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TECHNOLOGICAL CHANGE AND THE CAREERS OF OLDER WORKERS

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ABSTRACT

Recent research has shown that technological change has important labor market implications and in this paper we demonstrate one on 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. Second, an unexpected change in the industry's rate of technological change will induce older workers to retire sooner because the required amount of retraining will be an unattractive investment. We matched time-series data on rates of technological change and required amounts of training in 35 industrial sectors with data from the NLS Older Men Survey to test these hypotheses. Our results strongly support both hypotheses.

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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 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 paper, 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 focussed 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 towards earlier retirement in the United States can be explained by the incentives created by both social security benefit rules and private pension benefit rules. In this paper, we demonstrate how retirement decisions can be influenced by the pattern of technological change in the individual's industry.

The relationship between technological change and retirement decisions is a topic with significant policy implications. In the 1970s, as older men withdrew from the labor force, they were easily replaced by members of the baby boom generation who were entering the labor force. Today, the emergence of the baby bust generation has produced a labor shortage which many argue has been exacerbated by the change in skill requirements that has accompanied the introduction of new technologies into the work environment. Many policymakers contend that there is currently a mismatch between the skills employers need and the skills new workers possess, suggesting that the solution to this problem is reform of our educational institutions. An alternative approach, however, is to consider the extent to which the length of an individual's career depends on technological change in the industry. If employees find it optimal to work longer in industries that are undergoing technological change, 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 industry's "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. THEORETICAL FRAMEWORK

In order to predict the effect of technological change on the optimal time of retirement, we need to consider the means by which such a change might affect the optimal path of investment in human capital and, subsequently, labor supply. There are two main ways in which this can occur: 1) through the direct effect of technological change on the amount of on-the-job training and 2) through the effect of technological change on the depreciation of the stock of human capital.[1] We consider each of these in turn.

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[1]Higher rates of depreciation will in turn affect the demand for on-the-job training.

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. 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[2]. Given a positive correlation between technological change and OJT, human capital theory would predict that 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.

In addition, a steeper profile is likely to encourage leisure taken early in life and later retirement. This issue is discussed by Blinder and Weiss (1976) who generalized the Ben-Porath model. By including leisure in the utility function and assuming perfect capital markets, they allow for a period of retirement to be included in the optimal plan. One of their surprising findings concerns the timing of retirement. In the presence of exogenously increasing wages (perhaps due to productivity growth in the industry), it might be optimal (under certain conditions, including a steep enough wage profile) to have the retirement period before the working (and on-the-job training) period. The reason for not observing such behavior in reality is mainly due to imperfect capital markets. If one cannot pursue such a plan, the alternative might be to retire later with longer vacations during the working

[2]Such evidence is provided in this paper and has also been demonstrated by Mincer and Higuchi (1988) and Bartel (1989).

period. To test this hypothesis empirically, one has to see if industries with higher rates of technological change are characterized not only by later retirement ages, but also by shorter yearly working hours[3].

There are two questions concerning the effect of depreciation on the optimal date of retirement. 1) Other things equal, will workers who face higher rates of depreciation retire later or earlier? and 2) Given that a worker is "on" his optimal plan, how will an unexpected change in the rate of depreciation (rate of technological change) affect the optimal timing of retirement?

Within the Ben-Porath framework, higher rates of depreciation imply less investment in OJT at each period, and flatter investment profiles (i.e. OJT will be spread over more periods.) Since the Ben-Porath framework does not allow an endogenous retirement date, it does not predict the sign on the correlation between depreciation rates and retirement[4]. If, however, higher depreciation rates indeed imply less investment in OJT, then according to the discussion above, retirement will occur earlier. On the other hand, holding the amount of OJT constant, flatter profiles might imply later retirement because later investment will require more years to recoup the investment.

Suppose, however, that there is an unexpected increase (decrease) in the rate of technological change. This will produce an increase (decrease) in the depreciation rate of the stock of human capital, leading to a revised rate of optimal human capital investment. An increase in investment will be less attractive the older the worker because there are fewer

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[3]It should be pointed out that this result is separate from the income and substitution effects of a wage change.

[4]We are not aware of any theoretical work that directly addresses this question.

time periods during which to capture the returns[5]. Once the individual decides not to re-train, the existence of a higher depreciation rate will induce him to retire earlier because the market wage will fall below the value of leisure at an earlier time period.

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. This effect will be stronger the greater the positive correlation between on-the-job training and technological change. Nevertheless, later retirement should be observed even in the absence of such a correlation, if indeed higher depreciation rates imply flatter investment profiles. Second, when workers experience an unexpected increase in the rate of technological change, the older they are, they will be more likely to retire earlier.

III. MEASURING TECHNOLOGICAL CHANGE

Our analysis requires a measure of the rate of technological change in the industry in which the individual is employed. Since we wish to test our hypotheses on the entire nonagricultural male labor force, we need a measure of technological change that is available for all industry sectors, not just manufacturing. The best data for this purpose are the rates of productivity change calculated by Jorgenson et. al. (1987) for each of 35 industry sectors. 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 1959-1976 there was a

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[5]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.

significant relationship between an industry's intensity of private R&D expenditures and subsequent growth in productivity. Lichtenberg and Siegel (1990) also found that this relationship existed at the company level in the 1970s and 1980s.

Ideally one would prefer to use R&D intensity as the measure of technological change in the industry, but R&D data are only available for the manufacturing sector.[6] Hence we take a more indirect approach and utilize the Jorgenson estimates of rates of productivity growth (which we know are highly correlated with R&D) to proxy rates of technological change. Specifically, technological change is measured as the rate of change in productivity which 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 non constant 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 during the ten year period prior to time period t ($MTECH_t$). This variable is used to characterize permanent differences between industries in their rates of technological change. The second variable, (SHK_t), 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:

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

$$SHK_t = (TECH_t - MTECH_t)/\ SD(TECH_{t-10}...TECH_{t-1})\ , \qquad (1)$$

where $SD(TECH_{t-10}...TECH_{t-1})$ is the standard deviation over the previous ten year period.

