The Effects of Technological Change on Experience-Earning Profiles with Endogenous Industry Choice

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Abstract

This study examines how technological change affects experience-earning profiles, while correcting for self-selection on industry through a simultaneous estimation of industry choice and wage determination. Using data from the Current Population Survey, I find evidence for hierarchical sorting between high-tech and low-tech industries for workers with at least some college education. No evidence for self-selection on industry, however, is found for those with less education. I also find that experience-earning profiles are lower and steeper in high-tech industries than in low-tech industries for those with Bachelor's degree or higher. Thus, highly-educated workers have more learning opportunities and experience faster productivity growth in high-tech industries than in low-tech industries. Highly-educated workers, however, also suffer faster human capital obsolescence due to rapid technological change in high-tech industries than in low-tech industries. Differences in experience-earning profiles between the two sectors for the other three education groups are less pronounced.

Key Words: Technological Change, Human Capital Variation, Self-Selection on Industry

JEL Classification: J31, O33, C25

1 Introduction

Although technological progress has always been an important feature of the American economy, the introduction and diffusion of new technologies have proceeded at an especially rapid pace during the past three decades. Technological change exerts considerable impact on human capital stock: it increases the productivity of human capital,[1] but may also lead to human capital obsolescence,[2] which, in turn, affects the supply and demand of human capital. The purpose of this study is to examine the effects of technological change on experience-earning profiles that summarize the market value of individuals' human capital over their life cycles. Because technological change affects human capital supply and demand in various ways and possibly in opposite directions, studies with different emphases tend to generate different results on how technological change affects human capital and the return to human capital. Most empirical work, therefore, has focused on experience-earning profiles, which capture the combined effect of technological change on human capital supply and demand. Gill (1990), Lillard and Tan (1986), and Mincer and Higuchi (1988), for instance, find that, on average, the effect of higher productivity growth is to raise and steepen the experience- or tenure-wage profiles, especially for highly educated workers, which is interpreted as the result of more intensive formation of human capital under rapid technological change.[3] Rapid technological change, on the other hand, may cause faster obsolescence of existing human capital. Therefore, at later life cycle stages, when workers no longer invest in their human capital, experience-earning profiles start to decrease and decrease faster under a higher rate of technological change.

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[1] Complementarity between capital and skilled labor is a well-established finding in the literature on labor demand (Griliches, 1969; Hamermesh, 1993). When people adopt and implement a new and more advanced technology, they can enhance their productivity correspondingly (Weinberg, 2004).

[2] Technological change increases the rate of human capital obsolescence in two ways: vintage effects, i.e. schooling-specific obsolescence (Johnson, 1980; Rosen, 1976; Weiss and Lillard, 1978); and obsolescence of skills acquired on jobs due to introduction of new technology (MacDonald and Weisbach, 2004).

[3] Using the capital to labor ratio or the research and development to sales ratio as proxies for technological change, some studies on inter-industry wage differentials have shown that wages in industries characterized by higher rates of technological change are higher than in industries characterized by lower rates of technological change. (Dickens and Katz, 1987; Haworth and Rasmussen, 1971; Hodson and England, 1986; Lawrence and Lawrence, 1985; Loh, 1992).

The correlations between the height or curvature of experience-earning profiles and the rate of technological change, however, are likely to be confounded by the endogeneity of industry choice, which might lead to inconsistent estimates of wage equations. In particular, positive associations between the two measures could arise because of unobserved factors that are correlated with both measures. For example, individuals with higher innate ability may be more likely to choose high-tech industries, as suggested by Bartel and Sicherman (1999), and also more likely to earn higher wages than less able individuals. Moreover, individuals with a stronger desire for learning may be more likely to choose high-tech industries and also more likely to experience faster wages growth than their less aspiring peers. Most of the studies relying on inter-industry comparisons, however, have treated the industry that an individual works for simply as an exogenous variable without considering the self-selection problem inherent in industry choice. One exception is the study by Bartel and Sicherman (1999), which treats industry choice as an endogenous variable to identify individual and industry premia. They do not, however, model the choice of industries. To my knowledge, the study reported in this paper is the first to incorporate a self-selection model on industry choice.

