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The Speed of Technological Innovation and Returns to Experience

기술 발전 속도와 숙련 경험의 보상과의 관계

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Abstract

The Speed of Technological Innovation and Returns to Experience

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In this paper, we see that a worker in high-tech industry gets relatively less returns to tenure than those in low-tech industry. Using an earnings equation and classifying industries by their R&D intensity, I calculate returns to tenure and compare them by groups. The result using pooled OLS clearly shows negative impact of interaction between tenure accumulation and the speed of technological advances on wages. On the other hand, with IV-GLS, most coefficients of the tenure related variables are not statistically insignificant and require us further discussion. Many related studies have focuses on either the source of experience profile of wages or the impact of technological innovation on wages but not ones combining the two together. Therefore, although there are a couple of limitations, I believe my paper can have contribution to the labor literature that examines the roles of technological innovation on wages.

Key words : Returns to experience, R&D intensity, Technological Innovation, Earnings equation

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1 Introduction

Technological innovation has made our life more convenient and many people, in general, have highlighted its positive roles on society. However, we cannot ignore negative aspects lying behind of the development of technology such as income gap among skilled and unskilled workers, inequality issues across countries, climate changes and etc. Even though this dark side of the technological innovation has grown to a considerable extent, a social atmosphere that promotes the technological development is hard to be faded out. Therefore, more rigorous and various researches that measure a true impact of technological advances on society should be followed so that we have an insight with which we can sharply compare the pros and cons.

In this paper, we will see that high technological innovation can give negative impacts on worker's returns to tenure. To be specific, a worker in high-tech industry gets relatively less returns to tenure than those in low-tech industry. We should disentangle the fact that normally workers in high technology industry have comparably better income than those in low technology industry. My approach is to look at that the value of experience for a worker can be diminished quickly when he works in highly innovative industry. This is largely because the experiences that a worker has accumulated become depreciated quickly when he/she workers in highly innovative industry. Since new technologies in the industry tend to be introduced or updated in a relatively short period, the value of experiences that a worker has had becomes devalued. I believe this result leads to a negative impact on the worker's wage.

To investigate the relationship between returns to tenure and the speed of technological advances, this paper uses an approach for constructing tenure variables proposed by Kambourov and Manovskii (2009) and Brown and Light (1992). They start to construct the employer tenure from identifying tenure switch whenever the reported length of present employment is smaller than the time elapsed since the last interview date. Then, they expand to accumulate occupation and industry tenures using the similar way. After identifying the tenure variable and running an earnings equation, I calculate the returns to tenure and compare them by low and high technology worker group. For this analysis, I add an interaction term to the earnings equation between the tenure variables and a dummy variable which refers to the speed of technology in industry.

This paper is laid out as follows: Section 1 is an introduction, Section 2 reviews the literature related to my paper. In the Section 3 shows the research methodologies that I take. Next, Section 4 discusses the main results and, finally, Section 5 makes a conclusion.

2 Literature Review

There is little literature which articulates the relationship between a worker's returns to tenure and the speed of technological innovation. It is easy to encounter several papers focusing on either the source of experience profile of wages or the impact of technological advances on wages. However, they are not ones combining the two together. Now, we look at the several related researches which have been developed in the labor economics context.

2.1 Tenure and Wages

Many human capital related literature has focused on finding the source of experience profile of wages. To be specific, it has been still a subject of debate which component is more important for wage determination among distinct tenure characteristics. For example, many researches claim that wages rise with firm (or employer) tenure. Topel (1990) suggests a strong connection between job seniority and wages in the typical employment relationship. Dustmann and Meghir (2005) stresses the effect of firm tenure on wages using a unique administrative data-set for Germany. It proposes that the rise of experience premium might represent firm-specific tenure rather than general experience. However, Abraham and Farber (1987) and Altonji and Shakotko (1987), earlier points out that the measured positive cross-sectional return to tenure is largely a statistical artifact due to the correlation of tenure with omitted variables representing the quality of the worker, job, or worker-employer match. After controlling for the omitted factors, they find that earnings do not rise much with tenure.

There have been a number of papers which emphasize on industry or occupational specificity of human capital. Neal (1995) argues that workers receive compensation for some skills that are neither completely general nor firm-specific but rather specific to their industry or line of work. The author uses displaced workers who find new jobs in their predisplacement industry, and concludes that post-displacement returns to pre-displacement job tenure resemble cross-section estimates of the returns to current seniority. Also, Parent (2000) finds that firm (employer) tenure has insignificant impact on wages once industry-specific capital is controlled and finds out what matters most for the wage profile in terms of human capital is industry-specificity. Kambourov and Manovskii (2009), on the other hand, maintains that returns to occupational tenure are more crucial than any other type of tenures. The paper uses the Panel Study of Income Dynamics (PSID) data, compliments the measurement errors of original occupation and industry code by using the Retrospective Occupation-Industry Supplemental Data Files and concludes that human capital is occupation specificity. Gathmann and Schönberg (2010), also, shows that task-specific (occupational) human capital is an important source of individual wage growth.

2.2 Technological Innovation and Wages

Over the past years, a number of studies have documented the growing wage inequality and pointed to technological change for the rise, which is called skill-biased technical change (SBTC). Levy and Murnane (1992) claims that the wage inequality since the late 1970s is mainly originate from technological changes which occurred over the same period have resulted in a downward shift in the demand for low-skill workers and in comparably a upward shift in the demand for high-skill workers. Acemoglu (2000) argues that technical change has been skill-baised and increase in inequality is most likely due to acceleration in skill bias. The author says that the twentieth-century has been characterized by SBTC because the increased supply of unskilled workers in English cities made the introduction of these technologies portable.

However, there is some counterpart argument against SBTC. Card and DiNardo (2002) indicate problems and issues of that the SBTC that wage inequality stabilized in the 1990s despite continuing advances in computer technology. Also the author says that SBTC fails to explain the evolution of other dimensions of wage inequality, including the gender and racial wage gaps and the age gradient in the returns to education.

