# Technological Change and Wage Premium in a Small Open Economy: An Inter-Industry Analysis

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### Abstract

The aim of this paper is to show the direct evidence of the relationship between technological change and education premium in Korea and to analyze whether the premium reflects the returns to education per se or the returns to other unobserved characteristics of workers. The main findings are as follows: First, the educational wage premium is greater in the industries with rapid technological change than in the industries with slower technological change. This confirms the hypothesis of skill biased technological change in Korea and supports the pervasive skill biased technological change around the world. Second, only the highly educated workers in the industries with rapid technological change are paid higher than those in the industries with slower technological change. Finally, however, the panel analysis of earnings function implies that the wage premium of education associated with the technological change is mostly explained by the returns to worker's unobserved heterogeneities, such as one's intrinsic ability, rather than the returns to education per se.



**Keywords: Skill Biased Technological Change, Educational Wage Premium Double Fixed Effects Model**
**JEL classification codes: J3**

## I. Introduction

Recently, a considerable amount of research has demonstrated the positive relationship between technological change and the education premium. Despite the relative increase in supply of skilled workers since the 1980s, there has been a widening of educational wage differentials in the United States. Skill biased (or unskilled labor saving) technological change (called SBTC, hereafter) has been offered 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 (identified by sex, education, and age) are treated as distinct labor inputs, Katz and Murphy (1992) and Bound and Johnson (1992) show indirect evidence indicating that technological change is responsible for the widening of educational wage differentials. More direct evidence also shows the positive relation between technological change and the education premium. 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).

Another possible explanation for the demand shifts to more educated workers from less educated workers could be the increased exposure to international competition from the less developed countries. Leamer (1994) argues that the skill bias of *local* technological change is irrelevant to the wage structure in a Hecksher-Ohlin (H-O) model unless it is also sector-biased. On the other hand, Krugman (1995) points out that *pervasive* SBTC (i.e., SBTC around the world) will affect relative wages since an integrated world economy will respond to such technological change as a closed economy would.

Therefore, the answer to this issue critically depends on whether the skill-biased technological change is found only in the U.S. or is found everywhere, including developing countries. To illustrate this point, Berman, Bound and Machin (1998) had set up a H-O model with small open economies. They show that most industries in developed countries increased the proportion of the skilled workers despite the rising or stable relative wages for the skilled workers. For developing countries, they find that the relative wages of non-production workers in manufacturing increased, which indicates that the SBTC is pervasive. However, they did not directly test the SBTC hypothesis in developing countries. Therefore, the debate over *local* versus *pervasive* SBTC provides us with a good motivation to test the SBTC hypothesis in Korea, a good example of a small open economy.

Another advantage of using Korean data is that the supply of college graduates in Korea has been truly exogenous. In the literature covering the U.S. and other advanced countries using a supply-demand framework or analyzing changes in a wage bill, one of the key underlying assumptions is that of the exogeneity of the relative supplies across demographic groups classified by age, sex, and education. Age and sex are surely exogenous; on the other hand, education is rather endogenous because the people would attain more of an education when returns to education are high. In Korea, however, the entrance quota of college has been strictly controlled by the government. Before 1980, the government allowed only a gradual increase in college enrollment with the increase in population. The educational reform in 1980, however, restructured the quota system and increased the number of college graduates dramatically.[2] As a result, the ratio of college graduates in the labor force has substantially increased since the mid-1980s. This supply shift in college graduates can be considered to be a truly exogenous increase. Therefore, Korea during this period is an ideal setting to study how exogenous shocks in labor supply affect relative wages.

