Training and early Retirement

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Abstract

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In this paper we analyze how retirement behavior is affected by a worker's firm-specific or general training history. Using US data from the National Longitudinal Survey of Older Men and controlling for the effects of technological change and workers' retirement preferences, we find that workers with a firm-specific training history retire earlier than workers with a general training background. This indicates that shared investments in firm-specific training are embedded in upward sloping earning profiles that create productivity-wage differentials for older workers.

JEL Codes: J14, J26, J31

Keywords: retirement, training, upward sloping earning profiles

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1 Introduction

The burden of population aging on public and private pension plans is one of the major challenges in industrialized countries. Responses to population aging focus in particular on increasing labor supply and delaying retirement. However, life-cycle literature predicts that employers often provide upward sloping earning profiles to workers with firm-specific skills, which create a productivity-wage gap for older workers. Therefore firms have an incentive to send older workers with firm-specific skills into early retirement (see Lazear, 1979; Blinder, 1982). On the other hand, it is assumed that workers with general skills are paid equal to their value of marginal product. This makes firms indifferent to the retirement of workers with perfectly general training, under the condition that no other transaction costs exist.

In this paper we contribute to the existing life-cycle literature by estimating the impact of workers' firm-specific and general training background on the likelihood of early retirement. By using the training indicators of Johnson (1996), we are able to increase insights in the causality between training background and retirement behavior. Moreover, we control for the effects of technological change on retirement, workers' retirement preferences and business cycle effects.

The paper is related to the literature on the existence of a productivity-wage gap for older workers (e.g Lazear, 1979; Blinder, 1982; Medoff and Abraham, 1981; Kotlikoff and Gokhale, 1992 and Dostie, 2006). These studies measured wage equation slopes in order to test the prediction that the wage curve will be steeper than the productivity curve and found that (i) earnings exceed productivity when old, and that (ii) job tenure and wage growth affect the likelihood of early retirement positively. Our theoretical framework builds on Blinder (1982), who developed a theoretical model on the relationship between firm-specific training, upward sloping earning profiles, the productivity-wage gap and mandatory retirement.

We find that workers with a firm-specific training history retire earlier than workers with a general training background. This supports the hypothesis that a productivity-wage gap for workers with a firm-specific training history induces firms to dispose of these older workers, while they are indifferent to the retirement of workers with a general training background. These findings are robust when controlling for clustering of standard errors and correcting our initial training indicators for job mobility.

This paper is organized in six sections. In the next section, we will discuss our theoretical framework. The data is described in Section 3. In Section 4, we present our estimation method. In Section 5, we will estimate the impact of workers' training history on retirement behavior. Summarizing conclusions are given in Section 6.

2 Theory: Training investments, backward loading earning profiles and early retirement

We consider an economy in which two types of training exist (Becker, 1975): general training and firm-specific training. General training increases a worker's productivity independently of the firm where he or she is employed. Following human capital theory, we assume that the costs of training in skills that are perfectly transferable to other firms will be borne by the worker. As the risk that these workers will leave the current firm is very large, workers will pay for the training course by accepting lower wages during the time that they participate in a training course. In case of general training, workers will be paid their value of marginal product (VMP) which makes firms indifferent to the retirement of workers with perfectly general training, under the condition that no other transaction costs exist (Dorsey and Macpherson, 1997).

Workers with firm-specific training have human capital that is valuable to the firm where they work, but not to other firms. This makes firms willing to bear a share of the costs of firm-specific training. Following Blinder (1982), we expect firms to bear a share of the training costs by paying workers a wage that exceeds the VMP during the period in which firm-specific training investments are made (period t_0). After the training investment, the firm pays a lower wage than VMP_t to recoup investment costs (until t_1 when training costs have been recovered).[1]

After period t_1, firms will have to make an agreement with their workers to share the returns of the training investment.[2] However, as Kennan (1979) remarked, any rent-sharing rule remains vulnerable to threats to terminate the contract by either side (bilateral monopoly problem). These threats to terminate the contract arise because workers as well as firms have an incentive to extract extra rent from the other party. The inability of firms to bind their workers results in a risk that they are not able to fully reap the rents of the training investment.

[1]The wage after a firm-specific investment may still be higher than elsewhere, as workers with firm-specific skills are more productive in their present firm than in other firms.

