Global Competition, Technology Spillovers and Firm Dynamics: Evidence from Korean Micro-data

Preliminary and incomplete draft

Sanghoon Ahn

Hong Kong University of Science & Technology
and
Hitotsubashi University

Abstract

Competition has pervasive and long-lasting effects on economic performance by affecting economic actors' incentive structures, by encouraging their innovative activities, by stimulating technology spillovers, and by selecting more efficient firms from less efficient ones over time. A growing number of empirical studies using longitudinal micro-data confirm that firm dynamics (i.e., entry and exit, growth and decline of individual firms) is an important component of innovation and of aggregate productivity growth. The dynamism of Asian NIEs (Newly Industrializing Economies) revealed in their export-oriented growth paths has drawn substantial attention from researchers. But, empirical studies based on longitudinal micro-data in Asia are still rare, mainly due to the lack of readily available data. Based on the unpublished plant-level data underlying the *Annual Report on Mining and Manufacturing Survey of Korea* (1990-98), this study explores links between exporting and productivity. Main findings of the paper suggest that productivity gains associated with exporting tends to have strong industry-wide spillovers.

1. Introduction

[Under revision]

2. Theoretical and empirical background

2.1 Competition, firm dynamics and productivity growth

A theoretical framework for links between competition, firm dynamics and economic growth can be found in Schumpeterian "creative destruction" models of innovation.[1] When incumbents, which have already accumulated substantial experience with conventional technology, are less enthusiastic about taking risks of adopting new technology, new entrants aggressively experimenting with new technology can be a driving force for innovation. At the same time, competitive pressure from actual and/or potential entrants also forces incumbents to innovate themselves. If the innovation is successful, the innovators will be able replace the incumbents. If not, they will fail to survive. In this way, competition weeds out the unsuccessful firms and nurtures the successful ones.

Economic growth models based on the usual assumption of a representative producer/consumer have difficulties in explaining widely observed heterogeneity of producers (in size, age, technologies, productivity levels, etc.) even in a narrowly defined sector. Experimentation under uncertainty is an important source of micro-level heterogeneity and firm dynamics. Uncertainty about the demand for new products or the cost-effectiveness of alternative technologies encourages different firms to try different technologies, goods and production facilities. Experimentation by different firms generates differences in outcomes and competition drives firms to adjust themselves through learning about their environment and capabilities.[2]

1. See Schumpeter (1934), Nelson (1981), Aghion and Howitt (1992) and Cabellero and Hammour (1994, 1996), amongst others.

2. See Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995).

Main findings from existing empirical studies using longitudinal micro-data can be summarized roughly as follows. (1) There are large and persistent differences in productivity levels across producers even in the same industry. (2) Heterogeneity in technology use and in human capital is an important determinant of heterogeneity in firm-level productivity. And, (3) Aggregate productivity growth comes not only from within-firm productivity growth but also from firm dynamics, through which inputs and outputs are constantly reallocated from less efficient firms to more efficient ones.[3]

Results of comparative case studies of selected industries in the United States, Japan and Europe by Baily (1993) and by Baily and Gersbach (1995) suggest that competition (especially competition with best-practice producers in the global market) enhances productivity. Using micro-level panel data in the United Kingdom, Nickell (1996) and Disney *et al.* (2000) experimented with several indicators of competition in productivity regressions and concluded that competition has positive effects on productivity growth. Nickell (1996) found from a sample of 676 UK firms over the period 1975-86 that competition (measured by increased numbers of competitors or by lower levels of rents) was associated with higher productivity growth rates. From a more recent and much larger data set of around 143,000 UK establishments over the period 1980-1992, Disney *et al.* (2000) found that market competition significantly raised productivity levels as well as productivity growth rates.

Micro data also provide richer information on the effects of competition-promoting regulatory reform which is very likely to involve changes in firm dynamics. Olley and Pakes (1996) analysed the productivity dynamics in the telecommunications equipment industry in the United States using the unbalanced panel data for 1974-87 from the Longitudinal Research Database (LRD). They found that aggregate productivity increased sharply after each of the two periods in which the industry underwent changes that decreased regulation. Furthermore, the productivity growth that followed regulatory change appeared to result from a reallocation of capital from less productive plants to more productive ones rather than from an increase in average productivity. Their findings

3. For an overview of the literature on firm dynamics, see Caves (1998), Foster et al. (2001), Bartelsman and Doms (2000), and Ahn (2001, 2002).

suggest that competitive selection processes via entry and exit facilitated the reallocation of production factors.

2.2 International trade, competitive selection, and productivity

Positive contribution of increased import-competition to productivity growth has been detected in a number of studies. MacDonald (1994) analysed the US Bureau of Labour Statistics (BLS) data on labour productivity growth in manufacturing industries during 1972-87 and observed that increase in the import penetration ratio had a large and highly significant effect on the next three-year period's productivity growth in highly concentrated industries. Using the annual census data which cover all plants in the greater Istanbul area of Turkey from 1983 to 1986, Levinsohn (1993) demonstrated that the imports-as-market-discipline hypothesis was supported by the data spanning the course of a broad and dramatic import liberalisation of 1984. Bottasso and Sembenelli (2001) also found a jump in productivity growth rates of Italian firms in industries where non-tariff barriers were perceived to be high, after the announcement of the EU Single Market Programme which proposed 282 specific measures to reduce non-tariff trade barriers in the EU. Applying the methodology of Olley and Pakes (1996) for avoiding selection bias (induced by plant closings) and simultaneity bias (induced by firm dynamics) to the case of trade liberalization in Chile, Pavcnik (2002) finds that the productivity of in the import-competing sectors grew 3-10% more than in nontraded-goods sectors after trade liberalization.

An increasing volume of the evidence suggests that global competition can contribute to aggregate productivity growth by enforcing natural selection in the global market. Roberts and Tybout (1997) developed a model of exporting with sunk costs of entry. In the presence of such entry costs, only the relatively productive firms will choose to pay the costs and enter the foreign market. The implied relationship between exporting and productivity is positive in a cross-section of firms or industries, but the causality runs from productivity to exporting. In other words, exporting firms show higher productivity mainly because only firms with higher productivity can enter the export market and survive there. Empirical findings of Clerides *et al*. (1998) based on plant-level data from

Colombia, Mexico, and Morocco also supported the self-selection of the more efficient firms into the export market.

