Technological Change and Retirement Decisions of Older Workers

Ann P. Bartel, *Columbia University*

Nachum Sicherman, *Columbia University*

According to human capital theory, technological change will influence the retirement decisions of older workers in two ways. First, workers in industries with high rates of technological change will retire later if there is a net positive correlation between technological change and on-the-job training. Second, an unexpected change in the rate of technological change will induce older workers to retire sooner because the required amount of retraining will be an unattractive investment. We matched industry data on productivity growth and occupational data on required training with data from the National Longitudinal Surveys of Older Men to test these hypotheses. Our results support both hypotheses.

I. Introduction

Although economists have long been concerned about the role that technological change plays in the growth of an economy, it is only recently that the effects of technological change on the labor market have been addressed specifically. For example, Bartel and Lichtenberg (1987, 1990) showed how the introduction of new technology increases the demand

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for highly educated workers as well as individuals who are more able learners. Blackburn and Bloom (1987) identified the ways in which technological change has affected the distribution of earnings in the United States. Mincer and Higuchi (1988) showed that differences in rates of technological change can explain differences in on-the-job training, wage structures, and seniority across industries and countries.

In this article, we continue the research stream on technological change and labor markets by studying the effects of technological change on the careers of older workers. Much of the recent work on retirement behavior has focused on the role of income and leisure opportunities in determining the optimal age of retirement (e.g., Mitchell and Fields 1984.) This work has shown how the trend toward earlier retirement in the United States can be explained by the incentives created by both social security benefit rules and private pension benefit rules. Other work (e.g., Quinn 1977; Filer and Petri 1988) has analyzed the impact of job characteristics such as undesirable working conditions, physical demands, and required aptitudes on the decision to retire. Previous studies on retirement did not consider the important role played by the pattern of technological change in affecting this decision.

Our empirical analysis adds a unique perspective to the retirement literature and should, therefore, be of interest to those who study the retirement behavior of the American labor force. This study also provides useful data that can inform the debate regarding projected labor shortages in various industries. Some have argued that technological change may create labor shortages if sufficient numbers of properly trained workers are unavailable. We show that individuals in industries undergoing technological change have longer working careers, thereby suggesting that predictions regarding labor shortages may be overly pessimistic.

We begin in the next section with a discussion of the theoretical underpinnings of the relationship between the retirement decision and the rate of technological change in the worker's industry. In that section, we show why it is important to distinguish between the "permanent" rate of technological change in the industry and technological "shocks" experienced by the industry. Section III discusses our empirical measures of technological change. In Section IV, an econometric model of retirement, designed to test the hypotheses developed in Section II, is presented. The estimation results, using the National Longitudinal Survey of Older Men (NLS), are presented and discussed in Section V. Conclusions and suggestions for further research are given in Section VI.

II. Technological Change and Retirement—Some Hypotheses

There are two main ways in which technological change can affect retirement decisions: (1) through the direct effect of technological change on the amount of on-the-job training and (2) indirectly, through the effect of technological change on the depreciation rate of the stock of human capital. We consider each of these in turn.

Economic theory does not provide a clear prediction with regard to the effect of technological change on the optimal level of on-the-job training (OJT). This relationship will depend, for example, on the effects of technological change on the marginal return to training, and the complementarity and substitutability between schooling and training. Empirical evidence, however, suggests that industries with higher rates of technological change do indeed train their workers more intensively.[1] Given a positive correlation between technological change and OJT, human capital theory predicts that, ceteris paribus, workers in industries with higher rates of technological change will retire later. This can be derived from the Ben-Porath (1967) model, which shows that the amount of OJT is positively correlated with the slope of the wage profile. Since steeper profiles reward work in later years relative to work in earlier years, industries that provide more OJT will attract those workers who plan to retire later.[2]

Technological change will also affect the rate at which human capital depreciates. Specifically, in industries that have higher rates of technological change, human capital will depreciate at a faster rate. Since higher rates of depreciation reduce the returns to investment in human capital,[3] the optimal amount of investment in training will be lower in those industries, other things being equal, and, according to the discussion above, retirement will occur earlier. If *the amount of OJT is held constant,* higher depreciation rates imply flatter investment profiles (i.e., OJT will be spread over more periods). Flatter investment profiles, in turn, imply later retirement because more years are needed to recoup the returns on the later investment. We can conclude, however, that if the *net effect* of higher rates of technological change on training is *positive* (i.e., the direct positive effect of technological change on the profitability of training is stronger than the negative effect on training that occurs through the depreciation rate), industries with higher rates of technological change will be characterized by later retirement.

So far our analysis has concerned long-run variations in the rate of technological change across industries. We now turn our attention to the role played by unexpected increases (decreases) in the rate of technological change. An unexpected increase (decrease) in the rate of technological change will produce an increase (decrease) in the depreciation rate of the

[1] For empirical evidence, see Lillard and Tan (1986), Mincer and Higuchi (1988), and Bartel (1989).

[2] Although the wage profile will flatten as the employer's share in the cost of training increases, the employer will have a greater incentive to reduce turnover and delay retirement through compensation and pension policies.

