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Does Exporting Raise Productivity? Evidence from Korean Microdata

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ABSTRACT

Does competition enhance productivity growth of a developing economy? Is global competition conducive to economic development? Especially, does competition with more advanced producers in the global market promote productivity growth of domestic producers in a developing country? If the answer is a conditional yes, what makes global competition conducive to productivity growth and economic development?

Many researchers have been working to find a better answer to these, perhaps quite controversial, questions. The aim of this paper is to review recent empirical findings related to these questions, which have strong policy implications, and to offer some new evidence from Korean microdata.

The paper explores a plausible channel through which exporting could have made both a substantial and a persistent contribution to export-oriented economic growth in Korea and by extension other East Asian NIEs: namely, the spillovers (or externalities) of learning-by-exporting. Plant-level data for Korean manufacturing show that more export-intensive industries tend to have a higher productivity level. In addition, a substantial part of the variance in plant-level productivity is explained by the variance in industry-level export intensity.

These findings are consistent with the hypothesis that there exist spillovers of learning-by-exporting at least in some industries. As with the existence of the more usual intra-industry R&D spillovers, which are also demonstrated here, this raises the policy questions of how to get more benefits from such spillovers, whilst minimizing any side-effects from any policy intervention.

As in the case of other types of positive externalities, in theory a market solution will lead to a sub-optimal level of externality-generating output (in this case exports), indicating that government action could improve upon the market outcome. This is the implicit logic behind the active role played by the Japanese government or by the Korean government at earlier stages of their economic development. (Needless to say, however, the existence of such externalities does not justify the abuse or misuse of government intervention in the market.)

It should also be emphasized that competition in one segment of the market may not be a permanent substitute for competition in other areas. In other words, dynamic efficiency gains from competition in the export market cannot be fully realized and sustained without emerging competition in other areas of the economy.

An export-oriented development strategy has been highly successful for Korea, and some other countries in East Asia, in the past, but lack of competition outside the export market, partly due to insufficient institutional development in areas such as the capital market, the labor market, and the market for corporate control, restricts the productivity gains from exporting. Perhaps this is one important lesson to be learned from the long economic stagnation in Japan and from the financial crisis in Korea and other East Asian NIEs.

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1. Introduction

Does competition enhance productivity growth of a developing economy? Is global competition conducive to economic development? Especially, does competition with more advanced producers in the global market promote productivity growth of domestic producers in a developing country? If the answer is a conditional yes, what makes global competition conducive to productivity growth and economic development? Many researchers have been working to find a better answer to these, perhaps quite controversial, questions.[1] The aim of this paper is to review recent empirical findings related to these questions, which have strong policy implications, and to offer some new evidence from Korean microdata.

Achieving a perfectly competitive outcome in theory will bring about allocative efficiency gains by forcing price to converge to marginal cost. Efficiency gains from competition, however, are not limited to such static and allocative gains. As was pointed out by Leibenstein who contrasted allocative efficiency with so-called "X-efficiency", the empirical evidence suggests that "the welfare gains that can be achieved by increasing only allocative efficiency are usually exceedingly small" (Leibenstein, 1966). In an early study, for example, the costs of static resource misallocation due to lack of competition in the United States were estimated to be much less than one per cent of GNP (Harberger, 1954). 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).[2]

The Korean economy has achieved strong economic growth for the past several decades and showed successful examples of rapid technology learning and productivity growth in industries such as automobiles, electronics, and semiconductors. In the process of the past several decades' economic development in the Republic of Korea, interestingly, it appears that competition played a strong role only in limited areas. Free competition did not prevail in domestic product markets or in factor markets. Product markets, financial markets and labor markets were very highly regulated and price-control was widely used until the beginning of gradual reform in the early 1980s.

[1] See Sachs and Warner (1995) and Rodrik and Rodriguez (2000), amongst many others, for contrasting views on this issue revealed in recent empirical cross-country studies.

[2] For a further review of the literature from this perspective, see Ahn (2002).

Competition for corporate control in fact did not exist, either, until recently. If there were any substantial contribution of competition to the dynamic efficiency gains of Korean firms, therefore, perhaps the only important channel that we could consider would be the one through competition in the export market.

