The Impact of Technological Shock on Returns to Education: A Comparison of the Self-Employed and Wage Earners

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Abstract

The purpose of this paper is to analyze and to compare the impact of technological change upon the educational earnings premium between the self-employed and those who are wage earners in Korea. As the self-employed have more leverage than wage earners in their workplaces, the effect of education is presumed to be larger for the self-employed as compared to wage earners in conditions characterized by rapid technological changes.

Using data from the Korea Labor and Income Panel Survey, this paper has found the following: First, earnings dispersion is larger for the self-employed relative to wage earners, implying a larger heterogeneity in worker composition for the self-employed. Second, the earnings premium of schooling is greater in the industries experiencing rapid technological change than in the industries characterized by slower technological change. Third, the educational earnings premium associated with the benefits of technological change is larger for the self-employed than for wage earners.

Keywords: Skill-biased technological change, Educational earnings premium, Allocative ability, Self-employment, Wage earners

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I. Introduction

This paper intends to analyze and to compare the impact of technological change upon the educational earnings premium between the self-employed and wage earners in Korea. The self-employed and wage earners are presumed to differ in terms of the individual' ability, preference, and socioeconomic background as well as work environment and properties.[1] If that is the case, the self-employed and wage earners are also likely to differ with regard to how they respond to external technological shock and how their productivity and earnings are affected by 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. But there is a paucity of literature that compares the nature of the technological impact as it is experienced by both the self-employed and wage earners. This paper is unique in that it explicitly examines how the nexus between technological change and educational earnings premium differs for the self-employed and wage earners. It further suggests the (allocative) ability-enhancing education, which is more critical to self-employed workers, as a major source for the observed difference between the self-employed and wage earners.

For the empirical analysis, the Korean data are used. The advantage of using the Korean data is that the self-employed take an exceptionally large share of total employment in Korea, not only in total workforce but in the non-agricultural workforce, in contrast to most other OECD member countries. In Korea, therefore, a rich data set is available for the self-employed, unlike many other developed countries, and the self-employment issue is of great importance from the academic and political perspectives as well. Korea is thus a good test bed for analyzing the differing impact of technological change on the educational earnings premium for the self-employed and wage earners.

The paper is organized as follows: Section II puts forward the issue that the "allocative ability", among others, is an underlying factor for causing the differing impact of technological change on educational earnings premium for the self-employed and wage earners. Section III

[1] The empirical studies regarding the determinants of self-employment suggest that self-employed persons tend to be characterized more as jack-of-all-trades (Lazear, 2002), more concerned with autonomy in workplaces (Hamilton, 2000; Evans and Leighton, 1989), and financially less restricted (Evans and Jovanovic, 1989), as compared to wage earners. These are some of the salient factors that differentiate the self-employed from wage earners.

overviews the size and industrial distribution of the self-employed in Korea, and section IV describes the data used for the empirical analysis. Section Ⅴ analyzes the earnings determination of the self-employed compared to wage earners, with special reference to the impact of technological change upon the educational earnings premium. Section Ⅵ summarizes the major findings of the paper and draws some implications from them.

II. Technological Change, Allocative Ability, and Self-Employment

The enlargement of educational earnings differentials, accompanied by the relative increase in the supply of educated (skilled) workers, in the United States since the 1980s, has spawned a mushrooming body of literature on 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 offered as the leading possible explanation for the demand shifts favoring more educated workers relative to less educated workers.[2]

Using a supply and demand framework in which different demographic groups are treated as distinct labor inputs, Katz and Murphy (1992) and Bound and Johnson (1992) have rendered indirect bodies of evidences 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; Machin and van Reenen, 1998; Bartel and Sicherman 1999; Allen 2001).

The question that follows then regards the sources for the positive relationship between technological change and educational earnings premium. Why does complementarity exist between technological change and skilled workers? While substantial empirical work has confirmed the effect of skill-biased technological change, not much attention has been directed to the underlying sources for the skill-technology complementarity.

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

It is the early literature focusing upon allocative ability that provides an answer for the skill-technology complementarity. According to Schultz (1975), individuals consciously reallocate their resources in response to changes in economic conditions when there are external shocks such as technological change. The individuals respond to the shocks and adjust to the new environments in order to maximize their utilities or profits, and how efficiently they respond and adjust depends on their "allocative ability." That is what Schultz called "the ability to deal with disequilibria." He asserts that the allocative ability is not restricted to entrepreneurs, but applied to wage earners, self-employed workers, and even those not directly involved in paid work.[3]

Allocative ability can be enhanced by education. Welch (1970) bifurcated the effects of education into a "worker effect" and an "allocative effect." The "worker effect" is the marginal product of education or the increased output per unit of the worker's education, holding other factor quantities constant. It refers to the effect of education that enables a worker to accomplish more with the resources at hand. On the other hand, the "allocative effect" refers to the effect of education produces to enhance a worker's ability to acquire and decode information about costs and productive characteristics of other inputs. Workers are thereby able to use some "new" factors that otherwise would not be used. This "entrepreneurial capacity," which is not restricted to entrepreneurs, can be enhanced by education.[4]

To recapitulate, the allocative ability plays a key role in determining how efficiently each individual adapts to technological change (external shock); such a role is especially critical in a dynamic setting with fast technological change. Assuming that the allocative ability is enhanced by education, more educated persons tend to better adapt to technological change, all other things being equal, than less educated persons. Put differently, education pays off better in circumstances where fast technological change takes place, widening the earnings differential between those who are educated and those who are not.

