The Effects of Technological Change on Schooling and Training Human Capital

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Abstract

Technological change has considerable impact on human capital stock. Its impact, however, may be different on different types of human capital. As two major types of human capital investment, schooling and training are specialized to different degrees, therefore human capital obtained from schooling and that obtained from training embody different proportions of general and specific skills and may be affected differently by technological change. Focusing on the difference between human capital obtained from schooling and that from training, I develop a life-cycle human capital investment model to investigate the separate effects of technological change on schooling human capital and training human capital. Using data from National Longitudinal Survey of Youth 79 (1987-1994), I estimate the model parameters by using the method of nonlinear least squares. I find that training human capital is more vulnerable to obsolescence due to technological change than is schooling human capital, which suggests that individuals with more schooling enjoy an advantage in dealing with technological change over those with less schooling.

1 Introduction

Technological change has considerable impact on human capital stock: it may increase the productivity of human capital,[2] but may also lead to substantial human capital obsolescence.[3] This, in turn, may directly affect an individual's earning capacity and may also influence his or her investment in human capital and, subsequently, future wage growth. Many existing studies attribute the changing wage structures in the U.S. during the past three decades to technological change, especially computerization (Bound & Johnson, 1992; Goldin & Katz, 1998; Katz & Murphy, 1992; Levy & Murnane, 1992; Mincer, 1991).

The impact of technological change, however, may be different on different types of human capital. Although most researchers agree that technological change does affect human capital, there is little consensus on how technological change affects the supply and demand of different types of skills or human capital. Much of the current debate on the skills gap in the workforce revolves around the question of whether general or specific knowledge is more valuable in a rapidly changing environment. Gould (2002, 2003), for example, provides evidence on the increasing demand for general skills, either IQ or the general unobservable skills, due to technological change, which is consistent with the finding that highly-educated individuals have a comparative advantage in dealing with a changing environment and in implementing new technologies (Bartel & Lichtenberg, 1987; Goldin & Katz, 1998; Nelson & Phelps, 1966; Schultz, 1964, 1975;

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

Welch, 1970). Murnane, Willett, and Levy (1995), however, find that technological change leads to an increasing demand for cognitive skills as distinct from formal schooling.

Motivated by these findings, I develop a dynamic model of human capital investment that focuses on the distinction between schooling and training in an environment of rapid technological change, in an attempt to address empirically the following research question: How does technological change affect differently the human capital obtained from schooling and that obtained from training? As found by Heckman, Lochner, and Taber (1998) and Taber (2002), schooling and training have different production functions. Schooling mainly enhances general human capital, while training, especially on-the-job training, mainly enhances job-specific skills. Because schooling human capital and training human capital embody different proportions of general to specific skills, they may become obsolete at different rates, and their productivity may also change in different ways in response to technological change. Therefore, the above research question will also address the differential impacts of technological change on general skills and technology-specific skills.

As Allen (2001) notes, the theoretical literature provides little guidance for empirical work on technological change. Taken literally, the term "technological change" can mean two different things. The standard economic definition of the term is the ability to produce more output with the same amount of input, usually as a consequence of better knowledge or organization, which is typically measured by total factor productivity (TFP) growth, i.e., the growth in output that cannot be explained by changes in the quantity or quality of input. Alternatively, technological change can mean changes in equipment and job requirements, and the rate of technological change is defined as the rate of arrival of new tasks that workers must perform, as a result of which, some of their previously acquired skills become obsolete. The substitution of personal computers, software, and printers for typewriters, for example, would qualify as technological change under the latter definition, but not necessarily under the former. The recent changes in the wage structure in the U.S. may very well be attributable to the adoption of new technologies that are complementary with skilled labor. I therefore focus on the second aspect of technological change in this study.

Some studies have analyzed qualitatively the differential effects of technological change on general skills and technology-specific skills (Gould, Moav, & Weinberg, 2001; Helpman & Rangel, 1999), assuming that individuals invest in general skills through education or in technology-specific skills through on-the-job training. Gould, et al. (2001) further argue that technological change has disproportionate effects on the depreciation of general versus technology-specific skills, and conclude that compared with well educated workers, less well educated workers often have more investment in technology-specific skills, and will therefore suffer higher rates of human capital depreciation due to technological improvements.

This study is essentially addressing the same question as did Gould, et al. (2001) and Helpman, et al. (1999), but with a different approach. I introduce directly the rate of technological change into a human capital investment model, and model explicitly the potential differential impacts of technological change on skills obtained from education and those from training. Using data from National Longitudinal Survey of Youth 79 (NLSY79), I recover model parameters by matching the predicted wage profiles to the observed wage profiles from the data. Therefore, this study may be regarded as an empirical test of the theoretical analyses conducted by Gould, et al. (2001) and Helpman, et al. (1999).

The feature that distinguishes this study from prior empirical studies in this field is that this study takes into account the impacts of technological change on training and schooling simultaneously. Prior empirical studies on technological change and human capital, such as Bartel and Sicherman (1998, 1999), Lillard and Tan (1986), Mincer (1989), and Tan (1989), only analyze the impact of technological change on training without considering the inter-relationship and possible substitution between schooling and training. Thus, this study is likely to yield more accurate estimates on how technological change affects human capital. Moreover, this study also allows for part-time schooling while most studies on life-cycle human capital investment assume that entry into labor market precludes further schooling (Heckman, et al., 1998; Taber, 2002).