A growing number of empirical studies using longitudinal microdata confirm that firm dynamics (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 microdata in Asia are still rare, mainly due to the lack of readily available data. Based on the plant-level raw data underlying the *Annual Report on Mining and Manufacturing Survey of Korea* (1990–98), this study explores links between exporting and productivity. The main findings of the paper suggest that productivity gains associated with exporting tend to have strong industry-wide spillovers. This paper consists of four sections. Section 2 summarizes the theoretical and empirical background. Section 3 reports the results of quantitative analysis using Korean data. Section 4 concludes the paper.

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.[3] When incumbents who have already accumulated substantial experience with conventional technology are less enthusiastic about taking risks in 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 to 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) 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.[4]

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

[4] See Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995).

The main finding of existing empirical studies using longitudinal microdata 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.

(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.[5]

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.

Microdata also provide rich 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 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 overall productivity. Their findings suggest that competitive selection processes via entry and exit facilitated the reallocation of production factors.

2.2 International trade, competitive selection, and productivity

A positive contribution of increased import competition to productivity growth has been detected in a number of studies. MacDonald (1994) analysed the US Bureau of Labor Statistics (BLS) data on labour productivity growth in manufacturing industries during

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

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 in 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 non-traded goods sectors after trade liberalization.

However, whilst import competition has been found to induce productivity, growth evidence for the role of exports and export competition is more ambivalent. For example, 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 support the self-selection of the more efficient firms into the export market.

Similarly 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 Roberts and Tybout (1997) suggested. While exporting does not appear to improve productivity growth rates at the plant level, it is strongly correlated with increases in plant size. In other words, trade contributes to productivity growth by fostering the growth of high productivity plants, though not by increasing productivity growth at those plants.[6]

For deeper understanding on the links between exporting and productivity growth in the context of technological learning and economic development, however, aforementioned selected cases from a few developing and developed countries seem to be far from comprehensive: Colombia, Mexico, and Morocco are not a good case for

[6] 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.

economic development driven by export promotion; for technologically advanced economies such as the US and Germany, room for technological learning from exporting would be rather limited. It is probable that more interesting and more relevant cases would be found from experiences of a number of East Asian economies (as a success story of export-oriented development strategy). Therefore, after reviewing theoretical and empirical studies on technology diffusion through trade (in Section 2.3) and on trade and growth in East Asia (in Section 2.4), we will focus on another specific case of the Republic of Korea. If there are some actual cases supporting the idea of economic development based on technological learning through exporting, Korean experiences appear most likely to belong to those cases.

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 spillover (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 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; and Branstetter 2001). Others have stressed that international R&D spillovers may nevertheless be important. Based on 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 (2004), 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 microdata, Keller (2004) suspects that such results might be related with heterogeneity across industries or with heterogeneity across trading partners. We address this issue below in our empirical analysis the links between exports, productivity and spillovers.[7]

2.4 International trade and productivity growth in East Asia

The potential causal link between trade openness and high growth in East Asian Newly Industrializing Economies (NIEs) has been pointed out by many researchers and tested by much empirical research based on cross-country regressions. For example, Lucas (1993) tried to explain the "East Asian miracle" focusing on the fact that those East Asian miracle economies have become "large scale exporters of manufactured goods of increasing sophistication". Viewing the growth miracles as productivity miracles, he offered the following explanation:

(1) The main engine of growth is the accumulation of human capital, especially in the form of learning-by-doing on the job.

(2) For such learning to persist, workers and managers should continue to take on new tasks.

(3) For such learning to continue on a large scale, the economy must be a large scale exporter.

However, except for a series of studies on manufacturing in Taipei,China by Aw, Roberts and their associates, however, few studies have used microdata 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 Taipei,China, using longitudinal firm-level data from the *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 there 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 data from Taipei,China and comparable data from the *Korean Census of Manufactures* for 1983, 1988, and 1993. Interestingly, they found little evidence of links between plant

[7] As another potentially important source of productivity growth (particularly in developing economies), technology spillovers coming from domestic activities of foreign multinational firms can be considered. After a broad review of empirical evidence, Blomström and Kokko (1996, 1998) conclude that the nature of technology diffusion from foreign presence varies substantially depending on country characteristics and the policy environment. Findings from a recent study based on firm-level data in Lithuania (Javorcik, 2004) suggest that backward linkages make an important channel for technology diffusion from foreign multinationals to local firms. The empirical analysis part of the paper (Section 3), however, is focused on trade and productivity simply because the dataset does not have FDI statistics.

productivity and export decisions in the Republic of Korea, while they found some significant evidence of selection and learning effects in case of Taipei,China.