In sum, we have been able to find fruitful researches about the impact of tenures and technological development on wages respectively. However, there have been rarely the case for combining two factors together for explaining wage differentials which I try to analyze.

3 Research Method

3.1 Data

I use the Panel Study of Income Dynamics (PSID) panel data of years between 1976 and 1992. Specifically, I restricted sample of white male heads of household, aged 18 to 64, living in the continental US, and working in a manufacturing sector. Also, all observations that worked for the government or received real hourly wages of less than $1 in constant 1979 dollars are eliminated. Those who work less than 500 hours are excluded from the sample in that year. Self-employed or being simultaneously employed by someone else as well as workers in the military and farmer after 1975 are eliminated from the sample together. Earnings functions are estimated on the sample spanning the years 1981-1992.

In order to obtain returns to tenure, the first step is to construct employer tenures from the data. I follow the way Brown and Light

(1992) and Kambourov and Manovskii (2009) use. The basic idea of accumulating employer tenures starts from identifying whether a worker switches his job from the previous one. This employer switch is identified using Partition T that Brown and Light (1992) find acceptable. The Partition T identifies, roughly, an employer switch whenever the reported length of present employment is smaller than the time elapsed since the last interview date. Once employer switches are identified, employer tenure is increased by one year if an individual does not report an employer switch.

We also accumulate industry and occupation tenures by identifying their switches. The PSID provides 3-digits of occupation and industry codes for each individual. Since it is told that there is a significant number of measurement errors in the codes, Kambourov and Manovskii (2009) uses the Retrospective Occupation-Industry Supplemental Data Files to complement the errors. It claims that there is a significant degree of disagreement between the originally assigned PSID occupation and industry codes and the codes assigned to the same individuals in the Retrospective Files as well as there is a higher degree of misclassification of occupations and industries in the originally coded data. In my paper, I also use the Retrospective Files for identifying occupations and industries switches. The way to identify occupation and industry switches is similar with the one for employer tenure using Partition T as described above. I describe the information for constructing tenures in detail in Appendix 6.1. Table 1 shows the descriptive statistics of the sample used in the estimation.

3.2 Classification of Industry by R&D Intensity

A variable which helps classify industries and reflects technological innovation is required to analyze the main goal of this paper. I adopt the classification of manufacturing industries which is proposed by Hatzichronoglou (1997). In this classification, the concept of technology intensity has been expanded to take into account both the level of technology specific to the sector (measured by the ratio of R&D expenditure to value added) and the technology embodied in purchases of intermediate and capital goods. Hatzichronoglou (1997) divided manufacturing industries into four groups on the basis of the degree of technology intensity: High, Medium-High, Medium-Low and Low technology industries.

In the High-tech industry, for example, there are aircraft, pharmaceuticals, computing machinery and Electronics industries. On the other hand, industries related to paper printing, textile, clothing, wood, pulp or food products belong to the Low-tech industry. Table 3 displays the list of industries classified by this method. Each observation in the sample is grouped by this classification using the 3-digits industry code that PSID offers[1].

Table 2 shows the number of observations for each group in the sample. Due to the lack of observations in the high-tech group, I first run the regression with the technology (dummy) variable which is coded as 0 for Low and Medium-Low tech and as 1 for Medium-High and High technology. Then, I continue to run the regression with the whole four groups.

[1] source: PSID wave XIV - 1981 documentation, Appendix 2: Industry and Occupation Codes

3.3 Earnings Equation

The following earnings equation is used for looking at the negative impact of technological innovation on wages.

$$\begin{aligned}\log w_{ijmnt} =& \beta_1 Emp.Tnr_{ijt} + \beta_2 Ind.Tnr_{int} + \beta_3 Occ.Tnr_{imt} + \beta_4 Age_{it} + \\ & \beta_5 tech + \beta_6 tech \cdot Emp.Tnr_{ijt} + \beta_7 Edu_{it} + Dummies + \theta_{it}\end{aligned} \tag{1}$$

where w_{ijmnt} is real hourly wage of person i working in period t with employer j in occupation m and industry n. $Emp.Tnr$, $Occ.Tnr$, and $Ind.Tnr$ denote tenure with current employer, occupation and industry, respectively. Those variables have square terms in the equation. Age_{it} and Edu_{it} refer to the age and the level of education of person i in period t. $Tech$ is a dummy variable which indicates whether a worker's industry is in low or high technology and there are other dummies not specified above such as a martial status, year and region dummies.

Also, there is an interaction term $tech \cdot Emp.Tnr_{ijt}$. To support my argument about a negative correlation between tenures and whether an industry is highly innovative or not, I want to point out that the interaction term $tech \cdot Emp.Tnr_{ijt}$ has a crucial role in this paper. To be specific, if the coefficient of the interaction term is negative, we can infer that highly innovative industry negatively interacts with tenures, and as a result, it gives negative impact on wages. I will run two additional models by changing the tenure variable in this interaction term to $Occ.Tnr_{imt}$ and $Ind.Tnr_{int}$ and they allow us to have a closer look at the relationship between technology and tenure variables.

I consider that there are unobserved individual-specific characteristics and match components as well as observed variables which I described above. For example, individuals with the same level of firm experience would receive different wages due to matching quality. Therefore,

$$\theta_{it} = \mu_{ij} + \lambda_{im} + \nu_{in} + \epsilon_{it} \tag{2}$$

where μ_{ij} is a job-match component, λ_{im} - an occupation-match component, ν_{in} - an industry-match component, and ϵ_{it} is the error term.

