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Technological Change and Returns to Education: The Implications for the S&E Labor Market

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Abstract

This paper analyzes the earnings effect of skill-biased technological change (SBTC), focusing on the comparison of science and engineering (S&E) and non-S&E occupations. In the analysis, we assert that S&E occupations and non-S&E occupations differ in the nature of skill requirements and their susceptibility to technological change; and consequently the earnings effects of SBTC also demonstrate a similar impact. For the empirical analysis, the modified Mincerian earnings equations are estimated by quantile regressions as well as the OLS and two-stage estimation method.

Fitted to Korean panel data, the earning-enhancing effect of skill-biased technological change is observed for male workers, not only for those in S&E occupations but also for those in non-S&E occupations. Such an effect is not observed for women in S&E occupations, and rather turns even negative for women in non-S&E occupations; envisaging a relatively large occurrence of work interruption of married women in Korea, we conjecture that this may reflect women workers' skill deterioration taking place during a work interruption. The earnings effect of SBTC is most apparent for male workers in the higher quantiles of earnings distribution, implying that those who are highly educated and have high unobserved ability gain most from SBTC.

Ⅰ. Introduction

This paper intends to compare the impact of technological change upon the educational earnings premium between S&E occupations and non-S&E occupations. S&E and non-S&E occupations are presumed to differ according to the nature of primary job skills and the responsiveness to technological change. S&E occupations require more of R&D-related or S&E-specific professional skills, while non-S&E occupations require more of general multi-facet skills that can be applied to a relatively large spectrum of jobs. If that is the case, those who are employed in S&E occupations and those in non-S&E occupations are likely to differ with regard to how they respond to external technological shock and how their productivity and earnings are affected by such technological shock.

A substantial volume of research has recently demonstrated the positive impact of technological change on the educational earnings premium, strongly supporting the hypothesis of skill-biased technological change (SBTC). But there is a paucity of literature that examines the varying effects of technological change as it is experienced by those with skills of differing natures. This paper is unique in that it explicitly examines how the nexus between technological change and educational earnings premium differs for different skill traits – skills inherent in S&E and non-S&E occupations. Our hypothesis is that, given the differences in skill intensities of S&E and non-S&E occupations, the earnings effect of technological change will also differ, depending on the nature of the skill-bias of technological change.

We focus on the comparison between S&E workers and non-S&E workers in part because they contrast well in terms of the nature of skills and the susceptibility to technological change. Our interest in S&E occupations is also due to the fact that science and technology (S&T) are increasingly emphasized as essential to the national competitiveness and thus sustainable economic growth, yet suffer from a quantitative/qualitative mismatch between the demand for and supply of S&T personnel in many countries; the analysis of skill-biased technological change and its effect on S&E workers in comparison with non-S&E workers should shed sufficient light so as to enable the better understanding of the S&E labor market. For the empirical analysis, the Korean panel data of college graduates, classified into either S&E occupations or non-S&E occupations, are used. The earnings effect of skill-biased technological change is estimated by quantile regressions, along with the OLS and two-stage estimates of the modified Mincerian earnings equations.

The rest of the paper is organized as follows. Section II offers the conceptual framework for the alleged differences in the effect of skill-biased technological change between S&E and non-S&E occupations. Section III explains the econometric model and estimation methods for the testing of the hypothesis. Section IV describes the data used for the empirical analysis. Section Ⅴ analyzes the earnings determination of S&E occupations compared to non-S&E occupations, with special reference made to the earnings effect of skill-biased technological change, and taking into account the phenomenon of unobserved worker heterogeneity. Section Ⅵ summarizes the major findings of the paper and articulates some implications from them.

Ⅱ. Skill-Biased Technological Change: S&E vs. non-S&E Occupations

The enlargement of educational earnings differentials, accompanied by the relative increase in the supply of educated (skilled) workers in the United States and other OECD countries since the 1980s has spawned a mushrooming body of literature devoted to the examination of skill-biased technological change. The observed increase of the relative price (earnings) of educated workers despite the relative supply growth implies that there must have been a corresponding shift in demand to enable such a price increase. Skill-biased technological change has been advanced as the leading possible explanation for the demand shifts favoring more educated workers relative to less educated workers.[1]

Using a supply and demand framework in which different demographic groups are treated as distinct labor inputs, authors Katz and Murphy (1992) and Bound and Johnson (1992) have rendered indirect bodies of evidence indicating that technological change is responsible for the widening of educational earnings differentials. As for more direct evidence for skill-biased technological change, strong correlations have been found between the industry-level indicators of technological change (computer investments, the growth of employee computer use, R&D expenditures, utilization of scientists and engineers, changes in capital intensity measures) and the within-industry growth in the relative employment and wage bill share of more skilled workers (Berman, Bound and Griliches, 1994; Bartel and Sicherman 1999; Allen 2001).

The question that follows then regards the sources for the positive relationship between technological change and an educational earnings premium. Why does technological change raise the demand for highly educated (skilled) workers and thereby increase their earnings relative to those less educated (skilled)? Commonly acknowledged explanations pertinent to this question include: skill-technology complementarity, allocative ability to deal with disequilibrium, and technology-induced changes in work organization, among others.

The view based upon skill-technology complementarity finds its roots in the capital-skill complementarity hypothesized by Griliches (1969); under the assumption that capital is more complementary in its association with more highly skilled labor than with low skilled labor, it

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[1] Johnson (1997), Katz and Autor (1999), and Acemoglu (2002) present excellent reviews of literature treating the relationship between earnings inequality and technological change.

can be asseverated that technological change and associated capital deepening will shift the demand more toward skilled labor. According to the disequilibrium viewpoint (Schultz, 1975; Welch, 1970), the individuals' allocative ability – the ability to reallocate their resources in response to external shocks – is critical in a dynamic setting characterized by fast technological change; since the allocative ability is enhanced by education, with more educated persons tending to more readily adapt to technological change, all other things being equal, than less educated persons. The hypothesis of technology-induced changes in work organizations asserts that a technology-induced transition of a work organization from a "mechanistic" toward an "adaptive" character increases the demand for skills (Thesmar and Thoenig, 1999).

These hypotheses yield an interesting implication for the role of skill-biased technological change in the earnings determination of S&E and non-S&E occupations. Skills required in S&E occupations and those required in non-S&E occupations stand in stark contrast to each other. Skills in S&E occupations are mostly field-specific, so they are hardly transferable to other fields, while skills in non-S&E occupations are of a more general nature and therefore are relatively more easily transferable to other fields. S&E majors are thus characterized by a lower incidence of mismatch between work and degree field, but are subject to a larger wage penalty when mismatched, as compared to non-S&E majors (Robst, 2007). S&E jobs value measurable skills over less tangible skills, whereas the latter seem to be more important in non-S&E jobs such as management or services (Stephan, 1996). This trait explains to some extent why the average gender pay gap is smaller and discrimination is less substantial in S&E fields than in non-S&E fields (Graham and Smith, 2005).

Although none of these hypotheses confine the nature of skills to a narrowly defined area such as science/technology-related skills, we may draw subtle differences in the type of skills emphasized in each hypothesis. Whereas the skill-technology complementarity hypothesis seems more relevant to particular job-specific skills such as R&D-related or S&E-specific skills, both the allocative ability and skills demanded in adaptive work organizations seem to be more closely related to general, multi-faceted skills that are widely utilized in non-S&E occupations (e.g., those requiring managerial skills).