IV. AN ECONOMETRIC MODEL OF RETIREMENT AND FIRM MOBILITY

The econometric model of retirement and firm mobility that we estimate to test our hypotheses is presented below. Although the focus of the analysis is to estimate the determinants of retirement, changing employer is also an alternative faced by the worker. In order to consider these two possible outcomes, a multinomial framework is employed.[7]

At each period an individual will experience one of the three following alternatives described by j: retire from the labor force ($j = 1$), change employer ($j = 2$), or neither ($j = 0$).

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

$$Y^*_{imtj} = X_{it}\alpha_j + \delta_1(MTECH)_{imtj} + \delta_2(SHK)_{imtj} + e_{imtj} = Z_{itm}\beta_j + e_{imtj}, \qquad (2)$$

where i is the individual index, m is the industry index, t is time (the initial period), j is the alternative, and X_{it} is a vector of individual characteristics that may vary across time and are expected to affect the decision to retire or change employers. Since our theoretical discussion indicated that the effects of technological change on retirement and mobility behavior may depend on the individual's age, we will allow the coefficients on the technology variables to vary across age groups.

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[7]The use of this approach requires some simplifying assumptions concerning the two outcomes.

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

$$P_j = \frac{\exp(Z\beta_j)}{\sum_{k=0}^{2} \exp(Z\beta_k)}, \quad j = 0, 1, 2. \tag{3}$$

In order to identify the parameters, the normalization $\beta_0 = 0$ is imposed and the estimated parameters are obtained by maximum likelihood. Our econometric model differs from previous work on retirement and mobility in that we estimate both transitions simultaneously. This is more correct because estimating either transition separately without taking into account the non-random truncation due to the other transition is likely to bias the estimated results[8].

V. RESULTS

The model presented above is estimated using the 1966-1983 National Longitudinal Surveys of Older Men. The data permit us to study labor force transitions that occur between survey dates. 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. Information about the amount of training obtained in different industries is available from the Panel Study of Income Dynamics (PSID.) In that data set workers were asked to report the amount of time

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

it would take an average worker to be fully qualified for his job. We matched the mean responses to this question (RQT) by industry to the NLS data[9]. Hence for each individual in the NLS we have information on the mean rate of technological change (MTECH), the unanticipated deviation from that mean (SHK), and the required amount of training in the industry in which he is employed (RQT).

Table 1 presents the means of selected variables by the 2 digit industrial classification used by Jorgenson et. al. We also show for each of these industries the mean retirement age[10] and mean rate of employer change calculated from the NLS. Across the 35 industrial sectors, we find a significant positive correlation between technological change and retirement age as well as a significant negative correlation between technological change and firm mobility. Complete regression results are reported in the Appendix and selected coefficients are shown in the text tables.

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[9]We assume that the variation in this variable across industries is a good proxy for the actual variation in on-the-job training obtained by workers in different industries over the long run. The variation obtained based on the PSID is highly correlated with alternative measures of training (see Sicherman 1990.) Since the different data sets use different industrial classifications, we were unable to obtain unique measures of training for each of the industrial sectors. Hence the reader will note in Table 1 that some values of RQT are repeated for related industries.

[10]See the data appendix for definition.

Table 1
Mean Values of Selected Variables by Industry

Industry	Obs.	RQT	T71_80	T81_85	R. AGE	MOBILITY
Agr. forestry & fisheries	4699	58.986	0.00466	0.05042	63.40	.092389
Metal mining	44	32.333	-.01507	0.04104	62.33	.153846
Crude petroleum nat. gas	80	32.333	-.06740	-.02349	61.66	.282609
Nonmetal/metal mining	130	32.333	-.00820	0.00482	61.71	.095238
Construction	4912	3.089	-.01051	-.00047	62.56	.239294
Food & kindred products	1240	75.313	0.00264	0.00344	62.38	.071046
Tobacco manufactures	41	14.946	-.00689	-.03465	48.00	.187500
Textile mill products	329	2.000	0.00779	0.00806	62.88	.084112
Apparel & other textile	209	2.000	0.01781	0.00646	63.66	.165468
Lumber and wood products	976	40.022	-.00627	0.01116	63.01	.142023
Furniture and fixtures	317	40.022	0.01182	0.00138	64.66	.107143
Paper & allied products	454	9.828	0.00103	0.01130	62.42	.027875
Printing & publishing	467	17.605	0.00176	-.00301	63.96	.073482
Chemicals & allied	734	27.292	-.00792	0.01420	62.02	.039526
Petroleum refining	206	27.292	-.01673	0.04946	62.50	.016129
Rubber & plastic	152	27.292	0.00110	0.01589	63.00	.076923
Leather	87	27.292	-.00192	-.00629	66.00	.076923
Stone, clay and glass	428	40.004	-.00180	0.01504	61.50	.092050
Primary metals	1619	34.626	-.00233	0.00623	61.42	.027484
Fabricated metal	1007	34.641	0.00292	0.00175	62.66	.081301
Non-electrical machinery	1277	43.921	0.01689	0.02506	62.03	.088623
Electrical machinery	902	43.921	0.02405	0.00735	62.25	.055105
Motor vehicles	911	25.569	0.00443	0.00446	60.65	.017928
Other transp. equipment	944	25.569	-.00845	0.00301	60.75	.068333
Instruments	236	43.921	0.01336	0.01643	62.41	.064706
Misc. Manufactrng	209	31.600	-.00387	0.00941	62.80	.109589
Trnsprttn & Warehousng	2909	23.462	0.01449	-.00047	61.89	.069918
Communication	291	40.327	0.03414	0.02285	61.18	.014354
Electric Utilities	336	21.373	-.00801	-.00155	62.04	.040609
Gas Utilities	211	21.373	-.00852	-.02511	61.26	.000000
Trade	6273	37.366	0.00602	0.00904	62.83	.117513
Finance/ins./rl.estt	1749	29.496	0.00248	-.00510	63.07	.129816
Other services	7375	49.366	0.00386	-.00592	62.95	.132548
Gov't Enterprises	3280	24.742	0.00943	0.01071	60.69	.056985
Total	45034	35.158	0.00335	0.00702	62.40	.106489