I group industries into low-tech and high-tech categories, the latter of which is characterized by faster technological change than the former. Assuming that the two sectors are essentially the same except for the rates of technological change, any difference in experience-earning profiles between high-tech and low-tech industries would reflect the effects of technological change.[4] Specifically, the following research questions are addressed in this study: What is the nature of self-selection in high-tech and low-tech industries? How does self-selection on industry affect the inter-industry differences in experience-earning profiles? These questions are addressed by estimating a switching regression model of industry choice and wage determination with data from the March Supplement of Current Population Survey (2000, 2002, and 2004). By correcting for selection bias due to endogenous industry choice, this study yields more consistent estimates for wage equations and more accurate estimates of the effects of technological change on experience-earning profiles than do previous studies.

Specifically, findings from this study provide evidence for hierarchical sorting by absolute advantage between high-tech and low-tech industries for highly-educated workers, which also suggest that the skills valued in the two industries are positively correlated. Self-selection on industry, however, does not seem to be important for those with high-school education or less. Further, findings from this study indicate that experience-earning profiles are lower and steeper in high-tech industries than in low-tech industries for the highest-educated group, those with Bachelor's degree or higher. Thus, highly-educated workers have more learning opportunities and experience faster productivity growth in high-tech industries than in low-tech industries. Highly-educated workers, however, suffer faster human capital obsolescence due to rapid technological change in high-tech industries than in low-tech industries. Differences in experience-earning profiles between the two sectors for the other three education groups are less pronounced. In the remainder of this paper, I first describe the model. I then describe the data in Section 3, which is followed by a discussion of the empirical results in Section 4. Section 5 concludes the paper.

2 The Model

This section describes a switching regression model of wage determination and endogenous industry choice and the two-stage estimation procedure as developed by Lee (1978) and Heckman (1979). The model is specified as follows:

$$\ln W_{hi} = \beta_{h0} + X_{hi}\beta_{h1} + \varepsilon_{hi} \tag{1}$$

$$\ln W_{li} = \beta_{l0} + X_{li}\beta_{l1} + \varepsilon_{li} \tag{2}$$

$$I_i^* = \theta_0 + \theta_1(\ln W_{hi} - \ln W_{li}) + X_i\theta_2 + Z_i\theta_3 - \varepsilon_i \tag{3}$$

where $\varepsilon_h \sim IN(0,\sigma_1^{\ 2})$, $\varepsilon_l \sim IN(0,\sigma_2^{\ 2})$, and $\varepsilon \sim IN(0,\sigma_\varepsilon^{\ 2})$.

Equations (1) and (2) are the wage equations for high-tech and low-tech industries respectively, which are distinguished by subscripts h and l. I specify the wage equation following the traditional Mincer's equation, in which explanatory variables, X, include years of schooling, experience, experience squared, survey year, rate of technological change, race, native status, metropolitan status, employer size, and health status. Equation (3), the criterion function, determines whether an individual chooses high-tech or low-tech industries. In Equation (3), I_i^* represents the net gain from being in a high-tech industry rather than a low-tech industry.

[4] Bartel and Sicherman (1999) and Neuman and Weiss (1995) employ a similar approach.

If $I_i^* > 0$, then the individual chooses a high-tech industry since utility is maximized in this sector, and his or her wage will be determined by Equation (1). Otherwise, the individual chooses a low-tech industry, and his or her wage will be determined by Equation (2). The variable vectors X and Z in Equation (3) contain a set of individual characteristics, in which X represents the same set of variables as in Equations (1) and (2), excluding the measure of technological change. Z contains four dummy variables of place of residence and serves as the exclusion restriction required by the identification of the model with the Heckman two-stage estimation method. Based on the OLS estimation results of Equations (1), (2), and (3), place of residence is a highly significant determinant of industry choice, but generally not a significant determinant of wage.

The wage equations in this model generally cannot be consistently estimated using OLS because $E(\varepsilon_h \left| I_i^* > 0) \neq 0\right.$ and $E(\varepsilon_l \left| I_i^* \leq 0) \neq 0\right.$. Therefore, I apply a two-stage estimation method to obtain consistent OLS estimates (Heckman, 1979; Maddala, 1983). The basic idea of the two-stage procedure is to adjust the error terms in the wage equations so that they have zero means.

The effects of technological change on industry choice, wages, experience-earning profiles, and returns to education are likely to differ across different levels of education. Therefore, I estimate the above switching regression model for four different education groups separately. The experience-earning profiles for each education-industry group are then derived based on the consistent OLS estimates of the wage equation.