[3] The effect might be different for different types and vintages of schooling and training.

stock of human capital, leading to a revised rate of investment in human capital. An increase in investment will be less attractive for older workers because there are fewer time periods during which they could capture the returns to their investment. In addition, the costs of retraining are likely to be higher for older workers.[4] *Once the individual decides not to retrain* (the revised amount of investment does not increase), higher depreciation rates will induce earlier retirement because the market wage will fall below the value of leisure at an earlier time period. The opposite will occur if there is a negative shock. A lower depreciation rate than expected will slow the decrease in the returns to training obtained in the past and extend the profitability of that training for a longer period of time. An unexpected lower rate of technological change is, therefore, likely to delay retirement.

The hypothesis about the relationship between technological change and the retirement decision, therefore, has two components. First, workers in industries that are characterized by higher rates of technological change will have later retirement ages if there is a net positive correlation between on-the-job training and technological change. Second, when workers experience an unexpected increase in the rate of technological change, the older they are, the greater the likelihood of retirement.

III. Measuring Technological Change

Our analysis requires a measure of the rate of technological change in the industry in which the individual is employed. The best data for this purpose are the rates of productivity change calculated by Jorgenson, Gollop, and Fraumeni (1987) for each of 35 industry sectors.[5] There is substantial evidence from studies of the manufacturing sector that supports the claim that rates of productivity growth are indeed functionally related to technological change. Griliches and Lichtenberg (1984) showed that for the time period of 1959–76 there was a significant relationship between an industry's intensity of private research and development expenditures and subsequent growth in productivity. Lichtenberg and Siegel (1991) also found that this relationship existed at the company level in the 1970s and 1980s.

Ideally one would prefer to use research and development intensity as the measure of technological change in the industry, but research and development data are only available for the manufacturing sector.[6] Hence,

[4] It seems more likely that young workers will receive more new training, but the combined effect of the increased depreciation rate and the additional training leads to an ambiguous prediction on their mobility behavior.

[5] One major advantage of this measure is that it includes all industry sectors, not just manufacturing, as is the case in most alternative measures.

[6] Bartel and Lichtenberg (1987, 1990) have used the age of the industry's capital stock and the research and development to sales ratio as measures of technological change in studies restricted to the manufacturing sector.

we take a more indirect approach and utilize the Jorgenson estimates of rates of productivity growth (which we know are highly correlated with research and development) to proxy rates of technological change. Specifically, technological change is measured as the rate of change in productivity that is not accounted for by the growth in the quantity and quality of physical and human capital. This is the same approach that was taken by Tan (1988) in his study of private sector training, by Mincer and Higuchi (1988) in their study of interindustry and intercountry wage differentials, and by Gill (1989) in his study of experience-earning profiles.

Technological change, however, may not be the only cause of productivity growth. Other factors, such as fluctuations in capacity utilization, and nonconstant returns to scale, are also likely to affect productivity growth. In order to control for these effects, the empirical analysis will include variables that capture the cyclical nature of the industry.

Using the Jorgenson data, we have constructed two technological change variables to test the hypotheses described in Section II. The first is the mean annual rate of technological change (in industry m) during the 10-year period prior to time period t (MTECH_{mt}). This variable is used to characterize long-run differences between industries in their rates of technological change. The second variable, SHK_{mt}, designed to capture the unexpected change in the rate of technological change, or the deviation from the "permanent" rate, is defined as a z-score:

$$\mathrm{SHK}_{mt} = (\mathrm{TECH}_{mt} - \mathrm{MTECH}_{mt})/\mathrm{SD}(\mathrm{TECH}_{m,t-10} \ldots \mathrm{TECH}_{m,t-1}), \quad (1)$$

where TECH_{mt} is the rate of technological change in year t, and $\mathrm{SD}(\mathrm{TECH}_{m,t-10} \ldots \mathrm{TECH}_{m,t-1})$ is the standard deviation over the previous 10-year period.[7]

IV. An Econometric Model of Retirement

At each period an individual will experience one of the two following outcomes described by j: retire from the labor force ($j = 1$), or not ($j = 0$).

Transition j occurs when the latent variable $Y^*_{imtj} > 0$, where

$$\begin{aligned} Y^*_{imtj} &= X_{it}\alpha_j + \delta_{1j}(\mathrm{MTECH})_{mt} + \delta_{2j}(\mathrm{SHK})_{mt} + \varepsilon_{imtj} \\ &= Z_{imt}\beta_j + \varepsilon_{imtj}, \end{aligned} \quad (2)$$

where i is the individual index, m is the industry index, t is time (the initial period), j is the outcome, and X_{it} is a vector of individual characteristics

[7] Notice that both variables vary over time because they are each defined as of time period t.

that may vary across time and are expected to affect the retirement decision (e.g., age, health status, schooling, and tenure). Since our theoretical discussion indicated that the effects of technological change on retirement behavior may depend on the individual's age, we allow the coefficients on the technology variables to vary across age groups.