We start by estimating the econometric model (1) with the pooled OLS. However, unobservable match-specific components tend to be correlated with tenure variables and, as a consequence, with the dependent variable. A worker having a better occupation match is likely to have higher occupation tenure and receive higher wages. This correlation will bias the estimates in the pooled OLS. To minimize this endogeneity issues, I employ the instrumental variable similar to that proposed by Altonji and Shakotko (1987) and used by Parent (2000). Specifically, if X_{int} is the industry tenure of individual i who is in industry n in period t, $\bar{X}_{in}$ is the average industry tenure of individual i, then the instrumental variable is $\tilde{X}_{int} = X_{int} - \bar{X}_{in}$. We also apply this instrumental variables to employer and occupation tenure variables as well as their squared terms. Then, I estimate the instrumented model with IV-GLS method.

3.4 Returns to Tenure

Now, we see how to get the returns to tenure from the earnings equation. Following the earnings equation 1, we simplify the variables in the equation as follows.

$$\begin{aligned}\log w_{ijmnt} =& \beta_0 Emp.Tnr_{ijt} + \beta_1 Emp.Tnr_{ijt}^2 + \beta_5 tech + \\ & \beta_6 tech \cdot Emp.Tnr + OtherVars\end{aligned}$$

We substitute the variable $Emp.Tnr$ with x so that the wage equation can be a function of employer tenure. Then, the difference between the wage function at $Emp.tnr = x$ and at $Emp.tnr = 0$ can be derived as follows:

$$\begin{aligned}\log w(Emp.Tnr = x) &= \beta_0 x + \beta_1 x^2 + \quad \beta_5 tech + \quad \beta_6 tech \cdot x + OtherVars \\ \log w(Emp.Tnr = 0) &= \qquad\qquad\qquad \beta_5 tech \qquad\qquad\qquad + OtherVars \\ \log w(x) - \log w(0) &= \beta_0 x + \beta_1 x^2 + \qquad\qquad\qquad \beta_6 tech \cdot x\end{aligned}$$

After transforming the log wage form into the general form, we can obtain the returns to tenure by calculating the ratio of wage when employer tenure x to the wage when employer tenure is 0 given other variables are constant.

$$\begin{aligned}\frac{w(x)}{w(0)} &= e^{\beta_0 x + \beta_1 x^2 + \beta_6 tech \cdot x} \\ \text{Returns to Tenure} \equiv \frac{w(x) - w(0)}{w(0)} &= e^{\beta_0 x + \beta_1 x^2 + \beta_6 tech \cdot x} - 1 \qquad (3)\end{aligned}$$

Consequently, the equation 3 denotes to the returns to tenure.

4 Main Results

Now we discuss the results that I have obtained through pooled OLS and IV-GLS estimation using the above earnings equation 1. Due to the lack of the number of observations in high-tech group, first, we narrow down the classification of industry into two groups, Low and High, then we compare the returns to tenure for each group. After discussing the case, we expand it to the four-groups case.

4.1 Case 1 - Low and High

In this subsection, we consider the variable $TechDummy$ as a dummy which is coded 0 if an observation's current industry is either Low or Medium-Low, and 1 otherwise.

4.1.1 Estimation Results

Table 4 and Table 5 show the results of pooled OLS estimation and IV-GLS respectively. The column "Model 1" of each table represents the results when the interaction term of employer tenure and technology dummy is added. Similarly, the column "Model 2" and "Model 3" refer to the cases where the interaction term of technology dummy is combined with industry tenure or occupation tenure respectively. Lastly, "Model 4" is the result when all the interaction terms described above are added.

All the model have highly positive and significant coefficient for $TechDummy$ for both pooled OLS and IV-GLS estimations, which means that workers in high-tech industry have relatively higher wage than those in low-tech. Specifically, the impact of technology on wages is to some extent different among models, but there are approximately

15 to 20 percent wage differentials among workers in low-tech industry and those in high-tech when we run the pooled OLS estimation, and 8 to 12 percent for IV-GLS given that the worker has no accumulated tenure.

Compared to pooled OLS, the coefficients of tenure related variables in IV-GLS are less significant but both estimations agree with most signs of the coefficients. The coefficients of $Emp.Tnr$ and $Ind.Tnr$ of both estimations are positive and their square terms are negative, while only the square term of $Emp.Tnr$ in pooled OLS is strongly significant. When it comes to Occupation tenure, both $Occ.Tnr$ and its square term are positive and not significant in pooled OLS. On the other hand, the $Occ.Tnr$ and its square term have different signs in IV-GLS.

The impact of interaction term for tenure variables and technology dummy on wage tends to be negative in pooled OLS but not to be deterministic in IV-GLS and need further discussion. When we look at the Table 4, the interaction terms of column 1 to 3 have negative signs and it is statistically significant for the interaction term of occupation tenure and technology dummy. In the case of "Model 4", the coefficients of the interaction terms are not significant but they appear to be negative signs. This result coincides with my initial guess that high tech industry is negatively interacted with tenures. If we move on to the IV-GLS, however, it is hard to see the desired result. Looking at the Table 5, we can check that all the interaction terms in different models are not statistically significant. Especially, in the case of the interaction term for occupation tenure and technology dummy which is highly significant in OLS, the coefficient closes to zero and has a high variance.

4.1.2 Returns to Tenure

Table 6 and Table 7 show the returns to tenure derived from the equation 3.4 using the coefficients obtained from pooled OLS and IV-GLS respectively. There are three different columns in each table: Employer, Industry and Occupation. Each column links to the returns to Employer, Industry and Occupation tenures, respectively. I obtain the returns to tenure corresponding to the "Model" 1-3 in the estimation table. In the pooled OLS model, first, we are able to find that there are strong inclination that workers in low tech industry have higher returns to tenure than those in high tech industry. Specifically, although returns to employer tenure in both low and high tech groups and returns to occupation tenure in high tech group are not statistically significant, the tendency that returns to tenure in low tech are strongly higher in industry tenure and slightly higher in employer and occupation tenures than those in high tech.