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[3] For example, housewives reallocate their resources in household production for which they devote their time in combination with purchased goods and services. Students likewise reallocate their own time along with the educational services they purchase as they respond to changes in expected earnings or non-pecuniary benefits such as a personal satisfaction they expect to derive from their education (Schultz, 1975, p. 827).

[4] In explaining the phenomena that returns to education have not declined under the pressure of rapidly rising average education levels, Welch (1970) emphasized changing technology as a root for the sustaining wage differentials between college and high school graduates. Estimating the agricultural production function, using the agricultural research expenditures (federal and state expenditures) as a proxy for technological change, he found that the earnings differential between male college graduates and male high school graduates employed on a rural farm sector would fall substantially if the research expenditures per farm were to fall, holding factor ratios constant.

With the education-allocative ability-technological change nexus granted as a given, the allocative effect of education should be larger for workers who are frequently exposed to external shocks, who are in need of entrepreneurial capacity or multiple skills for their work, and who have more leverage in workplaces when external shocks occur. We can conjecture, then, that the earnings effect of education through enhancing allocative ability is larger for the self-employed as compared to wage earners in conditions characterized by rapid technological changes. This reasoning is in line with Welchs 1970 assertion that the allocative ability plays a critical role in determining education's productivity in agriculture (more critical than most industries), since farming includes a diversified set of activities for which allocative decisions are made continuously as part of the normal routine.[5]

III. Self-Employment in Korea: Size and Distribution

In Korea, self-employment continues to take a large share of total employment. The ratio of the self-employed in total workers had shown a large drop during the 1980's, but has remained relatively stable since then. As of 2004, some six million workers were the self-employed in Korea, accounting for 27.1% of the total employed, about 22.6 million workers. Together with non-paid family workers, which took another 6.9% of the total employed, non-wage earners accounted for 34% of total workers in 2004 (see Table 1).

Overall, about one-quarter of the self-employed are employers, with the remaining three-fourth being their own account workers. By gender, thirty-odd percent of those who are male self-employed are employers, while less than 20% of female self-employed are employers. Although the composition ratio of non-wage earners to total workers are almost same for men and women, the ratio of the self-employed is much larger for men (33.1%, 2004) than for women (18.6%, 2004). It is due to the fact that more than 40% of female non-wage earners are non-paid family workers, whereas the existence of non-paid male workers is almost nil.[6]

Self-employed workers are concentrated in agricultural sectors and service industries. About 60% of all agricultural employment is currently self-employed workers, and this ratio has been on the rise since the late 1990's. The composition ratio of self-employed workers has remained

[5] Self-employed workers and farmers seem to be common in that they are routinely involved in entrepreneurial decisions and have more leverage in workplaces when encountering external shocks. Considering that farmers are normally both self-employed workers and entrepreneurs (Schultz, 1975), the reasoning underlying the allocative effect of education in agriculture is expected to hold for the self-employed.

[6] Statistical figures calculated from *KOSIS* data.

almost stable since the mid-1990's in other sectors, around 11-13% in mining and manufacturing industries, and around 27-28% in service industries (see Table 2).

Table 1. Trend in Employment Pattern in Korea: Employees vs. Self-Employed

In thousand, %

	Total Employed	Employees	Non-wage earners		
				Self-employed	Family workers
1980	13,683 (100.0)	6,464 (47.2)	7,220 (52.8)	4,651 (34.0)	2,569 (18.8)
1990	18,085 (100.0)	10,950 (60.5)	7,135 (39.5)	5,069 (28.0)	2,067 (11.4)
1995	20,414 (100.0)	12,899 (63.2)	7,515 (36.8)	5,567 (27.3)	1,946 (9.5)
2000	21,156 (100.0)	13,360 (63.2)	7,795 (36.8)	5,864 (27.7)	1,931 (9.1)
2004	22,557 (100.0)	14,894 (66.0)	7,663 (34.0)	6,110 (27.1)	1,553 (6.9)

Source: NSO, *KOSIS*.
Note: Numbers in parentheses are the composition ratio of the total employed (%).