3 Data

This study uses the March Supplement of Current Population Survey (CPS) data. I pool together the CPS data from 2000, 2002, and 2004 as a cross-sectional data set for empirical analysis so that there would be sufficient number of observations in each education-industry group for stable and reliable statistical inference. Due to the rotational sampling method of CPS, fifty percent of the CPS sample is common from one year to the next for the same month (Madrian and Lefgren, 1999). There is no intentional overlap in CPS samples beyond 15 months. Therefore, by skipping the 2001 and 2003 surveys, severe auto-correlated disturbances in the data are avoided. Because the measurement of technological change outside the manufacturing sector is problematic (Griliches, 1994), I restrict the sample for this study to workers in the manufacturing sector, who are males, 18-65 years of age, and work full time (at least 35 hours per week) and full year (at least 50 weeks per year). Another reason for studying this restricted sample is data availability. Given that data on tenure on the current job are not available in CPS, I focus on a relatively stable segment of the work force, full-time and full-year male workers, because potential experience would be a more accurate proxy for tenure in the industry for this group compared with part-time and/or part-year workers, or women. Nominal weekly wages are converted to real weekly wages using the consumer price index (base years: 1982-84). To reduce measurement error and focus attention on workers with strong attachments to the labor force, those whose average weekly real wage is lower than \$70 or higher than \$7,000 are excluded from the sample. Based on levels of education, I divide the full sample into four groups: individuals without a high-school degree, high-school graduates, individuals with some college education or an associate degree, and individuals with a Bachelor's degree or higher.

In order to divide industries into high-tech industries and low-tech industries, I link CPS data with the ratio of Research and Development (R&D) funds to net sales (1999-2003) reported by the National Science Foundation.[5] I further restrict the analytic sample to the two tails of the R&D distribution to create a sharp contrast between the high-tech industries and low-tech industries.[6] Industries are considered high-tech if their R&D intensity is equal to or higher than 1.6 percent, i.e., above the 60th percentile. Those whose R&D intensity is equal to or lower than 1 percent, i.e. below the 40th percentile, are regarded as low-tech. Based on this distinction, high-tech industries in this study are mainly industries that produce transportation equipment, professional and scientific instruments, chemicals and allied products, electrical equipment, non-electric machinery. Low-tech industries mainly include industries that produce petroleum, fabricated metals, primary metals, paper, stone, clay, glass, rubber, textiles, food, tobacco, leather, miscellaneous manufacturing, lumber, furniture, printing, and apparel. Deleting observations with missing information on the R&D intensity results in a final sample size of 14,781, of which 7,083 are in high-tech industries and 7,698 are in low-tech industries. The divisions between high-tech and low-tech industries by using alternative indicators of technological change, such as the NBER total factor productivity (TFP) growth series (Bartelsman and Gray, 1996) and capital-to-labor ratio growth, are very similar to the division based on R&D intensity.

[5] Bartel and Sicherman (1999) and Allen (2001) provide detailed descriptions of R&D intensity as a measurement of technological change. One limitation of this measure is that it pertains to the industry where an innovation originates, not the industry where the innovation is actually used.

[6] Analyses using the full sample produce similar estimation results.

Because the primary use of measurement of technological change in this study is to divide the full sample into two sectors, the empirical results from this study are likely to be robust to the choice of measurement of technological change.[7] Table 1 provides the sample statistics for each of the eight education-industry groups. It shows that the average weekly wages in high-tech industries are higher than those in low-tech industries for all education groups except high-school graduates, who have similar wages in the two sectors. The sample characteristics also reveal that individuals with more education are more likely to work in industries with higher R&D intensity and earn more than those with less education.

4 Empirical Results

This section presents the main empirical results obtained from this study. These results pertain to the nature of industry choice, and the differences in the height and curvature of experience-earning profiles between high-tech and low-tech industries.

4.1 Choice of Industry

The maximum likelihood probit estimates of the coefficients and the corresponding Chi-square values for the industry choice equation (Equation (3)) illustrate the determinants of industry choice.[8] Generally the effects of individual characteristics on industry choice differ across education groups. For individuals with some college education or an associate degree, and individuals with a Bachelor's degree or higher, the number of years of schooling has strong positive effects on the probability of choosing high-tech industries, which is consistent with the higher demand for skills in those industries. For individuals without a high-school degree, however, the number of years of schooling has no effects on industry choice. Moreover, living in a metropolitan area is associated with a higher probability of entering high-tech industries for the two highest-educated groups, but not for the other two education groups. The inverse Mills ratio for each observation derived from the probit estimation in first-stage estimation is subsequently included in the wage equations, based on which, consistent OLS estimates for each education-industry group are obtained. Inverse Mills ratio summarizes the effects on wages of all unmeasured characteristics that are related to industry choice, and their coefficient estimates have important economic meanings.