Assuming that ε is logistically distributed gives rise to a logit model in which the underlying probabilities are

$$P_j = \frac{\exp(Z\beta_j)}{\sum_{k=0}^{1} \exp(Z\beta_k)}, \quad j = 0, 1. \tag{3}$$

In order to identify the parameters, the normalization $\beta_0 = 0$ is imposed, and the estimated parameters are obtained by maximum likelihood.[8]

V. Results

The model presented above is estimated using the 1966–83 National Longitudinal Surveys of Older Men. A sample of approximately 5,000 men, ages 45–59, was interviewed 12 times, in 1- and 2-year intervals, between 1966 and 1983. Individuals from the NLS were included in the analysis until the first time they reported retirement as their "main activity" or until they dropped out of the survey. By 1983, the sample size was 2,632 (see the Data Appendix for attrition rates and more details concerning the data). Although the data permit us to study labor force transitions that occur between survey dates, by construction, only one retirement per individual can be observed since observations were censored after the first retirement.[9]

In order to measure the rate of technological change in the industry in which the individual was employed, we matched the industry code in the NLS data with the relevant industry sector in the Jorgenson et al. (1987) productivity data. For each worker, in every year, we matched the mean rate of technological change over the previous 10 years in the industry in which he is employed (MTECH) and the unanticipated deviation from that mean (SHK).

Table 1 presents selected measures of our technological change variables. Specifically, we show the values of MTECH for the time periods of 1961–70 and 1971–80 and the values of SHK calculated for 1970 and 1980 for each of the two-digit industrial classifications used by Jorgenson et al.

[8] Since this approach does not deal with the panel nature of the data set, it is likely to produce inconsistent estimates.

[9] In Bartel and Sicherman (1990) we utilized the information on the individuals' job mobility over time to estimate the likelihood of a job change, in addition to retirement, using a multinomial framework.

Table 1
Mean Values of Selected Variables by Industry

Industry	N	Retirement Age	Mean Rates of Technological Change 1961–70	Mean Rates of Technological Change 1971–80	Technological "Shock" 1970	Technological "Shock" 1980
Agriculture, forestry, and fisheries	4,699	63.40	.0089	.0046	.2273	−.8685
Metal mining	44	62.33	.0170	−.0486	−.1325	1.8526
Crude petroleum and natural gas	80	61.66	.0122	−.0674	.1333	−1.0202
Nonmetal and metal mining	130	61.71	.0074	−.0082	−.1931	−.4997
Construction	4,912	62.56	.0006	−.0105	−.7118	.0176
Food and kindred products	1,240	62.38	.0061	.0026	.2300	.7095
Tobacco manufactures	41	48.00	.0078	−.0068	.6443	−.2825
Textile mill products	329	62.88	.0142	.0077	1.2747	−.2676
Apparel and other textile	209	63.66	.0096	.0178	−.4533	.0637
Lumber and wood products	976	63.01	.0125	−.0062	1.9684	1.2228
Furniture and fixtures	317	64.66	.0051	.0118	−2.1253	−.2418
Paper and allied products	454	62.42	.0106	.0010	−1.6037	−.8060
Printing and publishing	467	63.96	.0007	.0017	−1.9600	−.5114
Chemicals and allied	734	62.02	.0158	−.0079	−.3703	−.7627
Petroleum refining	206	62.50	.0126	−.0167	.3656	−.4261
Rubber and plastic	152	63.00	.0196	.0011	−1.1556	−.1264
Leather	87	66.00	.0044	−.0019	.2028	1.5260
Stone, clay, and glass	428	61.50	.0074	−.0018	−1.7619	−1.0154
Primary metals	1,619	61.42	.0038	−.0023	−1.9191	.9839
Fabricated metal	1,007	62.66	.0063	.0029	−1.9463	−.2051
Nonelectrical machinery	1,277	62.03	.0090	.0168	1.0734	−.1086
Electrical machinery	902	62.25	.0186	.0240	−1.4536	−.0964
Motor vehicles	911	60.65	.0056	.0044	−1.6706	−1.0398
Other transportation equipment	944	60.75	.0119	−.0084	−1.6965	−.8498
Instruments	236	62.41	.0111	.0133	−2.0488	−1.7647
Miscellaneous manufacturing	209	62.80	.0122	−.0038	−1.5614	−1.5119
Transportation and warehousing	2,909	61.89	.0135	.0144	.7318	−.8390
Communication	291	61.18	.0216	.0341	−.6428	.8284
Electric utilities	336	62.04	.0214	−.0080	−1.2121	.8800
Gas utilities	211	61.26	.0099	−.0085	−1.4583	1.4567
Trade	6,273	62.83	.0118	.0060	−1.3202	−.4778
Finance, insurance, and real estate	1,749	63.07	.0062	.0024	−1.8432	−2.2537
Other services	7,375	62.95	.0029	.0038	−.3252	−.7178
Government enterprises	3,280	60.69	.0017	.0094	−1.8853	.3703
Total	45,034	62.40				

NOTE.—N is the number of observations in the NLS. Retirement age is the mean age of first retirement as reported in the NLS.

Recall that the Jorgenson data actually measure productivity change that we use as a proxy for technological change. Table 1 also shows, for each of these industries, the mean retirement age calculated from the NLS.[10] These data show that the mean retirement age varies across industries from

[10] See the Data Appendix for the complete distribution of retirement ages for our sample.

a low of 60 to a high of 64.66.[11] The values of MTECH, based on the Jorgenson data, demonstrate that, in the 1960s, communications, electrical machinery, electrical utilities, and rubber and plastics ranked highest in terms of annual rates of technological change. In the 1970s, mean rates of technological change tended to be lower overall, with communications still ranking at the top followed by electrical machinery. In order to study the relationship between retirement age and industry technological change, controlling for the many other factors that have been previously shown to affect retirement, we turn to the results of estimating equation (3). Complete regression results are reported in the Appendix tables, and selected coefficients are presented in the text tables.