Put differently, the earnings effect of skill-biased technological change will take place via different routes for S&E workers and for non-S&E workers. For S&E workers, the earnings effect of skill-biased technological change will largely manifest returns to R&D-related or S&E-specific skills that are complementary with technological advances occurred. For non-S&E workers, on the other hand, it will largely reflect returns to general skills – whether put in as an allocative ability or as adaptive skills that are suitably matched with a new organizational form of firms. To recapitulate, the earnings effect of skill-biased technological change will be larger for S&E occupations if it accrues more from S&E-specific skill enhancement, while it will be larger for non-S&E workers if it relates more closely to returns based on more general skills.

Ⅲ. The Model

1. Earnings Determination and S&E Occupations

To compare the earnings of S&E and non-S&E workers, we employ the following semi-log earnings equation with the S&E occupation dummy variable.

$$\begin{aligned}(1)\qquad \ln W_{ij} &= \beta_0 + \beta_1 EDU_i + \beta_2 EXP_i + \beta_3 (EXP_i)^2/100 + \beta_4 TENURE_i + \beta_5 (TENURE_i)^2/100 \\ &+ \beta_6 AREA + \beta_7 MARRIED + \sum_t \beta_t YEAR_t + \sum_j \beta_j IND_j + \delta S\&E_i + u_{ij}\end{aligned}$$

where

W_{ij} = the hourly earnings of individual i in industry j,

EDU_i = years of schooling of individual i,

EXP_i = potential labor market experience (= age - years of schooling - 6) of individual i,

$TENURE_i$ = tenure year of individual i,

$AREA_i$ = 1 if individual i resides in Seoul area; otherwise $AREA_i$ = 0,

$MARRIED_i$ = 1 if individual i is married with spouse; otherwise $MARRIED_i$ = 0,

$YEAR_t$ = year dummies, with 1998 as a reference year,

IND_J = industry dummies, with manufacturing industry as a reference industry, and

$S\&E_i$ = 1 if individual i holds S&E occupations; otherwise $S\&E_i$ = 0.

The direct estimation of Equation 1 is subject to the potential endogeneity problem of the S&E dummy variable. That is, an individual is likely to choose a S&E job if the expected present value of the lifetime earnings of having S&E occupations surpasses that of non-S&E occupations. To correct for this potential selection bias accruing from the endogeneity of the S&E choice, we further estimate Equation 1 using the two-stage estimation method.

In the first stage, we estimate the determinants of an individual being in S&E occupations using the following probit function.

(2) $S\&E_i = \eta + \theta' X_i + \lambda Z_i + v_i$,

where X is a vector of variables which includes the human capital variables such as years of schooling, labor market experience, tenure and others. The variables in X influence both the choice of an S&E job of an individual and the subsequent earnings. Z includes the dummy variable of college major and the dummy variable of his/her parent's S&E occupation when the individual was fourteen years old. *Z* is chosen so that it influences an individual's choice of occupation, but not on earnings thereafter.

From the probit estimation of Equation 2, we obtain the inverse Mill's ratio (IMR). Adding the estimated IMR as an explanatory variable in the earnings equation, the least squares method yields a consistent estimator of the S&E wage *e*ffect. According to two-stage estimation results using the Korean data, however, the endogeneity problem turns out to be insignificant (with the IMR being statistically insignificant). Thus in the empirical analysis that follows in this study, we only report OLS estimation results instead of two-stage estimation results.[2]

2. Skill-Biased Technological Change and Earnings

We now turn to the earnings effect of skill-biased technological change. Following the previous study (Bartel and Sicherman, 1999), we add the proxy variable for technological change ($TECH_{ij}$) to Equation 1.[3] Also added is the interaction term between years of schooling and $TECH_{ij}$ to analyze the relationship between technological change and earnings across different education levels (i.e., returns to schooling).

(3) $\ln W_{ij} = \beta' X_i + \delta S\&E_i + \gamma_1 TECH_{ij} + \gamma_2 TECH_{ij} * EDU_i + u_{ij}$

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[2] Two-stage estimation results of the basic earnings equation are reported in Table A.3 in the Appendix.

[3] Another approach adopted in the previous studies is to divide the workers into various demographic groups (especially into different educational groups) and to analyze the changes in relative wages or the wage bill of college graduates over time (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman, Bound and Griliches, 1994; Berman, Bound and Machin, 1998). Although this approach has the advantage of utilizing longer time-series data and analyzing changes over time, it cannot control other observed and unobserved characteristics of an individual that affect his or her own earnings.

where $TECH_{ij}$ refers to technological change of industry j, to which worker i belongs.

If skill-biased technological change takes effect, then highly educated workers will reap the benefit of higher earnings as technology changes. That is, the coefficient of the interaction term in Equation 3 should be positive ($\gamma_2 > 0$).

To compare the size and/or direction of the earnings effect of skill-biased technological change between S&E and non-S&E occupations, we estimate Equation 3, while dropping the S&E dummy, for S&E and non-S&E occupations, respectively. We expect γ_2 positive and larger for S&E occupations than for non-S&E occupations if the skill-bias of technological change moves more toward the science/technology-specific rather than to general multi-faceted skills associated with non-S&E occupations. If the opposite holds true, then we will observe γ_2 as smaller, although positive, for S&E occupations.

To identify the role of the unobserved worker heterogeneity in earnings determination, we further estimate earnings equations by quantile regressions. First introduced by Koenker and Bassett (1978), quantile regression estimates the linear model of the dependent variable's conditional τ-quantile, while the classical OLS regression estimates the linear model of the dependent variable's conditional mean. Formally, the quantile regression model is formed as the following.

(4) $y_i = \beta_\tau' X_i + u_{\tau i}$ with $Q_\tau(y_i \mid X_i) = \beta_\tau' X_i$ (i = 1, 2, …, n)

where β_τ is a (k×1) parameter vector, X_i is a (k×1) vector of covariates, $u_{\tau i}$ stands for the error term, and $Q_\tau(y_i \mid X_i)$ denotes the τ-th conditional quantile of y given X. Note that $Q_\tau(u_{\tau i} \mid X_i) = 0$ for all i. The quantile regression estimator of β_τ is a solution to the following equation:

$$(5)\ Min\ \frac{1}{n}\left\{ \sum_{y_i \geq \beta' X_i} \tau \,|\, y_i - \beta' X_i \,| + \sum_{y_i < \beta' X_i} (1-\tau) \,|\, y_i - \beta' X_i \,| \right\},\ \text{for a given } \tau.$$

Ⅳ. Data

1. The Korean Labor and Income Panel Survey

The data were drawn from the Korean Labor and Income Panel Survey (KLIPS), a longitudinal survey of households and individuals in Korea. The KLIPS data provide information on the individuals' socioeconomic characteristics, such as labor market status, years of schooling, age, tenure, region of work place as well as monthly wages and working hours, for 1998 onward. The data for the years 1998-2005 (1st survey year through 8th survey year) were pooled together for the empirical analysis.

The target group assessed by our analysis is those who have the schooling level of a 2-year college graduation or above, since we are comparing S&E jobs and non-S&E jobs in terms of the effect of technological change. We further confine our analysis to those who are aged 15-64, employed in non-agricultural industries. The final data set consists of 7,878 observations when pooled together; 1,017 observations (681 men and 336 women) in S&E occupations and 6,861 observations (4,491 men and 2,370 women) in non-S&E occupations. The hourly earnings were calculated by dividing monthly earnings by monthly working hours, and converted into real term with the year 2000 as a reference year.

2. Measures of Technological Change

Technological change encountered by the individuals in their workplaces is not directly measurable. Instead, technological change can be measured at the industry level, albeit not perfectly. Thus, the individual characteristics from the KLIPS data are matched for the measures of technological change of each industry to which individual workers belong.