As shown in Table 2, for the highest-educated group, the coefficient of the inverse Mills ratio is positive and significant in the high-tech industries, and is negative and not significant in the low-tech industries. This suggests that there exists hierarchical sorting by absolute advantage between high-tech and low-tech industries for those with a Bachelor's degree or higher. Individuals who choose high-tech industries have above-average wages in both industries, and are better off in high-tech industries than in low-tech industries. Those who choose low-tech industries have below-average wages in both industries, but they are better off in low-tech industries than in high-tech industries. Such differences may be partly attributable to the larger variance of wages in high-tech industries than in low-tech industries. Individuals with better skills, therefore, tend to go into the sector with higher variance of wages and hence larger "reward to skills." This finding is consistent with the sorting of more able workers into high-tech industries found by Bartel and Sicherman (1999). For individuals with some college education or an associate degree, the coefficient of the inverse Mills ratio is negative and significant in the high-tech industries, and is positive and not significant in the low-tech industries. This suggests that individuals who choose high-tech industries have below–average wages in both industries, and they are better off in high-tech industries than in low-tech industries. One potential explanation for such sorting between the two industries is that the variance of wages in high-tech industries is smaller than that in low-tech industries for this particular education group.

The hierarchical sorting by the two highest-educated groups found in this study also suggests that the skills valued in the high-tech and low-tech industries are positively correlated. A highly-educated worker is likely to find that he or she is either good in both industries or bad in both industries. This study thus provides support for the idea that certain quantitative or analytical skills become increasingly important in today's so-called information and knowledge economy (Gould, 2002; Murnane, Willett, and Levy, 1995). For the two least-educated groups, i.e., those with an education not beyond high school, the coefficients of the inverse Mills ratio are not significant in either the high-tech or low-tech industries, suggesting that self-selection between the two sectors should not be strong for those with low levels of education. This finding is not surprising in light of the traditional vintage human capital theory or skill-biased technological change (SBTC) hypothesis,

[7] One thing to note is that the division of high-tech and low-tech industries is based on 1999, 2001, and 2003 R&D data while some workers made their industry choice back up to the 1970s. Although R&D intensity changes over time for an industry, National Science Foundation R&D Historical Database (1953-1998) shows that the division between high-tech and low-tech industries (using the method described above) has remained relatively stable over the past three decades.

[8] Due to space limitation, I do not report the results from the first-stage estimation.

both of which indicate that technological change tends to exert stronger effects on highly-educated individuals than on those with less education. The vintage theory (Rosen, 1976; Weiss and Lillard, 1978) postulates that technological change brings about more harm to experienced and better-educated people because they are more likely to suffer from significant obsolescence of their human capital. The SBTC hypothesis (Violante, 2007), on the other hand, maintains that shifts in the production technology favor skilled (e.g., more educated, more able, more experienced) labor over unskilled labor by increasing its relative productivity and, therefore, its relative demand.

4.2 Inter-Industry Comparisons of the Height of Experience-Earning Profiles

For the purpose of comparison, Table 3 presents the OLS estimates for the wage equations without correction for self-selection on industry. The experience-earning profile for each group based on OLS estimates without correction for self-selection and that based on the two-stage estimation with correction for self-selection are presented in Figures 1 and 2 respectively. Throughout, I abstract from endogenous labor supply variation. Hence, experience-earning profiles also represent experience-wage profiles. Based on both OLS estimates and Heckman two-stage estimation results as shown in Tables 2 and 3, the rate of technological change as measured by R&D intensity at the workplace has strong and positive effects on wages for the two highest-educated groups. This is consistent with the findings from previous studies on inter-industry wage differentials that have demonstrated higher wages in industries characterized by higher rates of technological change than in industries with lower rates of technological change, using the capital to labor ratio or the R&D to sales ratio as proxies for technological change (Dickens and Katz, 1987; Haworth and Rasmussen, 1971; Hodson and England, 1986; Lawrence and Lawrence, 1985; Loh, 1992).