[2]The sharing of rents from firm-specific training investments is discussed by Hashimoto (1981). In the context of a risk of a layoff or quit, the central focus of the model developed by Hashimoto is that worker productivity is costly to evaluate. Firms only know the current productivity of the workers who they employ, while workers know their potential productivity. In the presence of such information costs, firms and workers will share the returns to firm-specific training in order to minimize the loss of separation. However, Hashimoto implicitly assumes that firms and workers will honor the agreement on the rent sharing of the return to firm specific investments (Johnson, 1996).

Kennan (1979) showed that informal bonding is used to prevent bilateral monopoly problems and to decrease the level of turnover. In the context of firm-specific training investments, upward sloping earning profiles can be seen as a bond to compensate employers for quitting while the obligation to pay severance pay in the case of a layoff can be seen as a bond to compensate the workers. An upward sloping earnings profile means that workers are paid less than their VMP when they are young (from t_1 until t_2) and are paid more than their VMP when they become older (from t_2 until t_3, the retirement age).[3] This creates a productivity-wage gap for older employees and reduces the uncertainty of earning the rents after a firm-specific investment for the firms, because employees have an incentive to stay with the firm as they will earn a high future wage relative to the wage they are able to earn elsewhere, while firms will have less incentives to extract extra rents when workers are young and provide severance payments in the case of layoffs to retain their labor market reputation.[4]

So, the earning profiles of workers with a firm-specific training history can be divided in several parts. First, there will be a period in which the firm invests in training and recoups the training investments (from t_0 until t_1):

$$\int_0^{t_1} (W_t - VMP_t)e^{rt}dt = 0. \tag{1}$$

[3]During the labor contract negotiations, the worker and the firm make an agreement in advance on the steepness of the backward loading earning profile and the retirement age (Blinder, 1982).

[4]Other explanations for incentives for long-term employment relationships are given by Lazear (1979) and Lazear and Moore (1984) who argue that to encourage employees to be trustworthy (and not to shirk), long tenure incentives should be created. Another reason is that long-term employment relationships reduce the transaction costs that accompany recruitment and hiring. Moreover, employers have more information on the ability of their own employees than on prospective employees, which enables them to offer long tenures to their most productive workers (Johnson, 1996).

in which r is the discount rate. The second period is the period in which the firm still pays under the value of marginal product in order to create the upward sloping earnings profile (from t_1 until t_2).

$$\int_{t_1}^{t_2} (W_t - VMP_t)e^{rt}dt < 0. \tag{2}$$

After t_2, the firm will pay wages that are higher than the value of marginal product until retirement:

$$\int_{t_2}^{t_3} (W_t - VMP_t)e^{rt}dt > 0. \tag{3}$$

The rents have to be divided in such a way, that workers have no incentive to quit their jobs, while firms wish to retain labor contracts with these workers. Following Blinder (1982), we assume that the present discounted value of the underpayments between t_1 en t_2 must be equal to the present discounted value of the overpayments (during the productivity-wage gap) between t_2 and t_3:

$$\int_{t_1}^{t_3} (W_t - VMP_t)e^{rt}dt = 0. \tag{4}$$

Because older workers with firm-specific skills earn more than their productivity, they have an incentive to retire later. On the other hand, the productivity-wage gap makes firms willing to dispose of older workers. To guarantee that the present discounted value of underpayments is equal to that of the overpayments, mandatory retirement is necessary.[5]

Due to mandatory retirement, workers with firm-specific skills are forced to retire, while firms are indifferent to retirement of workers with a general training background. Therefore, it can be expected that workers with a general training background will retire later than workers with firm-specific skills.

Moreover, firms may also be able to justify disposal of workers with firm-specific skills well before the contract retirement age t_3 in case of unanticipated changes. Because of imperfect information or stochastic variation in the value of leisure, market wage rates or VMP, firms are able to dispose of older workers. To avoid damaging their reputation, firms pay severance pay which compensates workers for the loss of earnings. These lost earnings are equal to the difference between expected VMP and expected earnings based on the upward sloping earnings profile, and are lower than the actual productivity-wage gap due to the stochastic changes.[6]

So, we have derived the testable hypothesis that firms are indifferent towards the retirement behavior of workers with general skills, while firms have an incentive to send workers with firm-specific skills into an early labor market exit.[7]

[5] In theory, a mandatory retirement age is determined during labor contract negotiations.

[6] Without severance payments, firms destroy their reputation and would soon find themselves without a labor pool to hire from as workers would not be willing to work for a firm that pays them below VMP up to time t_2 and fires them before t_3.