Since pioneering exploratory studies on firm dynamics in Korean manufacturing by Hahn (2000) and Joh (2000), Korean longitudinal microdata still remain rather unexploited. In fact, longitudinal microdata in the Republic of 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 plants with no fewer 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 (2004) detects evidence of self-selection and (short-lived) "learning-by-exporting" effects in the relation between exporting and plant-level productivity in the Republic of Korea.

The findings in Hahn (2004) from the Korean data are in fact qualitatively similar to those of Bernard and Jensen (1999*a* and 1999*b*) from US data in the following aspects:

(1) Significant and positive contemporaneous correlations are observed between levels of exports and productivity.

(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 weak.

(3) New exporters grow faster around the time that 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, although such a reallocation effect would produce static rather than dynamic gains. In other words, Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2004) 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 the Republic of 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 the economic and technological environment. For example, exporting grain from the US to the People's Republic of China may well have little learning-by-exporting effects, while exporting cars from the Republic of Korea to the US seems far more likely to generate some technology learning. As Keller (2004) underlines, "an attempt to explain the post-World War II performance of South Korea, [sic] for instance, without making reference to its success in transferring technology from the rest of the world is bound to fall short". Thus international technology diffusion (where a firm employs technology that has been originally invented in another country) is assumed 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 elsewhere. However the existing empirical evidence from microdata does not seem 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 the empirical exploration pursued in this paper.

3. Testing for Spillovers from Learning-by-exporting in Korean Manufacturing

Using the same dataset hired in Hahn (2000, 2004) and Joh (2000), this paper aims to explore a plausible channel through which exporting could have made a 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 intra-industry spillovers of learning-by-exporting can provide an answer to the aforementioned puzzle and that the evidence from Korean microdata supports the existence of spillovers arising from exporting. This section explains this argument and tests hypotheses derived from it.

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

A number of recent empirical studies have shown that there still exists a considerable degree of geographic localization in knowledge spillovers.[8] 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".

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 (2004) found that, after controlling for year effects and industry effects, the productivity gap between exporting firms and non-exporting firms did not increase over time. They interpreted this finding as evidence showing that learning-by-exporting effects are only short-lived. Such a 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 the regression methods used in Bernard and Jensen (1999*a* and 1999*b*) and in Hahn (2004) are not adequate for testing the hypothesis of spillovers from learning-by-exporting.

If there exist large learning-by-exporting spillovers effects within an industry, inter-industry variance of productivity levels will outweigh intra-industry variance. In addition, the gap between the average productivity level in exporting industries and that

[8] See, among others, Jaffee *et al*. (1993), Branstetter (2001), and Keller (2002).

in non-exporting industries will tend to increase. Based on this reasoning we can derive the first hypothesis as follows.

Hypothesis 1. *If learning-by-exporting effects have strong intra-industry spillovers, export-intensive industries will have substantially higher aggregate productivity levels or higher aggregate productivity growth than other industries with lower export-intensity.*

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

3.2 Deriving testable hypothesis from productivity regression

A test of our hypothesis can be derived from specific 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 the industry-level, a variable reflecting the industry-wide R&D expenditure will have a significant and positive coefficient in the regression for firm-level productivity.[9] In the same spirit, we can test for industry-wide spillovers of learning-by-exporting by looking at the estimated coefficient for industry-level export intensity in Hypothesis 2.

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

Just as geographic and technical distance are considered for giving different weights to different sources of R&D spillovers, we could try using more sophisticated measures for sources of learning-by-exporting spillovers. In this paper, however, we use a relatively simple measure—industry-level export intensity. As will be shown in the following sections, however, even this simple variable gives quite strong evidence of the existence of learning-by-exporting spillovers. As a robustness check, we compare a variety of regressions and show that our basic findings on spillovers are robust across a

[9] In a more sophisticated approach, one can create an indicator for the size of the source of spillovers by giving different weights (reflecting geographic or technical proximity) to external R&D expenditures. For a literature review on measuring technology diffusion, see Keller (2004).

broad set of specifications where R&D expenditures and a proxy for human capital quality are controlled for at both industry- and plant-level.