As shown in Figure 1, after controlling for individual characteristics, employer size, and R&D intensity, the experience-earning profile based on OLS estimates is higher in high-tech industries than in low-tech industries for those without a high-school degree, slightly higher in low-tech industries than in high-tech industries for high-school graduates and those with some college education, and significantly higher in low-tech industries than in high-tech industries for those with a Bachelor's degree of higher. After correcting for self-selection on industry choice, the difference in the height of the experience-earning profiles between the two sectors increases for all education groups except those without a high-school degree (see Figure 2). This suggests that workers' self-selection on industries based on their absolute advantages might actually weaken inter-industry wage differentials.[9] If workers were randomly assigned to the two industries, the difference in the experience-earning profile between the two sectors for the average worker would be larger than that with self-selection.

4.3 Inter-Industry Comparisons of the Curvature of Experience-Earning Profiles

Consistent with the findings from Gill (1990), Mincer and Higuchi (1988), and Lillard and Tan (1986), OLS estimation results presented in Table 3 and Figure 1 indicate that working in a high-tech industry is associated with a steeper experience-earning profile for individuals with a Bachelor's degree or higher. Experience-earning profiles not only increase faster but also decease faster in high-tech industries than in low-tech industries for this highly-educated group. For those with some college education, the experience-earning profile has a very similar curvature in the two sectors. For the two least-educated groups, however, the experience-earning profile is slightly steeper in low-tech industries than in high-tech industries. The two-stage estimation, however, produces different results. As shown in Table 2 and Figure 2, for individuals with a Bachelor's degree or higher, the difference in the curvature of the experience-earning profile between the two sectors based on the two-stage estimation results is larger than that based on the OLS results. For high-school graduates, the profile in high-tech industries is slightly steeper than that in low-tech industries. For the other two education groups, the profiles are slightly steeper in low-tech industries than in high-tech industries.

In summary, the most pronounced difference in the curvature of the experience-earning profile between the two sectors is for individuals with a Bachelor's degree or higher. For the other three education groups, there is hardly any significant difference in the curvature of the profiles between the two sectors. For those highly-educated, the faster increase of the profiles in high-tech industries provides evidence for more intensive human capital formation through on-the-job training or learning-by-doing in high-tech industries than in low-tech industries. The theoretical argument for the faster decrease of experience-earning profiles in high-tech industries for those highly-educated is that workers suffer greater human capital obsolescence due to rapid technological change in high-tech industries than in low-tech industries. Another interesting finding is that the higher the level of education, the steeper the experience-earning profile in both high-tech and low-tech industries.

[9] A number of studies on union wage differentials, such as Heckman and Neumann (1977) and Robinson and Tomes (1984), also find that the estimated wage differential between union and non-union sectors increases with the correction for selectivity bias due to endogenous union status.

Thus, highly-educated individuals tend to invest more in their skills and human capital and experience faster increase in their productivity than those with less education. The finding that the experience-earning profile also decreases faster for people with more education in both industries is supported by the vintage human capital model, which posits that less well educated workers do not suffer from human capital obsolescence as much as better educated workers.

5 Conclusions

Technological change affects the supply and demand of human capital by influencing both the rate of human capital obsolescence and individuals' investment decisions on human capital. However, the impacts of technological change are likely to differ for individuals with different levels of education, with different years of experience, or from different industries. This study examines the effects of technological change on the market value of individuals' human capital over their life cycles by comparing the experience-earning profiles in high-tech industries with those in low-tech industries for four education groups. Employing a switching regression model of industry choice and wage determination, this study takes into account self-selection due to endogenous industry choice. The empirical results based on pooled March CPS data (2000, 2002, and 2004) reveal hierarchical sorting by highly-educated individuals between high-tech and low-tech industries, and suggest that self-selection on industry plays an important role in determining the differences in experience-earning profiles between high-tech and low-tech industries for those highly-educated.

The findings from this study offer important insights into inter-industry wage differential and the impacts of technological change on learning and skills formation as well as on human capital obsolescence. I find that highly-educated workers have more learning opportunities and experience faster productivity growth in high-tech industries than in low-tech industries. Meanwhile, highly-educated workers also suffer faster human capital obsolescence due to rapid technological change in high-tech industries than in low-tech industries. Experience-earning profiles as an approximation for human capital and its market value, however, are unable to reveal the mechanisms through which technological change affects human capital and its investment or wage structures. Therefore, a promising direction for future research is to investigate directly the process of human capital accumulation and depreciation, and explore how technological change affects individuals' life-cycle human capital investment.