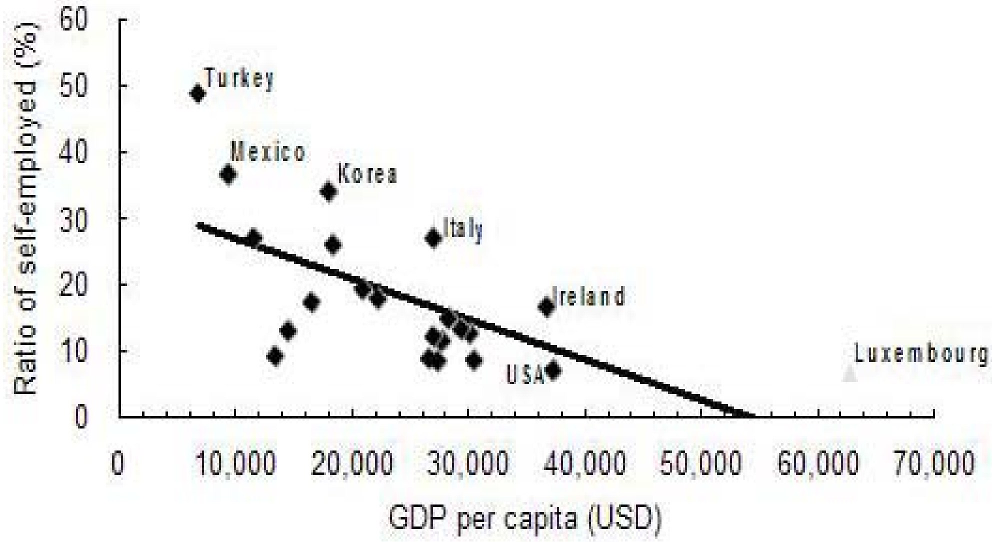
Table 2. Composition Ratio of Self-Employed: Industrial Comparison

In %

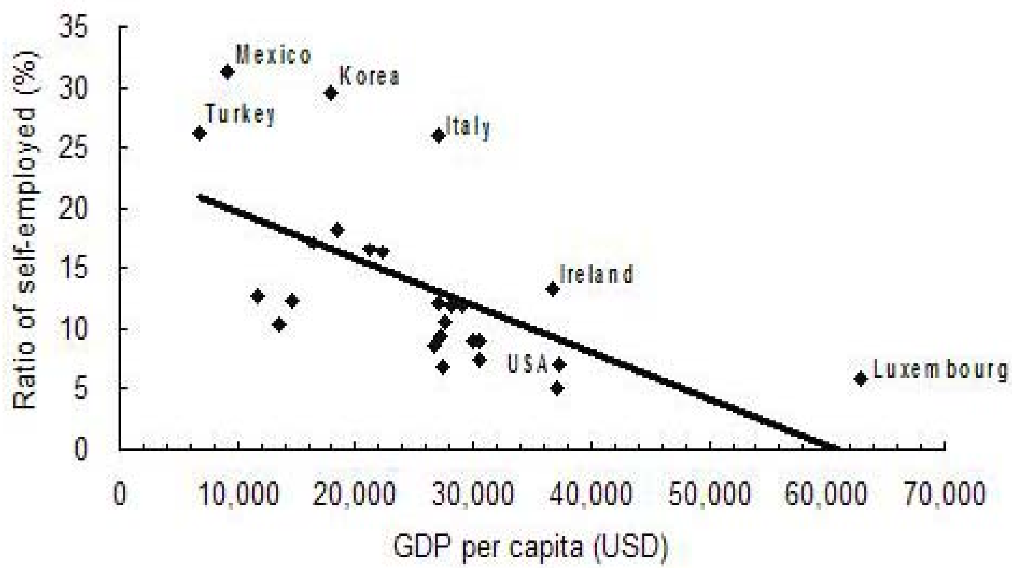
	Agriculture[1)]	Mining & Manufacturing	Services
1995	57.3 (92.7)	11.5 (15.0)	27.6 (34.6)
2000	57.6 (92.1)	13.0 (17.0)	27.5 (34.2)
2004	61.2 (90.6)	11.6 (14.8)	27.4 (32.7)

Source: NSO, *KOSIS*.
Note: 1) Includes agriculture, forestry, hunting and fishing.
2) Numbers in parentheses refer to the percentage of non-wage earners.

Figure 1. GDP per Capita and the Ratio of the Self-Employed (2003)



<Total Sectors>



<Non-agricultural sectors>

Source: OECD, *Labor Force Statistics 1983-2003*.
IMD, *World Competitiveness Yearbook 2004*.

The proportion of self-employed workers is exceptionally large in Korea, when compared to other OECD member countries. As seen in Figure 1, the composition ratio of the self-employed in Korea is currently the third highest for total sectors and the second highest for non-agricultural sectors among 30 OECD member countries. The large share of the self-employed in Korea is rather exceptional, when taking into account per capita GDP. [7]

IV. Data

1. Korea Labor and Income Panel Survey

For the empirical analysis, the data were drawn from the Korea 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.

Since the measurement of technological change in non-manufacturing sectors is problematic (Griliches, 1994; Bartel and Sicherman, 1999), the analysis herein is confined to the workers in the manufacturing industry. The disadvantage of limiting our analysis to the manufacturing sector is the loss of samples in the KLIPS, so the data for the years 1999-2001 are pooled together for the empirical analysis.[8]

The final data set includes 3,003 workers aged 15-64, either paid-employed or self-employed in the manufacturing sector. Those who work less than 16 hours a week were excluded from the final data set. Also excluded were workers with monthly earnings more than 10 million won or with hourly earnings more than 300 thousand won (one U.S. dollar is approximately 1,025 won). The hourly earnings were calculated by dividing monthly earnings by monthly working hours. The basic statistics of the final data set are as reported in the Appendix (see Table A.1).