Using plant-level data from the Longitudinal Research Database (LRD) in the United States, Bernard and Jensen (1999*a*) examined whether exporting had played any role in increasing productivity growth in US manufacturing. They found little evidence that exporting per se was associated with faster productivity growth rates at individual plants. The positive correlation between exporting and productivity levels appears to come from the fact that high productivity plants are more likely to enter foreign markets, as is suggested by Roberts and Tybout (1997). While exporting does not appear to improve productivity growth rates at the plant level, it is strongly correlated with increases in plant size. Trade fosters the growth of high productivity plants, though not by increasing productivity growth at those plants.[4]

2.3 International trade and diffusion of technology

In growth theory, technological progress is typically conceived either as a "free good", as a by-product (externality) of other economic activities, or as the outcome of intentional R&D activities pursuing profit (Fagerberg, 1987). While technological progress is treated as exogenous in neo-classical growth models, endogenous growth models have emphasized the importance of R&D in the production of knowledge for understanding technological progress and long-run growth. There have been various attempts to identify different types of spillover related to R&D activity. Griliches (1980) identifies two positive forms of spillovers. First, the quality of a new intermediate good cannot be fully captured as monopoly rent to the innovator (unless they can exercise perfect price discrimination), thus providing a spillover effect from innovator to users of intermediate goods (namely, "rent spillovers"). Second, knowledge is sometimes freely borrowed from others. This type of spillovers (namely, "knowledge spillovers") increases with the technical relatedness and geographical closeness of firms. International trade can contribute to technology diffusion through imported intermediate goods embodying new

4. According to the results of a parallel study for Germany by Bernard and Wagner (1997), sunk costs for export entry appear to be higher in Germany than in the United States, but lower than in developing countries.

technology and/or through increased interactions between domestic and foreign firms in the global market of final products and production factors.

A number of researchers have attempted to measure to what extent knowledge spillovers are limited by international barriers. Some evidence suggests that technology diffusion is considerably faster within than between countries, implying that international barriers to knowledge spillovers may be quite large (see, for example; Eaton and Kortum,1999; Branstetter 2001; and Narin *et al*.,1997). Others have stressed that international R&D spillovers may nevertheless be important. Based a sample of OECD countries (plus Israel), Coe and Helpman (1995) find that both domestic and foreign R&D capital stocks have important effects on total factor productivity. Based on estimates of international spillovers from previous studies, Bayoumi *et al*. (1999) run simulations of a model of the world economy which consists of the G-7 countries plus five industrial and developing country regions. The results imply that a country can raise its productivity not only by investing in R&D and but also by trading with other countries that have large ‘stocks of knowledge’ accumulated from R&D activities.

According to a recent review of literature in Keller (2003), however, the evidence on the importance of trade for technology diffusion is still mixed. Even though some studies have shown that imports play a significant role, not much is known about the quantitative importance of this effect. The overall evidence on the role of exports for technology diffusion is even weaker than that for imports. Not finding strong econometric evidence for “learning-by-exporting” effects in the existing studies based on micro-data, Keller (2003) suspects that such puzzling results might be related with heterogeneity across industries or with heterogeneity across trading partners. We will delve into this issue in the following sections, trying to detect stronger evidence of real links between exports and technology spillovers.

2.4 International trade and productivity growth in East Asia

Potential causal links between trade openness and high growth in East Asian Newly Industrializing Economies (NIEs) have been pointed out by many researchers and supported by a number of empirical researches based on cross-country regressions.[5] Except for a series of studies on Taiwanese manufacturing by Aw, Roberts and their associates, however, few studies have looked into micro-data to shed light on productivity and firm dynamics in East Asian NIEs.

Aw *et al*. (2001) measured differences in total factor productivity among entering, exiting, and continuing firms in Taiwan, using longitudinal firm-level data from the Taiwanese Census of Manufactures for 1981, 1986, and 1991. They found that the contribution of productivity differential between entering and exiting firms to aggregate productivity growth was more pronounced in Taiwan than in other countries in previous studies. In a parallel study, Aw *et al*. (2000) examined and compared links between productivity and turnover in the exports market using the aforementioned Taiwanese data and comparable data from the *Korean Census of Manufactures* for 1983, 1988, and 1993. Interestingly, they found little evidence of links between plant productivity and export decision in Korea, while they found some significant evidence of selection and learning effects in case of Taiwan.

Since pioneering exploratory studies on firm dynamics in Korean manufacturing by Hahn (2000) and Joh (2000), Korean longitudinal micro-data still remain rather unexploited. In fact, longitudinal micro-data in Korea are as rich as any other data used in existing studies. While Aw *et al*. (2000) focused on the 'five-yearly' census data, the Korea National Statistical Office compiles the plant-level data 'annually' covering all the plants with no less than five employees (see the next section for further description of the data). Taking advantage of this higher frequency data, and using the methods of Bernard and Jensen (1999*a* and 1999*b*), Hahn (2003) detects evidence of self-selection and (short-lived) learning-by-exporting effects in the relations between exporting and plant-level productivity in Korea.

Findings in Hahn (2003) from the Korean data are in fact qualitatively same as those of Bernard and Jensen (1999*a* and 1999*b*) from the US data in the following

5. Among others, Lucas (), and Krueger () are good examples. For empirical findings supporting close links between trade and growth see Sachs and , , , (Ahn and Hemmings, 2000) . As a critical review on, see Rodrik and Rodriguez ? ().

aspects: (1) Significant and positive contemporaneous correlations are observed between levels of exports and productivity levels; (2) While exporting plants have substantially higher productivity levels and bigger size than non-exporting plants, evidence that exporting increases plant productivity growth rates is rather weak; and yet, (3) New exporters grow faster around the time when they enter the export market. According to Bernard and Jensen (1999*b*), these findings contain both good and bad news for long run economic growth. Exporting will contribute to aggregate productivity growth by facilitating the growth of high productivity plants. But, such reallocation effect would produce static rather than dynamic gains.[6] In other words, Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2003) appear to suggest that exporting cannot be an engine of sustained economic growth, either for an innovating technology leader like the US or for an imitating follower like Korea.

