Chapter 9

Skill Upgrading, Technology Choice and the Role of Exporting in Korean Manufacturing Sector

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May 2012

This chapter should be cited as
Hahn, C. H. and C. G. Park (2012), 'Skill Upgrading, Technology Choice and the Role of Exporting in Korean Manufacturing Sector', in Hahn, C. H. And D. A. Narjoko (eds.), *Dynamics of Firm Selection Process in Globalized Economies*. ERIA Research Project Report 2011, no.3, pp.267-288. Available at: http:/www.eria.org/RPR_FY2011_No.3_Chapter_9.pdf

CHAPTER 9

Skill Upgrading, Technology Choice, and the Role of Exporting in Korean Manufacturing Sector

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We examine the role of export and innovation activitiesin skill upgrading of Korean manufacturing sector during 1990's utilizing a unique plant-level panel data. The paper offers three interesting empirical regularities. First, Korean manufacturing sector experienceda significant degree of skill upgrading during 1990's. The share of non-production workers in total employment increased very fast both at industry and plant levels. Second, the larger part of skill upgrading during 1990's can be attributable to reallocation of resources within plants rather than across plants. Third, we offer some evidence broadly supporting recent theoretical development in international trade that emphasizes the inter-connectedness of export market participation, innovation activities and skill upgrading.

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1. Introduction

The increase in the ratio of skilled and unskilled employment, accompanied by the rise in skilled wage premia, is a global phenomenon; these changes have been observed in both OECD and developing countries for the past decades. As well known, most early studies have considered trade and skill-biased technical change (SBTC) as two competing explanations for the rise in the relative demand for the skilled workers. One consensus from the literature is that skill-biased technical progress is an important part of the story while the role of trade is less clear-cut. However, several recent theories of trade based on heterogeneous firms and monopolistic competition[1] renewed our attention to the important role played by international trade in this phenomenon. That is, trade can raise the relative demand for the skilled workers by inducing exporters to invest in new technologies that are skill-biased. Thus, trade and SBTC could be complementary, rather than competing, explanations for the rising relative demand for the skilled workers.

In this paper, we aim to examine the effects of exporting and innovation on skill upgrading within plants, utilizing plant-product matched panel data on Korean manufacturing for the period 1990-1998. To set the stage, we start by examining the changes in skill composition in Korean manufacturing sector and then try to figure out the sources of the change in skill composition by decomposing the changes into two components: between- and within-effect. Next, we try to explain skill-upgrading within plants. Here, we first examine whether within-plant skill upgrading is related to exporting and innovation activities of plants based on cross-section regressions. Then, we explore whether there are inter-temporal complementarities between exporting and R&D as sources of within-plant skill upgrading. For this purpose, utilizing the propensity score matching framework, we examine whether the export market participation of plants affect the R&D participation and R&D intensity of plants and, symmetrically, whether the R&D participation of plants affect the export participation and export intensity of plants. We hope this approach may help us understand better the complicated inter-

[1] See, for example, Yeaple (2005), Bustos (2011), Costantini & Melitz (2008), and Bustos (2009).

relationship among exporting, innovation, and within-plant skill upgrading. To the best of our knowledge, this paper is an addition to the several early empirical studies that clarifies the role of exporting and innovation in the within-plant skill upgrading and, hence, in the increase in the aggregate skill intensity.

In Korea, at least since the early 1990s, the employment share of skilled workers in the manufacturing sector has increased steadily. Although the rising employment share of the skilled workers does not appear to have been accompanied by the rise in the relative wages of the skilled workers during the early 1990s, a recent study suggests that the wage gap has increased especially since the 1997/98 financial crisis[2]. It is worthwhile to note the context under which the rise in the employment share of the skilled workers has occurred. Firstly, while the manufacturing export growth rate increased slightly during the 1990s over the previous decade[3], the employment-creating effect of manufacturing exports decreased significantly. Nam (2008) uses input-output based approach and shows that employment created by export production for the manufacturing sector grew at an annual rate of 5.0 percent during 1975-1990, but at -2.2 percent during 1990-2000.