2. Measures of Technological Change

[7] The reason why the ratio of the self-employed is exceptionally high in Korea is beyond the scope of this study. What is clear is that the issue of the self-employed is of great importance in the Korean labor market.

[8] The 1998 data were not used to rule out the effect of any possible distortion in the earnings structure triggered by the onset of financial crisis in late-1997.

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 were matched for the measures of technological change of each industry to which individual workers belong.

Since no single measure is flawless in reflecting the actual technological change, we use five different measures as proxies for technological change. It is the growth of total factor productivity (TFP) that is most commonly utilized as a proxy for technological change. We rest on two different series of estimates of TFP growth, one for the period between 1980 and 2000 (TFP1) and other for the period between 1990 and 1997 (TFP2).[9] The estimates of TFP growth across two-digit industry categories were provided by the Korea Productivity Center (2001). A potential problem of using TFP change is that it is the residual of growth taken into account after controlling the growth in the quantity and quality of various inputs such as physical capital, human capital, energy, etc. Technological change, however, may not be the only cause of productivity growth, even after controlling for various inputs. Therefore, it reflects our ignorance of economic growth as well as technological change.

The other proxies for technological change are input-based measures. The ratio of R&D expenditures to sales has been cited as a good proxy for the rate of technological change. The advantage of this measure is that it is a direct measure of innovative activity in the industry. The disadvantage, however, is that R&D expenditures are the input to the innovation process, not the output. Not all inputs necessarily lead to innovative outcomes, especially in technology production. The ratio of scientists and engineers to the total number of workers, which is another input measure, has both a similar merit and demerit as the ratio of R&D expenditures to sales. The data for R&D expenditures to sales from 1991 to 1999 were provided by the Korean Ministry of Science and Technology. The ratio of scientists and engineers to the total number of workers from 1993 to 1999 were calculated from the *Report on the Survey of Research and Development in Science and Technology* (Korean Ministry of Science and Technology) and *The Annual Report on the Economically Active Population Survey* (National Statistical Office, Korea).[10]

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[9] The TFP growth rate for the years 1990-1997 was added, along with the growth rate for the years 1980-2000, to eliminate any possible distortion caused by financial crisis broken out at the end of 1997.

[10] Other possible proxy measures for technological change are output-based measures, such as the number of patents, applied or filed in the industry. Unfortunately, however, the data on the number of patents in Korea are disaggregated into only ten industries, thereby not providing enough variations across industries.

The last measure used as a proxy for technological change is the ratio of expenditures on information and communication technology (ICT) to GDP in each industry. It enables us to analyze whether the rapid change of ICT affects the earnings structure in Korea. Hur, Seo, and Lee (2002) calculated the ICT intensities using the Input-Output Tables from the Bank of Korea.[11]

In the empirical analysis, we used the level of technological change across industries rather than the growth rate of technological change within each industry over time. An alternative approach would be to conduct a within-industry time-series analysis using changes over time in each industry's rates of technological change. Such an analysis, however, would be problematic in that changes in the measurements of industries' rates of technological change should be utilized. As pointed out by Allen (2001) and also by Bartel and Sicherman (1999), year-to-year variations in these measures are likely to have significant measurement errors and would not capture variations across industries. All five measures of technological change across the two-digit level industry categories are reported in the Appendix (see Table A.2).

Ⅴ. Effects of Technological Change on The Earnings Premium

1. Earnings Distribution of the Self-Employed

Table 3 compares the mean values of hourly earnings of the self-employed and wage earners, who are further subdivided into managerial/professional workers and clerical/production workers. For all three years from 1999 to 2001, the average hourly earnings of self-employed workers were lower than those of managerial/professional workers, but higher than those of clerical/production workers. The hourly earnings gap between the self-employed and managerial/ professional workers has narrowed down since 1999 onward, while the gap between the self-employed and clerical/production workers has widened for the same period. In 2001, for men and women alike, the average hourly earnings of the self-employed are almost adjacent to those of managerial/professional workers. This trend basically obtains for monthly earnings.

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[11] Berman, Bound, and Griliches (1994) maintain that the ratio of investment in computers to total investment is a good proxy for technological change in an industry. Again, the industry-level data for investment in computers are not available in Korea, so we used instead the ratio of expenditures on the ICT to GDP across industries, estimated by Hur, Seo, and Lee (2002).