If we move on to the returns to tenure with IV-GLS, however, the tendency that low tech group has higher returns to tenure than high tech group becomes vague and this requires us to have further discussion. To be specific, Most returns to tenure obtained through IV-GLS are not significant except the one in high-tech group in industry tenure. This comes mainly from the fact that the interaction terms between technology and tenure variables in IV-GLS come out insignificant but positive and results in higher returns to tenure with statistically not significant in high-tech group compared with in low-tech group. To rigorously analyze this effect, we need to look at the case where the industry categorization is extended from two to four groups.

4.2 Case 2 - Low, Medium-Low, Medium-High and High

Now, we check the case where the variable $Tech$ is coded 0, 1, 2 and 3 when an observation's current industry is Low, Medium-Low, Medium-High and High respectively. When I run the regression, I use the variable as three dummy variables.

4.2.1 Estimation Results

Table 8 and Table 9 show the results of pooled OLS estimation and IV-GLS respectively. As we check in the Table 4 and Table 5, when technology is more subdivided, the impact of high technology on wages is strongly and positively detected. The higher the technology is, the higher returns to technology is observed both in OLS and IV-GLS. Also, the signs and statistical significance of tenure related variables in this analysis coincide with the case where technology is itemized with Low and High cases.

When it comes to the interaction terms for tenure variables and technology variable $Tech$, the similar results with the previous case are obtained. To be specific, in pooled OLS, the coefficients of interaction terms tend to have more negative effect on wages as the technology goes to higher level. We can get this result from the "Model" 1 to 3. However, in "Model 4" where all the interaction terms are put together, the tendency is not detected but somewhat the opposite result comes out in Employer and Industry tenures. In the case of the interaction term with occupation tenure and technology, the correlation between the interaction term and wage can be observed.

4.2.2 Returns to Tenure

Let's move on to the returns to tenure in the case of the four-grouped industries. Table 10 and Table 11 display the returns to tenure derived from pooled OLS and IV-GLS respectively. In the tables, there are four columns and each column means the level of technology. For example, the first column, Low, shows the returns to tenure for Low-tech workers and I put the 2, 5 and 8 years of returns to employer, industry and occupation tenures. In this Table 10, it is prone to have smaller returns to tenure as technology is developed. While returns to employer and occupation tenures are not statistically significant in the table, returns to industry tenure are strongly significant.

On the other hand, Table 11 does not show an apparent decline as technology goes to higher level, but excluding the Medium-High group make the result close to my argument. Except returns to employer and industry tenures in Medium-High, every return to tenure is not statistically significant. This comes from the fact that the regression coefficients of tenure variables and interaction terms in IV-GLS is not significant. Therefore, the calculated returns to tenure has high variances. As technology goes to higher level, the corresponding returns to tenure have less value when we somehow ignore the Medium-High group. For example, when we look at the 5 year returns to employer tenure, 0.0482 for Low, 0.0248 for Medium-Low, 0.0539 for Medium-High and 0.0132 for High are calculated. The value for Medium-High is considerably higher than any other group. I am sure that this group has a crucial role in disturbing the result in IV-GLS in both Case 1 and Case 2, and we need further discussion for solving this issue.

5 Conclusion

In Labor Economics, both the impact of technology on wage and finding the source of the experience profile of wages have been crucial research topics. Although there are some academically conflict points but solutions for the issues, such as skill-biased technical change and occupational, firm or industry specificity to human capital, have been developed well. However an approach that combines two issues together has been rarely investigated and my paper tries to analyze them together which can give us an important economic implication.

My paper suggests the value of a worker's experience in highly innovative industry can be less than the one in comparably not speedy innovative industry. I categorize manufacturing industries by R&D intensity proposed by Hatzichronoglou (1997) and use the Panel Study of Income Dyanmics (PSID) data to estimate an earnings equation with pooled OLS and IV-GLS methods. After then, I calculate the returns to tenure using the devised formula from earnings equation 1. In the result of pooled OLS, we can check out the tendency that high-tech industry workers have less returns to tenure than low-tech industry workers, although the impact of technology on wage is higher in high-tech than low-tech. However, with the IV-GLS which is used for reducing endogeneity issues, the result is not deterministic. To be specific, most coefficients for tenure related variables come out not statistically significant. As a consequence, there comes no convincing results for returns to tenure. When we divide the technology into four groups, fortunately, it is possible to see that there is somewhat strangely higher returns to tenure in Medium-High technology group than any other group. We need further discussion related to this fact in order to have more reliable results..

Although this study has meaningful implications, it has some limitations and requires further discussions. First of all, after reducing the endogeneity issues, the coefficients of tenure related variables are not statistically significant. We may consider it as a fact but we need to look at the procedures that I have constructed tenure variables. In the process of clearing data and making new tenure variables, there have been chances to code the variables in a wrong way. Second, we can take other method to measure the speed of technological innovation. For example, total-factor productivity (TFP) can be another method to measure the speed of technological advances for industry instead of using the R&D intensity. Each sector has different growth rate of TFP and we can categorize industries by looking at the growth rate and dividing them. This can be alternative measure and plays a role for strengthening my argument if the results coincide with my initial guess.

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6 Appendix

6.1 Constructing Tenures Variables

6.1.1 Employer Tenure

We identify the employer switch from the responses to the following questions in the PSID:

1976-1983: "How long have you had your present position?"

1984-1992: "In what month and year did you start working in your present (position/work situation)?"

To identify employer switches from the PSID using the length of employment series in 1976-1978 and 1981-1992, we use the Partition T method, similar to the method that (Brown and Light, 1992) uses. The details follow.

A employer switch is identified if:

1. In 1976 and the reported employer tenure is less than 15 months.
2. In any year after 1976 (inclusive) if the reported length of present employment is smaller than the time elapsed since the last interview.
3. In addition, in any year after 1977 (inclusive) if
   - the reported length of present employment is smaller than 10 months and the time elapsed since the last interview is not known.
   - the reported length of present employment is between 10 and 15 months, the reported length of employment in the previous year is higher than 5 months, and the time elapsed since the last interview is not known.