Since no single measure is perfect in reflecting actual technological change, we use three different measures as proxies: two input measures and one output measure. The input-based proxies for technological change we use are the ratio of R&D expenditures to sales (R&D intensity) and the ratio of scientists and engineers to the total number of workers, both measured as the average for the years 1998-2004. These data were obtained from the Korean Ministry of Science and Technology. As for the output-based measure, we use the estimates of TFP growth across two-digit industry categories for the period between 1972 and 2003, as provided by Pyo et al. (2006).[4] The first two measures - the R&D intensity and the percentage of scientists and engineers in total employment – are closely related to the science/technology intensity of each sector. The TFP measure, on the other hand, is more comprehensive in that, as the "catch-all" measure, it includes not only R&D-induced technological innovation but also non-R&D-induced innovations such as organizational and institutional innovations.

Ⅴ. Empirical Results

1. Earnings Determination and S&E Occupations

[4] For some industries, TFP growth was estimated at the three-digit industry level as in the Table A.1 in the Appendix. Other possible output-based measures for technological change include the number of patents, applied for or granted in the industry. The data on the number of patents in Korea, however, are not available at the disaggregated industry level.

Summary statistics of the variables in the econometric model, along with the definition and relevant measures, are presented in Table 1. The average years of schooling of the individuals in the final sample are 15.7 years, which approximates a 4-year college graduation. The male population takes up 66% of the total sample. The proportion of those holding S&E occupations amounts to 13% of the total sample population, whereas 2% of the sample population's parents held S&E occupations when they were 14 years old.[5] As for technological change measures, the R&D intensity and the percentage of scientists and engineers among the total employed are on average 7.25% and 6.68%, respectively. The average TFP growth rate over the last 30-year period is -0.21, but the industrial dispersion is quite large.

Table 2 compares the worker characteristics of S&E occupations with non-S&E occupations. The average log hourly earnings are higher for S&E occupations than for non-S&E occupations, for both men and women. Earnings dispersion, however, is larger for non-S&E occupations than for S&E occupations, implying that S&E workers are more homogeneous in worker composition, in comparison to non-S&E workers. A larger earnings dispersion of non-S&E occupations as compared to S&E occupations is also evident in Figure 1, where non-S&E occupations illustrate relatively long tails in the Kernel density function.

There is not much difference between S&E workers and non-S&E workers regarding human capital variables such as years of schooling, except that male S&E workers tend to be

[5] For S&E occupations, we included medical professions as well as science/engineering professionals. The reason is that medical professionals share similar traits to S&E professionals rather than to non S&E professionals, in terms of skill properties and responsiveness to technological change. Empirical results were not qualitatively different whether we included medical professions in S&E occupations or not, anyway. The parent's occupation refers to either parent who was main bread winner within the family at the individual's age of 14. Classifications of S&E occupations are explained in Table A.2 in the Appendix.

younger and shorter-tenured than their non-S&E male counterparts. Noteworthy here are the contrasting differences between S&E and non-S&E occupations by alternative measures when it comes to the degree of technological change. While S&E occupations are more centered in the R&D- or S&T-intensive sectors, non-S&E occupations are more centered in the sectors that have experienced more rapid TFP growth over the last 30-odd years. This may reflect that non-R&D-related innovations, such as organizational and institutional innovations, and a subsequent rise in the efficiency and value-added conditions in non-S&E fields have exceeded the concurrent TFP growth in S&E fields, as a whole.

The industrial distribution of each occupation group shows a clear distinction.[6] For men, S&E workers are heavily concentrated in the business services industry (35%), whereas non-S&E workers are employed in the following order: education (16%), elasticity/gas and construction (9%) and wholesale and retail services (9%). For women, 63% of women S&E workers are employed in the health industry, while 41% of non-S&E women workers are in education industry.

As for the determinants of earnings, the OLS estimates of the earnings equations are reported in Table 3. From the first and third column, we observe that the S&E earnings premium is positive and statistically significant for both sexes. Men and women workers who are functioning in S&E occupations earn 7 to 8 percent more than their non-S&E counterparts, *ceteris paribus.* The human capital variables all exhibit the significant effect in the expected direction for men and women as well.

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[6] So as to control for this difference in the industrial distribution, eight industry dummies are added in the earnings equations, where industries of similar properties are clustered to the same group. The manufacturing industry is dropped out of the regression equations as a reference. Industry classifications are explained in Table A.3 in the Appendix.

2. Skill-Biased Technological Change and Earnings

The hypothesis we set up in this study is that the earnings effect of skill-biased technological change will differ for S&E workers and non-S&E workers, due to the different nature of skills they primarily use in their job. We now turn to the test of this hypothesis.

The earnings premium of skill-biased technological change is captured by the coefficients of the interaction term between technological change and education (*R&D*EDU*) in Table 3. As seen in the 2nd and the 4th column, the coefficient of this interaction term is positive and statistically significant for men; it is negative and significant for women, however.[7] When measured by the R&D intensity, therefore, technological change manifests the skill-bias for men, but not apparently for women. Even controlled for skill-biased technological change, S&E occupations still exhibit a positive earnings premium.

Table 4 compares the estimation results of Earnings Equation 3 without the S&E dummy, focusing on the size and direction of the interaction term between technological change and education (γ_2), for three different technological change measures.

A couple of interesting findings merit discussion.

First, the estimated value of γ_2 is positive and significant for men, not only for those in S&E occupations but also for those in non-S&E occupations, when technological change is measured by the R&D intensity. The percentage of scientist/engineers of total employment as a technological change measure yields also the positive $\gamma_{2,}$ which is almost significant for S&E male workers and significant for non-S&E male workers. TFP growth, on the contrary,

[7] A possible explanation for this is in line with that given to explain the negative interaction term for non-S&E women workers in Table 4.

does not illustrate any meaningful earnings effect of technological change.[8] The observed similarity between S&E occupations and non-S&E occupations in regard to the earnings effect of technological change implies that technological change entails a skill upgrade in demand, where skills refer not only to S&E-specific skills but also to non-S&E-related general skills. The observed skill-bias of technological change also implies that technological advancement tends to enlarge the earnings gap among workers with different education levels in S&E and non-S&E occupations as well.

Secondly, contrary to the male case, the earning-enhancing effect of skill-biased technological change is not evident among female workers, regardless of the type of technological change measure. The estimated value of γ_2 is positive but not significant for female S&E workers; it is negative and significant (except for the STP measure) for female workers in non-S&E occupations. The interpretation of this result requires some caution. Bearing in mind that women (mostly married women) in Korea still have a relatively high ratio of work interruption (as evidenced by the typical M-type age-participation profile) and so are vulnerable to skill deterioration during the work interruption, the potential experience variable used in the earnings equation in this study tends to overestimate the actual experience of women. In this regard, the seemingly insignificant or even negative earnings effect of technological change for women may in fact reflect skill deterioration of career-interrupted women, which can be more detrimental when accompanied by skill-biased technological change. Further taking into account that work interruption of women is more prevalent in non-S&E occupations than in S&E occupations, the negative earnings effect of

[8] We need to be careful in interpreting the effect of TFP growth, though. The TFP estimates are highly vulnerable to the measurement problem; it is especially so in service industries for which consistent time-series data for capital stock are hard to obtain.

technological change observed for non-S&E women workers is explained on the same grounds.