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Table 1 Sample Statistics for Each Education-Industry Group

Data source: CPS March 2000, 2002, and 2004.

Education Group: Individuals with a B.A. Degree or Higher

Variable	High-tech industries		Low-tech industries	
	Mean	Standard deviation	Mean	Standard deviation
Log weekly wage	6.60	0.72	6.54	0.71
Age	42.24	9.75	42.86	10.07
Experience	19.25	9.64	20.17	9.95
Years of schooling	16.99	1.45	16.69	1.30
R&D intensity	5.69	3.00	0.75	0.31
Non-white	0.14	0.34	0.10	0.30
Non-native	0.15	0.36	0.12	0.33
Non-metro	0.28	0.45	0.31	0.46
Observations	2,512		2,103	

Education Group: Individuals with Some College Education

Variable	High-tech industries		Low-tech industries	
	Mean	Standard deviation	Mean	Standard deviation
Log weekly wage	6.04	0.54	6.00	0.55
Age	41.35	10.82	42.86	10.07
Experience	22.01	10.83	20.71	10.74
Years of schooling	13.35	0.48	13.32	0.47
R&D intensity	5.46	2.79	0.65	0.29
Non-white	0.17	0.38	0.11	0.32
Non-native	0.09	0.29	0.08	0.27
Non-metro	0.37	0.48	0.41	0.49
Observations	1,876		2,090	

Education Group: High-School Graduates

Variable	High-tech industries Mean	High-tech industries Standard deviation	Low-tech industries Mean	Low-tech industries Standard deviation
Log weekly wage	5.87	0.52	5.88	0.53
Age	40.18	10.56	39.94	11.07
Experience	22.18	10.56	21.94	11.07
Years of schooling	12	0	12	0
R&D intensity	5.43	2.84	0.64	0.29
Non-white	0.16	0.36	0.13	0.34
Non-native	0.11	0.31	0.11	0.31
Non-metro	0.45	0.50	0.45	0.50
Observations	2,063		2,704	

Education Group: Individuals without a High-School Degree

Variable	High-tech industries Mean	High-tech industries Standard deviation	Low-tech industries Mean	Low-tech industries Standard deviation
Log weekly wage	5.62	0.55	5.58	0.52
Age	40.60	11.40	40.19	11.86
Experience	25.62	12.02	25.41	12.66
Years of schooling	8.99	2.71	8.79	2.86
R&D intensity	5.41	2.86	0.68	0.30
Non-white	0.16	0.37	0.15	0.36
Non-native	0.37	0.48	0.43	0.50
Non-metro	0.36	0.48	0.35	0.48
Observations	632		801	

Table 2 Log Wage Regressions with Correction for Self-Selection on Industry

Dependent Variable: Log Average Weekly Wage

High-tech Industries

Variable	Without a High School Degree	High-school Graduates	Some College Education	BA or Higher
Experience	0.026	0.040	0.051	0.061
	(3.51)	(6.87)	(9.95)	(9.98)
Experience^2	-0.283E-03	-0.639E-03	-0.918E-03	-0.128E-02
	(-2.05)	(-5.05)	(-8.16)	(-8.17)
Schooling	0.030		0.078	0.210
	(3.20)		(2.26)	(11.69)
R&D intensity	0.011	-0.005	0.462E-04	0.011
	(1.28)	(-1.27)	(0.01)	(2.56)
Inverse Mills ratio	0.069	0.263	-0.657	0.729
	(0.29)	(0.87)	(-2.08)	(2.00)
Observations	632	2,063	1,876	2,512

Low-tech Industries

Variable	Without a High School Degree	High-school Graduates	Some College Education	BA or Higher
Experience	0.031	0.040	0.055	0.051
	(5.02)	(8.04)	(13.63)	(8.86)
Experience^2	-0.360E-03	-0.558E-03	-0.936E-03	-0.924E-03
	(-3.20)	(-5.16)	(-10.28)	(-6.41)
Schooling	0.048		0.079	0.166
	(6.43)		(2.80)	(9.71)
R&D intensity	0.022	0.038	0.104	0.226
	(0.30)	(0.98)	(2.23)	(3.96)
Inverse Mills ratio	-0.163	0.371	0.255	-0.301
	(-0.60)	(1.24)	(0.94)	(-1.01)
Observations	801	2,704	2,090	2,103

Note: The above tables present the Heckman two-stage estimates of the wage equation for each education-industry groups. All regressions control for survey year, race, native status, metropolitan status, five dummy variables for employer size, and four dummy variables for health status. The base category includes native-born white people surveyed in 2000, who were working for a small-sized employer, lived in a metropolitan area, and were very healthy. t-values are included in parentheses.