Table 1: Employment and Wage Bill in Korean Manufacturing Sector: 1990-97

(Unit: Person, Million Korean Won)

Year	Number of Plants	Total Workers	Non-production	Production	Total Wage Bill	Non-Production	Production
1990	68690	2951893	701851 (0.2378)	2250042 (0.7622)	19532300	5592167 (0.2863)	13940133 (0.7137)
1991	72213	2853563	720343 (0.2524)	2133220 (0.7476)	22830419	6735912 (0.2950)	16094507 (0.7050)
1992	74679	2734179	704997 (0.2579)	2029182 (0.7421)	25234409	7638439 (0.3027)	17595970 (0.6973)
1993	88864	2804591	754112 (0.2689)	2050479 (0.7311)	28834306	9039673 (0.3135)	19794633 (0.6865)
1994	91372	2848789	771047 (0.2707)	2077742 (0.7293)	32791213	9889262 (0.3016)	22901917 (0.6984)

[2]Kim (2007) shows empirical evidence indicating that the wage gap between skilled and unskilled workers has increased after the 1997/98 financial crisis in Korea. The fact that rising relative employment of the skilled workers was not apparently accompanied by the rising wage gap during the early 1990s suggests that the supply side factors, such as the rapid increase of the college graduates, also played a role in the changing skill structure of employment.

[3]Since the 1997/98 financial crisis, the ratio of exports to GDP became higher than pre-crisis period.

1995	96202	2865221	800121 (0.2793)	2065100 (0.7207)	37844431	11494509 (0.3037)	26349922 (0.6963)
1996	97130	2811974	775896 (0.2759)	2036078 (0.7241)	42327601	13115744 (0.3099)	29211857 (0.6901)
1997	92138	2618792	739138 (0.2822)	1879654 (0.7178)	41489165	13261271 (0.3196)	28227894 (0.6804)

Notes: 1) The table is constructed based on *Survey of Mining and Manufacturing* which includes all manufacturing and mining plants with five or more employees.
2) Numbers in parentheses are the proportion of workers or wage bill in non-production and production jobs, respectively.

Source: Hahn and Park (2011)

Secondly, during the 1990s, the manufacturing sector exhibited rapid increase in labor productivity. Since the late 1980s, the aggregate manufacturing employment has been declining not only as a share of total employment but also in absolute terms, while the value added share of manufacturing has remained stable since the late 1980s up until recently. This seems to suggest the potentially important role of technical progress in the declining manufacturing employment share. The last point to note is that the above changes have occurred roughly since the late 1980s when the pace of globalization is has accelerated. In our view, the Korean manufacturing sector during the 1990s provides an excellent case for studying the role of trade in the widening disparity between skilled and unskilled employment.

As well noted, most empirical studies conducted during the 1990s were based on the Heckscher-Ohlin framework. There are at least two observations to which advocates for traditional trade theory would find it hard to offer justification. According to the Heckscher-Ohlin theory, when a skill abundant country trades, it should experience a rise in the relative price of skill-intensive goods and a rise in the relative demand for the skilled workers. Furthermore, the rise in the relative demand for the skilled workers should be accompanied by the compositional shifts in sectoral employments. Thus, the theory predicts that the reallocation of factors of production across industries that differ in skill intensity, the so-called “between” effect, should be largely responsible for the increase in the aggregate relative employment of the skilled. However, most early studies found that the rise in the aggregate skill intensity are mostly accounted for by the “within” effect, the increase in the relative employment of the skilled within firms or a narrowly defined industries, and that skill upgrading tend to be more rapid in industries using computer more intensively (See, among others, Katz and Murphy 1992, Lawrence and Slaughter 1993, Berman, *et al.*1994, and Autor, *et al*. 1998). Another observation at odds with Heckscher-Ohlin theory is that a rising disparity between skilled and unskilled workers is observed not only in skill-abundant countries but also in skill-scarce developing countries. According to the theory, the reverse should be happening. Based on these findings, researchers have concluded that the skill-biased technical progress, not trade, is the main story behind the rising relative demand for the skilled workers.

With the availability of the firm- or plant-level micro datasets, this issue received renewed attention. Bernard & Jensen (1997) uses the U.S. plant-level data and shows that most of the increase in the aggregate skill intensity is attributable to the "between" effect and is accounted for by exporters. This study renewed our attention to the potentially important role of international trade in the rise in the relative employment of the skilled. However, Bernard and Jensen's finding of the large and dominant "between" effect and the dominance of the between effect as a mechanism of trade raising the aggregate skill intensity did not prove to be a universal phenomenon. Bustos (2011) uses Argentinean firm-level data during the early 1990s and shows that most of the increase in the aggregate skill intensity is attributable to the "within" effect. Unlike the early empirical literature based on the H-O theory, however, Bustos shows that the within effect or the skill upgrading within plants is an outcome of the interaction between firm's exporting and technology investment decisions. Later on, Bustos (2009) shows that the reduced trade cost (tariff) associated with Argentina's joining in MERCOSUR induced increased probability of export participation as well as increased investments in technologies. She also finds a sorting pattern of firms in their responses to the reduced trade cost as predicted by her own theoretical model.