3.3 Data analysis for Hypothesis 1

The empirical part of this paper is based on the plant-level raw 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. In general plant codes are followed consistently 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 a different plant coding system to those plants with fewer than five employees. [10] Therefore, this study will focus on plants with no fewer than five employees, as did previous studies such as Dunne *et al*. (1989) for the US, Joh (2000) for the Republic of Korea, and Hahn (2000, 2004) for the Republic of Korea. The data used in this paper is exactly the same data used in Hahn (2000, 2004).

Following Aw *et al*. (2001) and Hahn (2000, 2004), 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 the 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.

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

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 (productivity when all production factor inputs are

[10] A comparable database would be the *Census of Manufactures* in Japan. They have a very similar format. The Korean census/survey is richer in the sense that it has information on exporting and R&D for recent years while the Japanese census does not. On the other hand, the Korean census/survey does not have firm flags which are crucial for constructing a firm-level database, while the Japanese census has firm flags.

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. Descriptive Statistics (1990–1998)

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

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.

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 (2004)

Only around 11%–15% of the total plants are exporting each year, but the ratio of exports to shipments of exporters ranges around 35%–50%, suggesting that exporters are typically bigger than non-exporters.[11] As the comparison of exporters and non-exporters in Table 3 shows, on average, exporting plants are bigger, more capital intensive, hire more non-production workers, pay higher wages, and have higher labor productivity and higher total factor productivity.

[11] In Table 2 and Table 3, non-exporters are defined as those whose export of the year was zero. A sharp increase in the weighted average of exports to shipments ratio in 1998 suggests that larger exporters responded more sensitively to the depreciation of the Korean currency during the Asian financial crisis. See Hahn (2004) for a further discussion. Our data covered the period of 1990 through 1998. For now, the data can be backdated to 1980 and updated to 2001. Accumulating more observation years after 1998 would enable us to analyze further on the impact of the Asian financial crisis of 1997-98.

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)	a-1	b-1	1.2	0.6	1.4	0.6

Hahn (2004)

As documented in various studies, and noted earlier, microdata evidence suggests that causation runs from more productive firms entering export markets (selection effects), rather than exporting making firms more productive (learning effects). The somewhat weak evidence of learning effects reported in Bernard and Jensen (1999*a* and 1999*b*) for the US and Hahn (2004) for the Republic of Korea also suggests that such learning effects are only transient. However even without strong learning effects, selection effects from global competition could make a 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. Table 4 reveals great heterogeneity across industries in terms of their export intensity and also shows that the number of exporting plants can be relatively small even in high-export-intensity industries.

Table 4. Number of Exporting Plants and Export Intensity by Industry (KSIC 2–Digit)

	1990		*1994*		*1998*		*1990–1998*
Industry	Number of plants	Number of exporting plants	Number of plants	Number of exporting plants	Number of plants	Number of exporting plants	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%**
Elect. 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 Transportation 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 shows 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.

Aggregate productivity in a given industry can be represented by a weighted average of each individual plant's productivity in the industry. That is,

$$P_t = \sum_i \theta_{it} p_{it}$$

where P_t is an aggregate productivity measure for the industry at time t; θ_{it} is the share of plant i in the given industry at time t; and p_{it} is a productivity measure of an individual plant i at time t. Then, the decomposition method by Olley and Pakes (1996) is as follows.

$$P_t = \sum_i \theta_{it} p_{it} = \overline{p_t} + \sum_i (\theta_{it} - \overline{\theta_t})(p_{it} - \overline{p_t})$$

In this decomposition, positive covariance means that more output is produced by the more productive plants (allocative efficiency).

Industries in the left column of Table 5 are high export-intensity industries and those in the right 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%), electronics parts (54.3%), and other transportation equipment (55.3%), the weighted aggregate productivity growth is very strong even with deterioration in allocative efficiency. In the 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, the recycling industry also has low export intensity (5.8%), but shows strong productivity growth along with an improvement in allocative efficiency.

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 Equipment	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

(cont.)

Industry	Year	Aggregate productivity	Unweighted productivity	Covariance	Industry	Year	Aggregate productivity	Unweighted productivity	Covariance
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.

The findings in this subsection can be summarized in the following three points.