Table 3. Hourly Earnings of the Self-Employed and Wage Earners: The Mean

In thousand won

	Men			Women		
	Self-employed	Managers/ Professionals	Clerks/ Production workers	Self-employed	Managers/ Professionals	Clerks/ Production workers
1999	6.20	8.15	4.77	3.55	6.22	3.18
	(15.3)	(9.64)	(2.51)	(4.94)	(4.16)	(1.90)
2000	7.21	8.81	5.39	4.87	6.50	3.62
	(11.6)	(6.79)	(2.80)	(16.3)	(3.34)	(2.14)
2001	9.96	10.26	5.86	6.36	6.96	4.12
	(21.2)	(11.0)	(4.31)	(12.8)	(5.35)	(4.11)

Source: *KLIPS*.

Note: 1) Overtime payment included.

2) Standard deviations in parentheses.

Table 4. Hourly Earnings of the Self-Employed and Wage Earners: The Median

In thousand won

	Men			Women		
	Self-employed	Managers/ Professionals	Clerks/ Production workers	Self-employed	Managers/ Professionals	Clerks/ Production workers
1999	4.25	6.73	4.28	2.42	5.03	2.79
2000	4.84	7.58	4.84	2.77	5.81	3.01
2001	5.81	7.91	4.84	3.32	5.52	3.32

Source: *KLIPS*.

Note: Overtime payment included.

It should be noted here that income dispersion is larger for the self-employed than for wage earners, as evidenced by the size of the coefficient of variation.[12] In fact, the coefficient of variation is the largest for self-employed workers, followed by managerial/professional workers, and the smallest for clerical/production workers. It implies that the self-employed are more heterogeneous in worker composition, in comparison to wage earners, in which group managerial/professional workers are found to be more heterogeneous than among clerical/production workers.

In terms of median earnings, as seen in Table 4, the hourly earnings of self-employed workers are similar to those of clerical/production workers, whereas both are substantially lower than the hourly earnings of managerial/professional workers. For both men and women, however, the median hourly earnings of self-employed workers rose to a large extent in 2001, narrowing down the earnings gap with managerial/professional workers. This trend also obtains for monthly earnings.

The fact that the average hourly earnings of the self-employed are much higher than those of clerical/production workers, but the median hourly earnings are not significantly different for the two groups of workers indicates again that the earnings difference between the upper-tail groups and lower-tail groups is larger for the self-employed as compared to clerical/production workers. Likewise, the earnings dispersion looms larger for self-employed workers than managerial/professional workers, when the mean and median earnings are compared for each of them.

2. Skill-Biased Technological Change and Earnings Determination

First, we test if there exists a positive relationship between technological change and earnings of workers. Following the previous study (Bartel and Sicherman, 1999), we estimate the following Mincer-type earnings equation:[13]

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[12] Standard deviation divided by mean value in percentage terms.

[13] Another approach adopted in the previous literature is to divide the workers into various demographic groups (especially into different educational groups) and to analyze the changes in relative wage or 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.

$$lnW_{ij} = \beta' X_i + \gamma_1 T_{ij} + u_{ij} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{(1)}$$

where W_{ij} represents the hourly earnings of worker *i* in industry *j*, and X_i represents human capital characteristics of worker *i* as well as the characteristics of the establishment to which worker *i* is affiliated. X_i includes years of schooling, potential labor market experience (= age - years of schooling - 6), an experience square, tenure, a tenure square, an area dummy, a gender dummy, and year dummies. T_{ij} refers to the technological change of the industry *j*, to which worker *i* belongs.

We test whether the partial derivative of the log hourly earnings with respect to technological change (γ_1) is positive. If this is positive, then workers in the industries with rapid technological change are paid higher than workers (with the same observed characteristics) in the industries with slower technological change.

Table 5 reports the estimation results of earnings equation (1). The coefficient of education, which can be interpreted as the rate of return to education, is 0.0659 (6.59%) and is significantly different from zero. The signs of coefficients related to experience and tenure terms are all consistent with the prediction by the human capital theory. The dummy variable for the self-employed is also positive and statistically significant, implying that the earnings of self-employed workers tend to be higher than those of wage earners, *ceteris paribus*.

Our primary concern lies in the coefficient of T_{ij}. It is negative and insignificant in the case of R&D intensity, percentage of scientists and engineers, TFP1, and ICT Intensity. It is also negative but statistically significant in the case of TFP2. This result implies that technological change does not necessarily improve workers' productivity and thereby raises their earnings. This finding stands in contrast with the empirical result for the United States, which confirms a positive correlation between technological change and earnings (Bartel and Sicherman, 1999).

This finding, however, is subject to all workers regardless of their education levels. To analyze the relationship between technological change and earnings across different education levels (i.e., returns to schooling), we add an interaction term between years of schooling and T_{ij} in equation (1).

$$lnW_{ij} = \beta' X_i + \gamma_1 T_{ij} + \gamma_2 T_{ij} \cdot EDU_i + u_{ij} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{(2)}$$

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 (2) should be positive ($\gamma_2 > 0$).

As seen in Table 6, the estimated value of γ_2 is positive for every measure of technological change, and significantly different from zero in the case of R&D intensity, percentage of scientists and engineers, and TFP2. In addition, the partial derivative of log hourly earnings with respect to T_{ij} (=γ_1 + γ_2 EDU_i) becomes positive when the years of schooling of an individual worker are no less than 16 years. What it implies is that technological change bears the earnings-enhancing effect only for college graduates or those with advanced degrees.