Table 3 Log Wage Regressions without Correcting for Self-Selection on Industry
Dependent Variable: Log Average Weekly Wage

High-tech Industries

Variable	Without a High School Degree	High-school Graduates	Some College Education	BA or Higher
Experience	0.025	0.036	0.054	0.058
	(3.60)	(9.11)	(13.04)	(11.40)
Experience^2	-0.269E-03	-0.559E-03	-0.904E-03	-0.116E-02
	(-2.05)	(-6.65)	(-9.94)	(-9.34)
Schooling	0.030		0.115	0.182
	(3.20)		(4.76)	(19.72)
R&D intensity	0.011	-0.005	0.253E-03	0.012
	(1.27)	(-1.25)	(0.06)	(2.46)
R^2	0.124	0.114	0.201	0.209
Observations	632	2,063	1,876	2,512

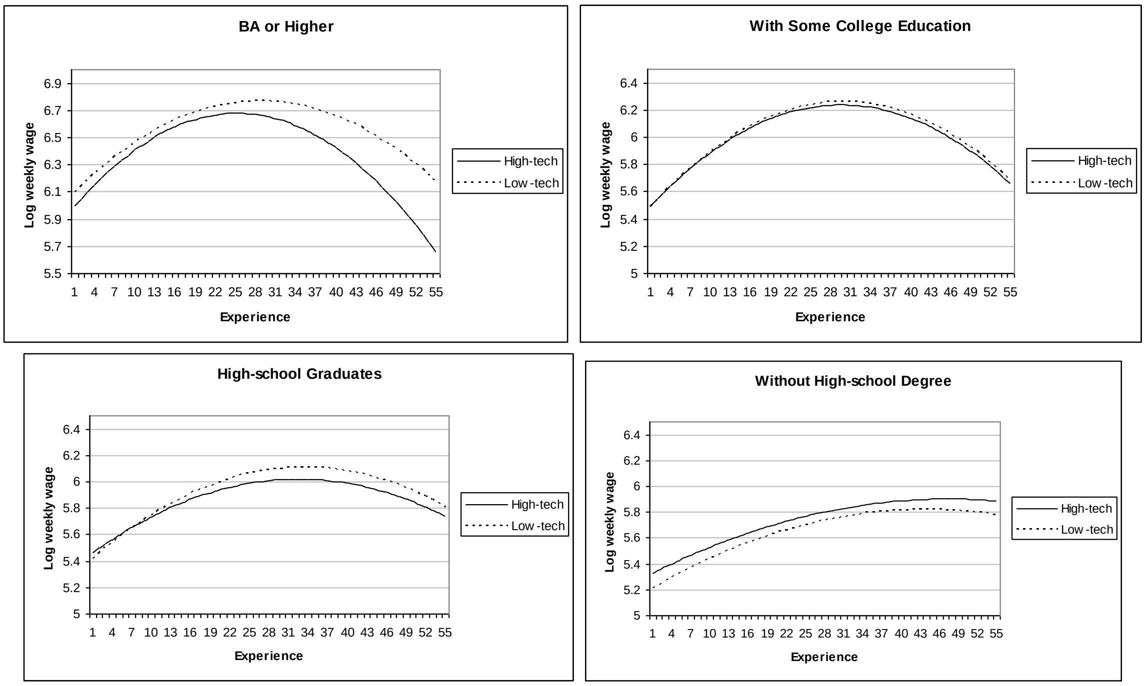
Low-tech Industries

Variable	Without a High School Degree	High-school Graduates	Some College Education	BA or Higher
Experience	0.029	0.044	0.055	0.050
	(5.37)	(13.69)	(14.47)	(9.03)
Experience^2	-0.329E-03	-0.655E-03	-0.926E-03	-0.871E-03
	(-3.31)	(-9.51)	(-10.59)	(-6.65)
Schooling	0.049		0.092	0.153
	(6.50)		(3.89)	(14.07)
R&D intensity	0.023	0.038	0.104	0.224
	(0.31)	(0.99)	(2.23)	(3.87)
R^2	0.159	0.162	0.196	0.208
Observations	801	2,704	2,090	2,103