(1) Exporting plants are a small portion of an industry and, when they are compared with non-exporting plants, have distinct features such as bigger size, higher wages, higher capital intensity and higher productivity. Interestingly, according to Bernard and Jensen (1999*a* and 1999*b*) and Hahn (2004), the average productivity gap between consistent exporters and consistent non-exporters is not widening over time. This is likely to be due to some form of spillover effect.

(2) Export intensity (the share of exports in output) varies substantially from industry to industry.

(3) Industries with higher export intensity tend to show faster productivity growth.

These findings seem to be consistent with the conjecture that technology or 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 need a regression analysis for formal hypothesis testing.

3.4 Data analysis for Hypothesis 2

Starting from an unbalanced panel data for all manufacturing plants with no fewer than 5 employees over the 9-year period from 1990 to 1998, we run pooled regressions with year dummies and industry dummies. The dependent variable is plant-level total factor productivity calculated with the aforementioned method of the chained-multilateral index number approach. What are the major determinants of plant-level productivity in addition to export intensity at the plant- and the industry-level?

First of all, plant-level productivity could be affected by macroeconomic conditions and these effects of the business cycle on productivity are controlled for by annual dummies. A substantial part of plant-level productivity will also rely on the technological environment, which will 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 “measured” plant-level productivity either through static or dynamic economies of scale or through big producers' market power in setting higher price for their products. If the level of technology is one of the determinants of plant-productivity, some indicator of R&D will be a good explanatory variable. Based on the conjecture that more advanced plants or firms will hire more non-production workers in their total labor force, one can also use the share of non-production workers in employment as proxy for technology level. Finally, we wish to establish whether exporting at the plant- and industry-level makes a positive contribution to plant-productivity. All these factors are considered in our regression exercise.

Table 6.1 Plant-level Total Factor Productivity Regressions (2-digit level)

	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

(*t*-ratio in parentheses)

Table 6.1 contains the 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 anticipate our conclusion, the null hypothesis that industry-level export intensity has no effect on plant-level productivity is always rejected, even at the 1% significance level. In case of Korean manufacturing in the 1990s, therefore, microdata suggest that there was significantly positive industry-wide contribution of exporting towards plant-level productivity.[12]

Column I of Table 6.1 gives the most generic case, where plant-level total factor productivity is 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 turns out to have a much larger coefficient. Moreover, this basic pattern remains stable across different specifications. In Column II of Table 6.1, the size variable (natural log of number of workers) is 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.

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 the expected signs, while the coefficients for plant-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 in order to compare spillovers in exporting and in R&D in a symmetric way. The coefficients for industry-level R&D intensity in Column V through Column X persistently show large R&D spillovers.[13]

Column V and Column VI of Table 6.1 have all of the variables export intensities, R&D intensities, and non-production worker employment shares together in the same format of plant-level and industry-level juxtaposition. It is noteworthy that the coefficients for plant-level and industry-level shares of non-production workers are

[12] Positive coefficient for the plant-level export intensity may well raise the issue of causality, in the sense that high productivity of plant may cause higher export intensity at the plant level. Note that such argument does not apply in the case of the relation between plant-level productivity and industry-level export intensity. In other words, industry-level export intensity is more likely to be exogenous in the plant-level productivity regression, while plant-level export intensity could be endogenous.

[13] More intriguingly, however, coefficients for plant-level R&D intensity are persistently negative. This pattern, which was also observed from the Japanese data, certainly requires further and deeper analysis. My preliminary conjecture is that it might be due to learning costs in technology upgrading in technology-followers. For producers who are distant from the 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 these could have temporary negative effects on productivity at the initial stage of upgrading. 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 from exporting. See Ahn (2003) and the references there for a further discussion on technology upgrading with learning costs.

similar in 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 a difference reflects the fact that labor spillover effects are not as important as spillovers in R&D and in learning-by-exporting.

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

In general, the following patterns are observed persistently across different specifications.

(1) Export intensities, both at the plant level and at the industry level, have positive and significant coefficients in explaining plant-level total factor productivity.

(2) The coefficients for industry-level export intensity are around 5–7 times bigger than those for plant-level export intensity.

(3) The coefficients for export intensity do not change greatly regardless of the inclusion or exclusion of the variables of size, R&D intensity, and non-production workers' employment share at both the plant and the industry-level.