[7] It should be noticed that the distinction between general and firm specific training is based on strong theoretical assumptions. Although it may be relevant to loosen these assumptions by introducing imperfect competition in our analysis (see Stevens, 1994; Acemoglu and Piscke, 1998), the database utilized for our empirical analysis contains no information on firm or sector characteristics. However, by correcting the general training indicator for job mobility in our robustness analysis, we are able to indirectly analyze the effect of transferable forms of training on the likelihood of early retirement.

3 Data

The effect of training on early retirement is estimated using data from the US National Longitudinal Survey of Older Men (NLSOM). The NLSOM is a nationally representative survey of 5,020 men in 1966 between the ages of 45 and 59 who were questioned periodically until 1983. Individuals were interviewed 12 times with 1- and 2-year intervals. The NLSOM is a rich longitudinal dataset with detailed information on employment history, health limitations, demographics and personal characteristics. Detailed information on the variables used is given in Annex 1.

During each interview, respondents were asked about their major activity during the survey week. Based on this variable, we limit our analysis to workers who were not self employed.[8] Retirement status was determined for those who answered for the first time that they were retired. Approximately 49% of the workers in our sample retired between 1966 and 1983. In 1983, 1,554 workers reported that they were retired, 434 individuals were still working and 127 individuals workers were not able to work. 1,582 workers died before 1983. Interestingly, the majority of the workers retired before the institutional mandatory retirement age of 65 years (average retirement age is 63 years).[9] Only 15% of the workers retired before they reached the age of 60.

[8]Also, workers who reported a wage below 100 dollar are excluded from our analysis. This reduces our sample to 4,549 men.

[9]The institutional mandatory retirement age was 65 until approximately 1979. After 1979, the institutional mandatory retirement age shifted to 70 years. The shift in the institutional mandatory retirement age is not visible in our database due to the fact that a substantial amount of workers retired before 1980. However, there exists a large literature on the abolishment of mandatory retirement in the US, due to the stepwise amendments of the Federal Age Discrimination in Employment Act (ADEA). The ADEA was passed in 1967, and protected all workers aged between 40 and 65 from discrimination in hiring, firing and promotion on the basis of age. The first amendments in 1978 led to the shift in the mandatory retirement age in 1979, when the enforcement of these amendments intensified. After 1986 mandatory retirement has been forbidden. Most studies find that the end of mandatory retirement led to an increase in the retirement age, indicating that workers are indeed motivated to work longer due to backward loading earning profiles (e.g. Smith, 1991, Ashenfelter and Card, 2002).

Human capital development is influenced by participation in formal and informal training. Based on the NLSOM, we are only able to analyze the formal training element.The most relevant independent variables in our analysis are the measures of formal general and firm-specific training. In 1966, respondents were asked whether they had ever received formal training. More specifically, questions were asked on participation in vocational training (excluding on-the-job training), the type and duration of vocational training, whether respondents used the skills acquired through training on the current or last job and who sponsored the longest vocational training program.

The training information of the 1966 wave is used to construct two dummy variables analogous to Johnson (1996). Using the training history prior to 1966 implies that there is a sufficiently long period between training participation and retirement, reducing possible causality issues between our measures for training investments and retirement.[10] Both dummy variables are based on the longest vocational training program. The first variable serves as an indicator for firm-specific training history and equals 1 if workers had ever received company-sponsored training and still benefit from this training in their current job. The second dummy variable is a proxy for general training and equals 1 if workers had ever received other training such as course work at universities or technical institutes. Possibly, the incidence of specific training is overstated. Pre-1966 training may have been completed on a previous job, which may imply that the formerly acquired skills are not specific to the present job. However, by restricting training participation in the training indicators to people who still use the acquired training in their current job, we partially

[10]When considering the relationship between training and retirement of workers at the end of their career, it is hard to establish causality. Workers may anticipate retirement and base the decision to train on the expected retirement age. Therefore, we do not use the information on training behavior after 1966.

account for the overstatement of the incidence of specific training.[11]

In our analysis, we also control for the effects of skills depreciation. Information on individual skills depreciation is not available in the NLSOM. Therefore, the rate of technological change per industry in which individuals are employed will be used as a proxy for skills depreciation. The technological change variables are based on the rates of industry productivity change calculated by Jorgenson, Gollop and Fraumeni (1987) for 35 industry sectors.[12] Technological change is measured as the rate of change in productivity that is not accounted for by growth in the quantity and quality of physical and human capital. In a seminal paper, Bartel and Sicherman (1983), showed that it is relevant to make a distinction between the effects of gradual technological change and technological shocks on retirement. We have replicated their two technological change variables. The first variable is measured by the mean annual rate of technological change over the 10-year period before period t, which characterizes the long run differences in technological change between industries. The second variable is measured by the unexpected change in the rate of technological change, which is defined as a z-score.