We thus assert that skill-biased technological change does affect skill requirements and thereby influences earnings of our sample of college-educated workers; it does certainly so for male workers in both S&E and non-S&E occupations, and presumably so for female workers in both occupational groups. Although S&E occupations and non-S&E occupations are believed to critically differ in the nature of skill requirements, the effect of technological change on the educational earnings premium is commonly found in both occupations. Whether in S&E or non-S&E, it is those who are highly educated that reap the benefit of higher earnings as technology changes (as evidenced by γ_2 in Table 3 and Table 4); the insignificance or negativity of γ_2 for women workers seems to reflect a human capital-deteriorating effect occurring during work interruption in the course of continuing technological change.

3. Worker Heterogeneity and Earnings: Quantile Regressions

The earnings effect of skill-biased technological change is likely to differ, not only between S&E and non-S&E occupations but within each occupational group, due to the unobserved worker heterogeneity. To control for the role of the unobserved worker heterogeneity in earnings determination, we compare the earnings effect of skill-biased technological change for different quantiles of earnings distribution.

According to the quantile regression estimates in Table 5, the earnings effect of skill-biased technological change, where technological change is measured by the R&D intensity, tends to increase when moving toward higher quantiles for male workers. The earnings premium of skill-biased technological change is significant only in the highest two quantiles of earnings distribution, i.e., for those who have high unobserved abilities, however it would be measured. It is also noteworthy that the earnings premium of education (excluding the effect through the interaction with technological change) turns larger for those who belong to upper quantiles than those in lower quantiles, whereas the separate S&E earnings premium dwindles in upper quantiles.

For women, as presented in Table 6, the earnings effect of skill-biased technological change remains negative and significant for all quantiles, which is not different from the earlier OLS estimates. The direct educational earnings premium (a coefficient of *EDU*) rises for higher quantiles as in the case of men, but the S&E earnings premium (a coefficient of *S&E*) remains relatively stable for all quantiles except the highest one where the S&E earnings premium is no longer significant.

Table 7 and Table 8 compare the estimated earnings effect of skill-biased technological change for male workers in S&E occupations and those in non-S&E occupations, respectively, for different technological change measures. Although varied by different measures, the earnings effect of skill-biased technological change tends to be significant for male S&E workers in upper quantiles.[9] The earnings premium of skill-biased technological change is less apparent for male non-S&E workers than for their S&E counterparts; it is significant only in the highest quantile of earnings distribution (with the R&D intensity measure) for male non-S&E workers.

For women S&E workers, the earnings effect of skill-biased technological change is mostly positive but not significant in all quantiles, regardless of which technological change measure is used (see Table 9). For women non-S&E workers, the earnings effect of skill-biased technological change is mostly negative but again insignificant in most quantiles. The

[9] This does not obtain for the TFP growth.

negative earnings effect of skill-biased technological change is statistically significant only for women non-S&E workers in the highest quantile (for the two out of three technological change measures), which may imply that human capital deterioration taking place during work interruption is most detrimental to women with high unobserved ability.

The quantile regression results tends to confirm the potential role of unobserved worker heterogeneity in the determination of the earnings effect of skill-biased technological change. The positive and significant earnings effect of skill-biased technological change for male workers in upper quantiles implies that those who are highly educated and also possess high unobserved ability are benefited most by skill-biased technological change. The negative and significant earnings effect of skill-biased technological change for female non-S&E workers in the highest quantile may also indicate that such an effect can be substantial, especially for those who are highly educated and have high unobserved ability, rather than working as a counter example of skill-biased technological change.

Ⅵ. Summary and Conclusions

The purpose of this paper was to compare the earnings effect of education for S&E occupations and non-S&E occupations, in circumstances where technological change takes place. The proposed hypothesis was that the earnings effect of education will be larger for S&E occupations than for non-S&E occupations, when encountering fast technological change, if the skill bias of technological change gears more toward S&E-specific skills such as research capability; the opposite will obtain in the incidence of technological change that favors general skills that are not directly related to S&E occupations. Given the potentially large worker heterogeneity, it was further assumed that the earnings effect of skill-biased technological change may differ, depending on the position on the earnings distribution of workers in each occupational group. To test this hypothesis, the modified Mincerian earnings equation was estimated for S&E and non-S&E workers, using the Korean panel data.

The major findings can be summarized as follows. Although varied by specific technological change measure, on the whole, we found a positive and significant earnings effect of skill-biased technological change for male workers, not only for those in S&E occupations but also for those in non-S&E occupations. Considering that science/technology-specific skills are more important for S&E workers whereas general skills (multi-faceted skills that are applied to a variety of occupations) are more critical to non-S&E occupations, it suggests that the skill bias of technological changes which have occurred in Korea has been dominant for S&E-specific skills and for general skills as well. Quantile regression results suggest that the earnings effect of skill-biased technological change is more apparent for male S&E workers as compared to non-S&E workers, albeit not by a large margin; it is also more apparent for those in upper quantiles, i.e., those who are presumed to have higher unobserved ability. For women workers, on the other hand, the earnings effect of skill-biased technological change is either positive but insignificant (for S&E workers) or negative (for non-S&E workers); this, as we conjecture, may reflect the earnings penalty for women workers with career interruptions during periods of skill-biased technological change.

In a nutshell, we conclude that skill-biased technological change has been occurring in the Korean labor market, whereas skill-bias is not confined to S&E-specific skills but is inclusive of general multi-faceted skills not directly related to S&E jobs. Highly educated workers with high unobserved ability gain most from skill-biased technological change, all other things being equal.

Some extensions of this study are in order to add to the robustness of our conclusion. The first line of extension may be an in-depth analysis of women workers to see if the observed negative earnings effect of skill-biased technological change is really due to their work interruption. Another may be a panel analysis to examine the size and/or direction of the effect of skill-biased technological change while controlling for the time-invariant fixed effect of unobserved worker heterogeneity.

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Table 1. Variable Definitions and Summary Statistics