Note: The above tables present the OLS estimates of the wage equation for each education-industry groups. All regressions control for survey year, race, native status, metropolitan status, five dummy variables for employer size, and four dummy variables for health status. The base category includes native-born white people surveyed in 2000, who were working for a small-sized employer, lived in a metropolitan area, and were very healthy. t-values are included in parentheses.

Figure 1 Experience-Earning Profiles by Level of Education without Correction for Self-Selection on Industry

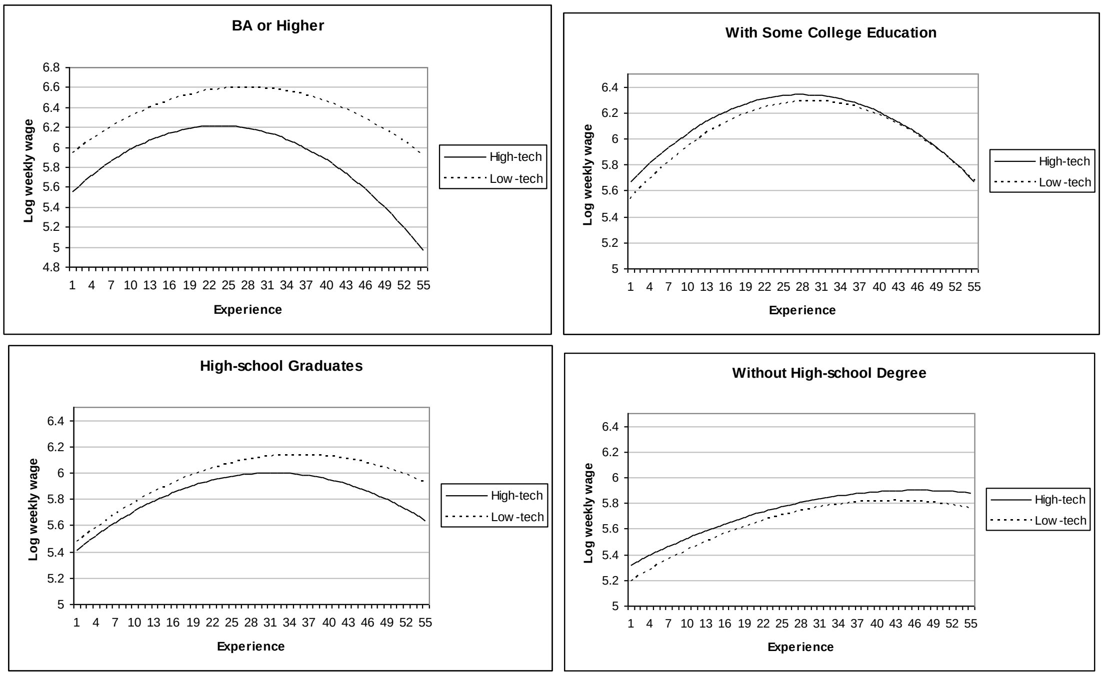
Data source: CPS March 2000, 2002, 2004.



Note: Experience-earning profiles were obtained based on the OLS estimates of the wage equation by conditioning on survey year, R&D intensity, race, native status, metro status, employer size, health status, and years of schooling except for high-school graduates. The intercept applies to the base category—native-born white people surveyed in 2000 who were working for a small-sized employer, living in a metropolitan area, and very healthy. Moreover, R&D intensity and years of schooling take on the values of their respective group means.

Figure 2 Experience-Earning Profiles by Level of Education with Correction for Self-Selection on Industry

Data source: CPS March 2000, 2002, 2004.



Note: Experience-earning profiles were obtained based on the Heckman two-stage estimates of the wage equation by conditioning on survey year, R&D intensity, race, native status, metro status, employer size, health status, and years of schooling except for high-school graduates. The intercept applies to the base category—native-born white people surveyed in 2000 who were working for a small-sized employer, living in a metropolitan area, and very healthy. Moreover, R&D intensity, years of schooling, and the inverse Mills ratio all take on the values of their respective group means.