The estimation results of the study show that the stock of schooling human capital increases under rapid technological change in spite of obsolescence, whereas the net effect of technological change on training human capital is obsolescence. These findings offer direct evidence for the theory that individuals with more schooling suffer lower rates of human capital depreciation due to technological improvements, and have an advantage in dealing with technological change than individuals with less schooling. In order to illustrate the effects of technological change on human capital and wages, I further conduct simulations of the wage profiles for different paths of life-cycle schooling and training choices under different paths of technological change.

In the remainder of this paper, I first develop a dynamic structural model of human capital investment, in which technological change affects differently the human capital obtained from schooling and that obtained from training. I then describe, in section 3, the NLSY79 data and the construction of the estimation sample. Section 4 details the estimation of the model, the empirical results, and the simulations of the model, which are followed by concluding comments.

2 The Model

In this section, I describe a dynamic model of an individual's schooling and training choices in an environment of rapid technological change. The basic structure of the model reflects the decision-making process of a single individual.

I assume that the objective of an individual at any age is to maximize her expected present value of remaining lifetime earnings through making human capital investment decisions. An individual does not make a once-and-for-all plan about human capital investment. Rather, each person is constantly modifying her plans in light of new information under a changing environment. The decision on human capital investment in the current period determines both current rewards and future earning capacity. I thus set up a dynamic model of schooling and training with a particular focus on the different impacts of technological change on the human capital obtained from schooling and that obtained from training.

To keep the model parsimonious and highlight the effects of interest, I assume that rapid technological change is the major source of uncertainty in human capital investment planning, especially in terms of the obsolescence of skills associated with old technology due to the introduction of new technology. Given that the focus of this study is on individual behavior, I assume that technological change is exogenous.

In this model, each individual has a finite decision horizon, which corresponds to time period t from 1 to T. At any period t, an individual decides the proportion of total working time devoted to schooling, S_t, and the proportion devoted to training, I_t. S_t and I_t can take on any value between 0 and 1 subject to the condition that the sum of S_t and I_t can not exceed 1. Both part-time and full-time schooling are allowed with S_t = 1 indicating full-time schooling. I focus on an individual's choice on human capital investment while ignoring the choice between work and leisure. Therefore, the proportion of time actually devoted to working on a job is: $L_t = 1 - S_t - I_t$. The total number of hours of working time is defined as $J_t = L_t \cdot J$, where the annual working hours, J, is assumed to be common across individuals.

An individual's choices are made conditional on the information sets available at the time of the decision-making. I assume that all past and current realizations of exogenous and control variables are known to the individual at the beginning of each time period, whereas future realizations of the exogenous variables are uncertain. Formally, an individual's problem can be expressed as

$$\max_{S_t, I_t} E_t \sum_{t=1}^{T} \delta^t \ y\left(R_t, h_{S,t-1}, h_{I,t-1}, S_t, I_t\right), \tag{1}$$

subject to the human capital production functions for schooling and training, the wage and earning determination process, and conditional on the information set at t. y is the annual earning at t, which is a function of the rental rate of human capital at period t, R_t, human capital obtained from schooling, $h_{S,t-1}$, and that obtained from training, $h_{I,t-1}$, at the beginning of period t, and annual working hours. Because human capital investments exchange current costs for a stream of benefits in the future, the investment is sensitive to the subjective discount factor, δ.

For simplicity, I assume that foregone earning is the only cost and ignore foregone leisure as a form of cost of human capital investment, as does the standard Becker-Ben Porath economic model of skill formation (Becker, 1964; Ben Porath, 1967). After a worker enters the labor force, her time can be decomposed into time spent investing in human capital and time spent producing the final goods. According to Ben Porath (1967), workers implicitly pay for the work time devoted to training through lower wages. Thus, they will be compensated only for the time devoted towards producing the final goods. Earnings in an industry equal the product of wage and total working time. The observed wage at period t, W_t, is defined as the product of the total human capital stock at the beginning of period t, H_{t-1}, and the rental rate at period t, R_t. Total human capital stock possessed by an individual is a function of schooling human capital and training human capital, which depend on the history of investment decisions. Thus,

$$W_t = R_t H_{t-1}(h_{S,t-1}, h_{I,t-1}), \tag{2}$$

$$y(R_t, h_{S,t-1}, h_{I,t-1}, S_t, I_t) = W_t J_t = R_t H_{t-1}(h_{S,t-1}, h_{I,t-1})(1 - S_t - I_t)\, J. \tag{3}$$

The dynamics of earning in this model can be summarized as follows. Human capital investments exchange current costs for a stream of future benefits. Although schooling leads to the forgoing of earnings in the current period, it increases the individual's human capital stock and future earning potential. It may also enhance the productivity of training in producing new human capital, and increases the individual's ability to deal with environmental changes. Training also increases the individual's human capital stock and future earning potential, although at the cost of forgone earnings in the current period.