The goal of this paper is twofold: First, the aim of the paper is to show the direct evidence of the relationship between technological change and education premium in Korea. We match a variety of industry-level indicators of technological

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

[2] Before the educational reform, most college entrants could graduate once they were admitted to college. Under the reformed system, each college was able to enroll 130 entrants for every 100 students they could graduate. Besides, the government allowed a large increase in the entrance quota as well. By allowing college students to compete against each other, the government claimed to improve the quality of college graduates. However, it was suspected that the real reason for the reform was to distract students from participating in the political demonstration against the military government that had taken its power

changes with the individual worker's information from the panel survey. We find that workers with a college degree receive higher wages in the industries with rapid technological change than in the industries with less rapid technological change. However, workers with less than a high school education are not necessarily paid higher even though they are in the industries with rapid technological change.

Second, the paper also aims to analyze whether the wage premium of skill (measured by the education level) associated with the technological change reflect the returns to education per se or to the other unobserved characteristics of workers. By exploiting the advantage of panel data, we examine both the role of workers' observed and unobserved heterogeneities. We show that workers' unobserved heterogeneities are important in explaining the wage premium of skill associated with the technological change.

The paper is organized as follows: Section II briefly reviews the changes in employment and wage in Korea. Section III depicts the data on industry-level indicators of technological changes and the panel data set. Section IV sets up an empirical framework and tests the SBTC in Korea. Section V identifies the role of unobserved characteristics of workers in the relationship between technological change and college premium. Section VI summarizes and concludes the paper.

## II. Changes in Employment and Wage

Due to the educational reform in 1980, the number of college graduates in the Korean labor market has continuously increased (see Figure 1). Consequently, the wage of college graduates relative to the wage of high school graduates has declined substantially since the mid-1980s.[3] The declining trend in the wage of college graduates, however, has stopped since the mid-1990s, although the supply of college graduates has continuously increased.

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through the military coup in 1980. This policy, however, was entirely ineffective in practice. Most students ended up graduating once they were admitted to college.

[3] As the number of young college graduates has increased dramatically, the wage of young college graduates relative to the wage of young high school graduates has declined substantially while the relative wage of older college graduates has not changed much. For more detail, see Choi and Jeong (2003).

Choi and Jeong (2003) set up a simple supply-demand framework and decomposed the relative wage change into supply shocks and demand shocks across different demographic groups classified by age, sex, and education. They find that relative wage changes from 1983 to 1993 were mostly explained by the shifts in labor supply. From 1993 to 2000, however, changes in relative wages were affected by both shifts in labor supply and in labor demand. The impact of shifts in labor demand is found to be greater than that of shifts in labor supply for this period (see Table 1). As a result, the relative wages of college graduates increased slightly, despite the continuing increase of college graduates. Moreover, they decompose the impact of demand changes into within-industry changes and between-industry changes, assuming a Cobb-Douglas production function. Table 1 illustrates that over 95% of demand changes from 1993 to 2000 were due to within-industry changes rather than between-industry changes. Therefore, they conclude that SBTC is more important than product demand shifts (such as the increase of international trade) in explaining relative wage changes during this period.

However, they did not show the direct evidence of SBTC and just interpreted within-industry changes (skill upgrading in every industry) as being an evidence of SBTC. Moreover, they did not properly explain why technology did not have labor market effects during the 1980s and began to have effects after mid-1990s. One possible answer relies on the hypothesis of "endogenous skill biased technological change." Acemoglu (2002) describes this hypothesis as follows:

> [N]ew technologies are endogenous and respond to incentives. It claims that the large increase in the supply of skilled workers induced the acceleration in the demand for skills. When skill-biased technologies are more profitable, firms will have greater incentives to develop and adopt such technologies. A key determinant of the profitability of new technologies is their market size.

According to this hypothesis, skill-biased technologies become more profitable as there are more skilled workers in the labor force. Therefore, a rapid increase in the skill workers first reduces the skill premium as the economy moves along a neutral technological change (Acemoglu, 2002). After a while, the technology starts adjusting to the labor market with more skilled workers. The adoption and/or invention of skill-biased technologies increase the demand for skilled workers and their wage premium.