RQT is the mean rate of (weeks of) required training as reported by workers in 1978 in the PSID.
T71_80 (T81_85) is the mean rate of technological change over the period 1971-1980 (81-85.) It is a simple mean of the yearly rates as reported by Jorgenson et. al. (1987).
RETAGE is the mean age of first retirement as reported in the NLS.
MOBILITY is the mean rate of employer change as reported in the NLS. It is a combination of annual and bi-annual rates because of varying intervals between survey dates in the NLS.

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 Table A-1. 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 especially strong for workers ages 65 and over. The effect is relatively small and less significant for workers between the ages of 61 and 64, ages in which other factors are likely to dominate the retirement decision.

Industries with higher rates of technological change are also characterized by lower turnover rates. The effect decreases as workers become older, and contrary to the retirement model, for workers ages 65 and over, the effect becomes positive. Our theoretical discussion does not consider firm mobility, and, therefore, does not predict these results.

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

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

In the case of firm mobility, the unexpected change in the rate of technological change has a negative effect on mobility which is significant for those aged 60 and younger. This result might indicate that among workers who choose not to retire (in spite of a technological shock), the need to retrain and adapt to the new technology results in an increase in firm specific training, thus increasing the attachment between the worker and the firm[11]. Since younger workers are more likely to re-train, it might explain why the estimated coefficients are stronger for those aged 60 and younger. It could also be that those workers who did not retire in spite of the technological shock are those who are (ex-ante) more attached to the firm, therefore less likely to change employer.

[11]This argument is used by Mincer and Higuchi (1988) to explain the differences in firm attachment between Japan and the U.S.

Table 2

The Effects of Technological Change on Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
Mean Rate of Technological Change				
	coef.	derivative	coef.	derivative
Age LE 60	-7.7394	-.44988	-33.435	-2.4684
	(1.274)		(7.947)	
61-64	-6.8370	-.39742	-22.263	-1.6436
	(1.239)		(2.503)	
65 +	-24.843	-1.4441	19.0859	1.40906
	(2.094)		(.9679)	
Deviation from the Mean				
Age LE 60	-.04535	-.00264	-.02589	-.00191
	(1.030)		(.9143)	
61-64	.038362	.002230	-.01951	-.00144
	(.9420)		(.2821)	
65 +	.156728	.009110	-.18985	-.01401
	(2.051)		(1.514)	

Log Likelihood -11146
Observations 24286

For full regression results, see Table A-1.
Absolute t-statistics 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.

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 hypothesis that such industries are characterized by higher rates of on-the-job training. In our data we do indeed find a positive correlation between technological change and our measure of required training. Human capital theory predicts, as discussed earlier, a positive correlation between the amount of training and the age of retirement.

In order to directly estimate the effect of training on retirement we re-estimated the model described in equation (3), adding the industry means of on-the-job training calculated from the PSID. Table 3 reports selected coefficients and the full regressions are shown in Tables A-2 and A-3. In Panel A of Table 3, the technology variables are excluded, and in Panel B we include the training information as well as the means and deviations of the rates of technological change. Since MTECH and RQT are positively correlated across the 35 industry sectors, we expect a weaker effect of MTECH on retirement and mobility behavior when RQT is included.

In Panel A of Table 3, we observe significant negative effects of RQT on the likelihood of retirement as well as the likelihood of changing employers. This effect is increases with age. In Panel B, when RQT is used in conjunction with MTECH and SHK, the coefficients on MTECH become insignificant, those on SHK become slightly weaker, while the earlier findings for RQT remain. In other words, it is the link between technological change and on-the-job training that explains the relationship between retirement ages and rates of technological change across industries.[12]

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[12]It could be argued that the amount of training required on the job varies substantially across occupations within an industry. Hence a more appropriate aggregation of the training data in the PSID is by occupation rather than by industry. All the results reported in this paper hold using this method of aggregation. In most cases the results are even stronger.

Table 3
The Effect of On-the-Job Training on
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

A. Without Tech. Change Variables

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
RQT (AGE LE 60)	-.00695	-.00041	-.00744	-.00055
	(3.089)		(5.652)	
RQT (61-64)	-.00858	-.00050	-.00677	-.00050
	(4.313)		(2.096)	
RQT (65 +)	-.01264	-.00074	-.00860	-.00064
	(3.538)		(1.500)	

B. With Tech. Change Variables

	Retirement coef.	Retirement derivative	Firm Change coef.	Firm Change derivative
RQT (AGE LE 60)	-.00639	-.00037	-.00638	-.00047
	(2.758)		(4.760)	
RQT (61-64)	-.00837	-.00048	-.00490	-.00036
	(4.078)		(1.465)	
RQT (65 +)	-.01156	-.00067	-.01032	-.00076
	(3.092)		(1.716)	
Mean Rate of Technological Change				
AGE LE 60	-4.6737	-.27064	-30.798	-2.2691
	(.7660)		(7.305)	
61-64	-1.6691	-.09665	-18.604	-1.3707
	(.2966)		(2.003)	
65 +	-12.740	-.73774	26.7178	1.96850
	(1.045)		(1.367)	
Deviation from the mean				
AGE LE 60	-.03994	-.00231	.002776	.000204
	(.9025)		(.0957)	
61-65	.033718	.001952	-.01789	-.00132
	(.8236)		(.2580)	
65 +	.145179	.008407	-.18056	-.01330
	(1.891)		(1.433)	

RQT is the mean required training per industry (in months) as reported in the PSID in 1978. For details, see the data appendix.