I use π_t to denote a random technology disturbance. Thus, $\{\pi_t\}_{t=0}^{T}$ is a sequence of independent and identically distributed random variables drawn from a fixed probability distribution prior to the current-period decisions and learned at the beginning of the period. On the one hand, technological change causes the obsolescence of both schooling human capital and training human capital. The two types of human capital, however, are likely to become obsolete at different rates because they embody different proportion of general and specific skills. On the other hand, technological change may also increase the return to human capital due to the technology-skill complementarity. Given the rental rate of human capital, such an augmenting effect of technological change may be interpreted as an increase in the human capital stock that is "valuable" in the market, even though there is no actual change in the stock. This augmenting effect may also be different for different types of skills as shown by prior research (Bartel & Lichtenberg, 1987; Gould, 2002; Iyigun & Owen, 1999; Murnane, Willett, & Levy, 1995; Nelson & Phelps, 1966; Schultz, 1975; Welch, 1970).

The specifications of human capital production function for schooling and training reflect the evolution process of human capital stock as well as the differential impacts of technological change on human capital obtained from the two different types of investment. The evolution of human capital stock is determined by two opposite forces, accumulation and depreciation. The accumulation of human capital is partly achieved through schooling and training according to their production functions. The depreciation of human capital results from a pure aging effect and obsolescence caused by technological change. It is reasonable to assume that there is not much difference in aging effect across individuals. Therefore, this study only considers obsolescence determined by the rate of technological change, which is industry-specific based on the data available.

For simplicity, I assume that training human capital depends only on time spent on training, with no inputs of market goods or services. This is not restrictive because we can always introduce goods into the model and solve them out as a function of I_t, thereby reinterpret I_t as a goods-time investment composite (Haley, 1976). In this case, the cost of the investment goods would be originally paid for by the firm, but then passed on to the worker through lower wages. Schooling human capital enters the production function of training because general human capital obtained through schooling may enhance the efficiency of training in producing new human capital.[4] Specifically, an individual's training human capital stock evolves according to the following equation:

$$h_{I,t} = \alpha_1 h_{S,t-1}{}^{\alpha_2} I_t^{\alpha_3} h_{I,t-1}{}^{\alpha_4} + (1 - \alpha_5 \pi_t) h_{I,t-1}, \tag{4}$$

in which α_1 and α_2 determine the marginal effect of schooling human capital on the efficiency of training; α_1, α_3, and α_4 determine the productivity of training in producing new human capital; and α_5 represents the net effect of technological change on training human capital. A positive value of α_5 suggests that the net effect of technological change is obsolescence of existing human capital. A negative value of α_5, however, indicates that technological change leads more to an increase in the productivity of existing human capital than to its obsolescence.

[4] General education helps in the learning process (Schultz, 1975). Shaw (1989) confirms that schooling augments post-school human capital production, mainly on-the-job training, or that the two are complements.

Similarly, I specify the human capital production function for schooling, as follows:

$$h_{S,t} = \beta_1 S_t^{\beta_2} h_{S,t-1}^{\beta_3} + (1 - \beta_4 \pi_t) h_{S,t-1}, \tag{5}$$

in which β_1, β_2, and β_3 determine the productivity of schooling in producing human capital; and β_4 represents the net effect of technological change on schooling human capital, or the combined effect on both the productivity and the obsolescence of schooling human capital.

Schooling human capital is general in nature, and is useful for almost all types of jobs. Training human capital, however, is mainly job-specific, and is useful only for the current job. How the two types of human capital combine will affect the total human capital stock, which will in turn determine an individual's wage. I assume that the production function for total human capital stock is a Cobb-Douglas function:

$$H_t = h_{S,t}^{\gamma_1} h_{I,t}^{\gamma_2}, \tag{6}$$

in which γ_1 and γ_2 denote the importance of schooling human capital and training human capital for getting market returns respectively. I assume that this production has the feature of constant return to scale (CRS), i.e., $\gamma_1 + \gamma_2 = 1$.

In summary, the decision-making process in the human capital investment model described above consists of an individual's optimization behavior, the wage and earning determination functions, and the human capital production functions for schooling and training separately, subject to stochastic technological shocks.

3 Data

The dataset used in this study, National Longitudinal Survey of Youth 79 (NLSY79), contains data from 12,689 respondents aged between 14 to 22 in 1979, and provides rich information on each respondent's labor force experiences, labor market attachment, and investments in education and training. NLSY79 is particularly suitable for this study for a number of reasons. First, it started to follow a cohort of young workers before they entered the labor market. Since most human capital investment takes place early in the life cycle, this dataset captures the main portion of such investment. Second, the time period covered by this survey captures a significant wave of technological change in the U.S.. Third, the survey includes a special measure of ability known as the Armed Force Qualifying Test (AFQT) score, which is useful for introducing population heterogeneity in ability to the model in a simple way.

The NLSY79 data used for this study cover the time period from 1987 to 1994. Respondents were surveyed annually from 1979 to 1994 and every other year since 1994. To avoid inconsistency in the measurement of some major variables in this study, such as the hourly wage rate, I do not use the data collected after 1994. Data collected before 1987 are not used either because the measure of training duration for the period between 1979 and 1986 is unreliable.