Other control variables in our analysis that deserve some attention are health status and job tenure. The health variable is a lagged variable that is constructed from answers to questions on the limitations of health in the working situation. Here, the health limitations variable is coded 1 if the individuals' health limits work and coded 0 otherwise. In non-interview years, we assume that individuals had the same health limitations as in the

[11] The specific training indicator equals 0 for workers who trained in the past, but do not use this training in the current job.

[12] As technological change variables such as research and development intensity and the extent of computer usage are not available for all industry sectors, we have to use the indirect measures of Jorgenson, Gollop and Fraumeni (1987).

preceding year. For 1968, we use the answers to the questions on health change (health change compared to the previous year) and the effects of the health change on limitations at work. Job tenure is measured by using answers on questions on job tenure or the year they started working in the current or last job.

Lastly, we include four variables in our analysis to control for business cycle effects and retirement preferences: unemployment rate, output growth, a work commitment variable and one year lagged self reported yearly wages (in logs). The unemployment rate and output growth indicators are included to account for changes in the business cycle. The unemployment rate is measured for the civilian non-institutional population of 16 years and older and is based on BLS Household Annual Averages data. Output growth, like the technological change indicators, have been divided into two different variables indicating the gradual change and shock in output growth. Similar to Bartel and Sicherman (1993), the Jorgenson database is used for our indicators of output growth. The indicators have been calculated in the same way as the technological change indicators. The work commitment variable is added in our analysis to account for job motivation and retirement preferences of employees. The work commitment variable is based on the 1966 question whether respondents would stop or continue working, if they got enough money to live comfortably. In this study, work commitment is coded 1 if workers replied that they would continue to work and 0 if they were undecided or answered that they would stop working. We presume that workers who indicated that they would continue to work, derive less utility of leisure than workers who indicated to stop working. Higher yearly wages may also contribute to earlier retirement as workers with higher earnings are likely to have more savings.[13]

Insert Table 1 *about here*

Sample means and standard deviations of selected variables are given in Table 1. The table shows that approximately 4% of all the workers has a firm-specific training background, while 19% has a general training history. The mean gradual technological change is rather low with 0,6%. On average, the workers in our sample are relatively low educated (average is 9 years of education). Workers have an average tenure level of 15 years, are 51 years old in 1966 and are largely committed to their work (75%). 84% of the men in our sample is married, 32% is non-white and 35% has health problems.

4 Method

The determinants of retirement behavior of workers can be modelled in hazard regression models. The hazard function analyzes the probability of entering retirement at a certain age t, conditional on that individuals do not retire before that age, and can be denoted as:

$$h(t) = \lim_{dt \to 0} \frac{Pr(t \leq T < t + dt \mid T \geq t)}{dt} = \lim_{dt \to 0} \frac{F(t + dt) - F(t)}{dtS(t)} = \frac{f(t)}{S(t)} \tag{5}$$

where T is a random variable with a continuous probability distribution $f(t)$, where t is the realization of T (retirement). $S(t)$ is the survival function which gives the probability

[13] On the condition that the wealth effect dominates the substitution effect between earnings and leisure.

that the spell in which workers remain working is at least t. To estimate the effect of training and technology on retirement behavior, we use a parameterized proportional hazard model with a Weibull distribution.[14] The Weibull hazard function and survival function are:

$$h(t) = p\lambda t^{p-1} \quad (6)$$

$$S(t) = exp(-\lambda t^{p})$$

where λ is parameterized $\lambda = exp(X\beta)$ and p is the ancillary parameter. X contains several covariates that are expected to influence the retirement decision. Robust standard errors are adjusted for intragroup correlations across industries.[15]

5 Results

5.1 Training and tenure

The theoretical framework of Blinder (1982) is based on the assumption that firm-specific training increases the demand for longer tenure, so that firms can benefit from the rents resulting from the investment. This can be established by providing upward sloping earning

[14]The Weibull distribution is suitable for modelling data with monotonous hazard rates that either increase ($p > 1$) or decrease with time ($p < 1$).

[15]We also estimated models accounting for unobserved heterogeneity across industries and occupations by including a frailty term. We used several distributions for the frailty term. However, the results are not fundamentally different from the models without a correction for unobserved heterogeneity.

profiles. Therefore, before we estimated the effects of training and technological change on retirement behavior, we first analyzed whether this assumption holds by estimating the correlation between training and tenure rates with OLS. The results of the OLS estimation are presented in Annex 2 and show that our indicator for a worker's firm-specific training history is significantly positively correlated with tenure, while a general training background is significantly negatively correlated with tenure.