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 re-estimated 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 through 1983 issues of Employment and Earnings. The results in Appendix Table A-4 show that, as expected, an increase in the industry unemployment rate induces an individual to retire (if over age 65) or change employers (for those less than 65), since the value of his time in this industry has diminished. When the unemployment rate is added to the regression that includes MTECH and SHK (see Appendix Table A-5), or to the regression that includes MTECH, SHK, and RQT (see Appendix Table A-6), our earlier results regarding these three variables remain 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 ten 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 A-7, 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 (LQ) directly in our equation with MTECH, SHK, and RQT (see Appendix Table A-8) and found that the results for these three variables remained as before, while LQ had a negative and significant effect on the probability of retirement. These results are important because they show that the productivity growth variables are indeed measuring technological change, not short-run output growth, and, furthermore, that technological change and output growth have quite different effects on retirement decisions that can be separately identified.

D. Other Variables

The coefficients on the other variables used in the transition model are shown in the Appendix tables[13]. The effects of age, schooling, tenure, health condition, self employment and government employment are similar to those reported in the retirement and mobility 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 have steeper wage profiles. Steeper profiles reward work in later years relative to work in earlier years, thus 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.

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[13]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. Since information on these variables was only reported in a few of the survey years, it decreased our sample size 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, indicating that the income effect outweighs the substitution effect. 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 paper 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. Second, an unexpected change in the industry's rate of technological change will induce older workers to retire sooner because the required amount of retraining will be an unattractive investment. We matched time-series data on rates of technological change and required amounts of training in 35 industrial sectors with data from the NLS Older Men Surveys to test these hypotheses. Our results strongly support both hypotheses.

These findings are important in light of the current debate about the role played by technological change in the creation of a labor shortage in some sectors. Our finding that workers exposed to higher rates of technological change have longer careers suggests that labor shortages are not likely to exist. The fact that we do find that older workers exposed to a "technological shock" retire earlier could be consistent with the prediction of a labor shortage if employers are unable to train young workers to adjust to the new technology. Whether the latter problem actually exists is a topic for further research.

Table A-1
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement coef.	Retirement derivative	Firm Change coef.	Firm Change derivative
CONSTANT	-17.928	-1.0421	-.67215	-.04962
	(17.86)		(1.598)	
Age (le 60)	.238688	.013874	-.00005	-.00000
	(13.79)		(.0065)	
Age = 61	15.1906	.883003	.096632	.007134
	(15.10)		(.2154)	
Age = 62	15.0695	.875960	-.22256	-.01643
	(14.97)		(.4871)	
Age = 63	15.7850	.917553	.123548	.009121
	(15.67)		(.2662)	
Age = 64	16.3277	.949099	.663679	.048998
	(16.19)		(1.415)	
Age = 65	1.24815	.072552	.233272	.017222
	(7.729)		(.9123)	
Age (ge 65)	.221907	.012899	-.00311	-.00023
	(14.98)		(.4365)	
RACE	-.30655	-.01782	-.15320	-.01131
	(4.325)		(2.502)	
If Married	-.03553	-.00206	-.10322	-.00762
	(.4305)		(1.449)	
Years of Schooling	-.03141	-.00182	-.01440	-.00106
	(3.883)		(1.964)	
Firm Tenure	.012479	.000725	-.07645	-.00564
	(5.717)		(27.31)	
If bad health	.416062	.024185	.031978	.002361
	(6.810)		(.5504)	
If Self employed	-.98787	-.05742	-.24375	-.01799
	(12.17)		(3.411)	
If Government emp.	.250193	.014543	-.91212	-.06734
	(2.780)		(8.492)	
TAGLE60	-7.7394	-.44988	-33.435	-2.4684
	(1.274)		(7.947)	
TAG6164	-6.8370	-.39742	-22.263	-1.6436
	(1.239)		(2.503)	
TAG65PL	-24.843	-1.4441	19.0859	1.40906
	(2.094)		(.9679)	
SAGLE60	-.04535	-.00264	-.02589	-.00191
	(1.030)		(.9143)	
SAG6164	.038362	.002230	-.01951	-.00144
	(.9420)		(.2821)	
SAG65PL	.156728	.009110	-.18985	-.01401
	(2.051)		(1.514)	
Y68	-.07818	-.00454	-.56880	-.04199
	(.2419)		(6.438)	
Y71	1.24625	.072442	.159155	.011750
	(4.879)		(1.940)	
Y73	1.98271	.115251	-.01982	-.00146
	(8.052)		(.2161)	
Y75	2.08174	.121007	-.31725	-.02342
	(8.449)		(2.902)	
Y76	1.32217	.076855	-.68129	-.05030
	(5.190)		(5.133)	
Y78	2.02751	.117855	.150517	.011112
	(8.075)		(1.249)	
Y80	2.05998	.119743	.332291	.024532
	(8.151)		(2.567)	
Y81	1.39145	.080882	-1.0417	-.07691
	(5.336)		(5.103)	
Y83	2.54678	.148039	-.08823	-.00651
	(9.788)		(.4437)	

Log Likelihood -10153
Observations 22365
Absolute t-statistics in parentheses. The derivatives are the means of the derivatives calculated for each observation.