A. Technological Change Variables

Table 2 reports the estimated parameters on the mean rate of technological change and the unexpected deviation from the mean. The complete regression from which this table is drawn is shown in column 1 of table A1; note that in this specification we do not control for the amount of training (as measured by RQT) the individual has received. As predicted, workers in industries with higher (average) rates of technological change retire later than workers in industries with lower rates of technological change. The effect is stronger and significant for older workers (ages 65 and over). Since we do not control for the amount of training the individual has received, this finding is due to the sum of two effects: the effect of technological change on the amount of training as well as its impact on the slope of the investment profile.

The effect of an unexpected change in the rate of technological change is the opposite of that of the permanent rate. The older the worker is, the stronger is the effect of a "technological shock" on the likelihood of retirement. These results support our central hypotheses:

HYPOTHESIS 1. Workers in industries with higher average rates of technological change retire later than workers in industries with lower rates of technological change.

HYPOTHESIS 2. Conversely, when there is an unexpected increase in the rate of technological change, it induces earlier retirement. The older the worker is, the stronger is the effect of an unexpected increase on the likelihood of retirement.

B. Required Training

The primary rationale for the prediction that industries with higher rates of technological change are also characterized by later retirement was the

[11] The exception is the tobacco industry, which has a mean retirement age of 48. Since this mean age is so much lower than the retirement ages in the other industries, we also estimated our equations excluding individuals employed in that industry. The results were virtually identical to those that we report in this article probably because these observations represented only .1 of 1% of the total sample.

Table 2
The Effects of Technological Change on Retirement Maximum-Likelihood Logit Estimation Results

	Coefficient	Derivative
Mean rate of technological change:		
Age ≤ 60	−6.215 (1.07)	−.373
61–64	−3.291 (.61)	−.198
65+	−27.430 (2.36)	−1.648
Deviation from the mean:		
Age ≤ 60	−.035 (.81)	−.002
61–64	.037 (.92)	.002
65+	.194 (2.58)	.012
Log likelihood	−4,504	
No. of observations	−22,079	

NOTE.—For full regression results, see col. 1 in table A1. Absolute *t*-statistics are in parentheses. The derivatives are the means of the derivatives calculated for each observation. The following additional variables are controlled for: age, race, marital status, schooling, firm tenure, health status, and year dummies.

hypothesis that such industries are characterized by higher rates of on-the-job training. Human capital theory predicts, as discussed earlier, a positive correlation between the amount of training accumulated over the life cycle and the age of retirement.

The NLS, like most data sets that report training, provides information *only* with regard to recently obtained training.[12] In order to obtain a proxy for the long-run investment in (formal and informal) training, we used another data set, the Panel Study of Income Dynamics (PSID). In that data set, employed male heads of households were asked (in 1978) to report the amount of time it would take an average worker to become fully trained and qualified for his job. We matched the mean responses to this question (RQT) by occupation to the NLS data. The variable used in the NLS to match the training data is the occupation of the longest held job as reported in 1966.[13] We assume that the variation in this measure across occupations is a good proxy for the actual variation in on-the-job training obtained by workers over the long run. The training measures reported in the PSID have been shown to be highly correlated with alternative measures of training (see Sicherman 1990).

[12] For details, see Lillard and Tan (1986).

[13] We used several options to match the training information from the PSID with the NLS. In Bartel and Sicherman (1990) we used the industry means rather than occupational means.

It should be noted that our objective is to measure the individual's rate of investment. The fact that we use *occupational* means, measured at one point in time, limits our ability to accurately measure the effects of training on retirement and its correlation with technological change. In addition, since workers change occupations during their careers, this further reduces the correlation between the RQT variable and the individual's amount of investment in human capital. This problem has been minimized by our use of the longest held occupation to match the training data.

We reestimated the model described in equation (3), first using RQT in place of MTECH and SHK, and then adding RQT to the regression that already includes MTECH and SHK. Table 3 reports selected coefficients, and the full regressions are shown in columns 2 and 3 of table A1. Panel A of table 3 shows the coefficients from the equation that excludes the technology variables, and panel B shows the coefficients when we include the technology variables.

Table 3
The Effect of On-the-Job Training on the Likelihood of Retirement Maximum-Likelihood Logit Estimation Results

	Coefficient	Derivative
A. Without technological change variables:		
RQT (age ≤ 60)	−.066	−.004
	(1.57)	
RQT (61–64)	−.253	−.015
	(6.48)	
RQT (65+)	−.197	−.012
	(3.00)	
B. With technological change variables:		
RQT (age ≤ 60)	−.070	−.004
	(1.66)	
RQT (61–64)	−.253	−.015
	(6.45)	
RQT (65+)	−2.15	−.013
	(3.25)	
Mean rate of technological change:		
Age ≤ 60	−7.098	−.423
	(1.22)	
61–64	−4.058	−.242
	(.750)	
65+	−27.449	−1.644
	(2.37)	
Deviation from the mean:		
Age ≤ 60	−.034	−.002
	(.78)	
61–65	.031	002
	(.77)	
65+	.205	.012
	(2.73)	

NOTE.—For full regression results, see table A1. RQT is the mean required training per occupation (in months) as reported in the PSID in 1978. For details, see the Data Appendix. See text for a definition of variables.