This paper takes the broad implications from the several heterogeneous firm trade theories with complementarity between exporting and innovation, such as Bustos (2011), Costantini & Melitz (2008), and Aw, *et al.* (2009), and tries to examine whether exporting and innovation are complementary factors inducing within-plant skill upgrading.

2. Skill Upgrading in Korean Manufacturing Sector in 1990's[4]

The increase in aggregate relative demand for skilled labor can be driven by factor reallocation towards skill-intensive firms holding skill intensity within firms or industries constant, between effects, or by the increase in skill intensity within firmsholding the share of each firm in total factor demand constant, within effects. Following Bernard and Jensen(1997), we first construct two measures to capture the level of high skilled labor relative to low skilled one; the ratio of non-production workers to total employment and wage bill for non-production workers to total wage bill and then decompose the changes in two ratios into between and within effects. The decomposition is conducted according to the following formulae;

$$\Delta NPL = \sum_{i=1}^{I}(\Delta L_i)(\overline{NPL_i}) + \sum_{i=1}^{I}(\Delta NPL_i)(\overline{L_i}) \quad (1)$$

$$\Delta NPW = \sum_{i=1}^{I}(\Delta W_i)(\overline{NPW_i}) + \sum_{i=1}^{I}(\Delta NPW_i)(\overline{W_i}) \quad (2)$$

whereL_i is the share of total employment of firm*i* and NPL_i the share of non-production workers[5] at firm*i*. In addition, Δ indicates time difference and upper bar means time average of the corresponding variable. The first term in (1) represents the change in employment share of firm*i* weighted by the average share of non-production workers of the firm so that it approximates the change of shares of non-production workers due to reallocation of labor force across firms, which is called between effect in the literature. The positive sign indicates that the share of total employment at firms with higher than average share of non-production workers has increased. That happens when labor force shifts towards firms whose skill intensity is relatively higher. The second term in (1) measures the change in the share of non-production workers at firm *I* weighted by average share of total employment of the corresponding firm.Since the term represents the changes in skill composition of a firm due to reallocation of labor inside the firm, it is called within effect. The

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[4]This section heavily draws from Hahn and Park (2011).

[5]We take non-production workers for skilled ones. Notwithstanding strong foreseeable arg ument against our strategy, there are two reasons we take this route. Our data set does not provide skill level or education achievement of individual workers so that it is impo ssible to obtain a direct or more accurate measure of skill intensity. In addition, many s tudies utilizing firm-level or plant-level data also took similar approach in measuring skil l intensity and offered many meaningful results. See Berman, *et al.* (1994), and Bernard and Jensen (1997), for example.

positive within effect results from increases in non-production worker ratio at firms with higher than average employment share. By separately aggregating the two effects across all firms and adding them all, we obtain the overall change in non-production worker ratios in manufacturing workforce and use the result as a measure of the overall change in skill intensity. Similarly, we can decompose the change in the share of wage bill paid to non-production workers into between and within effects with the same procedure as (1) after replacing employment with wage bill. W_i is the share of total wage bill offirm *i* and NPW_i the share of wage bill paid to non-production workers at firm *i*.A positive between effect indicates that shares of wage bill have increased at firms with higher than average proportion of non production workers and a positive within effect that the proportions of wage bill paid to non-production workers have increased at firms with higher than average size in terms of total wage bill.

Throughout the analysis, we utilize an unpublished plant-level annual census datain Korea, the *Survey of Mining and Manufacturing*. Our data set covers the period from 1990 to 1998 andincludes all plants with five or more employees in 580 manufacturing industries classified at KSIC (Korean Standard Industrial Classification) five-digit level. The data set is in unbalanced panel form reflecting frequent exits and entries. The survey reports several important variables especially relevant to our study such as the number of non-production and production workers, total wage bill paid to both production and non-production workers. Unfortunately, it does not provide detailed information on demographic and socio-economic variables of the labor force at plant level to accurately measure skill intensity. Following previous researches such as Berman, *et al.* (1994), and Bernard and Jensen (1997), we regard non-production workers as the skilled and production workers as the unskilled. Our data set includes information on exporting activities of a plant; value of products shipped for direct exports, and the value of products shipped for other exporters. In addition, it also includes information on the value of total production andshipments, the number of products produced, expenditure on research and development.