The hypothesis of endogenous SBTC explains the fluctuation of relative wages in the Korean labor market quite well: the decline of college wage premium during the 1980s (with the increase in relative supply of college graduates) and the rising college premium during the 1990s (despite the continuing influx of college graduates into the labor market). To accept this hypothesis, however, it is necessary to prove that SBTC has actually occurred in Korea during the 1990s. In the example above, Choi and Jeong (2003) just demonstrate that the within-industry changes in labor demand are mainly responsible for the changes in the relative wages of college graduates during the 1990s and do not prove that the changes were caused by SBTC.

This paper illustrates a direct evidence of SBTC during the late 1990s in Korea. To show this, we match four different industry-level proxies for the technological change with the individual worker's information from the Korean Labor and Income Panel Survey (KLIPS) collected by the Korea Labor Institute.

## III. Data

### A. Korean Labor and Income Panel Survey

The KLIPS, currently the only nationwide household panel survey in Korea, started in 1998; the sample size was five thousand households in its first year. It provides information on socio-economic characteristics, such as labor market status, years of schooling, age, tenure, region of working place as well as monthly wage and working hour.

Since the measurement of technological change outside the manufacturing sector is problematic, the analysis here is restricted to workers in the manufacturing industry (Griliches, 1994; Bartel and Sicherman, 1999). The disadvantage of limiting our analysis to the manufacturing sector is the loss of samples in the KLIPS. The number of individuals in the KLIPS was approximately 13,321 in 1998 and decreased to 11,051 in 2001. Among them, the number of wage workers was 4,012 in the first year. When we limit our analysis to the manufacturing sector and exclude the nonrespondents to certain questions used in the analysis, we have 2,643 observations during the four years. Although the number of observations is not big enough to analyze the inter-industry analysis, we can exploit the advantage of a panel data, which provides richer information than a single cross-section. The detailed explanation of the data used in the analysis is provided in the Appendix.

**B. Measures of Technological Change**

Technological change faced by the individual in his or her workplace is not directly measurable. Therefore, we need to utilize the industry-level measure of technological change. We match individual characteristics from the KLIPS and the measure of technological change of the industry to which an individual worker belongs.

Since no single measure would be perfect, we use four different measures as proxies for technological change. Change of total factor productivity (TFP) is the most commonly used measure for technological change. We use the estimates of the TFP changes for the period between 1980 and 2000. The estimates of TFP change across two-digit industry categories are from the Korea Productivity Center (2001). A potential problem of using TFP change is that it is the residual of growth accounting 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 the various inputs. Therefore, it reflects our ignorance of economic growth as well as reflecting technological change.

The other proxies for technological change are input-based measures. The ratio of R&D expenditure to sales has been shown to be good proxies for the rate of technological change. The advantage of using this measure is that it is a direct measure of innovative activity in the industry. The disadvantage, however, is that R&D is an input to innovation, not an output. Not all inputs necessarily lead to innovative outcomes, especially in technology production. The ratio of scientists and engineers to the total number of employed (another input measure) has a similar advantage and disadvantage of the ratio of R&D expenditure to sales. The data on R&D expenditure to sales and the ratio of scientists and engineers to total number of the employed are from the *Report on the Survey of Research and Development in Science and Technology* by the Korean Ministry of Science and Technology.

The last measure of technological change is the ratio of the expenditure on the information and communication technology (ICT) to GDP in each industry.[4] It enables us to analyze whether the rapid change of ICT affects the wage structure in Korea. Hur, Seo, and Lee (2002) calculated the ICT intensities using the Input-Output table from the Bank of Korea.

In the analysis, we use 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 industry rates of technological change. Such an analysis, however, would be problematic in that case because changes in the measures of industries' rates of technological change should be utilized. As pointed out both by Allen (2001) and 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 the above measures of technological change across the two-digit level industry categories are reported in the Appendix Table.