Moreover, we analyzed whether our data is compatible with upward sloping earning profiles. Although we are not able to establish the existence of upward sloping earning profiles, as we do not have information on the earning profiles of workers before the age of 46, we are able to compare the wage levels of workers older than 46. Based on our theoretical framework, we would expect that older workers with firm-specific skills earn more than workers with general skills. Figure 1 shows the earning profiles of workers aged 46 in 1967. To avoid possible selection effects due to early retirement of workers, we only display the profiles until this group reached the age of 55. As the figure shows, earnings of workers with firms-specific skills are indeed structurally higher than the earnings of workers with general skills or with no training background. This result, together with the strong correlation between firms-specific history and tenure, suggests that upward sloping earning profiles are present.

Insert Figure 1 *about here*

5.2 Training history and early retirement

In Table 2 we first present the estimation results of the parametric hazard specification.[16] Our estimation results in column 1 show that the human-capital variables affect workers' retirement behavior significantly in the way we expected. We find that older workers with a firm-specific training history have a significantly higher likelihood to retire earlier, while we do not find any effect of general training history on retirement behavior. This confirms our expectation that backward loading earning profiles lead to a productivity-wage gap for older workers with firm-specific training, giving firms an incentive to send these workers into an early labor market exit.

Considering the results for the other variables, we can see that they are consistent with expectations. The likelihood of retirement increases with a worker's age and wage level. The coefficient of the health limitations variable is strongly significant and has a positive sign, indicating that workers with bad health have a larger likelihood to retire earlier. Workers with more years of schooling retire later. White older workers retire earlier. Government employees retire earlier than non-government employees. Work commitment has a significantly negative effect on the likelihood to retire. Marital status does not affect retirement behavior. The results for the technological change indicators deviate from the earlier findings of Bartel and Sicherman (1993). We do not find that gradual technological change and technological shocks have a significant effect on the likelihood of early retirement.

Columns 2 and 3 of Table 2 present the same analysis with industry dummy vari-

[16] 1/p is positive, smaller than 1 and significant at the 1% level, which indicates that the hazard of failure (retirement) increases with time.

ables and interaction effects between technological shocks and our training indicators, respectively. As the table shows, including industry fixed effects does not lead to large deviations from our initial results. The interaction effects between technological shocks and the training indicators give an indication of the effects of stochastic changes in VMP on the labor market position of workers with firm-specific or general training. The coefficients of the interaction effects are not significant, suggesting that firms do not dispose of their older workers before the mandatory retirement age.[17]

Insert Table 2 about here

5.3 Business cycle effects

Both early-retirement incentives and our technological change indicators may be subject to disturbances caused by cyclical factors. Early-retirement incentives may be a consequence of mass layoffs and increased uncertainty resulting from a recession. Also, our technological change indicators are based on the productivity growth indicators of Jorgenson, Gollop and Fraumeni (1987), which may not only include technological change, but also the utilization rate. Consequently, we control for fluctuations in the business cycle and include unemployment variables and output variables in our analysis.

The results of our analysis with the additional control variables for business cycle effects are presented in columns 1 and 2 of Table 3. Column 1 shows the estimation results including the unemployment variable, while Column 2 contains the analysis with the output variables. The table shows that gradual output growth has a significant

[17]However, due to the imperfect measurement of training and due to the fact that we do not observe productivity on an individual level, we cannot draw direct conclusions from these results

positive effect on the likelihood of early retirement while a high rate of unemployment has a significant negative effect. However, adding these control variables does not lead to large differences with our earlier findings. The firm-specific training history of workers remains to have a significant positive effect on the likelihood of retirement, indicating the robustness of our earlier findings.

Insert Table 3 *about here*

5.4 Alternative training indicators

Next, we constructed a training indicator which contains information on workers' pre-1966 training participation as well as information on training participation after 1966. As the likelihood of causality problems (between training investments and retirement) rises with the use of training data after 1966, we only include the training incidence of workers younger than 53. The newly constructed training indicators are based on data in 1966, 1967, 1969, 1971, 1976 and 1981. The firm-specific training indicator now equals 1 if workers who are younger than 53 years participated in company-sponsored training and still benefit from this training in their present work. General training equals 1 if workers younger than 53 years responded that they participated in other forms of training.[18]

Table 4 presents the results of our analysis with our newly constructed training indicators. As the table shows, firm-specific training now only has a weak significant positive effect on the likelihood of retirement.