Table 2 reports the results of decomposition described in equations (1) and (2) conducted in both industry and plant levels. First, a significant degree of skill upgrading and increasing skill premiumoccurred in Korea manufacturing sector during 1990's. At five-digit level of KSIC, the share of non-production workers increased at the rate of 1.9427% per year and the share of wage bill paid to non-production workers at 1.3684% per year. The result is fairly robust to aggregation level of industries since we obtain almost the same magnitude of changes at four-digit classification of industries. Second, employment share of non-production workers increased faster than wage share of non-production workers, which indicates that the wage inequality between two types of laborhad been narrowedduring 1990's. The finding does not seem to be consistent with the conventionalbelief that increased demand for skilled labor driven by skill biased technological change orshift of product demand may have resulted in labor market conditions favorable to skilled labor. However, demand side story is not enough to account for the changes in Korean labor market during 1990's. For example, loosening restriction on college admission quota in early 1980's resulted ina massive entry of new college graduates into market for skilled labor beginning in early 1990's. That may have at least partially offset the upward pressure on wages of skilled labor from demand increase. In addition, we may offer an explanation on the narrowing wage gap based on different job tenure across industries. According to Table.2,asignificant chunk of changes in employment share of non-production workers occurred through reallocation of workers across rather than within industries. If high-skilled reallocated workers were relatively young with shorter job tenure than low-skilled staying workers at the same industries, a large increasein relative employment share of non-production workerscould be accompanied by less significant increase in their wages shares. Therefore, it would be too hasty to draw aconclusion solely based only on Table. 2 and we may need further investigation employing micro-level data with detailed information on worker characteristics. Third, skill upgrading in Korean manufacturing sector continued even after the foreign exchange crisis in 1997 and subsequent depression. Table. 3r eports that relative employment share of non-production workers increased by 1.5606% annually from 1999 to 2003 at five-digit level of industrial classification. Fourth, while between effect played bigger role in skill upgrading than within effect at industry level, reallocation of employment within a plant accounts for larger portion of skill upgrading. 61.1%

(1.0801% out of 1.9430%) of increase in the share of non-production workers can be attributed to reallocation across industries at four-digit level of industrial classification but the proportion shrinks to 42.8% (0.7540% out of 1.7611%) if the decomposition is done at individual plant level. The role of within effect in skill upgrading became more important during early 2000's. This is at odds with the findings for the U.S. and several Latin American countries where most skill upgrading are attributable to within effects both at industry and firm levels[6]. Fifth, contrary to employment share of non-production workers, both within and between effects seem to attribute to increase in wage share of skill labor.

Table 2: Changes in Employment and Wage Shares of Non-production Workers: 1991 - 1997

	Employment			Wages		
	Between	Within	Total	Between	Within	Total
Industry (four-digit)	1.0802	0.8628	1.9430	0.6529	0.7156	1.3685
Industry (five-digit)	1.2822	0.6605	1.9427	0.8635	0.5049	1.3684
Plant	0.7540	1.0071	1.7611	0.5695	0.4911	1.0806

Table 3: Changes in Employment Share of Non-production Workers: 1999-2003

	Employment		
	Between	Within	Total
Industry (four-digit)	0.5514	0.8857	1.4371
Industry (five-digit)	0.8770	0.6836	1.5606
Plant	0.3536	1.4882	1.8418

The finding that most of increase in the relative demand for skilled labor is explained by skill upgrading within firms implies that changes in production technologies could be the main driver for increase in the relative demand of skilled

[6]See Berman, *et al.* (1994) for U.S. and Goldberg & Pavcnik (2007) for Latin American countries.

labor. From now on, we will focus skill upgrading at plant level and pay more attention to the role of exporting and innovation in the process by investigating the patterns of skill upgrading across different groups categorized according to exporting status and innovation activities.

Since our data setcontains all plants with five or more employees, the sample changes substantially due frequent to entry of new plants and exit of dying ones. We include only those plants that had existed during the entire period from 1991 to 1997. The final sample contains 27,246 plants[7] and we perform the same decomposition after splitting the sample into four groups according to the following criteria. If a plant appears both in 1991 and 1997 and the value of products shipped for export in 1991 is positive, it is classified as an exporter. If a plant is observed in 1991, but not in 1997 and the value of products shipped for export in 1991 is positive, we regard it as an exporter. In addition, if a plant is observed in 1997, but not in 1991 and the value of products shipped for export in 1997 is positive, it is also classified as an exporter. All other plants are classified as non-exporter. The same classification rule is applied for innovation with expenditure on research and development as the criterion.

Table 4: Plant Characteristics and Skill Upgrading

	Employment: 1991-1997			Employment: 1999-2003		
	Between	Within	Total	Between	Within	Total
All plants	0.7540	1.0071	1.7611	-0.2619	1.2894	1.0275
Non-exporter	0.7788	0.1968	0.9756	1.1191	0.0151	1.1342
Exporter	-0.0248	0.8103	0.7854	-1.3810	1.2743	-0.1067
All plants	0.7540	1.0071	1.7611	n.a.	n.a.	n.a.
Non-innovator	-0.1738	0.3680	0.1942	n.a.	n.a.	n.a.
Innovator	0.9278	0.6391	1.5669	n.a.	n.a.	n.a.