## IV. Effects of Technological Change on Wage Premium

### A. Earnings Equation

There are two approaches to test SBTC in the previous literature. One 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; Choi and Jeong, 2003). Although this approach has the advantage of utilizing longer time-series data and

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[4] Berman, Bound, and Griliches (1994) shows that the ratio of investment in computers to total investment is a good proxy for technological change in an industry.

analyzing changes over time, it cannot control other observed and unobserved characteristics of an individual that affect his or her own wage.

Another approach is to analyze an earnings equation, which can control various characteristics of an individual (Bartel and Sicherman, 1999). As mentioned earlier, we use panel data covering a relatively shorter time period. Panel data enables us to control unobserved characteristics of an individual as well as observed characteristics affecting wage. Therefore, we estimated the following Mincer-type earnings equation as:

$$\ln W_{ijt} = \beta' X_{it} + \gamma_1 T_{jt} + \gamma_2 T_{jt} \cdot EDU_i + u_{ijt}, \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (1)$$

where $W_{ijt}$ represents the hourly wage of worker *i* in industry *j* during time period *t* and $X_{it}$ represents human capital characteristics of worker *i* during time period *t*. It includes years of schooling, potential labor market experience (= age - years of schooling - 6), experience square, tenure, tenure square, establishment size dummies, area dummy, job status dummy, industry dummies, sex dummy, production worker dummy, and year dummies. The $T_{jt}$ represents technological change of the industry *j,* of which worker *i* belongs to during time period *t*.

For the error term of equation (1), $u_{ijt}$, we adopt an error-component specification in line with the previous studies. We assume there exist industry random effects, $e_j$, that is, $u_{ijt} = e_j + v_{ijt}$.[5] For the error components, we assume $E(v_{ijt}) = E(e_j) = 0$, $Var(e_j) = \sigma_e^2$, $Var(v_{ijt}) = \sigma_v^2$, $Cov(e_j, v_{ijt}) = 0$ for all i, j, and t, and $Cov(e_j, e_m) = 0$ $Cov(u_{ijt}, u_{lmn}) = 0$ for all i≠l, j≠m, and t≠n. Unless $\sigma_e^2 = 0$, the random effect model will improve the efficiency of the estimation results over the simple OLS.[6]

First, we test if there exists a positive relationship between technological change and the wage premium. For this hypothesis, we test whether the partial derivative of the log hourly wage with respect to the technological change ($\gamma_1 + \gamma_2 EDU_i$) 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.

[5] Alternative error component models can be specified by allowing individual random effects and/or chronological random effects. In addition, some fixed effects models can be applied to test the same hypothesis. We have tried quite a few variations for this hypothesis, but found no qualitative differences in the test results. The detailed results are available from the authors upon request.

Table 2 reports the estimated results of equation (1) using industry random effect specification. The partial derivative of log hourly wage with respect to the R&D intensity ($\gamma_1 + \gamma_2 EDU_i$) is positive when the years of schooling of an individual are higher than 12 years. When other proxies of technological change are used, similar results are obtained. The estimated results of the full model are reported in the Appendix.

Second, we test whether the wage premium associated with the technological change ($\gamma_1 + \gamma_2 EDU$) increases as the years of schooling increase. If the SBTC is correct, then highly educated workers will receive higher wage as technology changes. That is, the coefficient of the interaction term on equation (1) should be positive ($\gamma_2 > 0$). As is seen in Table 1, the estimated value of $\gamma_2$ is significantly different from zero and is also positive in every model.

Based on the above results, for now, we can conclude the followings: First, we found that the educational wage premium is greater in industries with rapid technological change. This result confirms the hypothesis of skill biased technological change in Korea and also supports the pervasive SBTC around the world. Second, not all workers in the industries with rapid technological change are paid higher than those in the industries with slower technological change. However, workers with high education levels are paid higher in the industries with rapid technological change than those in the industries with slower technological change.