- the reported length of present employment is between 15 and 21 months, the reported length of employment in the previous year is higher than 11 months, and the time elapsed since the last interview is not known.
- the reported length of present employment is between 10 and 15 months and the person is a new entrant into the sample as head of a household.
- the reported length of present employment is between 10 and 15 months, is longer than the time elapsed since the last interview, and no employer switch could be identified in the previous year due to missing data on employer tenure in that year.
- the reported length of present employment is smaller than 18 months, is no longer than the time elapsed since the last interview, and no employer switch was identified in the previous year.
- the reported length of present employment is longer than the time elapsed since the last interview date, an employer switch was identified in the previous year, and the difference between reported employer tenure minus the time that elapsed since the last interview and employer tenure reported in the previous year is smaller or equal to -6.

We get information related to promotions in the PSID from the responses to the following questions:

1976-1978: "What happened to the job you had before-did the company fold, were you laid off, or what?"

1979-1983: "What happened to the job you had before-did the company go out of business, were you laid off, promoted, were you not working, or what?"

1984-1987: "What happened to that job-did the company go out of business, were you (HEAD) laid off, promoted, or what?"

The answers for these question in the 1976-1987 period are:

1. Company folded/changed hands/moved out of town; employer died/went out of business

2. Strike; lockout

3. Laid off; fired

4. Quit; resigned; retired; pregnant; needed more money; just wanted a change in jobs; was self-employed before; still has previous job (in addition to the job in C6)

5. No previous job; first full-time or permanent job ever had; was not working before this

6. Promotion

7. Other-(including drafted into service or any mention of service)

8. Job was completed; seasonal work; was a temporary job

After 1987, there is no question related to promotions and promotion is no longer among the separate possible answers.

Once employer switches are identified, we construct employer tenures as follows. Every person who is present in the sample in 1976 or enters the sample in a later year is assigned tenure equal to his/her employer tenure in that year. Whenever an employer switch is identified in a year, employer tenure is set equal to the reported tenure in that year. Then in 1976-1992 employer tenure is increased by one year (twelve months) if the individual does not report an employer switch and works more than 800 hours during that year. If the individual does not report an employer switch but works at most 800 hours during that year, his/her employer tenure is not incremented.

6.1.2 Industry and Occupation Tenures

An occupation (industry) switch is identified if an individual reports an occupational (industry) different from his/her most recent report of an occupation (industry). For example, an individual who works for two consecutive years would be regarded as switching occupations (industries) if he/she reports a current occupation (industry) different from the one he/she reported in the previous year. If an individual works in a year but was unemployed for the previous years, occupation (industry) switch is detected if the current occupation (industry) is different from one reported the most recently.

As (Kambourov and Manovskii, 2009) suggests, I adopt the Retrospective Files so that occupation and industry switches of 1976-1980 are identified using the files. After 1980, I use the occupation and industry codes which are originally coded in the PSID. After identifying the occupation and industry switches, we construct occupation and industry tenure as follows. Every person who is present in the sample in 1976 or enters the sample in a later year is assigned occupation and industry tenure equal to his/her employer tenure in that year. Occupation (industry) tenure is increased by one year if the individual does not report an occupational (industry) switch next year, works more than 800 hours during that year, and reports being employed. the occupational (industry) tenure is not incremented if the individual is unemployed or works at most 800 hours during that year. If an individual reports an occupation (industry) switch, his/her occupation (industry) tenure is reset to 6 months.

Variable	mean	sd	min	max
Age	42.72	9.13	24.00	64.00
Years of Education	12.27	2.70	3.00	17.00
Employer Tenure	8.18	6.16	0.00	26.00
Occupation Tenure	9.27	6.29	0.08	26.00
Industry Tenure	10.15	6.17	0.08	29.00

Table 1: Descriptive Statistics

[2]

Low	Medium-Low	Medium-High	High	Total
158	124	210	39	531

Table 2: Distribution of Sample for Technology Intensity (# of Individuals: 552)

[2] We have 3700 observations and 550 individuals in the period 1981-1992. Since a number of individuals pause to work and become unemployed for a couple of years, there are missing observations in an individual. Therefore this panel data is unbalanced.

Tech	Industry
High	Aircraft and spacecraft
High	Pharmaceuticals
High	Office, accounting and computing machinery
High	Radio, TV and communciations equipment
High	Medical, precision and optical instruments
Medium-High	Electrical machinery and apparatus, n.e.c.
Medium-High	Motor vehicles, trailers and semi-trailers
Medium-High	Chemicals excluding pharmaceuticals
Medium-High	Railroad equipment and transport equipment, n.e.c.
Medium-High	Machinery and equipment, n.e.c.
Medium-Low	Building and repairing of ships and boats
Medium-Low	Rubber and plastics products
Medium-Low	Coke, refined petroleum products and nuclear fuel
Medium-Low	Other non-metallic mineral products
Medium-Low	Basic metals and fabricated metal products
Low	Manufacturing, n.e.c.; Recycling
Low	Wood, pulp, paper, paper products, printing and publishing
Low	Food products, beverages and tobacco
Low	Textiles, textile products, leather and footwear