We can infer two important implications from Table 4.concerning the role of

[7]This may introduce some potential data problems such as size and survivorship bias. Siz e bias means that larger plants are more likely to stay at the sample than medium and small sizes plants. Survivorship bias points out the possibility that balanced panel appr oach may distort the whole picture when skill compositions of exiting and entering plan ts are significantly different from the existing ones. For example, average number of w orkers employed by plants in the sample was 55.30 in 1997 but plants excluded from t he sample employed only 17.06 workers the same year.

export and innovation activities. First, majority of the skill upgrading achieved through reallocation labor force with plants were driven by exporters. Even though the speed of skill upgrading by non-exporters was faster than that of exporters, 0.9756% vs. 0.7854%, 80% of within effect are accounted for by that of exporters during 1990's. Second, plants with positive R&D expenditure contributed more to both within and between effects in employment share of non-production workers. Consequently, 89% of growth of employment share, 1.5669% out of 1.7611%, was attributed to plants actively involved in R&D investments during 1990's. Moreover, innovators achieved skill upgrading in a faster pace both within and between plants than non-innovators.

3. The Roles of Export and Innovation in Skill Upgrading

In this section, we investigate the roles of export and innovation activities in skill upgrading of a firm. We try to figure out the complicated inter-relationship among three key variables by relating the changes in skill intensity between 1991 and 1997 to changes in exporting status and innovation activities.

$$\Delta\left(\frac{NPL}{L}\right)_i = \beta_0 + \beta_1{}'EXP_i + \beta_2 INNO_i + \gamma' X_{i,0} + \varepsilon_i \tag{3}$$

The dependent variable $\Delta\left(\frac{NPL}{L}\right)_i$ is the changes in the share of non-production workers at plant i between 1991 and 1997. EXP_i isan (1×3) column vector of dummy variables representing the changes in exporting status of plant i between 1991 and 1997. We define a plant as a non-exporter (NN) if it exported neither in 1991 nor 1997, anexporter (EE) if it exported both in 1991 and 1997, a starter (NE) if it did not export in 1991 but did in 1997, and a stopper (EN) if it exported in 1991 but not in 1997. We take non-exporter as the base case so that we include only three dummy variables. $INNO_i$ representsinnovation activities at plant i, measured as the average from 1991 to 1997 of R&D expenditure relative to total production (RND). $X_{i,0}$ is the vector of explanatory variables included to control the initial heterogeneity across plants in 1991. We include plant size, age, productivity, and capital intensity to control initial firm heterogeneity. Plant size is measured in terms of the natural log of total employment, age as the number of years since establishment, productivity as the total factor productivity calculated following multilateral chained index number method, and capital intensity as per worker stock of fixed assets[8].

The estimation results are reported in Table 5.First, export seems to play an important role in explaining changes in skill composition of a firm. Once we control for the initial heterogeneity of firms (Model II), starters (NE) that did not export in 1991 but did in 1997 showed a significantly faster skill upgrading than non-exporters (NN) that did not export in neither year. On the contrary, stoppers (EN) that exported only in 1991 but stop exporting in 1997 exhibited significantly slower skill upgrading than non-exporters (NN).The result implies that participation in export market may bring a significant change in skill mix of a firm by adopting more skill intensive technologies. Second, innovation activities are also strongly correlated to skill upgrading. Firms conducting more intensive innovation activities on average achieved faster skill upgrading. Third, initial size of a firm and capital intensity of a plant arestrongly associated with changes in skill intensity in the subsequent period. Larger and less capital intensive firms are more likely to be experiencing faster skill upgrading. Larger plants are in better position to overcome fixed cost for export market participation and more likely to upgrade skill mix faster than smaller ones. Moreover, since technology and capital are complementary factors in most cases, less capital intensive firm in initial state may experience much faster skill upgrading once they adopt more advanced technology. Fourth, differences in initial productivity across firms help predict changes in skill mix in the subsequent years. Firms with higher productivity in 1991 were more likely to achieve larger increase in the proportion of skilled workers in the following years.In sum, changes in skill mix of a firm seem to be closely related to export market participation and innovation activities as well as initial status of the firm.

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[8]Summary statistics of the variables are reported in Appendix 1.