In fact, however, the degree and the channels of exports' contribution to technology spillovers and to productivity growth vary from industry to industry, and also from country to country, depending on economic and technological environment. For example, exporting grain from the US to China may well have little learning-by-exporting effects, while exporting cars from Korea to the US seems far more likely to generate some technology learning. As Keller (2003) underlines, "[a]ny attempts to explain the post-World War II performance of South Korea, for instance, without making reference to its success in transferring technology from the rest of the world is bound to fall short". Then, international technology diffusion (which is reflected in "the fact that a firm in one country employs technology that has been originally invented in another country") is expected to have played an important role at least in the case of export-oriented economic growth in East Asian NIEs, if not in the case of the US or of some Latin American countries. But, exiting empirical evidence from micro-data does not seem

6. Indeed, recent theoretical and empirical studies on gains from competition have been paying increasing attention to "productive efficiency" and "dynamic efficiency", which can be broadly defined in terms of productivity growth through innovations. In short, "productive (or, technical) efficiency" gains come from productivity-enhancing innovations which introduce new and better production methods, and successful innovations will eventually raise the level and growth rate of productivity in the long run (i.e., "dynamic efficiency" gains). See Ahn (2002) for a literature survey on dynamic efficiency gains from competition.

to support the widely-shared conjecture that technology spillovers through exporting has been a major source of persistent high growth in East Asian NIEs. This puzzle is the starting point for empirical exploration tried in this paper.

3. Testing spillovers of learning-by-exporting in Korean Manufacturing

Using the same dataset hired in Hahn (2000, 2003) and Joh (2000), this paper aims to explore another plausible channel through which exporting could have been making substantial and persistent contribution to export-oriented economic growth in East Asian NIEs: namely, spillovers (or externalities) of learning-by-exporting. Our claim is that the idea of spillovers of learning-by-exporting can provide an answer for the aforementioned puzzle and that the evidence from Korean micro-data supports the existence of spillovers of learning-by-exporting effects. This section explains the idea and tests hypotheses derived from the idea. Next section will discuss the policy implications as well as remaining research questions.

3.1 Spillovers of learning-by-exporting effects and aggregate productivity

A number of recent empirical studies have shown that there still exists considerable degree of geographic localization in knowledge spillovers.[7] Similarly, it is reported that international barriers in technology spillovers are substantially higher than intra-national barriers. At the same time, as was reviewed in the previous section, trade (importing and exporting) and foreign direct investment (FDI) are considered as vehicles for overcoming such international barriers and facilitating technology diffusion. In other words, generally speaking, technology diffusion tends to be considerably faster within than between countries. To move one step further from this, we can expect that technology spillovers from abroad in the form of learning-by-exporting will also spillover to other domestic producers in the same or adjacent industries rather quickly. This is what is meant by "spillovers of learning-by-exporting".

7. See, among others, Jaffee *et al*. (1993), Branstatter (), and Keller ().

If there are strong spillovers (or externalities) in the learning effects from exporting, then it will become quite difficult to detect any long-lasting advantages in productivity growth for a new exporter firm over other non-exporter firms in the same industry. Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2003) found that productivity gap between exporting firms and non-exporting firms in the same industry did not increase over time in their samples. And they interpreted this finding as evidence showing that learning-by-exporting effects are only short-lived. Such pattern, however, could arise not only when learning-by-exporting effects are short-lived but also when persistent learning-by-exporting effects are rapidly diffused to non-exporters in the same industry. Therefore, regression methods used in Bernard and Jensen (1999*a* and 1999*b*) and in Hahn (2003) are not powerful in testing the hypothesis of spillovers of learning-by-exporting.

If and when there exist large learning-by-exporting spillovers effects, inter-industry variance of productivity level will outweigh intra-industry variance. In addition, the gap between average productivity level in exporting industries and that in non-exporting industries will tend to increase. Based on this thought experiment, we can derive the first hypothesis as follows.

Hypothesis 1. *If learning-by-exporting effects have strong spillovers within industry, export-intensive industries will have substantially higher aggregate productivity level or higher aggregate productivity growth rate than other industries with low export-intensity do.*

We will be able to consider this simple hypothesis in a casual way in Section 3.3. But, it is not possible to derive objective criteria for rejecting or accepting the hypothesis. Moreover, even when export-intensive industries would turn out to have higher productivity level or higher productivity growth seemly supporting the hypothesis, one cannot say whether it is due to exporting itself or due to some other missing factor(s). To overcome such problems, we need to derive a formal statistical hypothesis which can be tested based on multiple regression analysis.

3.2 Deriving testable hypothesis from productivity regression

More refined way of testing our hypotheses can be derived from well-specified regression equations for firm-level productivity. If there are no R&D spillovers, for example, other firms' R&D expenditures will be irrelevant in explaining an individual firm's productivity. On the other hand, if there exist strong R&D spillovers at industry-level, a variable reflecting the industry-wide R&D expenditures will have significant and positive coefficient in the regression for firm-level productivity. In a more sophisticated approach, one can create an indicator for the size of the source (or pool) of spillovers by giving different weights (reflecting geographic and/or technical proximity) to external R&D expenditures. In the same spirit, we can test industry-wide spillovers of learning-by-exporting by looking at the estimated coefficient for industry-level export intensity in the following way.

Hypotheses 2. *If knowledge/technology coming from learning-by-exporting is quickly diffused to other firms in the same industry, i.e., if such learning-by-exporting has strong externalities at industry-level, then industry-level export intensity will have a significantly positive estimated coefficient in firm-level productivity regressions (in addition to firm-level export intensity) after controlling for other relevant variables which affect firm-level productivity.*

Just as geographic and/or technical distances are considered for giving different weights to different sources to R&D spillovers, we could try using more sophisticated measures for sources of learning-by-exporting spillovers. In this exploratory paper, we will stick to one of relatively crude measures, i.e., industry-level export intensity. As will be shown in the following sections, however, even such crude measure gives us quite strong evidence of the existence of learning-by-exporting spillovers. As a robustness check, we will compare a variety of regressions and show that our basic findings of learning-by-exporting spillovers are robust across a broad set of specification.

3.3 Data analysis for Hypothesis 1

The empirical part of this paper is based on the unpublished plant-level data underlying the *Annual Report on Mining and Manufacturing Survey* by the Korea National Statistical Office. The *Survey* covers all plants with five or more employees in mining and manufacturing industries and contains information on outputs and inputs that are necessary to calculate plant-level total factor productivity. Plant codes are consistently followed over time so that it is possible to identify which plants first appeared in the data set and which plants disappeared. In addition, the industry code for each plant allows us to identify which plants moved to another industry. The National Statistical Office also conducts a census on all plants every five years, but they utilize an entirely different plant coding system to those plants with less than five employees. Therefore, this study will focus on plants with no less than five employees, as previous studies such as Dunne *et al*. (1989, US), Joh (2000, Korea) and Hahn (2000, 2003, Korea) did. Especially, the data used in this paper is a subset of the above data over 1990-98 period and exactly same data used in Hahn (2000, 2003).