## V. Returns to Education or Returns to Unobserved Skills

The education premium found earlier, however, could reflect the rise in the price of unobserved skills of workers rather than the rise in the returns to education itself. Juhn, Murphy, and Pierce (1993) illustrate that the wage inequality of men between 1963 and 1989 increased within narrowly defined education and labor market experience groups; much of the increase in wage inequality was due to increased returns to the components of skill other than years of schooling and years of experience. Bartel

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[6] Our test for $H_0$: $\sigma_e^2 = 0$ against $H_1$: $\sigma_e^2 \neq 0$ strongly rejects $H_0$.

and Sicherman (1999), using a variety of industry-level measures of technological change to a panel of young workers, found that the education premium associated with technological change is the result of a greater demand for the innate ability or other unobserved characteristics of more educated workers. Taber (2001) also suggested that an increase in the demand for unobserved ability could play a major role in the growing college premium.[7] Therefore, we will test if this argument is supported by the Korean data.

### A. Double Fixed-Effect Model

To identify the true causality of the education premium associated with the technological change, we estimate the following fixed effect model by adding individual premium:

$$\ln W_{ijt} = \beta' X_{it} + \gamma_1 T_j + \gamma_2 (T_j \cdot Edu_{it}) + ID_i + \varepsilon_{ijt}, \cdots\cdots\cdots\cdots(2)$$

where $ID_i$ is the individual fixed effect. This model is called the double-fixed effect model because the industry fixed effects are included in $X_{it}$. We assume that the individual fixed effect is not changed over time as well as over industry even though he or she moves into another industry.[8]

Table 3 presents the estimated results of equation (2). Interestingly, the positive correlation between technological change and wages observed in equation (1) becomes insignificant in equation (2). All the coefficients of proxies of technological change ($\gamma_1$) and their interaction terms with education ($\gamma_2$) become insignificant. We suspect that the educational wage premium associated with technological change is not caused by the education itself, but rather by the unobserved heterogeneities of individuals.

### B. Two-Stage Double Fixed Effects Model

When we control the observed characteristics only, there appears to be a positive correlation between education premium and technological change. After

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[7] The earnings premium associated with computer usage could also reflect unobserved ability, if more able workers are assigned to jobs using computers (Dinardo and Pischke 1997).

[8] As some workers in the sample moved to another industry at least once during the sample period, we can distinguish the individual fixed effect from the industry effect.

controlling the observed and unobserved heterogeneities among workers, the education premium associated with technological change disappears. Thus, it is likely that the positive correlation between education premium and technological change found in equation (1) reflects the wage premium due to workers' unobserved skills, which are positively correlated with education.

By estimating two-stage double fixed effects model, we provide a more direct evidence for the positive correlation between unobserved skills and technological change. In the first stage, we estimate the individual fixed effect $\hat{ID}_i$ in equation (2).

In the second stage, using the estimated value of individual fixed effect as the dependent variable, we analyze the relation between the individual fixed effect and technological change. As sex is fixed for individuals over time, it was not included in the first stage. Thus, the sex dummy is also included in the second stage. Consider the following model in the second stage:

$$\hat{ID}_i = \alpha SEX_i + \gamma_1 \overline{T}_i + \eta_i, \cdots\cdots\cdots (3),$$

where $\overline{T}_i$ is "the mean of the rates of technological change in the industries in which the worker was employed during the sample period." Therefore, $\overline{T}_i$ is an idiosyncratic shock to the individual worker *i* (invariant over time) whereas $T_j$ is a shock to every individual belonging to industry *j*. When a worker moves to another industry, the value of $\overline{T}_i$ remains the same while the value of $T_j$ changes. We assume that $\overline{T}_i$ reflects unobserved characteristics of an individual, which affects wage, and is correlated with his or her years of schooling. If the coefficient of $\overline{T}_i$ in equation (3) is significantly positive, then it implies that the wage premium not explained in the first stage (*i.e.*, $\hat{ID}_i$ ) is correlated with the (idiosyncratic) technological change. Since $\overline{T}_i$ is also correlated with the years of schooling, there appears to be a positive correlation between technological change and the years of schooling in equation (1). However, the true causality exists between the individual heterogeneity and wage premium (associated with technological change), not between the years of schooling and wage premium.

