectively. The results are reported in Table A.1 and Table A.2. When we test the relationship between export intensity and TFP growth for the whole sample, then we find statistically significant and positive effect of export intensity on subsequent TFP growth. However, such relationship does not emerge when we pursue the same estimation only for exporters' sample. These are largely consistent with our inference.

Third, we find that markup deterioration over the sample periods has been more severe for exporters than non-exporters. The extent of markup deterioration is the largest for exporters with export intensity of less than 20%, which are relatively more productive, have a higher capital-labor ratio and, most importantly, pay higher wages than others. And while all of exporters had higher markups than non-exporters in a reference year, markup gaps between exporters and non-exporters are shown to be reduced over time. Furthermore, the markup levels for exporters that sell a significant portion of their products to foreign market become even lower than non-exporters after 3 years. These all indicate that, unlike the TFP case, the rankings of markup level substantially change over the 3-year span.

Generally speaking, our estimation results indicate that increased global competition seems to have reduced markup differentials among plants, but at the same time has contributed to productivity improvement. From a policy perspective, our finding that the higher export intensity does not induce higher productivity growth among exporters seems to be disappointing, but as a matter of fact it does not necessarily imply that trade benefits, such as learning-by-exporting are non-existent. It is highly plausible that export intensity at a given time could be a weak measure to capture such effects. For instance, using a cumulative intensity of exposure to foreign markets rather than export intensity at a given time, Lee & Choi (2009) finds a strong evidence of learning-by-exporting in the Korean manufacturing plants.

At the same time, one finding to which we need to pay special attention here is that exporters' internationalization costs seem to be significant and thus policy efforts to reduce such costs would be very important.

As illustrated in Fryges & Wagner (2007), the costs of coordination and control 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. Furthermore, the costs could begin to escalate when a critical value of the export sales ratio is exceeded, which results in the inverted U-shaped relationship between export intensity and TFP, as we found in this paper.

Descriptive statistics from our data indicate that exporters who have relatively higher export intensity are on average younger, smaller in size and less productive than those with lower intensity. In the existing literature such firm attributes are often shown to be critical factors for seemly higher exit rates of these firms out of export markets. Therefore, government support to help these firms to reduce internationalization costs would be invaluable, in order for them to continue to engage in international activities and to benefit from exporting.

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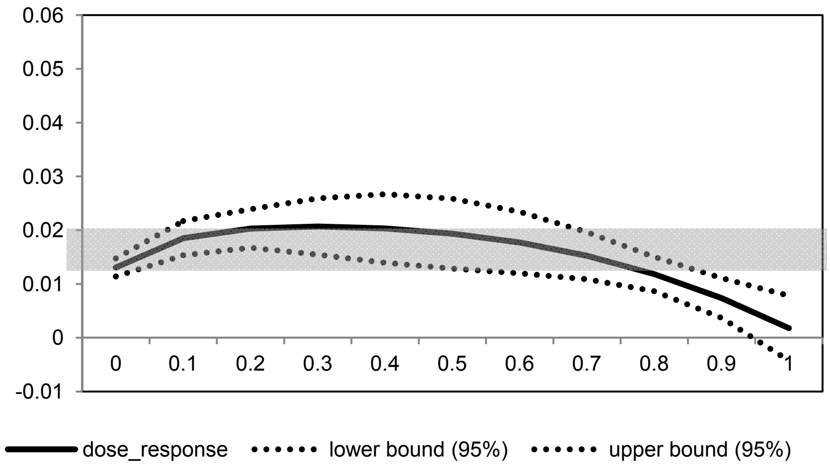
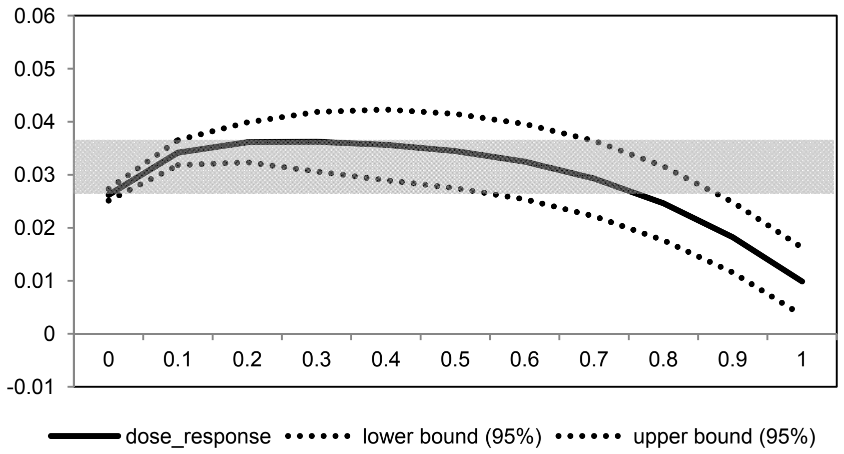
Appendix