3.1 Sample and Variable Definitions

The discrete decision period in this study is assumed to be one calendar year. I restrict the analytic sample to civilians in the core random sample who worked in manufacturing industries in each year between 1987 and 1994. Although the model does not consider the labor force participation, the sample is chosen to have strong labor market attachment. The data used in the estimation are panel data, as each respondent in the sample were followed for eight consecutive years from 1987 to 1994. . Those who have missing values on any variables used in the estimation are excluded from the sample. I also exclude those respondents whose real hourly wage was lower than 1 dollar or higher than 150 dollars. The final sample contains 351 respondents and 2,808 observations. A description of some of the major variables used in the estimation follows.

<u>Schooling</u> Each annual survey in NLSY79 provides information on whether the respondents were at a regular school each month since the last survey, which allows the creation of a variable representing the total number of months spent at a regular school in each calendar year. No information, however, was available on the actual amount of time out of each month that each respondent spent at a regular school. In calculating the ratio of annual working time devoted to schooling, I follow the conventional rule for conversion between full-time and part-time schooling by assuming that each respondent spent one third of a month on schooling if she reported being at a regular school in that month.

<u>Training</u> A variety of formal training questions were asked in all survey years except 1987. Training information in 1987, however, can be imputed from the 1988 data as was done by Bartel and Sicherman (1998). Although NLSY79 collected information about the occurrence and duration of all government-sponsored training programs and all privately supported training that lasted at least 4 weeks between 1979 and 1986, the measure of training duration for this period is unreliable because it is based on the starting and ending dates of the program. Therefore only data collected after 1987 were analyzed in this study. In subsequent years, respondents were asked about all types of training (up to eight programs) since the last interview, regardless of duration.

Potential sources of training include business schools, apprenticeships, vocational and technical institutes, correspondence courses, company training, seminars outside of work, and vocational rehabilitation centers. These sources exclude formal schooling as well as informal training such as observing coworkers, learning by doing, or speaking with supervisors.

Starting in 1988, in addition to asking when (month and year) different training programs started and ended, individuals were also asked, “Altogether, for how many weeks did you attend this training?” For each of the training programs, individuals were asked for the average number of hours per week spent on the training. I thus create a variable for the total number of hours spent on training in each calendar year by multiplying the number of hours per week in each program with the number of weeks in each program and summing up across programs. The ratio of total number of hours spent on training to annual working hours is used in the estimation as the share of working time devoted to training.

Rate of technological change As Allen (2001) observes, the theoretical literature provides little guidance for empirical work on technological change. Because there is not a direct measure of the rate of technological change experienced by individuals in their work place in NLSY79, I link the NLSY79 data with the ratio of Research and Development (R&D) funds to net sales for different industries reported by the National Science Foundation (2000). 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. Detailed description of this measurement of technological change can be found in Allen (2001) and Bartel and Sicherman (1999).

Because the measurement of technological change is not accurate for non-manufacturing industries (Griliches, 1994), the sample used in this study is restricted to those working in manufacturing industries for each year covered in the panel. An additional reason for the sample restriction is that the measure of R&D intensity is not available for most non-manufacturing industries before 1995 in the National Science Foundation report.

Wage Wage is measured as the hourly rate of pay in U.S. dollars adjusted for Consumer Price Index (CPI) reported by the U.S. Bureau of Labor Statistics with 1984 as the base year. Because the NLSY79 survey has been administered every other year since 1994, information on "hourly rate of pay of current/most recent job" is not available for the years of 1995, 1997, and 1999, which leads to the exclusion of data collected after 1994 in this study.

3.2 Descriptive Statistics

Table 1 provides the descriptive statistics of the sample for some important variables, such as the number of months spent on schooling, number of hours spent on training, and the ratio of R&D funds to net sales in the industry that the respondent was working for. I also present in Figure 1 the life-cycle profiles of schooling and training based on NLSY79 data, which illustrate the means of the two variables from the sample for each physical age between 22 and 37. Even though there are fluctuations of human capital investment over time, the overall trend is a decrease in human capital investment with aging. Starting from age 37, the investment through both schooling and training decreases towards zero.

4 Estimation and Simulations

In this section, I first specify the initial schooling and training human capital, and describe the methods for estimating the rental rate of human capital in each year and the model parameters. The estimation and simulation results are then presented and discussed.

4.1 Initial Schooling and Training Human Capital

Given that the data used in this study start from the year of 1987, which is in the middle of most sample individuals' work lives, the initial conditions for the optimization problem are those that prevailed at that life cycle point in 1987. Initial schooling human capital possessed by an individual at the beginning of 1987 thus can be modeled as a function of the total number of years of schooling completed by 1987 and the ability level of the individual. Consistent with the production function of schooling, I specify the initial schooling human capital as follows:

$$\ln h_{S,0} = \theta_1 + \theta_2 \cdot Grade + \theta_3 \cdot AFQT \,, \tag{7}$$

where *Grade* is the highest grade level completed by an individual in 1987. *AFQT* refers to Armed Force Qualifying Test score, which is a measure of ability.

Individuals in the sample were aged 22 to 30 in 1987. The specification of the initial training human capital should take into account this cohort effect. To be consistent with the production function of training, I specify the initial training human capital as follows,

$$\ln h_{I,0} = \lambda_1 + \lambda_2 \cdot Age \,, \tag{8}$$

where *Age* is the age of the individual in 1987.