Table A-2
The effect of On-The-Job Training
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
CONSTANT	-17.596	-1.0311	-.87420	-.06467
	(17.83)		(2.096)	
Age (le 60)	.235689	.013811	.001923	.000142
	(13.82)		(.2519)	
Age = 61	15.0548	.882218	.235482	.017421
	(15.18)		(.5134)	
Age = 62	14.9368	.875298	-.07761	-.00574
	(15.05)		(.1658)	
Age = 63	15.6344	.916182	.258780	.019145
	(15.74)		(.5443)	
Age = 64	16.2001	.949328	.807174	.059716
	(16.29)		(1.677)	
Age = 65	1.27067	.074462	.214783	.015890
	(7.894)		(.8424)	
Age (ge 65)	.220689	.012932	.003301	.000244
	(15.01)		(.4316)	
RACE	-.29868	-.01750	-.13902	-.01028
	(4.243)		(2.271)	
If Married	-.07560	-.00443	-.10391	-.00769
	(.9264)		(1.461)	
Years of Schooling	-.02938	-.00172	-.01176	-.00087
	(3.639)		(1.586)	
Firm Tenure	.012453	.000730	-.07753	-.00574
	(5.763)		(27.79)	
If bad health	.436971	.025607	.046182	.003417
	(7.191)		(.7955)	
If Self Employed	-.91131	-.05340	-.20124	-.01489
	(11.26)		(2.817)	
If Government Emp.	.287883	.016870	-.79896	-.05911
	(3.243)		(7.501)	
RQT (AGE LE 60)	-.00695	-.00041	-.00744	-.00055
	(3.089)		(5.652)	
RQT (61-64)	-.00858	-.00050	-.00677	-.00050
	(4.313)		(2.096)	
RQT (65 +)	-.01264	-.00074	-.00860	-.00064
	(3.538)		(1.500)	
Y68	-.05718	-.00335	-.54101	-.04002
	(.1769)		(6.140)	
Y71	1.27854	.074922	.250512	.018533
	(5.014)		(3.105)	
Y73	2.03019	.118970	.054810	.004055
	(8.329)		(.6225)	
Y75	2.18044	.127775	-.07399	-.00547
	(8.941)		(.7147)	
Y76	1.43554	.084123	-.43981	-.03254
	(5.706)		(3.426)	
Y78	2.12622	.124597	.336376	.024886
	(8.561)		(2.889)	
Y80	2.12935	.124781	.589610	.043620
	(8.499)		(4.738)	
Y81	1.47003	.086144	-.78951	-.05841
	(5.687)		(3.934)	
Y83	2.66662	.156264	.242006	.017904
	(10.40)		(1.270)	

Log Likelihood -10206
Observations 22381
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Table A-3
Technological Change and On-The-Job Training
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
CONSTANT	-17.752 (17.65)	-1.0280	-.55381 (1.312)	-.04080
Age (le 60)	.238451 (13.75)	.013808	.000806 (.1052)	.000059
Age = 61	15.2374 (15.09)	.882360	.090140 (.1956)	.006641
Age = 62	15.1292 (14.97)	.876091	-.21938 (.4664)	-.01616
Age = 63	15.8357 (15.66)	.917007	.126054 (.2640)	.009287
Age = 64	16.3975 (16.20)	.949538	.677983 (1.403)	.049952
Age = 65	1.24662 (7.695)	.072188	.231427 (.9032)	.017051
Age (ge 65)	.224796 (14.99)	.013017	.000157 (.0200)	.000011
RACE	-.30303 (4.268)	-.01755	-.14705 (2.398)	-.01083
If Married	-.05538 (.6701)	-.00321	-.10983 (1.540)	-.00809
Years of Schooling	-.02941 (3.603)	-.00170	-.01129 (1.524)	-.00083
Firm Tenure	.012896 (5.889)	.000747	-.07558 (26.97)	-.00557
If bad health	.424918 (6.939)	.024606	.041579 (.7145)	.003063
If Self Employed	-.92666 (11.35)	-.05366	-.22080 (3.082)	-.01627
If Government Emp.	.276180 (3.053)	.015993	-.89095 (8.289)	-.06564
TAGLE60	-4.6737 (.7660)	-.27064	-30.798 (7.305)	-2.2691
TAG6164	-1.6691 (.2966)	-.09665	-18.604 (2.003)	-1.3707
TAG65PL	-12.740 (1.045)	-.73774	26.7178 (1.367)	1.96850
SAGLE60	-.03994 (.9025)	-.00231	.002776 (.0957)	.000204
SAG6164	.033718 (.8236)	.001952	-.01789 (.2580)	-.00132
SAG65PL	.145179 (1.891)	.008407	-.18056 (1.433)	-.01330
RAGLE60	-.00639 (2.758)	-.00037	-.00638 (4.760)	-.00047
RAG6164	-.00837 (4.078)	-.00048	-.00490 (1.465)	-.00036
RAG65PL	-.01156 (3.092)	-.00067	-.01032 (1.716)	-.00076
Y68	-.07411 (.2292)	-.00429	-.56175 (6.354)	-.04139
Y71	1.25404 (4.903)	.072618	.168362 (2.049)	.012404
Y73	1.99040 (8.066)	.115259	-.04280 (.4641)	-.00315
Y75	2.11451 (8.571)	.122446	-.30282 (2.762)	-.02231
Y76	1.36332 (5.342)	.078946	-.68211 (5.121)	-.05025
Y78	2.06074 (8.193)	.119332	.147650 (1.223)	.010878
Y80	2.08521 (8.237)	.120749	.344296 (2.654)	.025367
Y81	1.41243 (5.407)	.081790	-1.0437 (5.106)	-.07690
Y83	2.59609 (9.957)	.150333	-.05871 (.2949)	-.00432