Table 5. Skill Upgrading: Export and Innovation

	Model I	Model II	Model III
CONSTANT	-13.0927*** (2.8277)	-13.7887*** (2.9520)	-13.8176*** (2.9267)
NE	1.6061*** (0.4081)	1.2664*** (0.4182)	1.2147*** (0.4181)
EN	-0.4571 (0.4334)	-0.9577** (0.4449)	-0.9875** (0.4448)
EE	1.4648*** (0.3230)	0.4912 (0.3836)	0.4514 (0.3839)
$SIZE_{91}$		0.6819*** (0.1248)	0.6621*** (0.1253)
AGE_{91}		0.0096 (0.0165)	0.0108 (0.0165)
TFP_{91}		0.7273** (0.3650)	0.7611** (0.3656)
$CAPINT_{91}$		-0.3980*** (0.1086)	-0.4070*** (0.1086)
RND			0.1279** (0.0600)
Industry Dummies	Yes	Yes	Yes
R^2	0.0055	0.0079	0.0082
# of Obs.	24,166	23,809	23,809

Notes: 1) Numbers in parentheses are standard errors of coefficient estimates. All standard errors are corrected for possible heteroskedasticity following White (1980).
2) ** and *** indicate statistical significance at 5% and 1%, respectively.
3) Four-digit KSIC industry dummies are included in all models.

The result inTable 5.may not berobust to the way we measure innovation activity of a firm. One may argue that introduction of a new product is the outcome of innovation efforts that can ultimately affect the skill composition of labor force employed by a firm. Fortunately, our data set is rich enough to include detailed information on products of individual plant that we can identify the number of new products introduced each year.For robustness reason, four different measures of product innovation are considered; dummy for introduction of new products between 1991 and 1997(ECDUM), the number of products newly introduced by a firm between 1991 and 1997 (EC), the ratio of the number of newly introduced products between 1991 and 1997 to the number of total products produced in 1997(ECR), and the ratio of theshipment of newly introduced products between 1991 and 1997 to the total shipment of a firm in 1997 (ER). All variables are measured at plant level and the estimation results are reported in Table 6. The main results in Table 5.are preserved even after we replace expenditure on R&D with various measures of product innovation. Starters (NE) experienced fastest skill upgrading. Unlike Table 5., exporters (EE) that exported both in 1991 and 1997 achieved a significantly faster increase in the proportion of non-production workers that non-exporters (NN). In addition, product innovation measures seem to maintain meaningful correlation with skill upgrading. Both ECDUM and EC are significant at 10% level. Though the estimated coefficients on ECR and ER do not show statistical significance at conventional levels, their p-values are 15.0% and 16.7%, respectively.

Table 6: Skill Upgrading: Export and Product Innovation

	Model III-1	Model III-2	Model III-3	Model III-4
CONSTANT	3.9465*** (1.2769)	4.3734*** (1.2185)	4.0541*** (1.2723)	4.0841*** (1.2696)
NE	2.0564*** (0.6315)	2.0730*** (0.6319)	2.0579*** (0.6314)	2.0595*** (0.6314)
EN	-0.8420** (0.6515)	-0.8522 (0.6516)	-0.8434 (0.6515)	-0.8450 (0.6514)
EE	1.1362* (0.5841)	1.1291** (0.5841)	1.1279** (0.5842)	1.1281** (0.5843)
$SIZE_{91}$	0.5247*** (0.1831)	0.5214*** (0.1831)	0.5256*** (0.1831)	0.5257*** (0.1831)
AGE_{91}	0.0069 (0.0241)	0.0061 (0.0241)	0.0068 (0.0242)	0.0061 (0.0242)
TFP_{91}	0.4073 (0.5184)	0.3949 (0.5185)	0.4062 (0.5184)	0.4048 (0.5184)
$CAPINT_{91}$	-0.4334*** (0.1537)	-0.4331*** (0.1537)	-0.4330*** (0.1537)	-0.4326*** (0.1537)
ECDUM	0.7164* (0.4210)			
EC		0.3109* (0.1751)		
ECR			0.0060 (0.0042)	
ER				0.0057 (0.0041)
Industry Dummies	Yes	Yes	Yes	Yes
R^2	0.0105	0.0105	0.0104	0.0104
# of Obs.	11,232	11,232	11,232	11,232

Notes: 1) Numbers in parentheses are standard errors of coefficient estimates. All standard errors are corrected for possible heteroskedasticity following White (1980).
2) *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.
3) Four-digit KSIC industry dummies are included in all models.

4. Complementarity between Exporting and R&D

The analyses above do not provide usthe answer the question oftemporal sequencebetween innovation and exporting. At conceptual level, causality can run in both directions. Firms with more R&D expenditure are more likely to participate in export market since they may possess better technology necessary to compete in international market. On the other hand, large market size associated with exporting may provide firms with greater incentive to do R&D. Therefore, a plausible conjecture is that there exist complementarities between exporting and R&D decisions. We now examine the possibility. Specifically, utilizing the propensity score matching procedure a la Becker & Ichino (2002), we examine whether the decision to participate in exporting strengthens the plants' incentive to do R&D and, conversely, whether the decision to participate in R&D activity strengthens the plants' incentive to export. We are interested in the effects of export (R&D) participation on R&D (exporting) at both extensive and intensive margins.