[18] Although this additional analysis takes the training incidence after 1966 into account, we did not use training information of workers who were older than 52 years in 1966, because of potential causality problems. As our training history indicators only measure whether workers ever received training, we now lose potential useful information for workers older than 52 who did train before 1966.

Insert Table 4 *about here*

5.5 Job mobility, earning profiles and intermediate training forms

It can be expected that especially workers with steep upward sloping earning profiles are less mobile across jobs. Therefore, we conducted an additional robustness analysis in which we corrected our initial training history indicators for job mobility, i.e. the firm-specific indicator is coded 0 for workers with a firm-specific training history who changed jobs after 1966. Table 5 gives the results of our analysis with the training history indicators, corrected for mobility. Column 1 shows the estimation results of a parametric model with the firm-specific training history indicator corrected for job mobility. As expected, the coefficient of the firm-specific training indicator is higher and more significant than the coefficient of our initial indicator.

Insert Table 5 *about here*

Secondly, we also corrected our general training history indicator for job tenure. The general training history indicator, corrected for job mobility, provides us with a proxy for 'transferable training forms'. As Stevens (1993) and Acemoglu and Pischke (1998) noted, when labor markets are imperfect and labor market frictions and institutions compress and distort the structure of wages, firms will also invest in the general skills of their employees. These studies relaxed the assumption of perfectly competitive labor markets that underlies human capital theory, and showed that firm-sponsored training arises as an equilibrium phenomenon. Apart from this prediction, contrasting with standard human capital theory, these studies showed that the distortion in the wage structure turns general skills into some intermediate form of skills which may have firm-specific value (transferable training). The key of the noncompetitive training model is the superior information of current employers regarding its employees' abilities relative to the information available for other firms, which creates *ex post* monopsony power. This leads to a situation in which trained workers with general skills are not paid their full marginal product when they change jobs, making general skills $de\ facto$ specific, creating a situation in which firms and workers will share in the costs of both firm-specific training and general training. This makes firms also willing to provide upward sloping earning profiles to workers with general training. Therefore, it can be expected that due to upward sloping earning profiles, workers with an intermediate training background and still working in the same firm, retire earlier than workers with a general training history and working in another firm.

Column 2 of Table 5 give the results of our analysis in which both training indicators are corrected for job mobility. We now find that both the firm-specific training history indicator and the proxy for transferable training are positive and significant, although the size of the coefficient of the firm-specific training history indicator is larger. This confirms the expectation that firms also provide upward sloping earning profiles to workers with a general training background, on the condition that they have shared in the training costs. This provides firms with an incentive to send workers with both a firm-specific training history and a transferable training background into an early labor market exit.[19]

Lastly, we conducted an analysis with interaction effects between training (corrected for mobility) and our indicator for technological shocks. The results are shown in column 3 of Table 5. Again, we do not find evidence that technological shocks lead to earlier

[19]However, cautioun is necessary when interpreting these results, as workers who are still working at the same firm may have distinct characteristics which influence the retirement decision.

retirement of workers with a firm-specific training background.

6 Conclusion

In this paper we analyzed the relationship between workers' training history and early retirement in the perspective of a productivity-wage gap caused by backward loading earning profiles. The main finding is that workers with a formal firm-specific training history retire at an earlier age than workers with a general training background. This indicates that a productivity-wage gap for workers with a firm-specific training history gives firms an incentive to dispose of older workers with specific training. Even after controlling for technological change, work commitment, the effects of the business cycle and clustering of standard errors, the result that a firm-specific training history induces early retirement remains significantly positive.

The results presented in this paper are highly relevant for public policies that intend to stimulate labor force participation of the elderly, which have become popular recently in industrialized countries that face the problems of an ageing population. As our study demonstrates, the effectiveness of institutional arrangements to postpone retirement also depends on the training policies of firms.