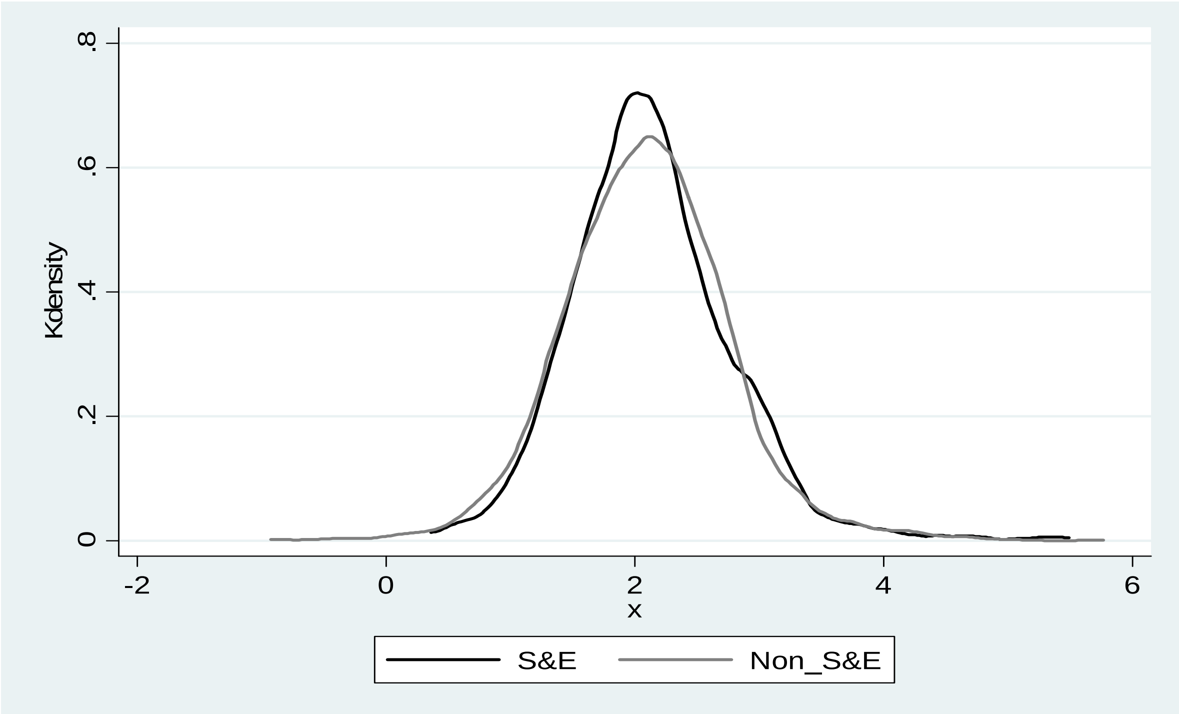
Variable	Definition and Measures	Mean	S.D.
Earnings			
ln W	Log of hourly earnings (earnings measured in 1,000 Korean won, 2000 prices)	1.98	0.67
Human Capital			
EDU	Years of schooling	15.68	1.46
AGE	Age in years	35.51	9.42
EXP	Potential labor market experience (=age-years of schooling-6)	13.93	9.14
TENURE	Tenure in years	6.20	7.13
AREA	1 if residing in Seoul 0 otherwise	0.30	0.46
MALE	Dummy variable (1=men, 0=women)	0.66	0.48
Married	Dummy variable (1=married with spouse, 0=otherwise)	1.66	0.50
S&E	1 if science/engineering/medical professionals 0 otherwise	0.13	0.34
Selection Variables			
S&E_Parent	1 if the parent had a S&E occupation at the individual's age of 14 0 otherwise	0.02	0.14
Technology			
R&D	R&D intensity, measured as a percentage of R&D expenditures out of total sales (1998-2004)	7.25	13.43
STP	Percentage of scientists and engineers out of the total employed (1998-2004)	6.68	8.25
TFP	Growth of total factor productivity between 1972 and 2003	-0.21	3.02
Year			
Year 1999	Dummy variable (1 for year 1999)	0.13	0.34
Year 2000	Dummy variable (1 for year 2000)	0.13	0.34
Year 2001	Dummy variable (1 for year 2001)	0.14	0.34
Year 2002	Dummy variable (1 for year 2002)	0.14	0.35
Year 2003	Dummy variable (1 for year 2003)	0.13	0.34
Year 2004	Dummy variable (1 for year 2004)	0.11	0.31
Year 2005	Dummy variable (1 for year 2005)	0.10	0.29
N		7,878	

Table 2. Variable Means: S&E vs. Non S&E Occupations

Variable	S&E				Non S&E			
	Men		Women		Men		Women	
Earnings								
In W	2.13	(0.64)	1.80	(0.54)	2.09	(0.66)	1.77	(0.64)
Human Capital								
EDU	15.86	(1.69)	15.19	(1.71)	15.73	(1.49)	15.27	(1.19)
AGE	34.91	(7.60)	30.84	(7.64)	38.67	(9.09)	30.34	(8.02)
EXP	13.06	(7.44)	9.65	(7.41)	16.95	(8.89)	9.08	(7.79)
TENURE	5.29	(5.84)	4.00	(5.53)	7.42	(7.58)	4.46	(6.26)
AREA	0.31	(0.46)	0.36	(0.48)	0.29	(0.45)	0.31	(0.46)
Married	1.66	(0.48)	1.52	(0.57)	1.80	(0.42)	1.41	(0.52)
Selection Variables								
S&E_Parent	0.02	(0.15)	0.07	(0.25)	0.01	(0.10)	0.03	(0.16)
Technology								
R&D	10.19	(18.9)	38.25	(26.4)	3.91	(6.88)	8.34	(12.2)
STP	12.22	(9.82)	24.98	(12.7)	5.32	(5.29)	5.09	(7.77)
TFP	-1.41	(3.75)	-4.04	(2.53)	0.04	(2.80)	0.21	(2.78)
Industry								
Ind1	0.13	(0.13)	0.01	(0.08)	0.09	(0.28)	0.02	(0.13)
Ind2	0.03	(0.03)	0.09	(0.30)	0.09	(0.28)	0.13	(0.37)
Ind3	0.03	(0.03)	0.01	(0.09)	0.05	(0.22)	0.02	(0.15)
Ind4	0.00	(0.00)	0.00	(0.00)	0.01	(0.12)	0.13	(0.34)
Ind5	0.35	(0.48)	0.15	(0.37)	0.06	(0.23)	0.02	(0.15)
Ind6	0.00	(0.00)	0.04	(0.21)	0.16	(0.36)	0.41	(0.49)
Ind7	0.13	(0.34)	0.63	(0.48)	0.01	(0.11)	0.05	(0.22)
Ind8	0.02	(0.16)	0.00	(0.00)	0.07	(0.25)	0.06	(0.24)
N	681		336		4,491		2,370	