Figure A.1: Dose Responses of TFP Growth (KSIC 2 digit classification applied)

a. TFP Growth after one year



b. TFP Growth after two years



c. TFP Growth after three years

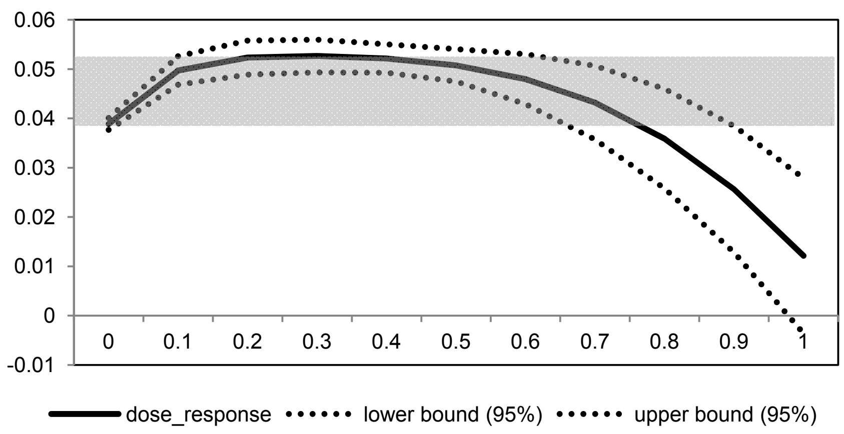
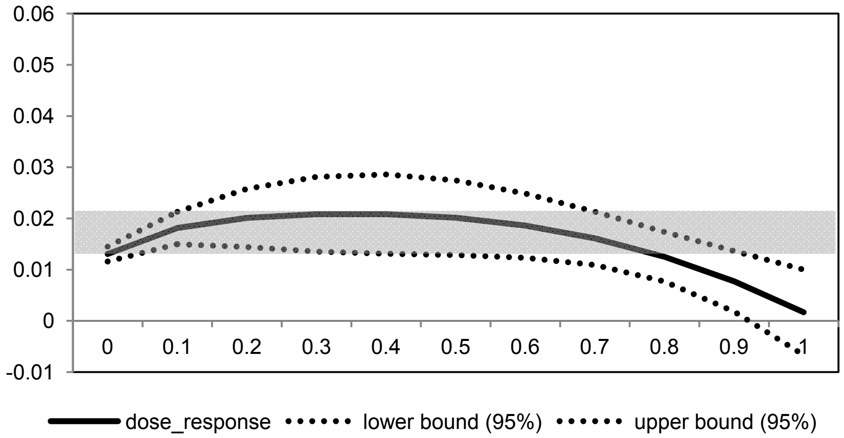
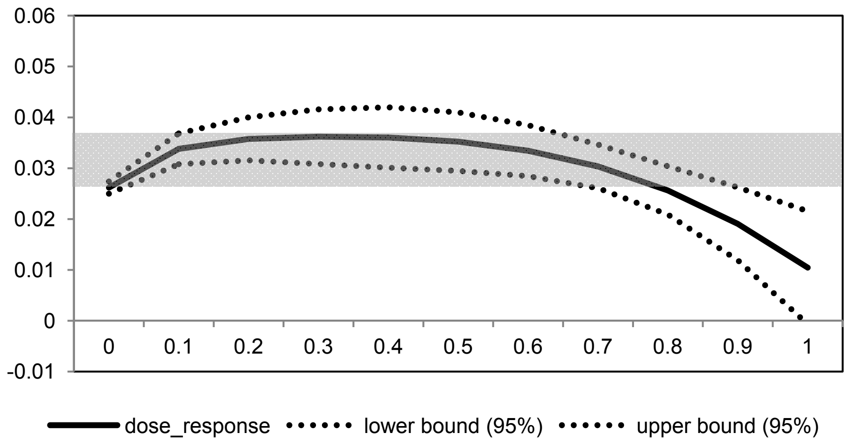