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Table 1
Descriptive statistics

	Min	Max	Mean	Std. Dev.	Dummy: % Obs. coded 1
Retirement	0	1			48.80
Firm-specific training	0	1			4.08
General training	0	1			18.74
Gradual technological change	-.145	.034	.006	.012	
Technological shocks	-4.05	4.86	-.173	1.37	
Race	0	1			31.59
Marital status	0	1			83.84
Years of schooling	0	18.00	9.24	3.90	
Tenure	0	67.00	15.04	12.10	
Health limitations	0	1			35.32
If government employee	0	1			19.66
Self-employed	0	1			17.40
Age	45.00	59.00	51.50	4.27	
Commitment to work	0	1			74.94
Unemployment	3.50	9.60	6.57	1.84	
Output growth	-.038	.265	.037	.020	
Output shock	-5.25	15.35	-.049	3.07	
Wage level	33.51	50,000.00	6,276.18	4,407.11	

N = 4,549. In the Table, we give the percentage of workers who retired between 1966 and 1983. Observations are censored after the first retirement or until individuals dropped out of the survey. The firm-specific training and general training indicators are based on the question asked in 1966 whether workers had ever received formal training. Gradual technological change is the mean of yearly rates of industrial productivity change based on Jorgenson, Gollop and Fraumeni (1987). The variable which measures unexpected technological shocks is defined as a z-score. The Table gives the mean years of schooling. Output growth and outputs shocks are calculated analogous to our gradual technological change and technological shock indicators. The wage level is converted to constant 1966 dollars.

Table 2

Weibull regression results: Retirement, training history and technological change (robust standard errors in parentheses)

Dependent variable: Retirement	**(1)**	**(2)**	**(3)**
Constant	-22.594	-23.764	-23.769
	(1.067)***	(1.170)***	(1.165)***
Firm-specific training	.285	.239	.238
	(.090)***	(.084)***	(.085)***
General training	.038	.035	.029
	(.064)	(.064)	(.061)
Gradual technological change	.012	.139	.140
	(.044)	(.104)	(.104)
Technological shocks	.032	.012	.019
	(.035)	(.029)	(.034)
Int. technological shocks and firm-specific training			.051
			(.129)
Int. technological shocks and general training			-.038
			(.032)
Race	-.167	-.182	-.182
	(.051)***	(.054)***	(.054)***
Marital status	-.063	-.061	-.059
	(.080)	(.077)	(.078)
Years of schooling	-.046	-.035	-.043
	(.007)***	(.007)***	(.007)***
Health limitations	.660	.647	.649
	(.039)***	(.039)***	(.039)***
If government employee	.209	.438	.436
	(.093)**	(.127)***	(.127)***
Age	.205	.219	.219
	(.013)***	(.016)***	(.016)***
Commitment to work	-.462	-.411	-.411
	(.039)***	(.047)***	(.048)***
Log wage	.319	.221	.221
	(.051)***	(.048)***	(.048)***
Industry dummy variables		included	included
1/p	.266	.253	.253
	(.008)***	(.008)***	(.008)***
Log-Likelihood	-971.87	-892.83	-892.33
N	3,696	3,696	3,696

$*** < 0.01$, $** < 0.05$, $* < 0.10$.

Table 3
Weibull regression results: Retirement, training history and technological change, controlled for business cycle effects (robust standard errors in parentheses)

Dependent variable: Retirement	**(1)**	**(2)**
Constant	-23.545	-24.401
	(1.171)***	(1.099)***
Firm-specific training	.251	.253
	(.083)***	(.085)***
General training	.043	.044
	(.063)	(.064)
Gradual technological change	.124	.105
	(.086)	(.069)
Technological shocks	.024	.016
	(.026)	(.021)
Race	-.186	-.182
	(.054)***	(.054)***
Marital status	-.060	-.054
	(.079)	(.078)
Years of schooling	-.034	-.034
	(.007)***	(.007)***
Health Limitations	.644	.646
	(.040)***	(.039)***
If government employee	.435	.431
	(.126)***	(.127)***
Age	.219	.218
	(.016)***	(.016)***
Commitment to work	-.410	-.409
	(.047)***	(.047)***
Log wage	.220	.221
	(.047)***	(.050)***
Unemployment	-.103	
	(.017)***	
Gradual output change		.126
		(.058)**
Output shocks		.022
		(.018)
Industry dummy variables	included	included
1/p	.241	.241
	(.007)***	(.007)***
Log-Likelihood	-881.62	-882.87
N	3,696	3,696

$*** < 0.01$, $** < 0.05$, $* < 0.10$.