Following Aw *et al*. (2001) and Hahn (2000, 2003), plant-level total factor productivity (TFP) is estimated by the chained-multilateral index number approach as developed by Good *et al*. (1996). It uses a separate reference point for each cross-section of observations and then chain-links the reference points together over time as in Tornqvist-Theil index. The reference point for a given time period is constructed as a hypothetical firm with input shares that equal the arithmetic mean input shares and input levels that equal the geometric mean of the inputs over all cross-section observations. Thus, the output, inputs, and productivity level of each firm in each year is measured relative to the hypothetical firm at the base time period. This approach allows us to make transitive comparisons of productivity levels among observations in a panel data set. The productivity index for firm *i* at time *t* is measured in the following way.

$$\begin{aligned}\ln TFP_{it} &= (\ln Y_{it} - \overline{\ln Y_t}) + \sum_{\tau=2}^{t} (\overline{\ln Y_\tau} - \overline{\ln Y_{\tau-1}}) \\ &- \Big\{ \sum_{n=1}^{N} \frac{1}{2}(S_{nit} + \overline{S_{nt}})(\ln X_{nit} - \overline{\ln X_{nt}}) + \sum_{\tau=2}^{t} \sum_{n=1}^{N} \frac{1}{2}(\overline{S_{n\tau}} + \overline{S_{n\tau-1}})(\overline{\ln X_{n\tau}} - \overline{\ln X_{n\tau-1}}) \Big\},\end{aligned}$$

where Y, X, S, and TFP denote output, input, input share, TFP level respectively, and symbols with upper bar are corresponding measures for hypothetical firms. The subscripts τ and n are indices for time and inputs, respectively. In this case, the change in a plant's TFP level (i.e., productivity when all production factor inputs are controlled for) over time can be decomposed into two parts: (1) the change in a plant's TFP relative to that of the industry's representative plant and (2) the change in TFP for the industry.

Table 1 provides summary statistics for the dataset during the period of 1990-98. Table 2 shows total numbers of plants, number of exporters, and export intensities in each year. Only around 11-15% of the total plants are exporting each year. But, the ratio of exports to shipments ranges around 35-50%, suggesting that exports are typically bigger than non-exporters. As the comparison of exporters and non-exporters in Table 3 shows, on average, exporting plants are bigger, more capital intensive, hiring more non-production workers, paying higher wages, and having higher labor productivity and higher total factor productivity.

As documented in Clerides *et al.* (1998) for Columbia, Mexico, and Morocco, in Bernard and Jensen (1999*a* and 1999*b*) for the US and in Hahn (2003) for Korea, micro-data evidences suggest that more productive firms enter exporting markets (selection effects) rather than that exporting makes firms more productive (learning effects). Moreover, somewhat weak evidences of learning effects reported in Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2003) also suggest that such learning effects are only transient. Even without strong learning effects, selection effects coming from global competition could make substantial contribution to aggregate productivity growth in the form of static efficiency gains. Previous studies, however, do not seem to have paid enough attention to heterogeneity across industries, not any more than trying to purge potential industry fixed effects in their regressions. Table 4 reveals great heterogeneity across industries in terms of their export intensity, which was hidden behind Table 2. Table 4 also shows that the number of exporting plants could be relatively small even in high-export-intensity industries.

Table 5 shows a reasonable support for the existence of learning-by-exporting spillovers presented in Hypothesis 1. Decomposition of productivity growth in Table 5 follows the method in Olley and Pakes (1996). The weighted aggregate productivity measure can be decomposed into two parts: (1) The unweighted aggregate productivity measure; and (2) the total covariance between a plant's share of the industry output and its productivity. In this decomposition, positive covariance means that more output is produced by the more productive plants (allocative efficiency). Industries on the left column are high export-intensity industries and those on the left column are low (less than 10%) export-intensity industries. In moderately export-intensive industries such as textiles (38.5%) and apparel (25.9%), the weighted aggregate productivity growth is moderately high and the covariance term shows improvement in allocative efficiency. In strongly export-intensive industries such as computers (45.6%), electronic parts (54.3%), and other transportation equipments (55.3%), the weighted aggregate productivity growth is very strong even with deterioration in allocative efficiency. In case of low export-intensity industries such as food (6.4%), tobacco (0.6%), wood (5.3%), publishing (1.7%), and non-metallic (7.0%), the weighted aggregate productivity growth is typically stagnant or even negative. At the same time, allocative efficiency is also deteriorating. As an exceptional case, recycling industry also has low export intensity (5.8%) but shows strong productivity growth along with improvement in allocative efficiency.

Findings in this subsection can be summarized in the following three points. First, exporting plants are a small portion of an industry and, when they are compared with non-exporting plants, they have distinct features such as bigger size, higher wages, higher capital intensity, higher productivity, etc. Interestingly, according to Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2003), the average productivity gap between consistent exporters and consistent non-exporters is not widening over time. It is very likely due to some sort of spillover effects. Second, export intensity (the share of exports in output) varies substantially from industry to industry. Third, industries with higher export-intensity tend to show faster productivity growth. These findings seem to be consistent with the conjecture that technology/knowledge spillovers coming from abroad through learning-by-exporting tend to spread to other domestic producers in the same industry faster than to those in other industries. To provide more objective evidence, we should do regression analysis for statistical hypothesis testing. It will be done in the next sub-session.

3.4 Data analysis for Hypothesis 2

Starting from an unbalanced panel data for all manufacturing plants with employees no less than 5 over the 9-year period from 1990 to 1998, we ran pooled regressions with year dummies and industry dummies. Dependent variable is plant-level productivity calculated with the aforementioned method of the chained-multilateral index number approach. What are the major determinants of plant-level productivity? First of all, plant-level productivity could be affected by macroeconomic conditions. Such effects of business cycle on productivity are controlled for by year dummies. Substantial part of plant-level productivity will also rely on technological environment which vary from industry to industry. Industry dummies will control for such industry fixed effects. It is well known that plant size can be an important factor which affects plant-level productivity through static and/or dynamic economies of scale. Capital-labor ratio is known as one of major factors affecting labor productivity, but it will be less relevant for explaining total factor productivity. If the level of technology is one of determinants of plant-productivity, some indicator of R&D will be a good explanatory variable. Based on the conjecture that more advanced plant/firm would hire more non-production workers, one can put the portion of non-production workers into the regression equation. Finally, we are interested to know whether exporting at the plant- and/or industry-level makes positive contribution to plant-productivity. All those factors were considered in our regression exercise.