4.2 Two-Stage Estimation Method

I use the nonlinear least squares method to estimate the rental rates of human capital and model parameters in two stages separately in order to reduce the computational burden. In Stage 1, I first identify the rental rate of human capital. Then in Stage 2, I estimate the model parameters based on the estimates obtained from Stage 1.

As specified in section 2, wage rate determination and human capital production are described by equations (2), (4), (5), and (6). Substituting equation (6) into equation (2) produces

$$\ln W_t = \ln R_t + \gamma_1 \cdot \ln h_{S,t-1} + \gamma_2 \cdot \ln h_{I,t-1} . \tag{9}$$

For those who did not invest in human capital by either schooling or training in period *t*, the growth of wage from period *t* to period *t*+1 was exclusively due to the change in the rental rate of human capital or the depreciation of human capital. This suggests that the rental rate of human capital could be estimated based on the sample of respondents who did not invest in human capital in a given year. Thus, the analytic sample for estimating the rental rate of human capital changes across years, and differs from the sample for estimating the model parameters in Stage 2. Another difference between the analytic samples used in the two stages is that I do not exclude those with missing values on AFQT or the highest grade completed in 1987 in estimating rental rates in Stage 1.

For those who did not invest in human capital in period *t*, i.e., those with zero I_t and S_t, equations (4) and (5) become

$$\ln h_{I,t} = \ln h_{I,t-1} + \ln(1 - \alpha_5 \cdot \pi_t), \tag{10}$$

$$\ln h_{S,t} = \ln h_{S,t-1} + \ln(1 - \beta_4 \cdot \pi_t). \tag{11}$$

Combining equation (9) with equations (10) and (11) produces

$$\ln\frac{W_{t+1}}{W_t} = \ln\frac{R_{t+1}}{R_t} + \gamma_1 \ln(1-\beta_4 \cdot \pi_t) + \gamma_2 \ln(1-\alpha_5 \cdot \pi_t). \tag{12}$$

I normalize the rental rate in 1987 to be 1, and then estimate R_2 in 1988, γ_1, γ_2, α_5, and β_4 using nonlinear least squares, which are later used in the estimation of R_t (t = 3,..., 8) for the period from 1989 to 1994. The estimation for each year is based on the sample of respondents who did not invest in human capital in the previous year. Estimation results are presented in Table 2.

Making use of the first-stage estimates of rental rate of human capital from 1987 to 1994, I further estimate all model parameters in the second stage under the assumption that all individuals face identical rental price in each year. One point to note is that I do not use the estimates for γ_1, γ_2, α_5, and β_4 from the first stage because the analytic samples for the two stages are different.

For any path of technological change $\tilde{\pi} = (\pi_1,...,\pi_T)$, any path of schooling choices $\tilde{S} = (S_1,\cdots,S_T)$, any path of training choices $\tilde{I} = (I_1,\cdots,I_T)$, any particular set of parameters $\nu = (\alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5,\beta_1,\beta_2,\beta_3,\beta_4,\gamma_1,\theta_1,\theta_2,\theta_3,\lambda_1,\lambda_2)$, any age, number of years of schooling, and ability level in initial year, I can simulate the model to form wage profiles as functions of these parameters and values. The predicted wage for individual i at time period t is denoted as $W_{it}(\nu; Grade, AFQT, Age, \tilde{\pi}, \tilde{S}, \tilde{I})$, and the observed wage for individual i at t is denoted as W_{it}^*. I obtain the estimate for the vector of parameters, ν, by using the nonlinear least squares method, which minimizes the distance between the predicted wage profiles and the observed ones,

$$\sum_i \sum_t \left\{W_{it}^* - W_{it}(\nu; Grade, AFQT, Age, \tilde{\pi}, \tilde{S}, \tilde{I})\right\}^2 \tag{13}$$

Because the data have finite horizon in this study, it is not surprising that α_2, α_3, α_4, β_2, or β_3 may exceed 1. Thus, I just restrict them to be positive in the estimation.

The nonlinear least squares iterations, which minimize the sum of squares error (SSE), converge very fast. The estimates of the parameters are robust in the sense that they do not change much, if any, with changes in the starting values or estimates of other parameters. However, this technique may have difficulty finding a global minimum when the SSE surface is irregular. To make sure that the estimate is a global minimum instead of a local minimum, I try different starting values for each parameter, and then choose the regression with the smallest SSE.

4.3 Estimation Results

Table 3 represents the nonlinear least squares estimates of parameters in the human capital production functions, which show clearly the differences between schooling and training in producing human capital. The results also answer the question of how schooling human capital and training human capital are affected differently by technological change.

Technological change exerts two types of effects on both schooling and training human capital: it will lead to an obsolescence of existing human capital, and will at the same time increase the productivity of human capital partly due to the complementarity between physical capital and human capital. The relative strength of these two types of effects determines the net effect of technological change on training and schooling human capital, which is represented by parameters α_5 and β_4 respectively.

As shown in Table 3, the estimate of α_5 is a positive value of 0.770, while the estimate of β_4 is a negative value of -0.279. A positive α_5 indicates that technological change mainly causes obsolescence of existing training human capital. A negative β_4, however, suggests that the increase in productivity of existing schooling human capital caused by technological change outweighs the obsolescence of existing schooling human capital. Therefore, the net effect of technological change on training human capital is obsolescence, whereas the productivity of schooling human capital actually increases under rapid technological change in spite of the obsolescence of existing schooling human capital. These findings suggest that individuals with more schooling enjoy an advantage in dealing with technological change over those with less schooling.