Table 4 illustrates that there exists a positive correlation between the individual heterogeneity and wage premium associated with technological change. The coefficient of ($\overline{T}_i$) is positive and significant in every case. This result implies that the wage premium associated with technological change is explained by the unobserved skill of an individual rather than the observed schooling years of an individual.

## VI. Summary and Conclusion

We have demonstrated the direct evidence of the relationship between technological change and education premium in Korea. First, we found that the educational wage premium is greater in industries with rapid technological change. This result confirms the hypothesis of skill biased technological change in Korea and also supports the pervasive SBTC around the world. Second, not all workers in the industries with rapid technological change are paid higher than those in the industries with slower technological change. But, workers with high education levels are paid higher in the industries with rapid technological change than those in the industries with slower technological change.

We also analyzed whether the premium reflects the returns to education per se or the returns to other unobserved characteristics of workers. The panel analysis of earnings function implies that the high education premium in the industries with rapid technological change is mostly explained by returns to worker's unobserved heterogeneities such as one's intrinsic ability rather than returns to education per se.

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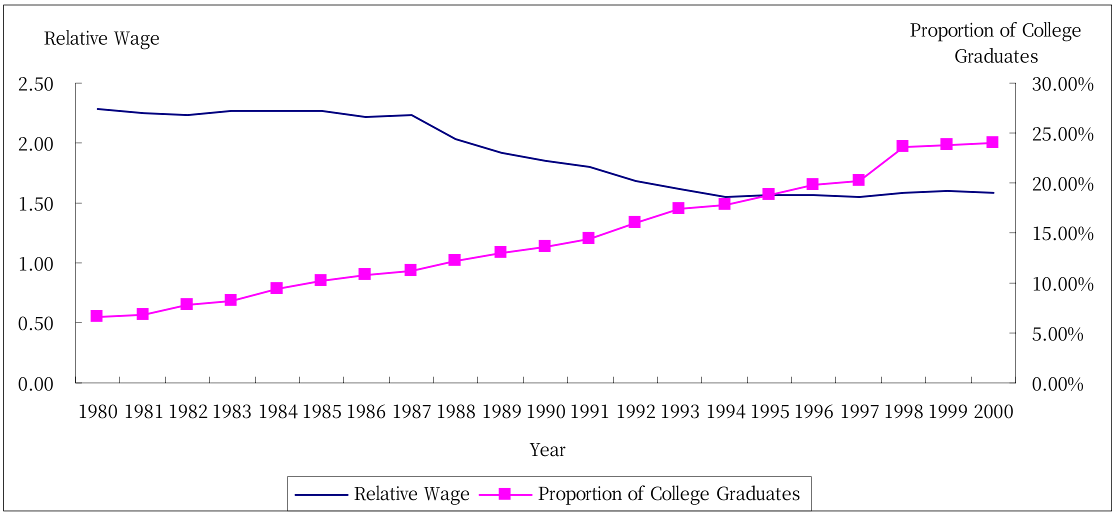
Figure 1. Changes in Relative Wage and Employment of College Graduates




Note: Relative Wage = Wage of College Graduates/ Wage of High-School Graduates
Proportion of College Graduates = Number of employed with a College Degree/ Total Number of Employed

<Table 1> Decomposition of Changes in Relative Wages: College vs. High School

(Unit: %)

| | 1983-1993 | | | | | 1993-2000 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Wage Change | Supply Change | Demand Change ($\sigma = 1$) Total | Between Change | Within Change | Wage Change | Supply Change | Demand Change ($\sigma = 1$) Total | Between Change | Within Change |
| Total | -0.333 | 0.279 | -0.053 | | | 0.040 | 0.212 | 0.252 | | |
| | | | (100) | (14.70) | (85.30) | | | (100) | (4.99) | (95.01) |
| Male | -0.299 | 0.253 | -0.046 | | | 0.065 | 0.180 | 0.245 | | |
| | | | (100) | (11.26) | (88.74) | | | (100) | (3.38) | (96.62) |
| Fem. | -0.372 | 0.737 | 0.366 | | | 0.031 | 0.347 | 0.378 | | |
| | | | (100) | (43.43) | (56.57) | | | (100) | (8.74) | (91.26) |