In panel A of table 3, we observe significant negative effects of RQT on the likelihood of retirement. This result supports the hypothesis that there is a negative correlation between on-the-job training and the likelihood of retirement; that is, training delays retirement. In panel B, the coefficients on MTECH and SHK remain similar to those estimated without a control for RQT, and the RQT coefficients also remain virtually unchanged. Hence, if RQT indeed properly measures the individual's accumulated stock of human capital, then the significant coefficient on MTECH is due to the impact of technological change on the slope of the investment profile; that is, delayed investments result in longer careers.

C. Controlling for Output Growth and Unemployment

As discussed in Section III, short-run measures of productivity growth may reflect technological change as well as cyclical factors such as short-run changes in demand. In order to determine if our results regarding the effects of MTECH and SHK are indeed due to technological change, we reestimated equation (3) and its variants, adding variables that standardize for cyclical variations across industries. The first measure we used is the annual male unemployment rate in the industry, obtained from the 1966–83 issues of *Employment and Earnings.* The results in table A2 show that, as expected, an increase in the industry unemployment rate induces an individual to retire (if over age 65) since the value of time in this industry has diminished. When the unemployment rate is added to the regression that includes MTECH and SHK, or to the regression that includes MTECH, SHK, and RQT, our earlier results regarding these three variables remain virtually unchanged.

The second method we used to control for short-run fluctuations utilized the annual output series from the Jorgenson data. We calculated the mean rate of output growth over the last 10 years (QAG) as well as the "shock" of output growth during the last year. These two variables are direct analogues of our MTECH and SHK variables for productivity growth. In table A3, we utilize these two output measures in place of MTECH and SHK, and we find that the "shock" of output growth has a negative effect on the probability of retirement, exactly the opposite of the effect of the "shock" of productivity growth. We also utilized the *annual* rate of output growth directly in our equation with MTECH, SHK, and RQT (see table A4) and found that the results for these three variables remained as before, with the exception of the coefficient on MTECH for individuals aged 65 and over. In particular, this coefficient drops by about 40% and is no longer significant. Output growth continues to have a negative and significant effect on the probability of retirement. These results show that, unlike our SHK measure of technological change, which is completely distinct from the shock measure of output growth, the permanent measure of technological change, MTECH, does partially reflect output growth.

D. Other Variables

The coefficients on the other variables used in the transition model are shown in the Appendix tables. The effects of age, schooling, tenure, health condition, self-employment, and government employment are similar to those reported in the retirement literature. While tenure in the firm decreases the likelihood of changing employer, it has a positive effect on the likelihood of retirement. This result is consistent with those reported by Burkhauser (1979) and Lazear (1982, 1983), who found that the rate of decline in pension value with deferred retirement increases with tenure.

Schooling has a negative and significant effect on retirement. As pointed out by Lazear (1986), this result can be explained by the relationship between schooling and age-earnings profiles. Mincer (1974) shows that age-earnings profiles are parallel in logs as education changes. This implies that more educated workers have steeper wage profiles. Steeper profiles reward work in later years relative to work in earlier years and thus are likely to encourage leisure taken early in life and later retirement than flatter profiles. Self-employed individuals retire later, while government employees retire earlier. Finally, individuals in poor health are significantly more likely to retire.

We also estimated some models in which we included the individual's wage rate, the value of his expected pension benefits, his wife's income, and his perceptions of on-the-job stress.[14] Since information on these variables was only reported in a few of the survey years, the sample size decreased considerably. The coefficients on these variables are not reported but are summarized here. We found that the wage rate had a positive and significant effect on the probability of retirement. The coefficients on pension benefits, wife's income, and on-the-job stress were also positive.

VI. Summary and Conclusions

Recent research has shown that technological change has important labor market implications, and in this article we have demonstrated one of the avenues through which this occurs. According to the theory of human capital, technological change will influence the retirement decisions of older workers in two ways. First, workers in industries that are characterized by high rates of technological change will have later retirement ages because these industries require larger amounts of on-the-job training. Higher rates of technological change, however, also imply higher depreciation rates that reduce the returns to training. The theory therefore pre-

[14] Unlike other data sets that have been used to study retirement, the NLS reports very limited information on pensions. In particular, it is impossible to estimate the change in the present value of pension income at different ages. See Mitchell and Fields (1984) for an empirical analysis of retirement behavior that incorporates this variable.

dicts that workers in industries that are characterized by higher rates of technological change will have later retirement ages if there is a *net* positive correlation between on-the-job training and technological change. Our second hypothesis regarding technological change and retirement behavior relates to the effect of unexpected changes in the rate of technological change. An unexpected increase in the industry's rate of technological change produces an increase in the depreciation rate, leading to a revised rate of investment in human capital. This will induce older workers to retire sooner because the required amount of retraining will be an unattractive investment.

In order to test both of these hypotheses, we matched data from the NLS Older Men Survey with time-series data on rates of productivity growth in 35 industrial sectors and data on required amounts of training by occupation. Our results support both hypotheses. First, we find that individuals in industries that have high "permanent" rates of technological change have longer careers and that this result is due to the effect of technological change on the amount of training as well as its impact on the slope of the investment profile. Second, we find that when individuals experience an unexpected change in the rate of technological change, the older they are, they are more likely to retire.