Based on the above results, it is clear that training human capital is more vulnerable to obsolescence due to technological change than is schooling human capital. Therefore, an individual may tend to invest more in schooling than in training under rapid technological change, while an industry may tend to employ a highly educated work force when it experiences fast technological change. These findings and implications are consistent with the empirical results from Gill (1990), Gould (2002, 2003), and Mincer (1989), as well as the theory proposed by Bartel and Lichtenberg (1987), Gould, et al. (2001), Schultz (1964, 1975), and Welch (1970).

The estimate of parameter α_2 is 0.05 with a very small t-value of 0.04, indicating that schooling human capital is not likely to improve training efficiency. Estimates of other parameters in the production function of schooling and training, α_1, α_3, α_4, β_1, β_2, and β_3, are all located in reasonable ranges according to human capital theory, and are close to the results obtained from previous studies (Heckman, et al., 1998; Taber, 2002).

Parameters γ_1 and γ_2 represent the contribution of schooling and training human capital to the total human capital stock respectively, and show the importance of schooling and training human capital in earning market returns. Estimate of γ_1 turns out to be 0.456. Therefore, the value of γ_2 is 1–0.456, or 0.544, under the CRS assumption. These estimates indicate that training human capital is more important than schooling human capital in earning market returns.

Estimates of the parameters in the initial human capital specifications are consistent with our expectation. The coefficients of age, AFQT score, and highest grade completed in 1987, λ_2, θ_2, and θ_3 respectively, are all positive and significant. Hence, individuals with higher ability levels or more schooling experiences in 1987 would have more initial schooling human capital. Older individuals would have more initial training human capital in 1987 because they tended to have more work experiences than younger individuals.

4.4 Simulations

An essential component of the analysis is to test the overall fit of the model. Thus, having estimated the model parameters, I conduct simulations of the model to examine the goodness-of-fit of the model as well as the economic meanings of the parameter estimates.

I first derive the wage profile from the data. Because the respondents were aged between 14 to 22 in 1979, the data from 1987 to 1994 cover the physical ages from 22 to 37. I calculate the sample means of wage for each physical age and plot the wage profile in Figure 2. One thing to note is that the sample size for calculating the average wage differs across physical ages. I then simulate the wage profile predicted from the model and compare it with the wage profile derived from the data.

Specifically, to conduct the simulation, I first use the method of bootstrap to generate randomly the age, AFQT score, and years of schooling for a given individual, and then compute the initial schooling and training human capital by using equations (7) and (8). The path of R&D intensity takes on the values of sample means from the data between 1987 and 1994 and is assumed to be 0.02 for the remaining time periods. The paths of schooling and training take the values of sample means for each physical age between 22 and 37 from the data. Because the estimated rental rate of human capital corresponds to calendar year instead of physical age, I assume the rental rate is a constant value of one for the simulation. Under this assumption, I obtain the predicted wage profile for a given individual from age 22 to 37 by applying equations (4), (5), and (6). I repeat this simulation process for 10,000 individuals and calculate the average wage for each physical age, which is plotted as the predicted wage profile in Figure 2.

The comparison between the predicted wage profile and the observed wage profile in Figure 2 suggests that the model fits the data very well. Even though the model fails to capture the fluctuations of wage at the two ends of the profile, it successfully predicts the overall trend of the wage profile.

In order to illustrate the effects of technological change on human capital stock and wages, I further conduct simulations of the wage profiles for different paths of life-cycle schooling and training choices under different paths of technological change. I first investigate the effects of technological change on human capital and wages when there is no human capital investment at all, as shown in Figure 3. I set schooling and training taken by each simulated individual to the value of zero for each physical age, and assume R&D intensity takes on a constant value of 0.005. I then simulate the wage profile for individuals aged between 22 and 60 in the same way as I simulate the wage profile to assess the model fit. Finally, I simulate the wage profiles when the R&D intensity takes on the values of 0.02 and 0.04 respectively.

The simulation results shown in Figure 3 indicate that the wage profile is lower and decreases faster under a higher rate of technological change. Even though the productivity of schooling human capital actually increases under rapid technological change in spite of its obsolescence, the net effect of technological change on total human capital stock, i.e., the combined schooling and training human capital, is obsolescence.

Figure 4 presents the simulation results when the paths of schooling and training take on the values of sample means for physical ages between 22 and 37 from the data and the value of zero after the age of 37. Due to the investment in human capital in early periods, the wage profile increases initially and then it starts to decline at age 38, when there is no longer any human capital investment. When the wage profile increases, it increases at a slower pace under a higher rate of technological change. When the wage profile decreases, it decreases faster under a higher rate of technological change. These results are consistent with those shown in Figure 3, suggesting that technological change causes substantial obsolescence of human capital.

5 Conclusions

This study introduces the rate of technological change into a dynamic structural model of human capital investment, and examines directly the differential effects of technological change on schooling human capital and training human capital. The estimation results illustrate the necessity and importance of distinguishing between schooling human capital and training human capital in an environment of rapid technological change.