To estimate the effect of exporting on R&D, we first select a sample of *starter* and *never* plants. Starters are those plants that were non-exporters in the first year they appear in the dataset but switched to exporters in some later year and remained as exporters. Never is a group of plants that were non-exporters in the first year they appear in the dataset and never switched to exporters during the sample period of 1990-1998. When the outcome variable of interest is the extensive margin of R&D, the following probit model is estimated for these sample plants.

$$\Pr(x_i = 1 \mid r_i, rndr_i, X_i) = E(x_i \mid r_i, rndr_i, X_i), \quad (4)$$

where x_i is a dummy variable indicating export-market and R&D participation and the left hand side of equation (4) is the probability of becoming an exporter for plant i conditional onthe vector of pre-exporting characteristics one year before export market participation.[9] As the pre-exporting characteristics, we include a dummy variable indicating whether the plant reported a positive amount of R&D expenditure (r_i), R&D intensity (rndr = R&D/production ratio), and other plant characteristics X_i which includes plant TFP (log) , number of workers (log) as a proxy for the plant size,

[9]For never plants, the plant characteristics are the values in 1995. Main results in this pa per do not change qualitatively when we use 1994 instead.

plant age, capital intensity (fixed tangible assets per worker), and skill intensity (the share of non-production worker). We also include year and ten industry dummy variables.

When the outcome variable of interest is the intensive margin of R&D, we further restrict our sample to those plants which reported a positive amount of R&D one year before export-market participation.

Thus, the probit model estimated in this case is as follows.

$$\Pr(x_i = 1 \mid r_i = 1, rndr_i, X_i) = E(x_i \mid r_i = 1, rndr_i, X_i) \tag{5}$$

Based on the estimated probability of exporting, we match starter plants with never plants one year before export market participation. We use nearest neighbor matching to estimate the average effect of exporting on the extensive and intensive margin of R&D. The intensive margin of R&D is measured as the R&D intensity, *rndr*. The extensive margin of R&D is measured as the probability of a plant doing R&D, which is estimated from the followingprobit model.

$$\Pr(Z_i) = \Pr(r_i = 1 \mid Z_i) = E(r_i \mid Z_i) \tag{6}$$

where Z_i is the contemporaneous plant characteristics, which includes plant TFP (log), number of workers (log), plant age, capital intensity, skill intensity, and a dummy variable which is equal to 1 if the plant is a multi-product plant.

By following a symmetric procedure, we estimate the effect of R&D on exporting. That is, we start by selecting a sample of *R&D starter* and *R&D never* plants. R&D starters are those plants that did not do R&D in the first year they appear in the dataset but switched to R&D-do*ers* in some later year and remained as R&D do*ers*. R&D never is a group of plants that did not do R&D in the first year they appear in the dataset and never switched to R&D-do*ers*.

Depending on whether the outcome variable of interest is extensive or intensive margin of exporting, each of the following probitmodel is estimated.

$$\Pr(r_i = 1 \mid x_i, xr_i, X_i) = E(r_i \mid x_i, xr_i, X_i) \tag{7}$$

$$\Pr(r_i = 1 \mid x_i = 1, xr_i, X_i) = E(r_i \mid x_i = 1, xr_i, X_i) \tag{8}$$

Here, *xr* denotes export intensity (=exports/production ratio). Based on the estimated probability of R&D participation, we match R&D starter with R&D never plants, and estimate the average effect of R&D participation on the extensive and intensive margin of exporting. Again, we use nearest neighbor matching. The intensive margin of exporting is measured as the export intensity, *xr*. The extensive margin of exporting is measured as the probability of a plant being an exporter, which is estimated from the following probit model.

$$\Pr(Z_i) \equiv \Pr(x_i = 1 \mid Z_i) = E(x_i \mid Z_i) \qquad (9)$$

Table 7.shows that export-market participation significantly strengthens the incentive to do R&D in subsequent years. It raises the subsequent probability of doing R&D, beginning from one year after export participation. There is some evidence that export participation also raises R&D intensity, but it is significant only for one year after export participation. We also find strong evidence indicating that R&D participation promotes subsequent exporting activity, particularly at extensive margin. Again, we find that R&D participation increases subsequent exporting intensity but with a time lag of about three years. In sum, our analysis shows that exporting and R&D activities are complementary to each other. There exists bi-directional causal relationship between exporting and R&D activities consistent with the underlying assumptions of Costantini & Melitz (2008) and Aw, *et al.* (2009).