Table 6.1 and 6.2 contain main results of our regression exercise. The total number of plant-year matches over the period 1990-1998 was 749,363. As our R&D data start only from 1991, the total number of observations for R&D included regressions was 681,736. To test Hypothesis 2, we should check whether the coefficient for industry-level export intensity (B) has a significantly positive sign. To tell the conclusion first, the null hypothesis that industry-level export intensity has no effects on plant-level productivity is always rejected at the 99% significance level. In case of the Korean manufacturing in the

1990s, micro-data suggest that there were significant industry-wide spillovers in productivity gains from exporting.

Column I of Table 6.1 started with a most generic case, where plant-level total factor productivity was regressed on plant-level export intensity, industry-level export intensity, and year and industry dummy variables. Interestingly, even though both plant-level export intensity and industry-level export intensity have the correct sign with statistical significance, the industry-level export intensity turned out to have much larger coefficient. Moreover, this basic pattern remains stable across different specifications. In Column II of Table 6.1, size variable (natural log of number of workers) was added to control for scale effects. Indeed, the regression results suggest the existence of economies of scale, but adding the size variable does not affect our basic findings.[8]

As revealed in Table 2, more than 80% of plants in our sample are non-exporters. Column III and Column IV of Table 6.1 separate them out using a dummy variable for no exporting. In addition, we have added the share of non-production workers both at plant level and at industry level. Estimated coefficients for all the three added variables show correct signs, while coefficients for plan-level and industry-level export intensities remain stable.

R&D intensities at the plant level and at the industry level are added to the regression equations as extra explanatory variables in Column V through Column X. Both plant-level and industry-level R&D intensities were put into the regression equations along with plant-level and industry-level export intensities, so that we can compare spillovers in exporting and in R&D in a symmetric way. There is a long literature of empirical studies measuring the size of R&D spillovers.[9] Coefficients for industry-level R&D intensity in Column V through Column X persistently show big R&D spillovers. More intriguingly, however, coefficients for plant-level R&D intensity

8. The same pattern of positive size effects persists across different specifications in Columns IV, VI, VIII, and X, without weakening our basic findings on spillovers of productivity gains from exporting.

9. To be added.

are persistently negative. This strange pattern certainly requires further and deeper analysis. At this stage, I suspect that it might be related with learning costs in technology upgrading in technology-followers. For producers who are distant from technology frontier, R&D expenditures are made typically when they try to adopt a new (but not frontier) technology from technology leaders. Discarding old and familiar technology and adopting a new technology often requires both tangible and intangible costs and could have temporary negative effects on productivity at the initial stage of upgrading.[10]

Column V and Column VI of Table 6.1 have all of export intensities, R&D intensities, and non-production worker shares altogether in the same format of plant-level and industry-level juxtaposition. It seems noteworthy that the coefficients for plant-level and industry-level shares of non-production workers are similar in the order of magnitude, while industry-level coefficients are much bigger than plant-level ones for R&D intensities and for export intensities. A casual conjecture suggests that such difference reflects that spillover effects are not as much important in labor composition as in R&D or in learning-by-exporting.

Remaining four columns focus on comparing contributions of export intensities and export intensities. Column VII and Column VIII are based on dummy variables for no-export and no-R&D plants, while Column XI and Column X are based on interaction terms for plant-effect and industry effect. It is shown that plants without exporting or without R&D activities tend to have significantly low productivity level. Positive contribution of an individual plant's exporting activity to productivity level tends to be stronger when it belongs to more export-intensive industry. However, such positive interaction is not observed in case of R&D.

All in all, the following patterns are persistently observed across different specifications. First, export intensities, both at the plant level and at the industry level, have positive and significant coefficients in explaining plant-level total productivity level. Second, the coefficients for industry-level export intensity are around 5-7 times bigger than those for plant-level export intensity. Third, coefficients for import intensity

10. See Ahn (2003) and references there for further discussion on technology upgrading with learning cost.

do not change very much regardless of inclusion/inclusion of size, R&D intensity, non-production workers' share both at the plant-level and at the industry-level. In Table 6.1, industry was defined at SIC 2-digit level and industry-level variables and industry dummy variables were calculated for each of 23 industries in manufacturing sector. Finally, as another robustness check, more detailed industry definition could be used at SIC 3-digit level. Table 6.2 reports results of regressions with industry-level variables and industry dummy variables calculated for each of 61 industries at 3-digit level. The findings from Table 6.1 do not change here. Perhaps the only notable difference is that, at the 3-digit level, non-production workers' share has bigger coefficients at the plant level that at the industry level.

4. Summary of findings and policy implications

[Under revision]

References

Aghion, P and P. Howitt (1992), "A Model of Growth through Creative Destruction", *Econometrica*, Vol.60, pp.323-5.

Ahn, S. (2001), "Firm Dynamics and Productivity Growth: A Review of Evidence from OECD Countries", *OECD Economics Department Working Papers* No. 297.

Ahn, S. (2002), "Competition, Innovation and Productivity Growth: A Review of Theory and Evidence", *OECD Economics Department Working Papers* No.317.

Ahn, S. and P. Hemmings (2000), "Policy influences on economic growth in OECD countries: An evaluation of the evidence", *OECD Economics Department Working Papers* No. 246.

Aw, B.Y., S. Chung, and M.J. Roberts (2000), "Productivity and Turnover in the Export Market: Micro Evidence from Taiwan and South Korea", *The World Bank Economic Review*, 14, pp. 65-90.

Aw, B.Y., X. Chen, and M.J. Roberts (2001), "Firm-Level Evidence on Productivity Differentials, Turnover, and Exports in Taiwanese Manufacturing", *Journal of Development Economics*, 66 (October 2001), pp.51-86.

Baily, M.N. (1993), "Competition, Regulation, and Efficiency in Service Industries", *Brookings Papers on Economics Activity: Microeconomics*, pp. 71-130.