Table 3: Classification of Manufacturing Industry by R&D Intensity

	Model 1	Model 2	Model 3	Model 4
Age	0.0042	0.0041	0.0044	0.0037
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Age^2	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Emp.Tnr$	0.0085	0.0077	0.0073	0.0037
	(0.0054)	(0.0053)	(0.0053)	(0.0056)
$Emp.Tnr^2 * 100$	-0.0913^{***}	-0.0910^{***}	-0.0889^{***}	-0.0875^{***}
	(0.0260)	(0.0260)	(0.0260)	(0.0260)
$TechDummy$	0.1459^{***}	0.1556^{***}	0.1865^{***}	0.1772^{***}
	(0.0202)	(0.0233)	(0.0216)	(0.0243)
$Ind.Tnr$	0.0119^{*}	0.0129^{**}	0.0121^{**}	0.0121^{*}
	(0.0046)	(0.0047)	(0.0046)	(0.0048)
$Ind.Tnr^2 * 100$	-0.0142	-0.0141	-0.0155	-0.0155
	(0.0218)	(0.0218)	(0.0218)	(0.0218)
$Occ.Tnr$	0.0021	0.0023	0.0052	0.0081
	(0.0054)	(0.0054)	(0.0055)	(0.0056)
$Occ.Tnr^2 * 100$	0.0399	0.0391	0.0390	0.0371
	(0.0253)	(0.0253)	(0.0252)	(0.0253)
Edu	-0.0468^{***}	-0.0466^{**}	-0.0467^{***}	-0.0468^{***}
	(0.0142)	(0.0142)	(0.0141)	(0.0141)
Edu^2	0.0057^{***}	0.0057^{***}	0.0057^{***}	0.0057^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Martial$	0.0502^{*}	0.0493^{*}	0.0484^{*}	0.0476^{*}
	(0.0197)	(0.0197)	(0.0197)	(0.0197)
$Emp.Tnr \cdot Tech$	-0.0013			0.0063^{*}
	(0.0019)			(0.0032)
$Ind.Tnr \cdot Tech$		-0.0020		0.0001
		(0.0019)		(0.0028)
$Occ.Tnr \cdot Tech$			-0.0055^{**}	-0.0102^{***}
			(0.0019)	(0.0029)
R^2	0.4268	0.4269	0.4281	0.4288
Adj. R^2	0.4236	0.4237	0.4248	0.4253
Num. obs.	3674	3674	3674	3674

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 4: Earnings Functions Estimates, Pooled OLS.

	Model 1	Model 2	Model 3	Model 4
Age	0.0122	0.0122	0.0123	0.0123
	(0.0069)	(0.0069)	(0.0069)	(0.0069)
Age^2	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Emp.Tnr$	0.0095	0.0106	0.0103	0.0119
	(0.0069)	(0.0066)	(0.0066)	(0.0073)
$Emp.Tnr^2 * 100$	-0.0321	-0.0333	-0.0321	-0.0337
	(0.0312)	(0.0312)	(0.0312)	(0.0312)
$TechDummy$	0.1146^{***}	0.0795^{*}	0.1250^{***}	0.0934^{*}
	(0.0331)	(0.0365)	(0.0369)	(0.0427)
$Ind.Tnr$	0.0088	0.0054	0.0087	0.0038
	(0.0062)	(0.0066)	(0.0062)	(0.0070)
$Ind.Tnr^2 * 100$	-0.0301	-0.0293	-0.0298	-0.0286
	(0.0288)	(0.0288)	(0.0288)	(0.0289)
$Occ.Tnr$	-0.0074	-0.0077	-0.0076	-0.0068
	(0.0065)	(0.0065)	(0.0069)	(0.0070)
$Occ.Tnr^2 * 100$	0.0380	0.0395	0.0380	0.0401
	(0.0301)	(0.0301)	(0.0301)	(0.0301)
Edu	-0.0403^{**}	-0.0402^{**}	-0.0404^{**}	-0.0402^{**}
	(0.0143)	(0.0143)	(0.0143)	(0.0143)
Edu^2	0.0055^{***}	0.0055^{***}	0.0055^{***}	0.0055^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Martial$	0.0546^{**}	0.0547^{**}	0.0548^{**}	0.0552^{**}
	(0.0200)	(0.0200)	(0.0200)	(0.0200)
$Emp.Tnr \cdot Tech$	0.0019			-0.0029
	(0.0045)			(0.0064)
$Ind.Tnr \cdot Tech$		0.0057		0.0081
		(0.0040)		(0.0053)
$Occ.Tnr \cdot Tech$			0.0004	-0.0019
			(0.0043)	(0.0052)
AIC	3294.0861	3292.4877	3294.3416	3313.0584
BIC	3473.9263	3472.3279	3474.1818	3505.2844
Log Likelihood	-1618.0431	-1617.2439	-1618.1708	-1625.5292
Num. obs.	3674	3674	3674	3674

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: Earnings Functions Estimates, IV-GLS.

year		Employer		Industry		Occupation	
		Low	High	Low	High	Low	High
2	Returns to Tenure	0.0134	0.0108	0.0257***	0.0216**	0.012	9e-04
	Std Deviation	(0.01)	(0.01)	(0.0089)	(0.0088)	(0.0101)	(0.0099)
5	Returns to Tenure	0.0199	0.0134	0.0631***	0.0527***	0.0363	0.0081
	Std Deviation	(0.0215)	(0.0213)	(0.0199)	(0.0194)	(0.0222)	(0.0214)
8	Returns to Tenure	0.0096	-7e-04	0.0992***	0.0819***	0.0687**	0.0226
	Std Deviation	(0.0286)	(0.0283)	(0.028)	(0.0271)	(0.0308)	(0.0292)

Table 6: Returns to Tenures with Two Industry Groups, Pooled OLS model

year		Employer		Industry		Occupation	
		Low	High	Low	High	Low	High
2	Returns to Tenure	0.0179	0.0218	0.0096	0.0211*	-0.0135	-0.0128
	Std Deviation	(0.0131)	(0.0136)	(0.0124)	(0.012)	(0.0126)	(0.0124)
5	Returns to Tenure	0.0403	0.0504	0.0196	0.049*	-0.0279	-0.0262
	Std Deviation	(0.0297)	(0.0313)	(0.0278)	(0.0272)	(0.0273)	(0.0271)
8	Returns to Tenure	0.0571	0.0736	0.0244	0.0721*	-0.0355	-0.0327
	Std Deviation	(0.0431)	(0.0461)	(0.0396)	(0.0389)	(0.0381)	(0.0377)