Figure 1. Kernel Density of Log Hourly Earnings Distribution

Panel A: Men



Panel B: Women

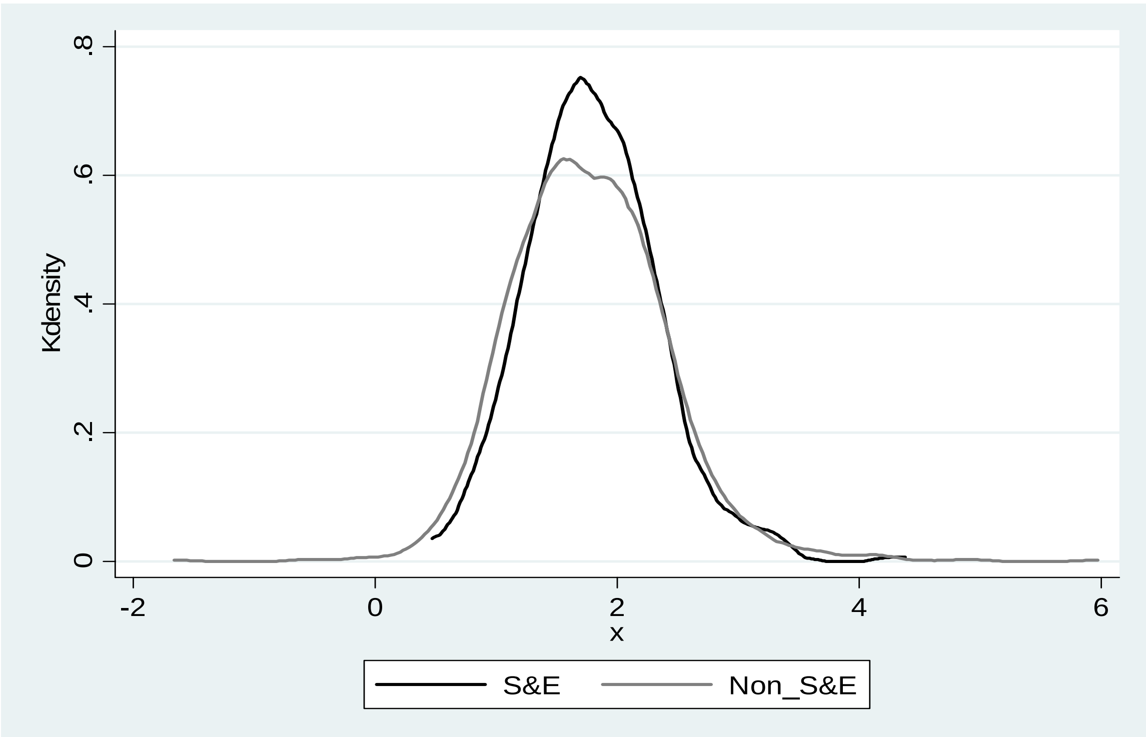


Table 3. Earnings Determination: OLS Estimates of Earnings Equations

Variable	Log of Hourly Earnings			
	Men		Women	
	I	II	I	II
Constant	-0.575***	-0.454***	-0.793***	-1.039***
	(0.088)	(0.102)	(0.126)	(0.159)
EDU	0.107***	0.098***	0.124***	0.146***
	(0.005)	(0.006)	(0.008)	(0.010)
EXP	0.048***	-0.096***	0.033***	0.033***
	(0.004)	(0.010)	(0.005)	(0.005)
$EXP^2/100$	-0.097***	0.030***	0.091***	-0.090***
	(0.010)	(0.003)	(0.016)	(0.016)
TENURE	0.031***	-0.063***	0.031***	0.033***
	(0.003)	(0.012)	(0.005)	(0.004)
$TENURE^2/100$	-0.064***	-0.063***	0.037*	-0.042**
	(0.012)	(0.012)	(0.019)	(0.019)
AREA	0.096***	0.099***	0.121***	0.119***
	(0.017)	(0.017)	(0.022)	(0.022)
Married	0.138***	0.141***	0.105***	0.096***
	(0.023)	(0.023)	(0.026)	(0.026)
S&E	0.072***	0.072***	0.077**	0.090**
	(0.025)	(0.025)	(0.038)	(0.038)
R&D		-0.015		-0.025
		(0.012)		(0.015)
*R&D*EDU*		0.001***		-0.001***
		(0.001)		(0.0003)
F-value	122.11	112.86	66.89	62.67
Adj. R^2	0.35	0.35	0.36	0.36
N	5,167	5,167	2,705	2,705

Note: 1) Standard errors in parentheses.
2) *** $p < 0.01$, ** $p < 0.05$, * $p<0.1$

Table 4. Effect of Technological Change on Earnings: S&E vs Non-S&E Occupations

Variable	S&E		Non-S&E	
	Men	Women	Men	Women
R&D				
R&D	-0.034 (0.026)	-0.112** (0.044)	-0.013 (0.017)	-0.009 (0.019)
*R&D*EDU*	0.001** (0.0006)	0.0003 (0.0006)	0.002* (0.0009)	-0.002** (0.0008)
STP				
STP	-0.024 (0.020)	-0.029 (0.026)	0.039** (0.018)	0.009 (0.019)
*STP*EDU*	0.002 (0.001)	0.00003 (0.001)	0.003** (0.001)	-0.001 (0.001)
TFP				
TFP	0.009 (0.065)	-0.083 (0.106)	0.034 (0.036)	0.120** (0.054)
*TFP*EDU*	0.0006 (0.004)	0.005 (0.007)	-0.002 (0.002)	-0.007* (0.004)

Note: 1) Standard errors in parentheses.
2) ***p < 0.01, ** p < 0.05, *p<0.1

Table 5. Quantile Regression Estimates of Earnings Equation: Men

Variable	Quantile (τ)				
	0.1	0.25	0.5	0.75	0.9
Constant	-0.740***	-0.589***	-0.430***	-0.327**	-0.237
	(0.163)	(0.099)	(0.114)	(0.131)	(0.197)
EDU	0.090***	0.089***	0.100***	0.110***	0.116***
	(0.010)	(0.006)	(0.007)	(0.008)	(0.013)
EXP	0.046***	0.041***	0.037***	0.037***	0.043***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
EXP2/100	-0.132***	-0.102***	-0.063***	-0.046***	-0.046**
	(0.016)	(0.016)	(0.013)	(0.014)	(0.021)
TENURE	0.038***	0.038***	0.032***	0.026***	0.025***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)
TENURE2/100	-0.042**	-0.060***	-0.069***	-0.067***	-0.087***
	(0.018)	(0.015)	(0.013)	(0.013)	(0.019)
AREA	0.027	0.055***	0.094***	0.121***	0.117***
	(0.024)	(0.019)	(0.017)	(0.018)	(0.028)
Married	0.082***	0.158***	0.143***	0.159***	0.165***
	(0.032)	(0.019)	(0.025)	(0.024)	(0.039)
S&E	0.107***	0.075***	0.054**	0.046	0.053
	(0.036)	(0.020)	(0.022)	(0.027)	(0.038)
R&D	0.031	0.011	0.003	-0.018	-0.062**
	(0.019)	(0.013)	(0.013)	(0.019)	(0.027)
*R&D*EDU*	-0.0004	0.0006	0.0005	0.002*	0.004**
	(0.001)	(0.0006)	(0.0005)	(0.001)	(0.002)
Pseudo R^2	0.23	0.25	0.25	0.24	0.22
N	5,167	5,167	5,167	5,167	5,167

Note: 1) Also included in the earnings equation are year dummies for 1999 through 2005 and 8 industry dummies.
2) Bootstrapped standard errors are in parentheses.
3) ***p < 0.01, ** p < 0.05, *p<0.1

Table 6. Quantile Regression Estimates of Earnings Equation: Women

Variable	Quantile (τ)				
	0.1	0.25	0.5	0.75	0.9
Constant	-1.54***	-1.01***	-0.954***	-0.741***	-0.888***
	(0.217)	(0.224)	(0.158)	(0.207)	(0.303)
EDU	0.138***	0.116***	0.135***	0.141***	0.167***
	(0.014)	(0.016)	(0.010)	(0.014)	(0.020)
EXP	0.045***	0.044***	0.028***	0.031***	0.034***
	(0.011)	(0.008)	(0.007)	(0.006)	(0.012)
EXP2/100	-0.224***	-0.183***	-0.072***	-0.059***	-0.027
	(0.042)	(0.029)	(0.026)	(0.021)	(0.052)
TENURE	0.026**	0.027***	0.036***	0.035***	0.025**
	(0.011)	(0.007)	(0.006)	(0.007)	(0.011)
TENURE2/100	0.084*	0.046	-0.050**	-0.071***	-0.080
	(0.048)	(0.031)	(0.024)	(0.028)	(0.057)
AREA	0.070*	0.109***	0.103***	0.124***	0.205***
	(0.036)	(0.024)	(0.023)	(0.029)	(0.041)
Married	0.083*	0.141***	0.123***	0.110***	0.135***
	(0.047)	(0.039)	(0.027)	(0.031)	(0.048)
S&E	0.093**	0.106***	0.087**	0.097**	0.024
	(0.048)	(0.038)	(0.038)	(0.040)	(0.089)
R&D	-0.022	0.003	-0.003	-0.021	0.006
	(0.020)	(0.022)	(0.023)	(0.021)	(0.040)
*R&D*EDU*	-0.001***	-0.0007*	-0.001**	-0.0007*	-0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Pseudo R^2	0.23	0.26	0.28	0.26	0.22
N	2,705	2,705	2,705	2,705	2,705

Note: 1) Also included in the earnings equation are year dummies for 1999 through 2005 and 8 industry dummies.
2) Bootstrapped standard errors are in parentheses.
3) ***p < 0.01, ** p < 0.05, *p<0.1