Baily, M.N. and H. Gersbach (1995), "Efficiency in Manufacturing and the Need for Global Competition", *Brookings Papers on Economic Activity: Microeconomics*, pp. 307-358.

Bartelsman, E.J. and M. Doms (2000), "Understanding Productivity: Lessons from Longitudinal Micro Datasets*", Journal of Economic Literature*, Vol. 38, September.

Bayoumi, T., D.T. Coe, and E. Helpman (1999), "R&D Spillovers and Global Growth", *Journal of International Economics*, 47, pp. 399-428.

Bernard, A. and J.B. Jensen (1999*a*), "Exceptional Exporter Performance: Cause, Effects or Both", *Journal of International Economics*, 47, pp.1-25.

Bernard, A. and J.B. Jensen (1999*b*), "Exporting and Productivity", *National Bureau of Economic Research Working Paper Series*, No.7135.

Bernard, A. and J. Wagner (1997), "Exports and success in German manufacturing", *Weltwirtschaftliches Archiv*, Vol. 133, No. 1, pp. 134-57.

Blomström, M. and A. Kokko, (1996), "The Impact of Foreign Investment on Host Countries: A Review of the Empirical Evidence," *mimeo*.

Blomström, M. and A. Kokko, (1998), "Multinational Corporations and Spillovers," *Journal of Economic Surveys*, 12(3), pp.247-77.

Bottasso, A. and A. Sembenelli (2001), "Market power, productivity and the EU single market program: evidence from a panel of Italian firms", *European Economic Review*, 45(1), pp.167-86.

Branstetter, L. (2001), "Are Knowledge Spillover Intranational or International in Scope? Microeconomic Evidence from US and Japan", *Journal of International Economics*, 53, pp.53-79.

Caballero R.J. and M.L. Hammour (1994), "The Cleansing Effect of Creative Destruction", *American Economic Review*, 84(5), pp. 1350-68.

Caballero R.J. and M.L. Hammour (1996), "On the Timing and Efficiency of Creative Destruction", *Quarterly Journal of Economics*, 111, pp. 1350-68.

Caves, R.E. (1998), "Industrial Organization and New Findings on the Turnover and Mobility of Firms", *Journal of Economic Literature*, Vol. 36:4, pp. 1947-82.

Clerides, S.K., S. Lach and J.R. Tybout (1998), "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico and Morocco", *Quarterly Journal of Economics*, August, pp.903-47.

Coe, D.T. and E. Helpman (1995), "International R&D spillovers", *European Economic Review*, 39, pp. 859-87.

Disney, R., J. Haskel and Y. Heden (2000), "Restructuring and Productivity Growth in UK Manufacturing", CEPR Discussion Paper, No. 2463, May.

Eaton, J. And S. Kortum (1999), "International Patenting and Technology Diffusion: Theory and Measurement", *International Economic Review*, 40, pp.537-70.

Ericson, R. and A. Pakes (1995), "Markov Perfect Industry Dynamics: A Framework for Empirical Analysis", *Review Of Economic Studies*, Vol. 62, No. 1, pp. 53-82.

Fargerberg, J. (1987), "A technology gap approach to why growth rates differ," *Research Policy*, 16(2-4), pp. 87-99, August.

Foster, L., J.C. Haltiwanger and C.J. Krizan (2001), "Aggregate Productivity Growth: Lessons from Microeconomic Evidence", in E. Dean, M. Harper, and C. Hulten (eds.), *New Contributions to Productivity Analysis*, University of Chicago Press.

Geroski, P.A. (1989), "Entry, innovation and productivity growth", *Review of Economics and Statistics*, 71, pp. 572-578.

Griliches, Z. (1980), "Returns to research and development expenditures in the private sector," in *New Development in Productivity Measurement and Analysis*, J. Kendrick and B. Vaccara (eds) University of Chicago Press, Chicago, pp. 419-454.

Hahn, C.-H. (2000), "Entry, Exit, and Aggregate Productivity Growth: Micro Evidence on Korean Manufacturing", *OECD Economics Department Working Paper* No. 272, OECD, Paris.

Hahn, C.-H. (2000), "Entry, Exit, and Aggregate Productivity Growth: Micro Evidence on Korean Manufacturing", *OECD Economics Department Working Paper* No. 272, OECD, Paris.

Hahn, C.-H. (2003),

Hopenhayn, H.A. (1992), "Entry, exit, and firm dynamics in long run equilibrium", *Econometrica*, Vol. 60, No. 5, pp. 1127-1150.

Joh, S. W. (2000), "Micro-Dynamics of Industrial Competition: Evidence from Korean Manufacturing Plants", *Korea Development Institute Policy Study*, Policy Study Series 2000-05.

Jovanovic, B. (1982), "Selection and the Evolution of Industry", *Econometrica*, Vol. 50, No. 3, May, pp.649-70.

Keller, W. (2003), "International Technology Diffusion," *Journal of Economic Literature*, forthcoming.

Klette, T.J., J. Moen, Dnd Z. Griliches (1999), "Do subsidies to commercial R&D reduce market failures? Microeconomic evaluation studies", *NBER Working Paper*, No. 6947.

Levinsohn, J. (1993), "Testing the imports-as-market-discipline hypothesis", *Journal of International Economics*, 35(1-2), pp. 1-22.

MacDonald, J. M. (1994), "Does import competition force efficient production?" *Review of Economics and Statistics*, 76(4), pp.721-27.

Nelson, R.R. (1981), "Research on Productivity Growth and Productivity Differences: Dead Ends and New Departures", *Journal of Economic Literature*, Vol. XIX, pp. 1029-1064.

Nickell, S.J. (1996), "Competition and Corporate Performance", *Journal of Political Economy*, Vol. 104, No. 4, pp. 724-46.

Olley, G.T. and A. Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, Vol. 64(6), pp. 1263-1297.

Pavcnik, N. (2002), "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants", *Review of Economic Studies*, Vol. 69, pp. 245-276.

Roberts, M.J. and J.R. Tybout (1997), "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs", *American Economic Review*, Vol. 87, No. 4, September, pp. 545-64.

Schumpeter, J. A. (1934), *The Theory of Economic Development*, Harvard University Press, Cambridge.

Smarzynska, B. K. (2002), "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages", World Bank Policy Research Working Paper, No. 2923.