This article has shown that technological change does indeed play an important role in the retirement decisions of male workers. Researchers and policymakers interested in retirement behavior should benefit from our analysis as they embark on future studies of retirement. Our findings may also bear some relevance to the current debate about the role played by technological change in the creation of labor shortages due to skill mismatches in some industrial sectors. The fact that individuals in industries undergoing technological change have longer working careers suggests that predictions regarding labor shortages due to technological change may be overly pessimistic.

Data Appendix

The data are taken from the National Longitudinal Survey of Older Men. A sample of approximately 5,000 men ages 45–59 was drawn in 1966 and followed until 1983. Below are the number of individuals observed in each of the surveys:

Year	*Observations*	*Year*	*Observations*
1966	5,017	1975	3,732
1967	4,743	1976	3,487
1968	4,648	1978	3,291
1969	4,379	1980	3,001
1971	4,175	1981	2,832
1973	3,951	1983	2,632

Below is the frequency of retirement at different ages as observed in the sample:

Age	*Frequency*	*Age*	*Frequency*
43	1	61	335
47	3	62	352
48	5	63	292
49	8	64	333
50	5	65	346
51	12	66	143
52	14	67	93
53	22	68	51
54	33	69	44
55	58	70	26
56	47	71	19
57	78	72	10
58	96	73	6
59	119	74	3
60	174	75	2
		78	1

DEFINITION. "Retirement" is defined as follows: At each survey individuals were asked to indicate their main activity during the previous week. A transition into retirement is defined as the first time the individual reported himself as retired. Transition from retirement to work and back to retirement is ignored. Also ignored are hours of work when defining retirement. See Lazear (1986) for different options of defining retirement.

Table A1
Technological Change and On-the-Job Training: The Likelihood of Retirement Maximum-Likelihood Logit Estimation Results

	(1)		(2)		(3)	
	Coeffi-cient	Deriv-ative	Coeffi-cient	Deriv-ative	Coeffi-cient	Deriv-ative
CONSTANT	−18.858	−1.133	−18.927	−1.1425	−19.071	−1.1376
	(18.76)		(19.16)		(18.90)	
Age (≤ 60)	.251	.015	.251	.0151	.254	.0151
	(14.51)		(14.71)		(14.63)	
Age = 61	15.879	.954	16.173	.9762	16.358	.9757
	(15.78)		(16.33)		(16.18)	
Age = 62	15.810	.950	16.095	.9715	16.293	.9719
	(15.70)		(16.23)		(16.10)	
Age = 63	16.438	.988	16.742	1.0105	16.944	1.0106
	(16.31)		(16.87)		(16.73)	
Age = 64	16.950	1.018	17.285	1.0433	17.484	1.0429
	(16.81)		(17.40)		(17.24)	

Table A1 (*Continued*)

	(1)		(2)		(3)	
	Coefficient	Derivative	Coefficient	Derivative	Coefficient	Derivative
Age = 65	1.201	.072	1.263	.0762	1.215	.0724
	(7.56)		(7.99)		(7.63)	
Age > 65	.233	.014	.234	.0141	.240	.0143
	(15.73)		(15.89)		(15.94)	
RACE	−.310	−.019	−.387	−.0233	−.389	−.0232
	(4.43)		(5.46)		(5.45)	
If married	.014	.001	.025	.0014	.042	.0025
	(.17)		(.30)		(.51)	
Years of schooling	−.029	−.002	−.013	−.0008	−.012	−.0007
	(3.66)		(1.58)		(1.42)	
Firm tenure	.016	.001	.016	.0009	.017	.0010
	(7.62)		(7.64)		(7.91)	
If bad health	.404	.024	.424	.0256	.414	.0247
	(6.72)		(7.08)		(6.85)	
If self-employed	−.967	−.058	−.847	−.0511	−.854	−.0509
	(12.05)		(10.42)		(10.45)	
If government employee	.336	.020	.348	.0210	.335	.0200
	(3.81)		(3.98)		(3.78)	
Technological change (age ≤ 60)	−6.215	−.373	. . .	. . .	−7.098	−.4234
	(1.07)				(1.22)	
Technological change (61–64)	−3.291	−.198	. . .	. . .	−4.068	−.2421
	(.61)				(.75)	
Technological change (65+)	−27.430	−1.648	. . .	. . .	−27.449	−1.6373
	(2.36)				(2.37)	
Technological "shock" (age ≤ 60)	−.035	−.002	. . .	. . .	−.034	−.0020
	(.81)				(.78)	
Technological "shock" (61–64)	.037	.002	. . .	. . .	.031	.0019
	(.92)				(.77)	
Technological "shock" (65+)	.194	.012	. . .	. . .	.205	.0122
	(2.58)				(2.73)	
RQT (age ≤ 60)	. . .	. . .	−.066	−.0039	−.070	−.0042
			(1.57)		(1.67)	
RQT (61–64)	. . .	. . .	−.253	−.0152	−.253	−.0151
			(6.48)		(6.45)	
RQT (66+)	. . .	. . .	−.197	−.0118	−.215	−.0128
			(3.00)		(3.25)	
Y68	.135	.008	.151	.0091	.132	.0079
	(.43)		(.49)		(.43)	
Y71	1.268	.076	1.287	.0077	1.256	.0749
	(4.96)		(5.07)		(4.93)	
Y73	1.949	.117	1.998	.1201	1.940	.1157
	(7.92)		(8.17)		(7.89)	
Y75	2.067	.124	2.139	.1291	2.057	.1227
	(8.39)		(8.78)		(8.36)	
Y76	1.375	.083	1.447	.0873	1.351	.0806
	(5.42)		(5.77)		(5.32)	
Y78	2.100	.126	2.155	.1300	2.073	.1237
	(8.41)		(8.72)		8.30)	