Table 7. Quantile Regression Estimates of Earnings Equation: A Comparison of Different Technological Change Measures (S&E, Men)

Technological Change Measures	OLS	Quantile (τ)				
		0.1	0.25	0.5	0.75	0.9
R&D						
R&D	-0.034	-0.009	-0.027	-0.011	-0.057**	-0.135**
	(0.026)	(0.037)	(0.026)	(0.029)	(0.026)	(0.066)
*R&D*EDU*	0.001*	0.0003	0.001**	0.0003	0.003**	0.006*
	(0.001)	(0.001)	(0.0006)	(0.001)	(0.001)	(0.004)
STP						
STP	-0.024	0.064	-0.023	-0.005	-0.057*	-0.091
	(0.020)	(0.043)	(0.026)	(0.029)	(0.032)	(0.075)
*STP*EDU*	0.002	-0.004	0.002	0.0007	0.004*	0.006
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.005)
TFP						
TFP	0.009	-0.127	-0.008	0.054	0.124	-0.042
	(0.065)	(0.122)	(0.087)	(0.064)	(0.099)	(0.151)
*TFP*EDU*	0.001	0.011	0.002	-0.002	-0.007	0.002
	(0.004)	(0.008)	(0.006)	(0.004)	(0.006)	(0.010)

Note: 1) Standard errors (for OLS) and bootstrapped standard errors (for quantile regression) in parentheses.
2) ***p < 0.01, ** p < 0.05, *p<0.1

Table 8. Quantile Regression Estimates of Earnings Equation: A Comparison of Different Technological Change Measures (Non-S&E, Men)

Technological Change Measures	OLS	Quantile (τ)				
		0.1	0.25	0.5	0.75	0.9
R&D						
R&D	-0.013	0.021	0.024	0.018	0.027	-0.055
	(0.017)	(0.025)	(0.022)	(0.020)	(0.034)	(0.040)
*R&D*EDU*	0.002**	0.0002	0.00003	0.0003	-0.0004	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
STP						
STP	-0.039**	-0.002	-0.014	-0.035*	-0.028	-0.021
	(0.018)	(0.028)	(0.020)	(0.021)	(0.022)	(0.041)
*STP*EDU*	0.003**	0.0006	0.001	0.003*	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
TFP						
TFP	0.034	0.114*	0.051	0.044	0.047	0.004
	(0.036)	(0.064)	(0.042)	(0.049)	(0.035)	(0.067)
*TFP*EDU*	-0.002	-0.007	-0.002	-0.003	-0.003	-0.0004
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)

Note: 1) Standard errors (for OLS) and bootstrapped standard errors (for quantile regression) in parentheses.
2) ***p < 0.01, ** p < 0.05, *p<0.1

Table 9. Quantile Regression Estimates of Earnings Equation: A Comparison of Different Technological Change Measures (S&E, Women)

Technological Change Measures	OLS	Quantile (τ)				
		0.1	0.25	0.5	0.75	0.9
R&D						
R&D	-0.112** (0.044)	-0.139** (0.069)	-0.075 (0.075)	-0.079 (0.050)	-0.091 (26.05)	-0.155** (0.070)
*R&D*EDU*	0.0002 (0.001)	0.00001 (0.001)	0.0007 (0.001)	0.0002 (0.0008)	0.0003 (0.139)	0.0008 (0.001)
STP						
STP	-0.029 (0.026)	-0.037 (0.048)	-0.029 (0.048)	-0.023 (0.041)	-0.024 (0.036)	-0.052 (0.046)
*STP*EDU*	0.00003 (0.001)	-0.0006 (0.076)	0.0006 (0.002)	0.0005 (0.002)	0.0002 (0.002)	0.0004 (0.002)
TFP						
TFP	-0.083 (0.106)	0.292 (0.230)	0.028 (0.163)	-0.124 (0.116)	-0.062 (0.161)	-0.192 (0.172)
*TFP*EDU*	0.005 (0.007)	-0.023 (0.015)	-0.0008 (0.012)	0.009 (0.008)	0.004 (0.011)	0.011 (0.012)

Note: 1) Standard errors (for OLS) and bootstrapped standard errors (for quantile regression) in parentheses.
2) ***p < 0.01, ** p < 0.05, *p<0.1

Table 10. Quantile Regression Estimates of Earnings Equation: A Comparison of Different Technological Change Measures (Non-S&E, Women)

Technological Change Measures	OLS	Quantile (τ)				
		0.1	0.25	0.5	0.75	0.9
R&D						
R&D	-0.009 (0.019)	-0.019 (0.023)	0.003* (0.030)	0.008 (0.025)	-0.003 (0.024)	0.029 (0.041)
*R&D*EDU*	-0.002** (0.001)	-0.0003 (0.001)	-0.0003 (0.001)	-0.0002 (0.0008)	-0.0009 (0.0007)	-0.003** (0.001)
STP						
STP	0.009 (0.019)	0.006 (0.029)	-0.002 (0.024)	-0.012 (0.018)	0.002 (0.017)	0.068** (0.029)
*STP*EDU*	-0.001 (0.001)	-0.001 (0.002)	-0.0005 (0.002)	0.0007 (0.001)	-0.0003 (0.001)	-0.004** (0.002)
TFP						
TFP	0.034 (0.036)	0.037 (0.086)	0.077 (0.064)	0.108** (0.054)	0.032 (0.053)	0.016 (0.129)
*TFP*EDU*	-0.002 (0.002)	-0.0001 (0.006)	-0.002 (0.004)	-0.005 (0.004)	-0.002 (0.004)	-0.00003 (0.009)

Note: 1) Standard errors (for OLS) and bootstrapped standard errors (for quantile regression) in parentheses.
2) ***p < 0.01, ** p < 0.05, *p<0.1

Appendix

Table A.1. Measures of Technological Change Across Industries

Industry	Industry Code (KSIC)	R&D Intensity (98-04)	% of Scientists/ Engineers (98-04)	TFP Growth (72-03)
All Industries	**01-99**	**2.17**	**7.58**	
Manufacturing	15-37	2.46	8.11	
Food and Beverages	15	0.57	2.48	-0.73
Tobacco	16	2.03	9.63	1.09
Textiles	17	0.76	2.17	0.49
Wearing Apparel	18	1.09	3.86	-0.69
Leather and Footwear	19	1.52	3.64	-1.25
Wood and Wood Products	20	0.63	1.88	1.34
Paper and Paper Products	21	0.39	3.17	0.34
Printing and Publishing	22	3.05	5.71	
Publishing	221	3.05	5.71	0.48
Service Activities Related to Printing	222, 223	3.05	5.71	-0.61
Coke & Refined Petroleum Products	23	0.33	4.83	-0.55
Chemicals	24	1.65	7.28	1.14
Rubber and Plastic Products	25	1.94	4.47	1.28
Non-metallic Mineral Products	26	0.57	3.13	0.49
Basic Metals	27	0.62	1.96	1.57
Fabricated Metal Products	28	0.66	1.56	0.66
Other Machinery and Equipment	29	3.71	8.41	1.18
Computers and Office Machinery	30	3.04	18.31	1.91
Electrical Machinery & Apparatuses	31	2.33	7.57	
Insulated Wires and Cables	313	2.33	7.57	-0.37
Other Electrical Equipment	311, 312 314, 315 319	2.33	7.57	2.45
Electronic Components/Equipment	32	5.1	16.35	
Semiconductor and Other Electronic Components	321	5.1	16.35	2.87
Television and Radio Transmitters	322	5.1	16.35	2.13
Television and Radio Receivers	323	5.1	16.35	0.98
Medical/Precision Instruments	33	5.74	13.49	0.36
Motor Vehicles & Trailers	34	3.11	6.41	0.29
Other Transport Equipment	35	1.5	3.33	
Building of Ships and Boats	351	1.5	3.33	0.21
Other Transport Equipment	352, 359	1.5	3.33	-1.78