Figure A.2: Dose Responses of TFP Growth (KSIC 3 digit classification applied)

d. TFP Growth after one year



e. TFP Growth after two years



f. TFP Growth after three years

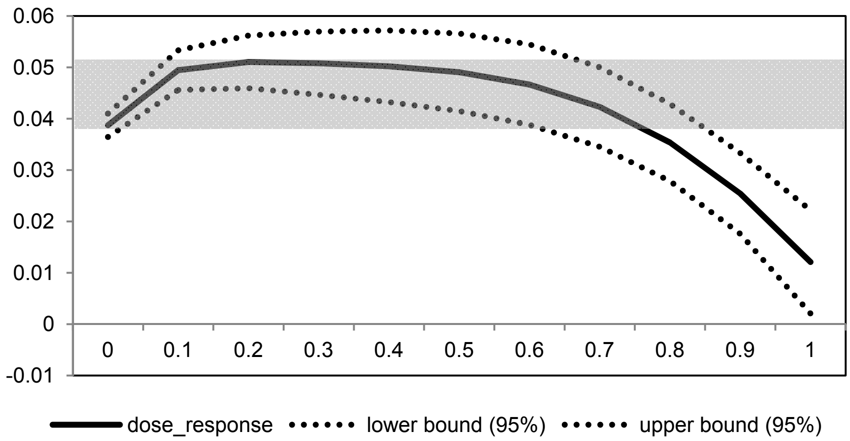
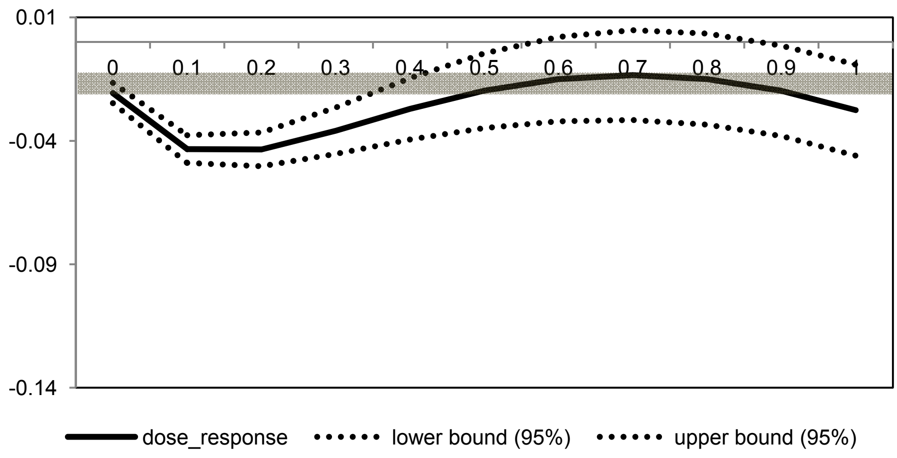
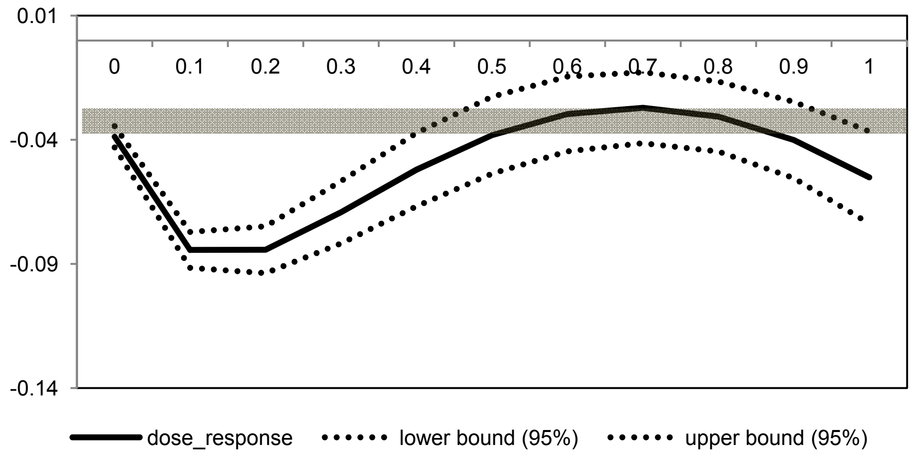