Table A1 (*Continued*)

	(1)		(2)		(3)	
	Coefficient	Derivative	Coefficient	Derivative	Coefficient	Derivative
Y80	2.126	.128	2.153	.1299	2.097	.1251
	(8.47)		(8.64)		(8.35)	
Y81	1.425	.086	1.450	.0875	1.375	.0820
	(5.48)		(5.62)		(5.28)	
Y83	2.599	.156	2.649	.1599	2.561	.1527
	(10.04)		(10.38)		(9.88)	
Log likelihood	−4,504		−4,532		−4,479	
No. of observations	22,079		22,103		22,079	

NOTE.—Absolute t-statistics are in parentheses. The derivatives are the means of the derivatives calculated for each observation. See text for a definition of variables.

Table A2
Technological Change and On-the-Job Training, Industry Unemployment Rate, and the Likelihood of Retirement Maximum-Likelihood Logit Estimation Results

	(1)		(2)		(3)	
	Coefficient	Derivative	Coefficient	Derivative	Coefficient	Derivative
CONSTANT	−18.822	−1.1441	−18.814	−1.1305	−19.064	−1.1373
	(19.03)		(18.65)		(18.83)	
Age (≤ 60)	.251	.0152	.253	.0151	.256	.0152
	(14.66)		(14.56)		(14.68)	
Age = 61	15.784	.9594	15.858	.9528	16.331	.9742
	(15.96)		(15.70)		(16.09)	
Age = 62	15.699	.9542	15.788	.9486	16.266	.9703
	(15.86)		(15.62)		(16.02)	
Age = 63	16.325	.9922	16.414	.9863	16.915	1.0091
	(16.48)		(16.23)		(16.64)	
Age = 64	16.840	1.0235	16.926	1.0170	17.454	1.0412
	(16.99)		(16.72)		(17.15)	
Age = 65	1.239	.0753	1.201	.0721	1.215	.0725
	(7.87)		(7.57)		(7.64)	
Age > 65	.224	.0135	.229	.0137	.237	.0141
	(15.28)		(15.21)		(15.45)	
RACE	−.307	−.0186	−.311	−.0186	−.389	−.0231
	(4.41)		(4.44)		(5.44)	
If married	−.002	.0001	.014	.0008	.042	.0025
	(.02)		(.17)		(.51)	
Years of schooling	−.029	−.0017	−.030	−.0017	−.012	−.0007
	(3.61)		(3.69)		(1.41)	
Firm tenure	.015	.0009	.016	.0009	.017	.0010
	(7.28)		(7.50)		(7.81)	
If bad health	.413	.0251	.405	.0243	.413	.0246
	(6.92)		(6.72)		(6.84)	
If self-employed	−.966	−.0587	−.960	−.0576	−.855	−.0509
	(11.85)		(11.70)		(10.26)	
If government employee	.349	.0212	.339	.0203	.336	.0200
	(4.01)		(3.83)		(3.78)	

Table A2 (*Continued*)

	(1)		(2)		(3)	
	Coefficient	Derivative	Coefficient	Derivative	Coefficient	Derivative
Technological change (age ≤ 60)	...	...	−9.317 (1.50)	−.5598	−9.687 (1.56)	−.5779
Technological change (61–64)	...	...	−4.073 (.70)	−.2447	−3.959 (.68)	−.2362
Technological change (65+)	...	...	−24.998 (2.11)	−1.5020	−24.733 (2.10)	−1.4755
Technological "shock" (age ≤ 60)	...	...	−.026 (.59)	−.0015	−.026 (.58)	−.0015
Technological "shock" (61–64)	...	...	.037 (.90)	.0022	.029 (.68)	.0017
Technological "shock" (65+)	...	...	.163 (2.028)	.0098	.173 (2.14)	.0103
RQT (age ≤ 60)	...	...	...	...	−.069 (1.63)	−.0041
RQT (61–64)	...	...	...	...	−.252 (6.42)	−.0150
RQT (66+)	...	...	...	...	−.215 (3.24)	−.0128
Industry unemployment (age ≤ 60)	−0.12 (.74)	−.0007	−.024 (1.38)	−.0014	−.020 (1.12)	−.0011
Industry unemployment (61–64)	−.000 (.04)	−.0000	−.006 (.43)	−.0003	−.000 (.01)	−.0000
Industry unemployment (age 65+)	.049 (2.01)	.0029	.022 (.85)	.0013	.026 (.97)	.0015
Y68	.150 (.48)	.0091	.132 (.43)	.0079	.131 (.42)	.0078
Y71	1.290 (5.08)	.0784	1.256 (4.93)	.0754	1.255 (4.93)	.0748
Y73	2.018 (8.21)	.1226	1.986 (8.03)	.1193	1.968 (7.95)	.1174
Y75	2.162 (8.85)	.1314	2.083 (8.46)	.1251	2.073 (8.41)	.1236
Y76	1.483 (5.75)	.0901	1.435 (5.54)	.0862	1.390 (5.36)	.0829
Y78	2.193 (8.72)	.1333	2.150 (8.50)	.1292	2.108 (8.33)	.1257
Y80	2.201 (8.79)	.1337	2.154 (8.56)	.1294	2.121 (8.42)	.1265
Y81	1.499 (5.73)	.0911	1.462 (5.56)	.0878	1.396 (5.30)	.0833
Y83	2.694 (10.41)	.1637	2.634 (10.09)	.1582	2.582 (9.88)	.1540
Log likelihood	−4,555		−4,503		−4,479	
No. of observations	22,103		22,079		22,103	