Table 6.2 Plant-level Total Factor Productivity Regressions (3-digit level)

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

(*t*-ratio in parentheses)

In Table 6.1, industry was defined at the SIC 2-digit level and industry-level variables and industry dummy variables were calculated for each of the 23 industries in the manufacturing sector. Finally, as another robustness check, a more detailed industry definition at the SIC 3-digit level was used. Table 6.2 reports the results of regressions with industry-level variables and industry dummy variables calculated for each of the 61 industries at the 3-digit level. The basic findings from Table 6.1 do not change in this analysis. Perhaps the most notable differences at the 3-digit level are:

(1) The coefficient on the industry-level export intensity variable, whilst it remains positive and significant, is now lower.

(2) Contrary to this result, the coefficient on the industry-level R&D intensity variable, whilst it remains positive and significant, is now higher.

(3) The variable non-production workers' share in employment now has a larger coefficient at the plant level than at the industry level.

The first of these results is consistent with a-priori expectation since as the definition of an industry is narrowed to the 3-digit level the scope for intra-industry externalities should be reduced. The second results work in the opposite direction and may imply that spillovers from R&D activity are more closely focused in technologically similar sub-sectors than are spillovers from exports. The relative shift in regard to the non-production workers variable is due principally to a fall in the coefficient on the industry-level variable. However this latter variable seems to be picking up in part the effect of the industry-level R&D (when the non-production worker variable is excluded the coefficient on the latter rises) and the rise in the coefficient on the industry-level R&D variable in the 3-digit level analysis may partly explain the fall in the coefficient on the non-production worker variable.

4. Conclusions

Arguably, competition is a main source of innovation, technological progress, and economic growth, not only for an economy at the technological frontier, but also for a developing economy distant from the technology frontier. Increased global competition—either increased domestic competition with imported goods and services or fiercer competition with foreign competitors in the export market—is expected to bring about higher aggregate productivity growth. If the persistently high economic growth in the Republic of Korea over the past several decades was due to high productivity growth and technology diffusion, there must be a strong expectation that export growth played an important role in this productivity performance. Until the 1980s in the Republic of Korea both product markets and factor markets were highly regulated and even now competition for corporate control remains relatively weak, so that until relatively recently competition really existed only in the export market.

A positive correlation between exporting and productivity has been reported in research on various countries. Recent studies such as Bernard and Jensen (1999*a* and 1999*b*) suggest the existence of both selection and learning effects around the point in time when a firm (or a plant) starts exporting. A very similar pattern is detected from Korean microdata in Hahn (2004). These findings, however, also suggest that such a learning effect (productivity gains from exporting) is temporary rather than persistent.

This paper explores a plausible channel through which exporting could have made both a substantial and a persistent contribution to export-oriented economic growth in the Republic of Korea and by extension other East Asian NIEs: namely, the spillovers (or externalities) of learning-by-exporting. Plant-level data for Korean manufacturing show that more export-intensive industries tend to have a higher productivity level. In addition, a substantial part of the variance in plant-level productivity is explained by the variance in industry-level export intensity. These findings are consistent with the hypothesis that there exist spillovers of learning-by-exporting at least in some industries. As with the existence of the more usual intra-industry R&D spillovers, which are also demonstrated here, this raises the policy questions of how to get more benefits from such spillovers, whilst minimizing any side-effects from any policy intervention.

As in the case of other types of positive externalities, in theory a market solution will lead to a sub-optimal level of externality-generating output (in this case exports), indicating that government action could improve upon the market outcome. This is the implicit logic behind the active role played by the Japanese government or by the Korean government at the earlier stage of the economic development. Needless to say, however, the existence of such externalities does not justify the abuse or misuse of the government's intervention into the market. After all, as succinctly put by Stiglitz (1999), "the objective of the government is not to pick winners, but to identify externality-generating innovations."

It should be also emphasized that competition in one segment of the market may not be a permanent substitute for competition in other areas. In other words, dynamic efficiency gains from competition in the export market cannot be fully realized and sustained without emerging competition in other areas of the economy. An export-oriented development strategy has been highly successful for the Republic of Korea, and some other countries in East Asia, in the past, but lack of competition outside the export market, partly due to insufficient institutional development in areas such as the capital market, the labor market, and the market for corporate control, restricts the productivity gains from exporting. Perhaps this is one important lesson to be learned from the long economic stagnation in Japan and from the financial crisis in the Republic of Korea and other East Asian NIEs.

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