Stiglitz, J.E. (1999), "Knowledge in the modern economy", conference paper presented at *The Economics of the Knowledge Driven Economy* organised by DTI and CEPR, London, 27 January.

Table 1. Descriptive Statistics (1990-1998)

Variable	Unweighted Average	Std. Dev.	Number of observations
Production	3672.1	61089.3	758,987
Workers	33.4	225.1	760,832
Production workers	23.8	157.9	760,832
Non-production workers	8.7	77.8	760,832
Capital	1849.9	36049.1	760,832
Materials	2597.7	44666.3	758,987
Export	942.9	28022.7	760,832
R&D	53.2	2820.5	692,142

Table 2. Number of Exporters and Export Intensity

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

Hahn (2003)

Table 3. Comparison of Exporters and Non-exporters

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

Hahn (2003)

Table 4. Number of Exporting Plants and Export Intensity by Industry

Industry	1990 Number of Plants	1990 Number of Exporting Plant	1994 Number of Plants	1994 Number of Exporting Plants	1998 Number of Plants	1998 Number of Exporting Plants	1990-1998 Export Intensity
Food and Beverages	4,638	767	5,858	717	5,824	763	**6.4%**
Tobacco	20	8	16	7	14	5	**0.6%**
Textiles	7,621	1,368	9,838	1,557	8,103	1,485	**38.5%**
Apparel	6,607	816	8,460	604	6,781	462	**25.9%**
Leather, Luggage and Footwear	3,038	776	3,085	652	2,284	521	**51.8%**
Wood	2,050	137	2,505	105	1,677	81	**5.3%**
Pulp and Paper	2,128	219	2,600	251	2,300	257	**10.3%**
Publishing	2,900	73	4,366	47	3,962	30	**1.7%**
Coke, Petroleum and Nuclear Fuel	70	25	76	30	55	30	**17.0%**
Chemicals	1,804	466	2,644	657	2,694	802	**28.5%**
Rubber and Plastic	4,365	609	5,416	666	5,139	875	**22.4%**
Non-metallic Mineral Products	3,764	459	4,657	404	3,378	294	**7.0%**

Basic Metals	1,821	342	1,921	343	1,908	484	**22.0%**
Fabricated Metal Products	4,955	518	8,790	646	8,038	739	**11.4%**
Other Machinery	7,858	834	11,582	1,249	10,251	1,668	**13.7%**
Computers and Office Machinery	302	69	599	92	571	119	**45.6%**
Electrical Machinery	2,590	437	4,043	574	3,811	661	**19.3%**
Electronic Components, Communication Equipment, etc.	3,208	755	3,434	754	2,829	754	**54.3%**
Medical, Precision, and Optical Instruments	1,104	282	1,801	400	1,779	498	**27.1%**
Motor Vehicles and Trailers	2,138	270	2,815	297	2,604	357	**24.0%**
Other Transportion Equipment	538	46	808	72	936	95	**55.3%**
Furniture	5,103	1,021	5,896	920	4,311	769	**22.6%**
Recycling	68	1	162	9	295	28	**5.8%**
Total	**68,690**	**10,298**	**91,372**	**11,053**	**79,544**	**11,777**	

Table 5. Decomposition of Aggregate Productivity Growth in Selected Industries

Industry	Year	Aggregate Productivity	Unweighted Productivity	Covariance	Industry	Year	Aggregate Productivity	Unweighted Productivity	Covariance
Textiles	1990	0.000	0.000	0.000	Food	1990	0.000	0.000	0.000
	1991	0.058	0.048	0.009		1991	0.130	0.056	0.074
	1992	0.119	0.094	0.025		1992	0.131	0.059	0.072
	1993	0.183	0.170	0.013		1993	0.110	0.092	0.018
	1994	0.194	0.188	0.005		1994	0.152	0.141	0.011
	1995	0.224	0.220	0.005		1995	0.186	0.196	-0.009
	1996	0.248	0.240	0.008		1996	0.160	0.184	-0.023
	1997	0.313	0.277	0.036		1997	0.173	0.176	-0.002
	1998	0.365	0.282	0.082		1998	0.133	0.150	-0.017
Apparel	1990	0.000	0.000	0.000	Tobacco	1990	0.000	0.000	0.000
	1991	0.022	0.006	0.015		1991	0.096	0.113	-0.016
	1992	0.132	0.060	0.072		1992	0.047	0.208	-0.161
	1993	0.129	0.060	0.069		1993	-0.044	0.368	-0.412
	1994	0.179	0.101	0.078		1994	-0.159	0.312	-0.471
	1995	0.203	0.150	0.053		1995	0.058	0.510	-0.453
	1996	0.272	0.173	0.099		1996	0.092	0.319	-0.227
	1997	0.218	0.112	0.105		1997	-0.026	0.355	-0.381
	1998	0.264	0.075	0.189		1998	-0.059	0.354	-0.413
Computers and Office Machinery	1990	0.000	0.000	0.000	Wood	1990	0.000	0.000	0.000
	1991	0.040	0.126	-0.085		1991	0.139	0.086	0.053
	1992	0.041	0.206	-0.165		1992	0.089	0.086	0.003
	1993	0.144	0.330	-0.186		1993	-0.205	-0.177	-0.028
	1994	0.307	0.477	-0.170		1994	-0.105	-0.085	-0.020
	1995	0.514	0.724	-0.211		1995	-0.038	-0.002	-0.036
	1996	0.738	0.810	-0.072		1996	0.011	0.044	-0.033
	1997	0.635	0.865	-0.230		1997	0.000	0.017	-0.017
	1998	0.818	0.945	-0.127		1998	0.000	0.019	-0.019
Electronics	1990	0.000	0.000	0.000	Publishing	1990	0.000	0.000	0.000
	1991	0.089	0.110	-0.021		1991	-0.045	0.077	-0.122
	1992	0.114	0.160	-0.046		1992	-0.079	0.094	-0.173
	1993	0.202	0.247	-0.045		1993	-0.004	0.191	-0.195
	1994	0.376	0.345	0.031		1994	0.036	0.167	-0.132
	1995	0.594	0.462	0.132		1995	0.021	0.121	-0.100
	1996	0.637	0.525	0.112		1996	-0.013	0.067	-0.079
	1997	0.603	0.607	-0.005		1997	0.020	0.097	-0.076
	1998	0.715	0.724	-0.010		1998	-0.008	0.043	-0.051