Table 7: Returns to Tenures with Two Industry Groups, IV-GLS model

	Model 1	Model 2	Model 3	Model 4
Age	0.0019	0.0018	0.0018	0.0010
	(0.0066)	(0.0066)	(0.0065)	(0.0065)
Age^2	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Emp.Tnr$	0.0081	0.0076	0.0062	-0.0022
	(0.0054)	(0.0053)	(0.0053)	(0.0059)
$Emp.Tnr^2 * 100$	-0.0893^{***}	-0.0901^{***}	-0.0827^{**}	-0.0858^{***}
	(0.0257)	(0.0258)	(0.0257)	(0.0257)
$Tech(MLow)$	0.1586^{***}	0.1362^{***}	0.2485^{***}	0.1884^{***}
	(0.0289)	(0.0333)	(0.0307)	(0.0344)
$Tech(MHigh)$	0.2085^{***}	0.2158^{***}	0.2846^{***}	0.2546^{***}
	(0.0241)	(0.0284)	(0.0257)	(0.0294)
$Tech(High)$	0.2413^{***}	0.2476^{***}	0.3192^{***}	0.2860^{***}
	(0.0433)	(0.0488)	(0.0451)	(0.0503)
$Ind.Tnr$	0.0132^{**}	0.0134^{**}	0.0147^{**}	0.0117^{*}
	(0.0046)	(0.0049)	(0.0046)	(0.0051)
$Ind.Tnr^2 * 100$	-0.0151	-0.0142	-0.0223	-0.0233
	(0.0217)	(0.0218)	(0.0216)	(0.0221)
$Occ.Tnr$	0.0032	0.0034	0.0093	0.0172^{**}
	(0.0053)	(0.0053)	(0.0055)	(0.0058)
$Occ.Tnr^2 * 100$	0.0307	0.0296	0.0354	0.0386
	(0.0250)	(0.0250)	(0.0250)	(0.0251)
Edu	-0.0457^{**}	-0.0450^{**}	-0.0471^{***}	-0.0457^{**}
	(0.0140)	(0.0140)	(0.0140)	(0.0140)
Edu^2	0.0057^{***}	0.0057^{***}	0.0058^{***}	0.0057^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Martial$	0.0561^{**}	0.0547^{**}	0.0547^{**}	0.0509^{**}
	(0.0195)	(0.0195)	(0.0194)	(0.0195)
$Emp.Tnr \cdot Tech(MLow)$	0.0001			0.0112^{*}
	(0.0028)			(0.0047)
$Emp.Tnr \cdot Tech(MHigh)$	-0.0011			0.0120^{**}
	(0.0023)			(0.0038)
$Emp.Tnr \cdot Tech(High)$	-0.0015			0.0140
	(0.0042)			(0.0076)
$Ind.Tnr \cdot Tech(MLow)$		0.0024		0.0107^{**}
		(0.0028)		(0.0041)
$Ind.Tnr \cdot Tech(MHigh)$		-0.0016		0.0022
		(0.0023)		(0.0033)
$Ind.Tnr \cdot Tech(High)$		-0.0018		0.0026
		(0.0040)		(0.0057)
$Occ.Tnr \cdot Tech(MLow)$			-0.0096^{***}	-0.0247^{***}
			(0.0027)	(0.0042)
$Occ.Tnr \cdot Tech(MHigh)$			-0.0092^{***}	-0.0194^{***}
			(0.0023)	(0.0035)
$Occ.Tnr \cdot Tech(High)$			-0.0100^{*}	-0.0222^{**}
			(0.0041)	(0.0068)
R^2	0.4404	0.4408	0.4434	0.4476
Adj. R^2	0.4366	0.4369	0.4395	0.4430
Num. obs.	3674	3674	3674	3674

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 8: Earnings Functions Estimates, Pooled OLS.

	Model 1	Model 2	Model 3	Model 4
Age	0.0102	0.0104	0.0105	0.0101
	(0.0068)	(0.0068)	(0.0068)	(0.0068)
Age^2	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Emp.Tnr$	0.0111	0.0107	0.0106	0.0151*
	(0.0071)	(0.0066)	(0.0066)	(0.0077)
$Emp.Tnr^2 * 100$	-0.0332	-0.0345	-0.0343	-0.0338
	(0.0309)	(0.0309)	(0.0309)	(0.0310)
$Tech(MLow)$	0.1839***	0.1506**	0.1364*	0.1389*
	(0.0462)	(0.0531)	(0.0538)	(0.0616)
$Tech(MHigh)$	0.1825***	0.1329**	0.1756***	0.1415**
	(0.0381)	(0.0430)	(0.0432)	(0.0504)
$Tech(High)$	0.2586**	0.2178**	0.2477**	0.2479**
	(0.0796)	(0.0787)	(0.0770)	(0.0943)
$Ind.Tnr$	0.0088	0.0050	0.0089	0.0026
	(0.0061)	(0.0070)	(0.0061)	(0.0076)
$Ind.Tnr^2 * 100$	-0.0286	-0.0273	-0.0294	-0.0289
	(0.0286)	(0.0286)	(0.0286)	(0.0287)
$Occ.Tnr$	-0.0069	-0.0069	-0.0078	-0.0080
	(0.0064)	(0.0065)	(0.0072)	(0.0074)
$Occ.Tnr^2 * 100$	0.0365	0.0365	0.0370	0.0370
	(0.0298)	(0.0299)	(0.0298)	(0.0299)
Edu	-0.0389^{**}	-0.0389^{**}	-0.0391^{**}	-0.0387^{**}
	(0.0142)	(0.0142)	(0.0142)	(0.0142)
Edu^2	0.0055***	0.0055***	0.0055***	0.0055***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$Martial$	0.0595**	0.0598**	0.0600**	0.0603**
	(0.0198)	(0.0198)	(0.0198)	(0.0198)
$Emp.Tnr \cdot Tech(MLow)$	-0.0045			-0.0108
	(0.0063)			(0.0093)
$Emp.Tnr \cdot Tech(MHigh)$	0.0011			-0.0060
	(0.0052)			(0.0072)
$Emp.Tnr \cdot Tech(High)$	-0.0068			-0.0085
	(0.0108)			(0.0153)
$Ind.Tnr \cdot Tech(MLow)$		0.0003		0.0042
		(0.0059)		(0.0081)
$Ind.Tnr \cdot Tech(MHigh)$		0.0067		0.0101
		(0.0047)		(0.0062)
$Ind.Tnr \cdot Tech(High)$		-0.0007		0.0051
		(0.0087)		(0.0117)
$Occ.Tnr \cdot Tech(MLow)$			0.0021	0.0065
			(0.0063)	(0.0077)
$Occ.Tnr \cdot Tech(MHigh)$			0.0018	0.0004
			(0.0050)	(0.0060)
$Occ.Tnr \cdot Tech(High)$			-0.0045	-0.0027
			(0.0089)	(0.0102)
AIC	3249.9584	3249.2131	3251.0724	3305.6791
BIC	3454.5679	3453.8226	3455.6819	3547.4260
Log Likelihood	-1591.9792	-1591.6065	-1592.5362	-1613.8395
Num. obs.	3674	3674	3674	3674