I find that schooling and training human capital have different production functions and, more importantly, are affected differently by technological change. The net effect of technological change on training human capital is obsolescence, whereas the net effect of technological change on schooling human capital is an increase in productivity in spite of the obsolescence. These results suggest that training human capital is more vulnerable to obsolescence due to technological change than is schooling human capital, and that individuals with more schooling have an advantage in dealing with technological change over those with less education.

Simulations of wage profiles for different paths of life-cycle schooling and training choices under different rates of technological change indicate that the net effect of technological change on total human capital stock, i.e., the combined schooling and training human capital, is still obsolescence. By taking into account the interrelationship and distinction between schooling and training human capital under rapid technological change, this study provides insights into the effects of technological change on human capital in a way different from previous research.

Admittedly, there are limitations to the measurement of technological change in this study. First, the measurement of technological change used in the estimation, the R&D intensity, is industry-specific instead of individual-specific given the nature of the data. Second, the R&D intensity measure pertains to the industry where an innovation originates, which is not necessarily the industry where the innovation is actually used. The obsolescence of human capital caused by technological change, however, is likely to be determined by the actual use of new technology.

While technological change exerts a substantial impact on human capital, human capital and its investment also affect technological change according to the theory of endogenous technological change (Romer, 1990). Human capital investment by individuals will ultimately determine the pace of technological change because human capital or effective labor force is a necessary and important input in the production of technological change. The supply of human capital may even determine the type of technological change that may occur. Acemoglu (2002), for instance, demonstrates that the increase in total human capital supply in the market induced the development of skill-complementary technologies, which became more profitable compared to skill-replacing technologies. In this study, however, I assume that the rate of technological change is exogenous given the nature of the model. An avenue for further research is to construct a dynamic general equilibrium model where an endogenous technological change is determined by the total human capital stock.

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Table 1
Descriptive Statistics
Data Source: NLSY79 (1987-1994)
Sample Size: 351

Variable	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
Age in 1979	17.66	2.30	14	22
Grade in 1987	12.44	1.94	6	19
AFQT	45.68	28.14	1	99
Schooling in 1987	0.24	1.32	0	12
Schooling in 1988	0.10	0.62	0	6
Schooling in 1989	0.21	1.16	0	10
Schooling in 1990	0.22	1.07	0	7
Schooling in 1991	0.14	0.80	0	8
Schooling in 1992	0.11	0.80	0	9
Schooling in 1993	0.14	0.84	0	6
Schooling in 1994	0.20	1.06	0	8
Training in 1987	5.55	43.86	0	675
Training in 1988	7.16	64.17	0	1125
Training in 1989	22.83	141.77	0	1600
Training in 1990	10.12	67.92	0	840
Training in 1991	5.27	23.47	0	192
Training in 1992	17.20	125.28	0	1080
Training in 1993	12.80	98.20	0	1120
Training in 1994	10.35	77.70	0	1216
R&D in 1987	0.0197	0.015	0.006	0.079
R&D in 1988	0.0210	0.020	0.006	0.077
R&D in 1989	0.0210	0.019	0.006	0.079
R&D in 1990	0.0222	0.020	0.006	0.080
R&D in 1991	0.0215	0.020	0.005	0.091
R&D in 1992	0.0208	0.021	0.005	0.094
R&D in 1993	0.0195	0.017	0.005	0.097
R&D in 1994	0.0084	0.014	0.001	0.101

Note: "Schooling" is the number of months that a respondent spends in a regular school. "Training" is the number of hours that a respondent spends on formal training. "R&D" is the ratio of R&D funds to net sales in the industry that the individual is working for.

Table 2
Nonlinear Least Squares Estimates of Rental Rate of Human Capital

Year	*Estimate*	*Approximate St. Error*	*Approximate*	*95% Confidence*	*Number of Observations*
1988	1.0627	0.0315	1.0008	1.1246	373
1989	1.0652	0.0271	1.0119	1.1186	381
1990	1.0895	0.0276	1.0353	1.1438	365
1991	1.0475	0.0258	0.9967	1.0983	363
1992	1.0636	0.0226	1.0193	1.1080	363
1993	1.0796	0.0242	1.0320	1.1272	350
1994	1.1102	0.0318	1.0476	1.1728	351

Note: The rental rate of human capital in 1987 is normalized to be one.

Table 3
Nonlinear Least Squares Estimates of Parameters in Human Capital Production Functions
Data Source: NLSY79 (1987-1994)
Number of Observations: 351×8

Parameter	*Estimate*	*Approximate Standard Error*	*t-value*
α_1	0.338	0.564	0.60
α_2	0.050	1.423	0.04
α_3	0.304	0.080	3.83
α_4	0.807	1.912	0.42
α_5	0.770	0.389	1.98
β_1	0.102	0.055	1.85
β_2	0.395	0.475	0.83
β_3	0.860	0.287	3.00
β_4	-0.279	0.602	-0.46
γ_1	0.456	0.152	3.00
θ_1	0.449	0.793	0.57
θ_2	0.089	0.028	3.13
θ_3	0.006	0.002	2.58
λ_1	0.869	0.767	1.13
λ_2	0.060	0.020	2.92

Figure 1
Life-cycle Profiles of Schooling and Training From Data
Schooling: corresponds to ratio of annual working time spent in regular school;
Training: corresponds to ratio of annual working time spent on formal training.