Source: Table 5 and Table 6 from Choi and Jeong (2003)

<Table 2> Effect of Technological Change on Wage:
Industry Random-Effect Model

| Measure of Technological Change | Equation (1) | |
|---|---|---|
| | $\gamma_1$ | $\gamma_2$ |
| R&D Intensity | -0.0808** | 0.0057** |
| | (-3.911) | (3.438) |
| Percentage of Scientist and Engineers | -0.0462** | 0.0041** |
| | (-2.763) | (3.127) |
| TFP (1980-2000) | -0.0909** | 0.0053** |
| | (-2.985) | (2.309) |
| ICT Intensity | -0.0651** | 0.0045** |
| | (-3.410) | (2.873) |

Note: Other explanatory variables included in the regressions are years of schooling, experience, experience square, tenure, tenure square, establishment size dummies, area dummy, job status dummy, industry dummies, sex dummy, production worker dummy, year dummies and constant term.
"t-value" is in the parenthesis.
** : p < .01 , * : p < .05 (for one tailed test)

<Table 3> Effect of Technological Change on Wage: Double Fixed Effects Model

| Measure of Technological Change | Equation (4) | |
|---|---|---|
| | $\gamma_1$ (Coefficient of $T_j$) | $\gamma_2$ (Coefficient of $T_j$ * EDU) |
| R&D Intensity | 0.1318 | -0.0065 |
| | (1.239) | (-0.847) |
| Percentage of Scientist and Engineers | -0.0042 | 0.0015 |
| | (-0.055) | (0.272) |
| TFP (1980-2000) | -0.1357 | 0.0128 |
| | (-0.861) | (1.087) |
| ICT Intensity | -0.0102 | 0.0012 |
| | (-0.141) | (0.208) |

Note: See <Table 2> for other explanatory variables included in the regressions.
"t-value" is in the parenthesis.
None is significant, so no * appears.

<Table 4> Effect of Technological Change on Individual Fixed Effect
(Second Stage of Double Fixed Effects Model)

| Measure of Technological Change | $\gamma_1$ in Equation (3) (Coefficient of $\overline{T}_i$) |
|---|---|
| R&D Intensity | 0.0628** |
| | (5.124) |
| Percentage of Scientist and Engineers | 0.0572** |
| | (5.985) |
| TFP (1980-2000) | 0.0413** |
| | (2.267) |
| ICT Intensity | 0.0195* |
| | (1.650) |

Note: "t-value" is in the parenthesis.
** : $p < .01$ , * : $p < .05$ (for one tailed test)

Appendix A. Data

We limit our sample to workers in manufacturing sectors, working more than 15 hours a week. We used the log hourly wage as a dependent variable in our analysis. The hourly wage is obtained by dividing monthly wage by monthly working hours. We exclude workers with monthly wage more than 10 million won or with hourly wage more than 300 thousand won (one U.S. dollar is approximately 1,200 won). The number of workers in the sample in each survey year is reported below.