Figure A.3: Dose Responses of Markup Change (KSIC 2 digit classification applied)

a. Markup Changes after one year



b. Markup Changes after two years



c. Markup Changes after three years

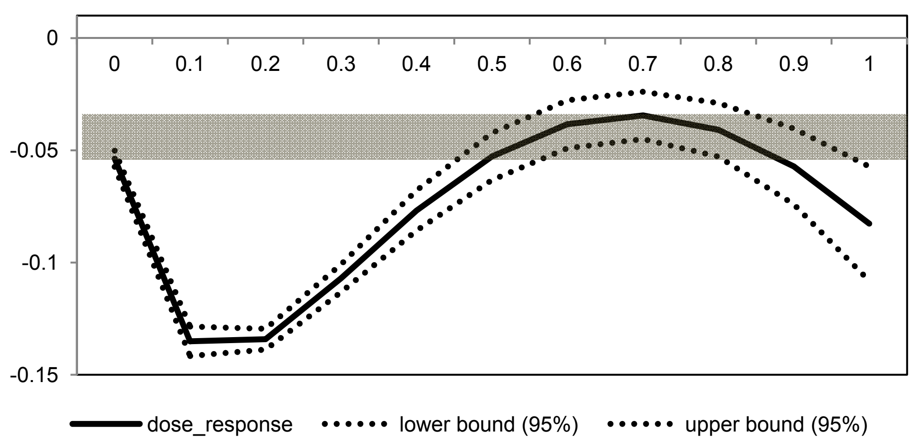
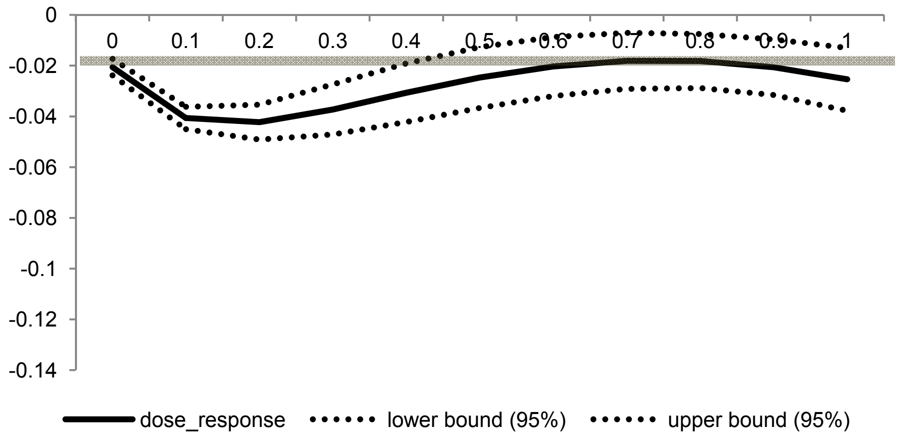
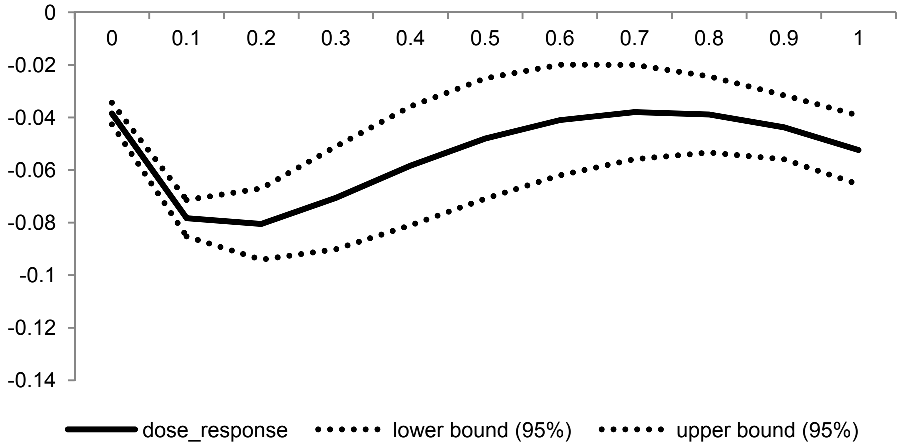