NOTE.—Absolute *t*-statistics are in parentheses. The derivatives are the means of the derivatives calculated for each observation. See text for a definition of variables.

Table A3
Output Growth and the Likelihood of Retirement
Maximum-Likelihood Logit Estimation Results

	Coefficient	Derivative
CONSTANT	−18.681 (18.54)	−1.1226
Age (≤ 60)	.249 (14.45)	.0149
Age = 61	15.763 (15.49)	.9472
Age = 62	15.693 (15.41)	.9430
Age = 63	16.323 (16.02)	.9808
Age = 64	16.834 (16.51)	1.0116
Age = 65	1.251 (7.88)	.0751
Age > 65	.229 (15.23)	.0137
RACE	−.310 (4.43)	−.0186
If married	.016 (.20)	.0009
Years of schooling	−.027 (3.33)	−.0016
Firm tenure	.016 (7.41)	.0009
If bad health	.403 (6.70)	.0242
If self-employed	−.977 (12.08)	−.0587
If government employee	.355 (4.04)	.0213
Output growth (age ≤ 60)*	−3.516 (1.23)	−.2113
Output growth (61–64)	−2.453 (.91)	−.1474
Output growth (65+)	−4.902 (.86)	−.2946
Shock of output (age ≤ 60)	−.090 (1.84)	−.0053
Shock of output (61–64)	−.031 (.67)	−.0018
Shock of output (65+)	−.127 (1.71)	−.0076
Y68	.119 (.38)	.0071
Y71	1.171 (4.48)	.0703
Y73	2.008 (8.17)	.1206
Y75	1.971 (7.83)	.1184
Y76	1.320 (5.16)	.0793
Y78	2.161 (8.66)	.1298
Y80	2.124 (8.50)	.1276

Table A3 (*Continued*)

	Coefficient	Derivative
Y81	1.328 (5.04)	.0798
Y83	2.490 (9.55)	.1495
Log likelihood	−4,507	
No. of observations	22,079	

NOTE.—Absolute *t*-statistics in parentheses. The derivatives are the means of the derivatives calculated for each observation. See text for a definition of variables.

* Mean of last 10 years yearly rates of output growth in the industry, interacted with age.

Table A4
Technological Change, On-the-Job Training, Output Growth, and the Likelihood of Retirement Maximum-Likelihood Logit Estimation Results

	Coefficient	Derivative
Constant	−19.121 (18.90)	−1.1369
Age (≤ 60)	.256 (14.71)	.0152
Age = 61	16.475 (16.26)	.9795
Age = 62	16.417 (16.19)	.9760
Age = 63	17.066 (16.81)	1.0147
Age = 64	17.619 (17.33)	1.0476
Age = 65	1.199 (7.51)	.0713
Age > 65	.243 (16.04)	.0144
RACE	−.388 (5.42)	−.0230
If married	.037 (.44)	.0021
Years of schooling	−.010 (1.14)	−.0005
Firm tenure	.016 (7.46)	.0009
If bad health	.411 (6.80)	.0244
If self-employed	−.842 (10.27)	−.0500
If government employee	.386 (4.31)	.0229
Technological change (age ≤ 60)	−3.246 (.53)	−.1930
Technological change (61–64)	1.736 (.30)	.1032
Technological change (65+)	−16.477 (1.36)	−.9797

Table A4 (*Continued*)

	Coefficient	Derivative
Technological "shock" (age ≤ 60)	−.015 (.33)	−.0009
Technological "shock" (61–64)	.055 (1.33)	.0032
Technological "shock" (65+)	.219 (2.87)	.0130
RQT (age ≤ 60)	−.066 (1.56)	−.0039
RQT (61–64)	−.249 (6.33)	−.0148
RQT (65+)	−.205 (3.07)	−.0121
Output growth (age ≤ 60)	−2.065 (2.66)	−.1227
Output growth (61–64)	−3.025 (3.96)	−.1798
Output growth (65+)	−4.940 (3.14)	−.2937
Y68	.081 (.26)	.0048
Y71	1.129 (4.39)	.0671
Y73	1.985 (8.05)	.1180
Y75	1.922 (7.74)	.1142
Y76	1.154 (4.46)	.0686
Y78	2.137 (8.54)	.1270
Y80	2.106 (8.37)	.1252
Y81	1.176 (4.45)	.0699
Y83	2.378 (9.07)	.1413
Log likelihood	−4,466	
No. of observations	−22,079	

NOTE.—Absolute *t*-statistics in parentheses. The derivatives are the means of the derivatives calculated for each observation. See text for a definition of variables.

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