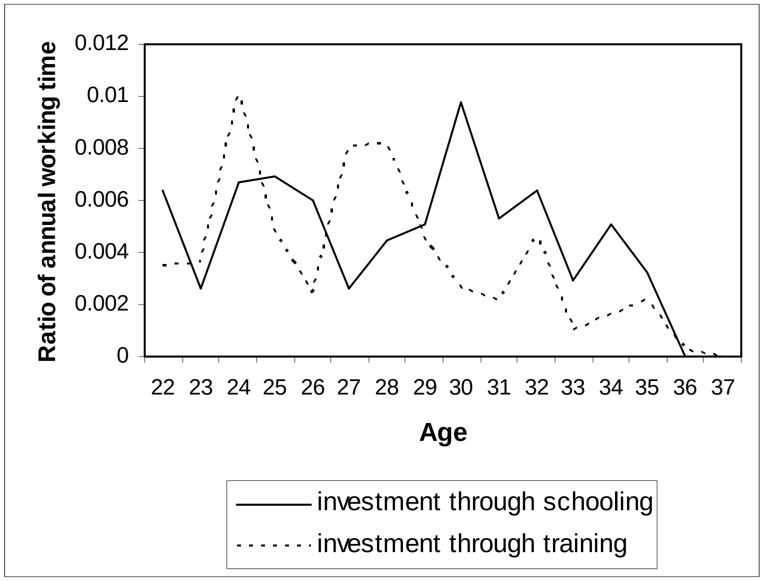

Figure 2
Predicted vs. Observed Wage Profile

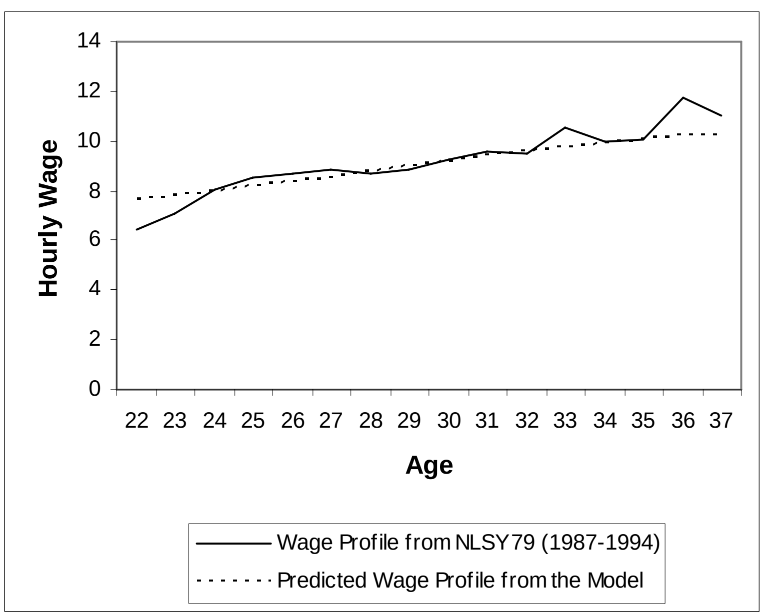

Figure 3
Simulated Wage Profiles under Different Rates of Technological Change without Schooling and Training

Note: Human capital investments are set to zero at each time period for all individuals.

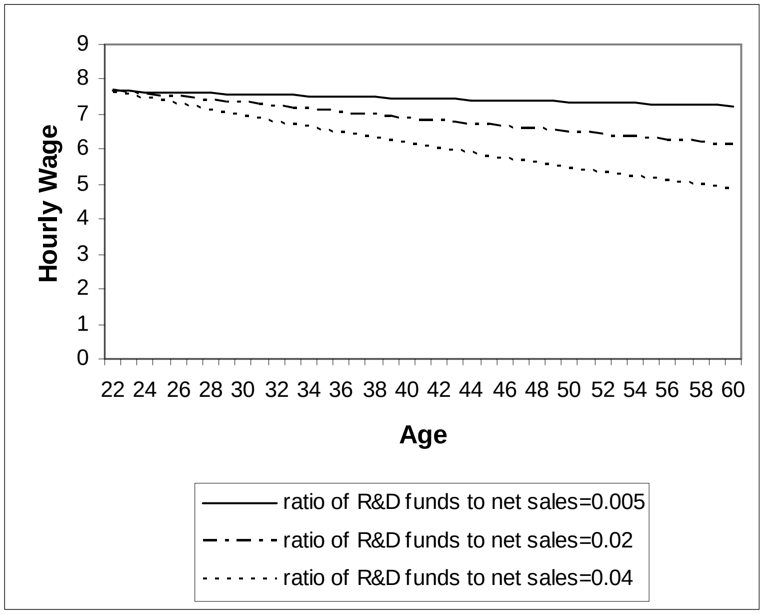

Figure 4
Simulated Wage Profiles under Different Rates of Technological Change with Schooling and Training

Note: Human capital investments through schooling or training take on the values of sample means for physical ages between 22 and 37 from NLSY79 (1987-1994). Starting at age 37, there is no longer any human capital investment.