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 9: Earnings Functions Estimates, IV-GLS.

	year		Low	Medium-Low	Medium-High	High
Employer	2	Returns to Tenure	0.0127	0.0129	0.0105	0.0096
		Std Deviation	(0.0101)	(0.0105)	(0.0099)	(0.0121)
	5	Returns to Tenure	0.0183	0.0187	0.0128	0.0105
		Std Deviation	(0.0219)	(0.0231)	(0.0213)	(0.0276)
	8	Returns to Tenure	0.0076	0.0083	-0.001	-0.0047
		Std Deviation	(0.0295)	(0.0315)	(0.0283)	(0.0397)
Industry	2	Returns to Tenure	0.0267***	0.0315***	0.0234***	0.0229**
		Std Deviation	(0.0093)	(0.0094)	(0.0087)	(0.0117)
	5	Returns to Tenure	0.0658***	0.0784***	0.0573***	0.0561**
		Std Deviation	(0.0211)	(0.0217)	(0.0193)	(0.0276)
	8	Returns to Tenure	0.1035***	0.1246***	0.0895***	0.0875**
		Std Deviation	(0.0303)	(0.0316)	(0.027)	(0.0415)
Occupation	2	Returns to Tenure	0.0201**	8e-04	0.0015	0
		Std Deviation	(0.0102)	(0.0104)	(0.0098)	(0.0122)
	5	Returns to Tenure	0.0567**	0.0074	0.0091	0.0053
		Std Deviation	(0.023)	(0.0229)	(0.0212)	(0.0278)
	8	Returns to Tenure	0.1016***	0.0205	0.0232	0.0171
		Std Deviation	(0.0328)	(0.032)	(0.029)	(0.0408)

Table 10: Returns to Tenures with Four Industry Groups, Pooled OLS model

	year		Low	Medium-Low	Medium-High	High
Employer	2	Returns to Tenure	0.021	0.0119	0.0233*	0.0073
		Std Deviation	(0.0136)	(0.0155)	(0.0136)	(0.0235)
	5	Returns to Tenure	0.0482	0.0248	0.0539*	0.0132
		Std Deviation	(0.0315)	(0.0363)	(0.0315)	(0.0574)
	8	Returns to Tenure	0.0696	0.0317	0.079*	0.0132
		Std Deviation	(0.0466)	(0.0544)	(0.0467)	(0.0894)
Industry	2	Returns to Tenure	0.009	0.0096	0.0226*	0.0076
		Std Deviation	(0.0133)	(0.014)	(0.0121)	(0.019)
	5	Returns to Tenure	0.0184	0.0199	0.0531*	0.0148
		Std Deviation	(0.0303)	(0.0325)	(0.0274)	(0.0458)
	8	Returns to Tenure	0.0228	0.0252	0.0792**	0.0171
		Std Deviation	(0.0441)	(0.0483)	(0.0396)	(0.0705)
Occupation	2	Returns to Tenure	-0.0139	-0.0098	-0.0104	-0.0227
		Std Deviation	(0.0132)	(0.0149)	(0.0126)	(0.019)
	5	Returns to Tenure	-0.0291	-0.0189	-0.0204	-0.0505
		Std Deviation	(0.0291)	(0.0339)	(0.0276)	(0.0439)
	8	Returns to Tenure	-0.0377	-0.0215	-0.0238	-0.0714
		Std Deviation	(0.0415)	(0.0499)	(0.0389)	(0.0658)

Table 11: Returns to Tenures with Four Industry Groups, IV-GLS model

국문초록

기술 발전 속도와 숙련 경험의 보상과의 관계

박용준
경제학부 경제학 전공
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본 논문은 기술 발전 속도가 높은 산업에 속한 임금 노동자가 낮은 산업의 노동자보다 숙련 경험에 대한 보상이 낮음을 보인다. 임금 방정식과 기술 집적도에 따른 산업 분류를 바탕으로, 숙련 경험에 대한 보상을 정의 및 계산하고 이를 산업 그룹별로 분류한다. Pooled OLS 결과, 기술 발전 속도와 숙련 경험 축적 사이에 음의 상관관계가 있음이 확인되지만, 도구 변수를 활용한 IV-GLS의 결과 대부분의 숙련 경험 관련 변수가 통계적으로 유의미하지 않게 나와 추가적인 논의가 필요하다. 많은 관련 연구들은 기술 발전과 숙련 경험에 대한 연구를 독립적으로 진행한다. 따라서 결과적인 제약에도 불구하고, 본 논문은 기술 발전이 임금에 미치는 영향과 관련한 노동 경제학 문헌에 기여할 수 있다고 본다.

주요어: 숙련 경험의 가치, 기술 집적도, 기술 발전, 임금 방정식

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