Log Likelihood -10125
Observations 22356
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Table A-4
Industry Unemployment Rates
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
CONSTANT	-17.969 (18.21)	-1.0574	-1.6485 (3.908)	-.12075
Age (le 60)	.237651 (13.89)	.013985	-.00111 (.1442)	-.00008
Age = 61	15.0624 (15.25)	.886396	.358600 (.7850)	.026267
Age = 62	14.9326 (15.10)	.878760	.043638 (.0940)	.003196
Age = 63	15.6430 (15.81)	.920563	.431724 (.9130)	.031623
Age = 64	16.1880 (16.34)	.952633	.966876 (2.018)	.070822
Age = 65	1.28045 (7.993)	.075352	.224698 (.8794)	.016459
Age (ge 65)	.214889 (14.68)	.012646	.010556 (1.328)	.000773
RACE	-.29678 (4.222)	-.01746	-.14787 (2.406)	-.01083
If Married	-.05388 (.6614)	-.00317	-.10171 (1.423)	-.00745
Years of Schooling	-.02853 (3.507)	-.00168	.002089 (.2783)	.000153
Firm Tenure	.011755 (5.444)	.000692	-.07416 (26.56)	-.00543
If bad health	.424315 (6.997)	.024970	.027880 (.4786)	.002042
If Self Employed	-1.0075 (12.21)	-.05929	-.33684 (4.663)	-.02467
If Government Emp.	.259029 (2.920)	.015243	-.87541 (8.195)	-.06412
Ind. Unemp. (Age le 60)	.009574 (.5840)	.000563	.133743 (12.34)	.009796
Ind. Unemp (61 le age le 64)	.016946 (1.212)	.000997	.089364 (4.477)	.006546
Ind. Unemp (age ge 65)	.043741 (1.734)	.002574	.034218 (.8659)	.002506
Y68	-.05775 (.1787)	-.00340	-.51615 (5.839)	-.03781
Y71	1.28980 (5.058)	.075902	.335496 (4.122)	.024574
Y73	1.99864 (8.129)	.117616	-.24906 (2.711)	-.01824
Y75	2.17206 (8.881)	.127822	-.20041 (1.910)	-.01468
Y76	1.33960 (5.175)	.078833	-1.2016 (8.159)	-.08801
Y78	2.04639 (8.090)	.120426	-.21434 (1.693)	-.01570
Y80	2.11027 (8.375)	.124186	.321314 (2.521)	.023536
Y81	1.40808 (5.366)	.082863	-1.2986 (6.260)	-.09512
Y83	2.60085 (10.00)	.153055	-.25352 (1.285)	-.01857

Log Likelihood -10165
Observations 22381
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Table A-5
Technological Change and Industry Unemployment Rate
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
CONSTANT	-17.977 (17.85)	-1.0451	-1.3493 (3.154)	-.09871
Age (le 60)	.239639 (13.80)	.013930	-.00137 (.1787)	-.00010
Age = 61	15.1751 (15.04)	.882153	.228119 (.4767)	.016689
Age = 62	15.0545 (14.91)	.875141	-.08342 (.1717)	-.00610
Age = 63	15.7714 (15.61)	.916814	.306996 (.6236)	.022460
Age = 64	16.3137 (16.12)	.948341	.850606 (1.702)	.062230
Age = 65	1.24972 (7.739)	.072648	.239408 (.9340)	.017515
Age (ge 65)	.220319 (14.59)	.012807	.002074 (.2352)	.000152
RACE	-.30570 (4.310)	-.01777	-.15343 (2.494)	-.01122
If Married	-.03389 (.4107)	-.00197	-.10509 (1.469)	-.00769
Years of Schooling	-.03018 (3.670)	-.00175	.000524 (.0698)	.000038
Firm Tenure	.012478 (5.708)	.000725	-.07340 (26.20)	-.00537
If bad health	.415820 (6.804)	.024172	.026255 (.4500)	.001921
If Self Employed	-1.0009 (12.05)	-.05818	-.33567 (4.637)	-.02456
If Government Emp.	.246078 (2.729)	.014305	-.93012 (8.642)	-.06805
TAGLE60	-8.3673 (1.295)	-.48640	-19.522 (4.342)	-1.4282
TAG6164	-5.6297 (.9524)	-.32726	-8.5838 (.8049)	-.62799
TAG65PL	-22.836 (1.885)	-1.3275	24.5787 (1.221)	1.79816
SAGLE60	-.03694 (.8279)	-.00215	.015799 (.5536)	.001156
SAG6164	.034453 (.8247)	.002003	-.02448 (.3357)	-.00179
SAG65PL	.137088 (1.672)	.007969	-.19325 (1.427)	-.01414
Ind. Unemp. (Age le 60)	-.00112 (.0621)	-.00006	.117454 (10.10)	.008593
Ind. Unemp (61 le age le 64)	.008881 (.5776)	.000516	.082612 (3.442)	.006044
Ind. Unemp (age ge 65)	.020475 (.7526)	.001190	.063657 (1.447)	.004657
Y68	-.07643 (.2365)	-.00444	-.53160 (6.007)	-.03889
Y71	1.25501 (4.910)	.072956	.271240 (3.268)	.019844
Y73	1.97465 (7.974)	.114789	-.29295 (3.032)	-.02143
Y75	2.08965 (8.475)	.121474	-.32655 (2.964)	-.02389
Y76	1.29601 (4.988)	.075339	-1.2833 (8.514)	-.09388
Y78	2.00818 (7.899)	.116738	-.27982 (2.161)	-.02047
Y80	2.06162 (8.138)	.119845	.197431 (1.507)	.014444
Y81	1.36913 (5.193)	.079589	-1.4140 (6.753)	-.10345
Y83	2.52902 (9.638)	.147015	-.39094 (1.935)	-.02860