Other Transport Equipments	1990	0.000	0.000	0.000	Non-Metallic	1990	0.000	0.000	0.000
	1991	0.169	0.250	-0.080		1991	0.067	-0.010	0.078
	1992	0.223	0.158	0.064		1992	-0.003	0.006	-0.008
	1993	0.083	0.235	-0.152		1993	0.056	0.068	-0.012
	1994	0.214	0.357	-0.142		1994	0.111	0.175	-0.064
	1995	0.297	0.475	-0.178		1995	0.214	0.254	-0.039
	1996	0.255	0.578	-0.323		1996	0.168	0.262	-0.094
	1997	0.322	0.618	-0.296		1997	0.193	0.282	-0.088
	1998	0.436	0.713	-0.277		1998	0.207	0.300	-0.093
All manu-facturing	1990	0.000	0.000	0.000	Recycling	1990	0.000	0.000	0.000
	1991	0.067	0.057	0.010		1991	-0.051	0.071	-0.122
	1992	0.089	0.074	0.015		1992	0.042	0.105	-0.064
	1993	0.108	0.126	-0.019		1993	0.298	0.174	0.123
	1994	0.170	0.182	-0.011		1994	0.387	0.190	0.197
	1995	0.250	0.236	0.014		1995	0.620	0.330	0.289
	1996	0.252	0.247	0.005		1996	0.617	0.310	0.307
	1997	0.259	0.253	0.006		1997	0.484	0.285	0.199
	1998	0.280	0.265	0.015		1998	0.497	0.336	0.162

Reported growth figures are relative to 1990.

Table 6.1 Plant-level Total Factor Productivity Regressions

	I	II	III	IV	V	VI	VII	VIII	IX	X
Plant-level export intensity (A)	0.0935	0.0745	0.0575	0.0604	0.0731	0.0694	0.0670	0.0733	0.0676	0.0530
	(45.12)	(34.9)	(18.05)	(18.89)	(32.98)	(30.63)	(19.67)	(21.46)	(15.01)	(11.71)
Industry-level export intensity (B)	0.4340	0.4258	0.4740	0.4716	0.3713	0.3697	0.3537	0.3475	0.3425	0.3366
	(40.35	(39.61)	(43.07)	(42.84)	(29.17)	(29.03)	(27.97)	(27.49)	(26.91)	(26.47)
Interaction term (A x B)									0.1104	0.1002
									(7.91)	(7.19)
No export dummy			-0.0095	-0.0029			-0.0228	-0.0062		
			(-4.73)	(-1.37)			(-10.71)	(-2.81)		
Plant-level R&D intensity (C)					-0.1098	-0.1100	-0.1134	-0.1098	-0.0769	-0.0787
					(-28.56)	(-28.6)	(-28.82)	(-27.91)	(-12.65)	(-12.96)
Industry-level R&D intensity (D)					1.1084	1.1070	1.3293	1.3303	1.3644	1.3603
					(8.82)	(8.81)	(10.71)	(10.73)	(10.99)	(10.96)
Interaction term (C x D)									-1.2506	-1.2399
									(-4.94)	(-4.91)
No R&D dummy							-0.0332	-0.0213		
							(-16.97)	(-10.61)		
Size		0.0173		0.0054		0.0040		0.0142		0.0161
		(36.72)		(10.6)		(7.82)		(26.42)		(32.38)
Plant-level non-production worker share			0.2131	0.2062	0.2159	0.2100				
			(88.6)	(82.73)	(87.17)	(81.16)				
Industry-level non-production worker share			0.5337	0.5376	0.3543	0.3565				
			(14.68)	(14.78)	(8.71)	(8.76)				
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	Yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	Yes
R-squared (adjusted)	0.1040	0.1056	0.1138	0.1140	0.1003	0.1004	0.0908	0.0917	0.0902	0.0916
Number of observations	749,363	749,363	749,363	749,363	681,736	681,736	681,736	681,736	681,736	681,736

Industry: KSIC 2-digit (In parenthesis is *t*-ratio)

Table 6.2 Plant-level Total Factor Productivity Regressions

	I	II	III	IV	V	VI	VII	VIII	IX	X
Plant-level export intensity (A)	0.0907	0.0711	0.0523	0.0556	0.0708	0.0659	0.0628	0.0687	0.0741	0.0583
	(43.31)	(32.95)	(16.36)	(17.33)	(31.58)	(28.75)	(18.42)	(20.12)	(16.35)	(12.79)
Industry-level export intensity (B)	0.3104	0.3028	0.3235	0.3205	0.2667	0.2650	0.2519	0.2467	0.2436	0.2388
	(31.63)	(30.88)	(32.29)	(31.99)	(22.9)	(22.76)	(22.00)	(27.49)	(21.11)	(20.71)
Interaction term (A x B)									0.0714	0.0641
									(5.52)	(4.96)
No export dummy			-0.0122	-0.0044			-0.0240	-0.0073		
			(-6.10)	(-2.09)			(-11.29)	(-3.30)		
Plant-level R&D intensity (C)					-0.1097	-0.1099	-0.1133	-0.1098	-0.0701	-0.0716
					(-28.66)	(-28.71)	(-28.98)	(-28.07)	(-12.05)	(-12.32)
Industry-level R&D intensity (D)					1.1509	1.1425	1.4224	1.4158	1.4944	1.4781
					(5.48)	(5.44)	(6.96)	(6.93)	(7.31)	(7.23)
Interaction term (C x D)									-4.3191	-4.3304
									(-6.99)	(-7.02)
No R&D dummy							-0.0318	-0.0199		
							(-16.3)	(-9.93)		
Size		0.0174		0.0065		0.0052		0.0143		0.0162
		(36.80)		(12.57)		(10.07)		(26.57)		(32.60)
Plant-level non-production worker share			0.1993	0.1909	0.2059	0.1981				
			(80.68)	(74.61)	(80.68)	(74.39)				
Industry-level non-production worker share			0.1315	0.1322	0.1671	0.1696				
			(5.20)	(5.23)	(5.06)	(5.14)				
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared (adjusted)	0.1137	0.1153	0.1218	0.1140	0.1092	0.1093	0.1013	0.1022	0.1008	0.1022
Number of observations	749,363	749,363	749,363	749,363	681,736	681,736	681,736	681,736	681,736	681,736

Industry: KSIC 3-digit (In parenthesis is *t*-ratio)