Table 5. Earnings Equation (1): Pooled Regression (1999-2001)

Variables	R&D	PSE[1)]	TFP1	TFP2	ICT
EDU	0.0659 **	0.0652 **	0.0655 **	0.0660 **	0.0654 **
	(-16.3)	(-16.1)	(-16.3)	(-16.43)	(-16.3)
EXP	0.0144 **	0.0147 **	0.0145 **	0.0143 **	0.0147 **
	(-5.38)	(-5.47)	(-5.43)	(-5.35)	(-5.52)
$EXP^2/100$	-0.0167 **	-0.0172 **	-0.0170 **	-0.0166 **	-0.0173 **
	(-2.89)	(-2.97)	(-2.94)	(-2.86)	(-2.99)
TEN	0.0448 **	0.044 **	0.0442 **	0.0445 **	0.0439 **
	(-11.9)	(-11.7)	(-11.8)	(-11.84)	(-11.7)
$TEN^2/10$	-0.0110 **	-0.0108 **	-0.0109 **	-0.0110 **	-0.0107 **
	(-6.78)	(-6.65)	(-6.72)	(-6.78)	(-6.62)
Technological Change	-0.0085	-0.0004	-0.0084	-0.0201 *	-0.0051
	(-1.41)	(-0.09)	(-1.59)	(-2.23)	(-0.95)
Area (Seoul=1)	0.0804 **	0.0823 **	0.0822 **	0.0789 **	0.0824 **
	(-3.17)	(-3.25)	(-3.25)	(-3.12)	(-3.26)
SELF (Self-employed=1)	0.2547 **	0.2568 **	0.2555 **	0.2534 **	0.2573 **
	(-9.69)	(-9.73)	(-9.74)	(-9.65)	(-9.81)
2000 Dummy	0.1217 **	0.1216 **	0.1206 **	0.1197 **	0.1216 **
	(-4.25)	(-4.24)	(-4.21)	(-4.18)	(-4.24)
2001 Dummy	0.2149 **	0.2152 **	0.2140 **	0.2128 **	0.215 **
	(-7.23)	(-7.23)	(-7.2)	(-7.16)	(-7.23)
GENDER (Men=1)	0.3338 **	0.3335 **	0.3308 **	0.3341 **	0.3351 **
	(-16.5)	(-16.4)	(-16.3)	(-16.51)	(-16.51)
Intercept	-0.0268	-0.0390	-0.0216	-0.0277	-0.0283
	(-0.42)	(-0.61)	(-0.33)	(-0.43)	(-0.44)
N	3,003	3003	3003	3003	3,003
R^2	0.3857	0.3853	0.3859	0.3864	0.3855

Note: 1) Percentage of scientists and engineers out of the total employed.
2) t-value's in parentheses.
3) **p<0.01 , *p<0.05 (for one-tailed test).

Based on the aforementioned empirical results, we can conclude the following: First, the educational earnings premium is larger in the industries with rapid technological change. This result confirms the hypothesis of skill-biased technological change in Korea and thus adds another form of support to the argument articulating pervasive skill-biased technological change around the world. Secondly, not all workers in the industries with rapid technological change are paid higher than their counterparts in the industries with slower technological change. Only those who are highly educated are paid higher earnings in the industries with rapid technological change than those in the industries with slower technological change. It thus follows that the introduction of new technology or technological advancement does not necessarily raise the productivity (and thus earnings) of all workers, but tends to enlarge the earnings gap among workers with different education levels.

Table 6. Effect of Technological Change on Earnings

Measure of Technological Change	Equation (1)	Equation (2)	
	γ_1	γ_1	γ_2
R&D Intensity	-0.0085	-0.0748**	0.0055**
	(-1.41)	(-2.89)	(2.64)
% of Scientists and Engineers	-0.0004	-0.0796**	0.0064**
	(-0.09)	(-3.87)	(3.95)
TFP1	-0.0084	-0.0225	0.0011
	(-1.59)	(-0.94)	(0.61)
TFP2	-0.0201*	-0.0946**	0.0059*
	(-2.23)	(-2.38)	(1.93)
ICT Intensity	-0.0051	-0.0149	0.0009
	(-0.95)	(-0.67)	(0.46)

Note: 1) Other explanatory variables included in the equation are years of schooling, experience, an experience square, tenure, a tenure square, an area dummy, a gender dummy, and year dummies. The estimation results of full models are available from the authors upon request.
2) t-value's in parentheses.
3) **p <0.01 , *p <0.05

3. The Earnings Effect of Technological Change: Self-Employed vs. Wage Earners

We now turn to the comparison of the self-employed and wage earners, regarding the earnings effect of skill-biased technological change. Our hypothesis is that the educational earnings premium associated with the benefits of technological change will be larger for the self-employed than wage earners, for the allocative effect of education is more critical for the self-employed than wage earners. To test this hypothesis, we add another interaction term of years of schooling (EDU_i), $T_{ij,}$ and a self-employment dummy ($SELF_i$) in equation (2), which leads to the following:

$$lnW_{ij} = \beta' X_i + \gamma_1 T_{ij} + \gamma_2 T_{ij} \cdot EDU_i + \gamma_3 T_{ij} \cdot EDU_i \cdot SELF_i + u_{ij} \quad \cdots\cdots\cdots\cdots(3)$$

If the educational earnings premium associated with the benefits of technological change is larger for the self-employed than for wage earners, then the coefficient of the interaction term ($T_{ij} \cdot EDU_i \cdot SELF_i$) in equation (3) should be positive ($\gamma_3 > 0$).