Log Likelihood -10100
Observations 22356
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Table A-6
Technological Change, On-the-Job Training, and Industry Unemployment Rate
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement coef.	Retirement derivative	Firm Change coef.	Firm Change derivative
CONSTANT	-17.681 (17.50)	-1.0237	-1.2924 (2.998)	-.09453
Age (le 60)	.239227 (13.74)	.013850	-.00108 (.1398)	-.00008
Age = 61	15.2076 (14.99)	.880465	.216898 (.4311)	.015864
Age = 62	15.0998 (14.87)	.874224	-.09318 (.1820)	-.00681
Age = 63	15.8050 (15.55)	.915052	.295801 (.5711)	.021635
Age = 64	16.3685 (16.08)	.947679	.845300 (1.602)	.061827
Age = 65	1.24604 (7.694)	.072141	.237318 (.9235)	.017358
Age (ge 65)	.222834 (14.53)	.012901	.007225 (.7378)	.000528
RACE	-.30535 (4.296)	-.01768	-.15158 (2.463)	-.01109
If Married	-.05469 (.6619)	-.00317	-.10669 (1.490)	-.00780
Years of Schooling	-.03006 (3.625)	-.00174	.000652 (.0867)	.000048
Firm Tenure	.012748 (5.812)	.000738	-.07322 (26.11)	-.00535
If bad health	.425947 (6.952)	.024661	.029871 (.5115)	.002185
If Self Employed	-.91621 (10.91)	-.05304	-.32293 (4.430)	-.02362
If Government Emp.	.279979 (3.086)	.016210	-.92434 (8.580)	-.06761
TAGLE60	-6.8520 (1.064)	-.39670	-19.501 (4.340)	-1.4263
TAG6164	-2.4616 (.4133)	-.14252	-8.1158 (.7533)	-.59361
TAG65PL	-12.153 (.9795)	-.70361	30.3991 (1.508)	2.22345
SAGLE60	-.02960 (.6583)	-.00171	.021087 (.7255)	.001542
SAG6164	.036185 (.8606)	.002095	-.02593 (.3562)	-.00190
SAG65PL	.136356 (1.657)	.007894	-.17765 (1.302)	-.01299
RQT (AGE LE 60)	-.00699 (2.920)	-.00040	-.00155 (1.092)	-.00011
RQT (61-64)	-.00863 (4.109)	-.00050	-.00147 (.4227)	-.00011
RQT (65 +)	-.01156 (3.068)	-.00067	-.00882 (1.454)	-.00064
Ind. Unemp. (Age le 60)	-.01606 (.8868)	-.00093	.111974 (8.827)	.008190
Ind. Unemp (61 le age le 64)	-.00651 (.4176)	-.00038	.080701 (3.204)	.005903
Ind. Unemp (age ge 65)	.005300 (.1962)	.000307	.051530 (1.167)	.003769
Y68	-.07510 (.2322)	-.00435	-.53161 (6.006)	-.03888
Y71	1.25037 (4.886)	.072392	.268822 (3.237)	.019662
Y73	2.00957 (8.103)	.116347	-.28562 (2.950)	-.02089
Y75	2.12509 (8.611)	.123035	-.32406 (2.936)	-.02370
Y76	1.40226 (5.384)	.081186	-1.2575 (8.231)	-.09198
Y78	2.09061 (8.210)	.121038	-.25897 (1.981)	-.01894
Y80	2.10304 (8.289)	.121758	.205898 (1.567)	.015060
Y81	1.44040 (5.454)	.083394	-1.4001 (6.660)	-.10241
Y83	2.62214 (9.969)	.151812	-.36388 (1.791)	-.02661

Log Likelihood -10082
Observations 22356
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Table A-7
OUTPUT GROWTH and
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement coef.	Retirement derivative	Firm Change coef.	Firm Change derivative
CONSTANT	-17.714 (17.60)	-1.0291	-.69816 (1.652)	-.05170
Age (le 60)	.236495 (13.70)	.013743	.000508 (.0664)	.000038
Age = 61	15.0289 (14.76)	.873353	.018703 (.0388)	.001385
Age = 62	14.9090 (14.63)	.866381	-.29924 (.6104)	-.02216
Age = 63	15.6237 (15.33)	.907915	.027612 (.0555)	.002045
Age = 64	16.1669 (15.85)	.939485	.555715 (1.110)	.041151
Age = 65	1.27404 (7.872)	.074036	.179123 (.6985)	.013264
Age (ge 65)	.216337 (14.38)	.012572	-.00616 (.7490)	-.00045
RACE	-.30569 (4.314)	-.01776	-.14342 (2.343)	-.01062
If Married	-.03447 (.4176)	-.00200	-.09395 (1.321)	-.00696
Years of Schooling	-.02911 (3.522)	-.00169	-.00639 (.8464)	-.00047
Firm Tenure	.011772 (5.434)	.000684	-.07856 (28.24)	-.00582
If bad health	.416761 (6.820)	.024218	.031475 (.5424)	.002331
If Self Employed	-.99619 (12.17)	-.05789	-.26095 (3.644)	-.01932
If Government Emp.	.280960 (3.142)	.016327	-.78872 (7.396)	-.05840
QAGLE60 ♪	-4.2237 (1.450)	-.24544	-10.524 (5.012)	-.77935
QAG6164	-2.7244 (.9957)	-.15832	-4.7126 (.9992)	-.34897
QAG65PL	-2.2558 (.3910)	-.13109	5.21678 (.5402)	.386305
Shock of output (age le 60)	-.11013 (2.216)	-.00640	-.04621 (1.402)	-.00342
Shock of output (61-64)	-.04108 (.8558)	-.00239	.052442 (.7630)	.003883
Shock of output (65+)	-.20258 (2.661)	-.01177	-.08158 (.7201)	-.00604
Y68	-.09811 (.3030)	-.00570	-.54434 (6.103)	-.04031
Y71	1.12955 (4.305)	.065640	.182840 (1.952)	.013539
Y73	2.05323 (8.341)	.119316	.094722 (1.029)	.007014
Y75	1.96193 (7.786)	.114011	-.16801 (1.450)	-.01244
Y76	1.24919 (4.870)	.072592	-.58988 (4.404)	-.04368
Y78	2.10740 (8.399)	.122464	.271631 (2.250)	.020114
Y80	2.07283 (8.240)	.120455	.516960 (4.110)	.038281
Y81	1.27180 (4.820)	.073906	-.87836 (4.235)	-.06504
Y83	2.43839	.141698	.101025 (.5016)	.007481