Figure A.4: Dose Responses of Markup Change (KSIC 3 digit classification applied)

d. Markup Changes after one year



e. Markup Changes after two years



f. Markup Changes after three years

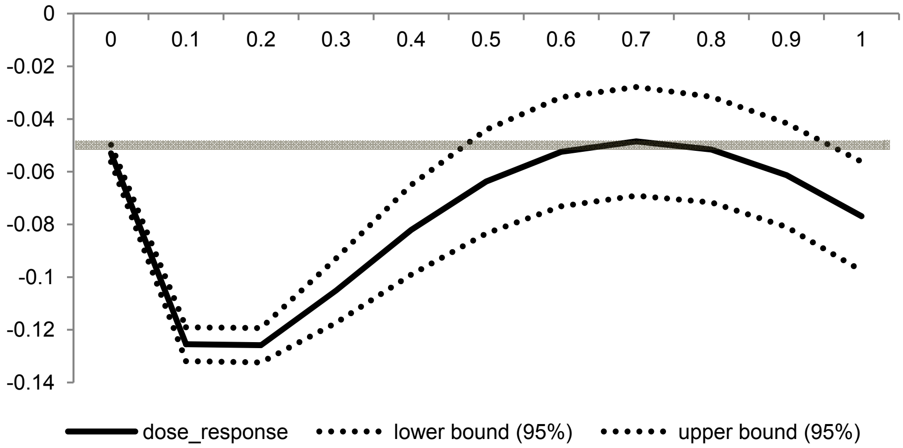


Table A.1: Fixed-effect Model Estimation Results (Exporters and Non-exporters)