Table 7. The Effect of Technological Change on Earnings: Self-Employed vs. Wage Earners

Measure of Technological Change	Equation (3)		
	γ1	γ2	γ3
R&D Intensity	-0.0747**	0.0047*	0.0088**
	(-2.88)	(2.25)	(9.21)
% of Scientists and Engineers	-0.0752**	0.0053**	0.0056**
	(-3.60)	(3.19)	(5.22)
TFP1	-0.0235	0.0005	0.0083**
	(-0.98)	(0.26)	(8.30)
TFP2	-0.0985**	0.0049	0.0146**
	(-2.46)	(1.60)	(6.94)
ICT Intensity	-0.0122	-0.0002	0.0056**
	(-0.55)	(-0.13)	(8.58)

Note: 1) Other explanatory variables included in the equation are years of schooling, experience, an experience square, tenure, a tenure square, an area dummy, a gender dummy, and year dummies.
2) t-value's in parentheses.
3) **p < 0.01 , *p < 0.05

Table 7 confirms our hypothesis for the self-employed. The estimated value of γ_3 is positive and statistically significant in every model with different measures of technological change. This implies that, when technological shocks occur, highly educated self-employed workers benefit more, relative to wage earners with a corresponding schooling level. The benefit comes from the allocative effect of education in adjusting technological shocks. On the contrary, the self-employed with a lower level of schooling are more vulnerable to technological shocks, as compared to wage earners with the same level of schooling. In the wake of that, the educational earnings gap gets larger for the self-employed than for wage earners when technology changes rapidly. The estimation results for men and women, respectively, are shown in the Appendix (see Table A.3), which leads to the same conclusion as the case of total workers.

Ⅵ. Summary and Conclusion

The purpose of this paper was to compare the earnings effect of education for the self-employed and wage earners, in circumstances where skill-biased technological change takes place. The proposed hypothesis was that the earnings effect of education will be larger for the self-employed than for wage earners, when encountering fast technological change, since the allocative effect of education should be of great significance for the self-employed as compared to wage earners.

To test this hypothesis, the modified Mincerian earnings equation was estimated for manufacturing workers, for paid employees and self-employed workers as well, using the Korea Labor and Income Panel Survey data. The major findings can be summarized as follows: First, the average earnings of the self-employed are higher than those of clerical/production workers but lower than those of managerial/professional workers. The dispersion of earnings is much larger for the self-employed than for wage earners, both for clerical/production workers and for managerial/professional workers. It implies that the self-employed are more heterogeneous than wage earners, in terms of worker composition.

Secondly, we found direct evidence for the earnings effect of skill-biased technological change in Korea, using a variety of industry-level measures of technological change. The earnings premium of schooling is greater in the industries experiencing rapid technological change than in the industries characterized by slower technological change. However, it is only the highly educated workers who earn more when affiliated with the industries with rapid technological change. It thus implies that technological advancement does not necessarily raise productivity and therefore earnings of all workers, but rather benefits intensely those with a high educational attainment level, that is, those who can efficiently adapt to new technological shocks.

Finally, the educational earnings premium associated with the benefits of technological change is larger for the self-employed than for wage earners, lending support to our hypothesis. This implies that, encountering external technological shocks, highly educated self-employed workers have more leverage to exercise their allocative ability (enhanced by education) to better adjust to technological shocks and therefore reap more benefits from technological change, relative to wage earners of the same schooling level. In contrast, less-educated self-employed workers are more vulnerable to external technological shocks than wage earners with the same level of schooling, but are not well equipped with allocative ability to respond to external shocks. Consequently, the educational earnings gap tends to be larger for the self-employed relative to wage earners when technology changes fast. Education is thus important, especially for the self-employed, in the era of fast technological change, enabling workers to better adjust to technological shocks and thereby reap more economic gains.

If workers with high education levels earn more, other things being equal, in the industries with rapid technological change than in the industries with slower technological change, then those working in the industries with slower technological change will have incentives to move to the industries in which technological change is occurring fast. By the same token, wage earners with high education levels will have incentives to become the self-employed, rather than remaining in the status of employees.

The question is then why workers do not move to other industries, or change their job status. For one thing, institutional factors may interfere with the labor market mobility. For another, the educational earnings premium associated with technological change could reflect the rise in the price of unobserved skills of workers, which are positively correlated with education, rather than the rise in the returns to education itself. These issues remain but not tackled here; rather they remain as a topic for subsequent studies.