<Table A1> Number of Samples in KLIPS

| | 1998 Survey | 1999 Survey | 2000 Survey | 2001 Survey |
|---|---|---|---|---|
| Number of Households | 5,000 | 4,379 | 4,045 | 3,865 |
| Number of Individuals | 13,321 | 12,039 | 11,205 | 11,051 |
| Number of Employed | 4,012 | 3,901 | 3,603 | 3,649 |
| Number of Employed in Manufacturing sector | 1,203 | 1,084 | 1,013 | 964 |
| Number of observations used in the regressions | 637 | 935 | 635 | 436 |

<Table A2> Basic Statistics of the Sample

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Average Years of Schooling | 11.58 years | 11.43 years | 11.34 years | 11.48 years |
| Average Tenure | 7.81 years | 5.15 years | 5.74 years | 5.54 years |
| Ratio of Seoul Residents | 21.98% | 20.21% | 19.21% | 15.14% |
| Ratio of Permanent Workers | 91.05% | 87.38% | 91.97% | 92.43% |
| Average Monthly Earnings* | 1,104.4 | 1,049.2 | 1,177.7 | 1,304.7 |
| Average Hourly Earnings* | 5.00 | 4.67 | 5.23 | 5.81 |
| Ratio of Male | 68.76% | 65.24% | 68.03% | 67.20% |
| Ratio of Production Workers | 57.61% | 71.55% | 70.57% | 70.18% |

(* unit: thousand Korean won)

<Table C1> Industry Random Effect Model: Full Results
(Dependent variable = Log of Hourly Wage)

| | R&D Intensity | % of Scientist & Engineers | TFP (1980-2000) | ICT Intensity |
|---|---|---|---|---|
| Education (EDU) | 0.0344** (7.058) | 0.0393** (9.634) | 0.0418** (10.440) | 0.0333** (6.000) |
| Experience | 0.0182** (8.098) | 0.0185** (8.243) | 0.0179** (7.963) | 0.0183** (8.160) |
| Squared Experience | -0.0226** (-4.681) | 0.0229** (-4.744) | 0.0219** (-4.536) | 0.0228** (-4.728) |
| Tenure | 0.0019** (6.954) | 0.0018** (6.721) | 0.0019** (6.912) | 0.0019** (6.885) |
| Squared Tenure | -0.00004** (-4.335) | 0.0000** (-4.062) | 0.0000** (-4.370) | 0.0000** (-4.188) |
| Seoul Dummy | 0.0501** (2.291) | 0.0496** (2.267) | 0.0482** (2.203) | 0.0542** (2.475) |
| Permanent Worker Dummy | 0.1571** (6.366) | 0.1513** (6.150) | 0.1488** (6.044) | 0.1502** (6.100) |
| Prod Worker Dummy | -0.1750** (-9.964) | -0.1759** (-10.012) | -0.1764** (-10.040) | -0.1783** (-10.159) |
| 1999 Dummy | 0.0275* (1.784) | 0.0251 (1.630) | 0.0281* (1.821) | 0.0282* (1.827) |
| 2000 Dummy | 0.1016** (6.032) | 0.0998** (5.914) | 0.1027** (6.080) | 0.1028** (6.089) |
| 2001 Dummy | 0.1869** (9.908) | 0.1840** (9.742) | 0.1885** (9.975) | 0.1888** (9.994) |
| Small Firm Dummy | 0.0251 (1.009) | 0.0223 (0.896) | 0.0252 (1.012) | 0.0248 (0.998) |
| Medium Firm Dummy | 0.0543 ** (2.112) | 0.0477* (1.848) | 0.0555** (2.154) | 0.0523** (2.037) |
| Large Firm Dummy | 0.1625** (5.771) | 0.1548** (5.446) | 0.1677** (5.946) | 0.1608** (5.728) |
| Male Dummy | 0.3777** (22.205) | 0.3783** (22.197) | 0.3777** (22.185) | 0.3793** (22.281) |
| Technological Change (TC) | -0.0808** (-3.911) | 0.0462** (-2.763) | 0.0909** (-2.985) | 0.0651** (-3.410) |
| TC*EDU | 0.0057** (3.438) | 0.0041** (3.127) | 0.0053** (2.309) | 0.0045** (2.873) |
| Intercept | 0.3514** (4.980) | 0.2733** (4.261) | 0.2690** (4.196) | 0.3744** (4.837) |

Note: ** : p < .01 , * : p < .05 (for one tailed test)