Log Likelihood -10171
Observations 22356
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

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

Table A-8
Technological Change, On-the-Job Training, and <u>OUTPUT GROWTH</u>
The Likelihood of Retirement and Firm Mobility
Multinomial Logit Estimation Results

	Retirement		Firm Change	
	coef.	derivative	coef.	derivative
CONSTANT	-17.820 (17.67)	-1.0285	-.57244 (1.355)	-.04215
Age (le 60)	.240380 (13.83)	.013874	.000751 (.0980)	.000055
Age = 61	15.3478 (15.17)	.885805	.054209 (.1174)	.003992
Age = 62	15.2437 (15.06)	.879799	-.25559 (.5422)	-.01882
Age = 63	15.9505 (15.74)	.920595	.072750 (.1519)	.005357
Age = 64	16.5236 (16.28)	.953669	.611375 (1.261)	.045022
Age = 65	1.23189 (7.581)	.071099	.228900 (.8929)	.016856
Age (ge 65)	.226621 (15.07)	.013079	-.00016 (.0202)	-.00001
RACE	-.30487 (4.288)	-.01759	-.14623 (2.384)	-.01077
If Married	-.05606 (.6770)	-.00323	-.10913 (1.530)	-.00804
Years of Schooling	-.02686 (3.277)	-.00155	-.01208 (1.627)	-.00089
Firm Tenure	.012045 (5.473)	.000695	-.07540 (26.85)	-.00555
If bad health	.422879 (6.893)	.024407	.041384 (.7107)	.003047
If Self Employed	-.92041 (11.22)	-.05312	-.21998 (3.070)	-.01620
If Government Emp.	.321261 (3.528)	.018542	-.89618 (8.330)	-.06599
TAGLE60	-1.1246 (.1767)	-.06491	-31.325 (7.279)	-2.3068
TAG6164	2.92269 (.4939)	.168685	-22.990 (2.444)	-1.6930
TAG65PL	-1.8797 (.1490)	-.10849	28.1337 (1.406)	2.07179
SAGLE60	-.02236 (.4778)	-.00129	-.00529 (.1670)	-.00039
SAG6164	.052516 (1.253)	.003031	-.06070 (.8402)	-.00447
SAG65PL	.165216 (2.114)	.009535	-.16794 (1.324)	-.01237
RQT (AGE LE 60)	-.00592 (2.542)	-.00034	-.00652 (4.851)	-.00048
RQT (61-64)	-.00760 (3.679)	-.00044	-.00568 (1.678)	-.00042
RQT (65 +)	-.01009 (2.678)	-.00058	-.01025 (1.689)	-.00075
Output growth (Age le 60)	-1.9973 (2.535)	-.11528	.643303 (1.024)	.047373
Output growth (61 le age le 64)	-2.6308 (3.383)	-.15184	3.46394 (2.293)	.255087
Output Growth (age ge 65)	-5.4156 (3.382)	-.31256	.112802 (.0387)	.008307
Y68	-.12562 (.3880)	-.00725	-.54474 (6.065)	-.04011
Y71	1.12848 (4.362)	.065131	.210801 (2.376)	.015523
Y73	2.03458 (8.229)	.117427	-.06237 (.6723)	-.00459
Y75	1.97976 (7.945)	.114263	-.24278 (2.108)	-.01788
Y76	1.17224 (4.504)	.067657	-.60575 (4.285)	-.04461
Y78	2.12272 (8.418)	.122514	.114524 (.9378)	.008434
Y80	2.09401 (8.259)	.120857	.340861 (2.613)	.025101
Y81	1.21591 (4.587)	.070177	-.95321 (4.533)	-.07019
Y83	2.41632 (9.153)	.139459	.055780 (.2712)	.004108

Log Likelihood -10082
Observations 22356
Absolute t-statistics in parentheses.
The derivatives are the means of the derivatives calculated for each observation.

Data Appendix

The data is taken from the National Longitudinal Survey (NLS) of Older Men. A sample of approximately 5,000 men age 45 to 59 was drawn in 1966 and followed until 1983.

Below are the number of individuals observed in each of the surveys:

Year	Observations
66	5017
67	4743
68	4648
69	4379
71	4175
73	3951
75	3732
76	3487
78	3291
80	3001
81	2832
83	2632

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

Age	Freq.	Age	Freq.
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

Definitions:

Retirement: 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 are ignored. Also ignored are hours of work when defining retirement. See Lazear (1986) for different options of defining retirement.

Mobility: Whether the individual has changed an employer since the last survey.

On-the-Job Training (RQT): Our measure of RQT is taken from the 1978 wave of the Panel Study of Income Dynamics (PSID.) In that year individuals were asked: "on a job like yours, how long would it take the average new person to become fully trained and qualified?" Minor modifications were made with the original reports in order to correct or delete obvious errors. Individuals' reports were aggregated by industry and occupational classification. The results reported in the paper are based on aggregation by industry. See the text for details.

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