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Appendix

Table A.1. Basic Statistics of the Sample

	Total	1999	2000	2001
Average Years	11.53	11.64	11.48	11.49
of Schooling	(3.00)	(3.15)	(2.94)	(2.93)
Average Tenure	5.20	5.38	5.31	4.91
(years)	(5.81)	(5.88)	(5.94)	(5.59)
Average Experience	19.84	19.51	20.00	19.95
(years)	(11.31)	(11.27)	(11.24)	(11.43)
Average Hourly Earnings	5.46	5.12	5.32	5.95
(1,000 Korean won)	(5.12)	(4.59)	(4.38)	(6.24)
Ratio of Men	0.68	0.68	0.68	0.67%
(%)	(0.47)	(0.47)	(0.47)	(0.47)
Ratio of the	0.14	0.16	0.14	0.12
Self-Employed (%)	(0.35)	(0.37)	(0.35)	(0.32)

Note: Standard deviations in parentheses.

Table A.2. Measures of Technological Change across Industries

Industry	Industry Code (KSIC)	R&D Intensity	% of Scientists/ Engineers	TFP1	TFP2	ICT Intensity
Manufacturing (Total)	D	2.3889	1.26	0.70	1.76	2.380
Food and Beverages	15	0.5667	1.17	0.24	0.54	1.009
Tobacco	16	0.5667	1.17	8.28	16.21	1.009
Textiles	17	0.8556	0.07	-0.13	1.55	0.777
Wearing Apparel	18	0.8556	0.07	0.21	2.41	2.822
Leather and Footwear	19	0.8556	0.07	0.63	1.96	2.822
Wood and Wood Products	20	0.2333	0.07	0.88	0.61	0.501
Paper and Paper Products	21	0.6667	0.35	-0.14	-0.39	1.341
Printing and Publishing	22	2.5778	0.10	0.12	-0.39	3.157
Coke & Refined Petroleum Products	23	0.4444	4.41	-0.54	0.89	1.092
Chemicals	24	1.8778	4.21	0.23	0.87	1.625
Rubber and Plastic Products	25	2.1333	0.65	0.89	1.23	2.069
Non-metallic Mineral Products	26	1.2778	0.43	0.91	2.30	7.091
Basic Metals	27	0.6333	0.94	0.58	1.07	0.441
Fabricated Metal Products	28	1.7778	0.25	0.60	2.35	2.243
Other Machinery and Equipment	29	2.7111	0.81	1.40	1.88	5.604
Computers and Office Machinery	30	3.4444	6.24	2.73	4.00	3.589
Electrical Machinery & Apparatuses	31	2.2889	1.66	0.67	1.80	3.589
Electronic Components/Equipment	32	5.1222	6.23	2.73	5.40	3.589
Medical/Precision Instruments	33	4.9889	1.49	0.70	2.39	3.724
Motor Vehicles & Trailers	34	4.0778	3.27	1.60	1.44	3.005
Other Transport Equipment	35	1.7222	1.55	-0.67	0.15	3.005
Manufacturing of Articles n.e.c.	36	1.4778	0.14	0.11	0.18	1.389

Source: TFP data are from the Korea Productivity Center (2001), R&D intensity and percentage of scientists and engineers are from Korean Ministry of Science and Technology (various years) and National Statistical Office (various years), ICT intensity are from Hur, Seo, and Lee (2002).

Table A.3. The Effect of Technological Change on Earnings: Self-Employed vs. Wage Earners

Men

Measure of Technological Change	Equation (3)		
	γ_1	γ_2	γ_3
R&D Intensity	-0.0924**	0.0069*	0.0066**
	(-2.15)	(2.09)	(6.52)
% of Scientists and Engineers	-0.1424**	0.0106**	0.0037**
	(-3.87)	(3.83)	(3.34)
TFP1	-0.628*	0.0042	0.0063**
	(-1.76)	(1.61)	(5.87)
TFP2	-0.1220*	0.0076*	0.0105**
	(-2.04)	(1.73)	(4.81)
ICT Intensity	0.0032	-0.0009	0.0040**
	(0.10)	(-0.37)	(5.79)

Women

Measure of Technological Change	Equation (3)		
	γ_1	γ_2	γ_3
R&D Intensity	-0.0283	0.0002	0.0405**
	(-0.92)	(0.06)	(8.34)
% of Scientists and Engineers	-0.0520*	0.0036*	0.0796**
	(-2.18)	(1.73)	(7.46)
TFP1	0.0362	-0.0063*	0.0224**
	(1.12)	(-2.25)	(6.73)
TFP2	-0.0154	-0.0031	0.1758**
	(-0.30)	(-0.68)	(10.76)
ICT Intensity	0.0357	-0.0063*	0.0223**
	(1.14)	(-2.11)	(8.43)

Note: 1) Other explanatory variables included in the equation are years of schooling, experience, experience square, tenure, tenure square, area dummy, gender dummy, and year dummies.
2) t-value's in parentheses.
3) **$p < 0.01$, *$p < 0.05$