Table 7: The Effect of Export (R&D) Participation on R&D (Exporting)

Treatment	Outcome Variable	No. Treated	ATT[a]				
			s=-1	s=0	s=1	s=2	s=3
export participation	Probability of doing R&D	4,231	-0.001 (0.003)	0.003 (0.003)	0.021*** (0.004)	0.038*** (0.005)	0.034*** (0.008)
	R&D intensity	460	0.918 (4.123)	0.499 (0.674)	0.747*** (0.333)	0.277 (0.779)	0.409 (0.614)
R&D participation	Probability of being exporter	3,442	0.023*** (0.005)	0.036*** (0.005)	0.098*** (0.008)	0.148*** (0.011)	0.094*** (0.023)
	export intensity	746	-1.570 (3.752)	-3.995 (4.097)	-3.910 (7.415)	16.071 (11.600)	47.332*** (16.122)

Note: a.The average treatment effect on the treated a la Becker &Ichino (2002) using nearest neighbor matching. The treated units are matched with the untreated one year before export or R&D participation. The numbers in the parenthesis are standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

5. Conclusion

We examine the role of export and innovation activitiesin skill upgrading of Korean manufacturing sector during 1990’s utilizing a unique plant-level panel data. Considering the vital role of export in economic development and industrial changes in Korea over the last decades, we believe that our exercise offers an excellent opportunity to investigate the impacts of export on labor market.

Korean manufacturing sector experienceda significant degree of skill upgrading during 1990’s. For instance, the share of non-production workers at plant level increased at the rate of 1.7611% per year between 1991 and 1997. More interestingly, larger portion of skill upgrading was achieved within plants rather than through reallocations across plants. Within-plant skill upgrading explains 57.2% of total increase in the share of non-production workers between 1991 and 1997 while between-plant effect accounts for 42.8% of total skill upgrading. Finally, we found some evidence broadly supporting recent theoretical development that emphasizes the inter-connectedness of export market participation, innovation activities and skill upgrading. In regression analyses, we confirmed that both exporting and innovation are important factors in explaining changes in skill composition of a firm. Results of propensity score matching implies that once initiated, R&D activities and exporting show the tendency to reinforce each other in subsequent years.

We can draw a few important policy implications from our study. A large share of aggregate skill upgrading was achieved through rebalancing of skill composition within firms rather than between firms in Korean manufacturing sector. Moreover, we found the evidence that there exist interactions between export market participation and skill mix choice of firms. Exporting firms experienced much faster skill upgrading than non-exporting ones and the process was further accelerated when export market participation was accompanied by more intensive innovation activities. Based on these findings, we can argue that policies to promote exporting and R&D activities of firms may bring faster skill upgrading and consequently higher aggregate productivity. Next, our empirical results suggest that skill upgrading associated with exportinghad been achieved mainly through within effects andexporting, or more broadly, trade liberalization may have differential effects on skilled and unskilled labors. Even though export market participation may have beneficial effects on both skilled and unskilled labors, the impact seems to be stronger for the former than the latter. Many countries adopted trade adjustment assistance (TAA) program to mitigate adverse impacts on the losers due to institutional changes in international trade. TAA may include cash transfer program to directly compensate for the loss as well as technical assistance such as job training and information provision to facilitate smoother transition. Most traditional TAA programs are designed to be triggered when total sales of an adversely affected firm drop to the pre-specified threshold. Our study suggests that trade may have distributional implication even among winners such as exporters and these subtle implications should be seriously taken into account in designing TAA program. It might be better idea to take individual workers rather than firms as the basic unit of TAA program since regime change in trade policy may result in both winners and losers for an individual firm. Lastly, now that exporting contributes to skill upgrading and subsequent increase in wage gap in a significant manner, we can offer another rationale for active labor market policy to help unskilled labor.

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Appendix 1. Descriptive Statistics

	Num. of Obs.	Mean	S. D.	Min	Max
NN	24174	0.7188	0.4496	0	1
NE	24174	0.0798	0.2710	0	1
EN	24174	0.0719	0.2584	0	1
EE	24174	0.1294	0.3356	0	1
$SIZE_{91}$	24173	733.1990	731.1062	761.0986	1210.3813
AGE_{91}	24175	8.8173	7.5927	1	92
TFP_{91}	23816	0.0058	2.3515	-3.4166	4.0517
$CAPINT_{91}$	24157	2.4939	1.2413	-3.8027	10.2277
RND	24175	0.5519	2.3505	0	120.7107
ECDUM	11448	0.8354	0.3708	0	1
EC	11448	1,0970	0.8874	0	16
ECR	11448	81.1021	37.5220	0	100
ER	11448	80.6480	38.2948	0	100