Aircraft, Spacecraft and its Parts	353	1.5	3.33	4.62
Manufacturing of Articles n.e.c.	36	1.67	5.79	0.65
Recycling	37	-	-	-
Electricity, Gas, Steam and Hot Water Supply	40-41	0.72	2.24	
Collection and Distribution of Electricity	401	0.72	2.24	1.24
Gas, Distribution of Gaseous Fuel	402, 403	0.72	2.24	10.34
Distribution of Water	41	0.72	2.24	2.46
Construction	45-46	0.83	2.88	0.39
Wholesale & Retail	50-52	1.31	6.46	
Sale of Motor Vehicles and Motorcycles	50, 922	1.31	6.46	-8.71
Wholesale Trade and Commission Trade	51	1.31	6.46	-1.95
Retail Trade	52, 923	1.31	6.46	-1.36
Hotels and Restaurants	55	0	0	-4.11
Transportation	60-63	2.84	10.42	
Land Transport	60	2.84	10.42	2.09
Water Transport	61	2.84	10.42	2.52
Air Transport	62	2.84	10.42	-2.97
Activities of Travel Agencies	63	2.84	10.42	0.54
Post and Telecommunications	64	2.09	2.62	4.56
Financial & Insurance	65-67	1.26	1.61	
Financial Institutions	65	1.26	1.61	4.93
Insurance and Pension Funding	66	1.26	1.61	3.47
Activities to Financial Intermediation	67	1.26	1.61	-3.46
Real Estate & Renting	70-71	2.29	2.33	
Real Estate Activities	701	2.29	2.33	-4.03
Service Related to Real Estate	702	2.29	2.33	-1.79
Renting of Machinery and Equipment	71	2.29	2.33	2.66
Business Services	72-75	3.99	12.98	
Computer and Related Activities	72, 921	3.99	12.98	-6.45
Research and Development	73	3.99	12.98	-0.82
Professional, Scientific and Technical Services	74	3.99	12.98	-0.97
Business Support Services	75	3.99	12.98	-2.46
Public Administration and Defence	76	-	-	-10.36
Education	80	10.58	0.8	1.68
Health, Veterinary Activities and Social Work	85-86	58.36	34.4	-5.27
Entertainment	87-88	0.66	2.47	

Motion Picture, Broadcasting and Performing Arts Industries	87	0.66	2.47	-2.92
Other Recreational, Cultural and Sporting Activities	88	0.66	2.47	-3.71
Personal Services	90, 91, 93	1.6	2.9	
Sewage and Refuse Disposal, Sanitation and Similar Activities	90	1.6	2.9	..
Membership Organizations n.e.c.	91	1.6	2.9	-0.7
Other Services Activities	93	1.6	2.9	-8.74
Private Households	95	-	-	-8.95
Extra-Territorial Organizations	99	-	-	-

Table A.2. Classification of Occupations

			KSCO (based in 2000)
Professionals	Science Professionals	Natural Science Professionals	111
		Life Science Professionals	112
		Social Science Professionals	113
	Computer Related Professionals	Computer Related Professionals	120
	Engineering Science Professionals	Architects and Civil Engineers	131
		Electrical, Electronic and Mechanical	132
		Chemical Engineers and Metallurgists	133
		Surveyors	134
		Engineers n.e.c	135
	Health and Medical Professionals	Medical Examination Professionals, Except Nursing	141
		Pharmacists	142
		Nursing and Midwifery Professionals	143
		Medical Treatment Professionals	144
		Dietitians	145
Technicians and Associate Professionals	Science Related Associate Professionals	Natural Science Related Associate Professionals	211
		Life Science Related Technicians	212
		Social Science Related Associate Professionals	213
	Computer Related Associate Professionals	Computer Related Associate Professionals	220
	Engineering Science Technicians	Architect and Civil Engineering Technicians	231
		Electrical, Electronic and Mechanical Engineering Technicians	232
		Chemical Engineering and Metallurgical Technicians	233
		Draught Persons, Included Cad	234
		Optical and Electronic Equipment Operators	235
		Ship and Aircraft Controllers and Technicians	236
		Safety and Quality Inspectors	237
		Engineering Technicians n.e.c	238
	Health and Medical Associate Professionals	Medical Examination Assistants	241
		Medical Technicians	242

Source: National Statistical Office, *Korean Standard Classification of Occupations*, 2000.

Table A.3. Industry Classifications

Variable	Scope of Industry
D_ind0	Manufacturing
D_ind1	Electricity, Gas, Steam and Hot Water Supply & Construction
D_ind2	Wholesale & Retail
D_ind3	Transportation
D_ind4	Real Estate & Renting
D_ind5	Business Services & Public Administration and Defence
D_ind6	Education
D_ind7	Health, Veterinary Activities and Social Work
D_ind8	Entertainment, Personal Services, Private Households & Extra-Territorial Org.

Table A.4. Earnings Determination: Two-Stage Estimates of Earnings Equation

Variable	Men: Probability of S&E Job (1st stage)	Men: Log of Hourly Earnings (2^{nd} stage)	Women: Probability of S&E Job (1st stage)	Women: Log of Hourly Earnings (2nd stage)
Constant	-2.58***	1.48**	-2.04***	0.480
	(0.331)	(0.742)	(0.468)	(0.565)
EDU	0.078***	0.169***	-0.005	0.048***
	(0.019)	(0.030)	(0.030)	(0.016)
EXP	-0.029*	0.052**	0.033	0.040***
	(0.016)	(0.026)	(0.022)	(0.015)
EXP2/100	0.032	-0.095	-0.053	-0.190***
	(0.040)	(0.064)	(0.068)	(0.050)
TENURE	0.0007	0.049**	-0.064***	0.028*
	(0.013)	(0.021)	(0.020)	(0.015)
TENURE 2/100	-0.032	-0.160*	0.148*	0.021
	(0.055)	(0.096)	(0.080)	(0.069)
AREA	0.109*	0.159*	0.084	0.147**
	(0.063)	(0.095)	(0.087)	(0.061)
Married	-0.050	-0.066	0.220**	0.303***
	(0.084)	(0.127)	(0.110)	(0.080)
S_Major	0.982***	-	1.39***	-
	(0.063)		(0.081)	
S&E_Parent	-0.143	-	0.313	-
	(0.286)		(0.295)	
S&E_hat [1]	-	-4.36***	-	-0.519
		(1.26)		(0.687)
D_ind1	-	-0.083	-	-0.040
		(0.094)		(0.385)
D_ind2	-	0.563***	-	0.345***
		(0.160)		(0.135)
D_ind3	-	-0.096	-	-0.009
		(0.166)		(0.252)
D_ind5	-	-0.064	-	0.068
		(0.076)		(0.112)
D_ind7	-	0.299***	-	0.198
		(0.088)		(0.160)
D_ind8	-	-0.045	-	0.113
		(0.180)		(0.104)
Log likelihood	-1331.2		-615.4	
Pseudo R^2	0.12		0.23	
Wald X^2		222.72		263
N	4,027	4,027	2,160	2,160

Note: 1) The estimated probability of being S&E (obtained from the 1st stage estimation).
2) Standard errors in parentheses.
3) ***p < 0.01, ** p < 0.05, *p<0.1