	TFP growth			Markup change		
	one year	two years	three years	one years	two years	three years
Export intensity$_{t-1}$	0.017** (0.007)	0.024*** (0.007)	0.013* (0.007)	-0.012 (0.016)	-0.010 (.017)	-0.010 (0.017)
lnTFP$_{t-1}$	-0.916*** (0.004)	-1.035*** (0.004)	-1.047*** (0.004)	-0.865*** (0.010)	-0.945*** (0.010)	-0.959*** (0.010)
Markup $_{t-1}$	0.002** (0.001)	-0.000 (0.001)	0.001 (0.001)	-0.060*** (0.002)	-0.065*** (0.002)	-0.071*** (0.002)
Age$_{t-1}$	-0.037 (0.026)	-0.035 (0.027)	0.010 (0.027)	0.364*** (0.063)	0.168*** (0.065)	0.087 (0.066)
(Age$_{t-1}$)^2	0.050 (0.053)	0.089* (0.054)	-0.023 (0.055)	-0.595*** (0.126)	-0.247* (0.131)	-0.044 (0.136)
Size$_{t-1}$	0.055*** (0.002)	0.036*** (0.002)	0.022*** (0.002)	0.043*** (0.004)	0.069*** (0.004)	0.077*** (0.005)
Wage$_{t-1}$	0.003 (0.003)	0.003 (0.003)	0.008*** (0.003)	0.885*** (0.006)	0.898*** (0.007)	0.860*** (0.007)
NP share$_{t-1}$	-0.000 (0.001)	0.001 (0.001)	0.002 (0.001)	-0.002 (0.002)	0.003 (0.002)	0.004* (0.002)
K/L ratio$_{t-1}$	0.005*** (0.001)	0.006*** (0.001)	0.003*** (0.001)	-0.055*** (0.002)	-0.064*** (0.002)	-0.065*** (0.002)
R&D dummy$_{t-1}$	0.003 (0.002)	0.004** (0.002)	-0.001 (0.002)	0.009** (0.005)	0.002 (0.005)	-0.003 (0.005)
HHI$_{t-1}$	-0.049* (0.026)	0.004 (0.026)	0.037 (0.027)	-0.024 (0.062)	0.009 (0.064)	-0.121* (0.065)
(HHI$_{t-1}$)^2	0.131** (0.053)	-0.005 (0.054)	-0.101* (0.055)	-0.076 (0.126)	-0.087 (0.131)	0.313** (0.133)
Observations	117,635	117,635	117,635	117,635	117,635	117,635
R-Squares						
(within)	0.477	0.527	0.524	0.549	0.545	0.529
(between)	0.030	0.032	0.032	0.318	0.339	0.350
(overall)	0.042	0.041	0.038	0.301	0.321	0.332

Note: Year dummies and a constant term are not reported but included in the regression. The robust standard errors are in the parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% level, respectively.

Table A.2: Fixed-effect Model Estimation Results (Exporters Only)

	TFP growth			Markup change		
	one year	two years	three years	one years	two years	three years
Export intensity$_{t-1}$	0.003	0.013*	0.010	-0.004	0.009	0.015
	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.016)
lnTFP$_{t-1}$	-0.835***	-0.961***	-1.021***	-0.656***	-0.749***	-0.802***
	(0.011)	(0.011)	(0.011)	(0.022)	(0.023)	(0.023)
Markup$_{t-1}$	-0.004*	-0.005**	0.001	-0.119***	-0.137***	-0.140***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
Age$_{t-1}$	-0.116**	-0.057	0.039	0.152	0.063	0.064
	(0.055)	(0.057)	(0.057)	(0.114)	(0.120)	(0.118)
(Age$_{t-1}$)^2	0.174	0.126	-0.036	-0.310	-0.037	0.212
	(0.108)	(0.110)	(0.112)	(0.221)	(0.233)	(0.231)
Size$_{t-1}$	0.072***	0.045***	0.033***	0.038***	0.044***	0.048***
	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)
Wage$_{t-1}$	-0.006	-0.013	0.004	0.733***	0.735***	0.731***
	(0.008)	(0.008)	(0.008)	(0.016)	(0.017)	(0.016)
NP share$_{t-1}$	-0.003*	0.003	0.003	-0.009**	0.009**	0.005
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
K/L ratio$_{t-1}$	0.004*	0.008***	0.004	-0.041***	-0.058***	-0.071***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
R&D dummy$_{t-1}$	0.003	0.008**	-0.001	0.004	0.004	0.006
	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.007)
HHI$_{t-1}$	-0.066	-0.065	0.110*	-0.113	0.002	0.268**
	(0.060)	(0.061)	(0.062)	(0.123)	(0.129)	(0.128)
(HHI$_{t-1}$)^2	0.244*	0.082	-0.173	0.108	-0.033	-0.503*
	(0.128)	(0.131)	(0.133)	(0.264)	(0.278)	(0.275)
Observations	23,203	23,203	23,203	23,203	23,203	23,203
R-Squares						
(within)	0.432	0.491	0.503	0.495	0.505	0.517
(between)	0.016	0.020	0.019	0.205	0.231	0.258
(overall)	0.028	0.027	0.025	0.211	0.231	0.261

Note: Year dummies and a constant term are not reported but included in the regression. The robust standard errors are in the parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% level, respectively.