Table 4
Weibull regression results: Retirement, training (including training incidence after 1966) and technological change (robust standard errors in parentheses)

Dependent variable: Retirement	**(1)**	**(2)**
Constant	-24.593	-24.596
	(1.084)***	(1.082)***
Firm-specific training	.178	.177
	(.104)*	(.103)*
General training	.086	.084
	(.086)	(.083)
Gradual technological change	.098	.098
	(.071)	(.070)
Technological shocks	.017	.022
	(.021)	(.025)
Int. technological shocks and firm-specific training		.074
		(.143)
Int. technological shocks and general training		-.042
		(.036)
Race	-.186	-.186
	(.054)***	(.054)***
Marital status	-.054	-.053
	(.077)	(.078)
Years of schooling	-.035	-.035
	(.007)***	(.006)***
Health Limitations	.641	.643
	(.039)***	(.039)***
If government employee	.431	.429
	(.125)***	(.125)***
Age	.222	.222
	(.016)***	(.016)***
Commitment to work	-.414	-.415
	(.048)***	(.048)***
Log wage	.219	.219
	(.051)***	(.051)***
Gradual output change	.127	.128
	(.059)**	(.058)**
Output shocks	.021	.021
	(019)	(.019)
Industry dummy variables	included	included
1/p	.242	.242
	(.009)***	(.009)***
Log-Likelihood	-882.88	-882.45
N	3,696	3,696

$*** < 0.01$, $** < 0.05$, $* < 0.10$. The constructed training indicators are based on data in 1966, 1967, 1969, 1971, 1976 and 1981. The firm-specific training indicator equals 1 if workers younger than 53 years responded that they had received compony sponsored training and still benefit from this training in their present work. General training equals 1 if workers younger than 53 years responded to have received other forms of training. Although this additional analysis takes the training incidence after 1966 into account, we do not use training information of workers who were older than 52 years in 1966. As our training history indicators measure if workers ever received training, we may lose potentially useful information. Moreover, the likelihood of causality problems rises with the use of training data after 1966.

Table 5

Weibull regression results: Retirement, training history and technological change, corrected for mobility and business cycle effects (robust standards errors in parentheses)

Dependent variable: Retirement	**(1)**	**(2)**	**(3)**
Constant	-24.379	-24.322	-24.333
	(1.096)***	(1.078)***	(1.070)***
Firm-specific training	.378	.444	.444
(*corrected for mobility*)	(.119)***	(.121)***	(.121)***
General training	.046		
	(.064)		
General training		.338	.333
(*corrected for mobility*)		(.069)***	(.069)***
Gradual technological change	.104	.103	.103
	(.069)	(.069)	(.069)
Technological shocks	.015	.016	.019
	(.021)	(.021)	(.025)
Int. technological shocks and firm-specific training			.089
(*corrected for mobility*)			(.121)
Int. technological shocks and general training			-.029
(*corrected for mobility*)			(.052)
Race	-.182	-.168	-1.68
	(.054)***	(.052)***	(.052)***
Marital status	-.056	-.051	-.051
	(.077)	(.076)	(.077)
Years of schooling	-.035	-.038	-.038
	(.007)***	(.007)***	(.007)***
Health Limitations	.643	.656	.657
	(.040)***	(.041)***	(.041)***
If government employee	.434	.439	.439
	(.126)***	(.121)***	(.121)***
Age	.218	.217	.217
	(.016)***	(.016)***	(.016)***
Commitment to work	-.416	-.426	-.427
	(.048)***	(.050)***	(.049)***
Log wage	.219	.207	.208
	(.050)***	(.048)***	(.047)***
Gradual output change	.127	.131	.131
	(0.58)**	(0.58)**	(0.58)**
Output shocks	.021	.021	.022
	(.018)	(.019)	(.019)
Industry dummy variables	included	included	included
1/p	.241	.240	.240
	(.009)***	(.009)***	(.004)***
Log-Likelihood	-881.28	-870.41	-869.94
N	3,696	3,696	3,696

$***<0.01$, $**<0.05$, $*<0.10$. The training-history indicators are corrected for job mobility. The indicators are coded 0 for workers (with a training history in their previous job) who left their initial job after 1966.

Annex 1

For our analysis on the relationship between training, technological change and retirement behavior, we used data from the US National Longitudinal Survey of Older Men (NLSOM) for the period between 1966 and 1983. Our indicators for technological change originate from the KLEM database of Jorgenson, Gollop and Fraumeni (1987), which are matched to the NLSOM on industry level (2 digit).

Tables A1.1 and A1.2 show the frequency of retirement transitions for each year and cumulative percentages of retirement transitions at different ages. Table A1.1 shows that most retirement transitions took place after 1971 while it becomes clear from Table A1.2 that most workers retired between the age of 60 and 65. Lastly, definitions of all variables, utilized in our analysis, are given.

Table A1.1
Retirement transitions by year

Year	Retirement
1967	23
1968	52
1971	147
1973	390
1975	470
1976	244
1978	416
1980	346
1981	173
1983	330
Total	**2,591**

Table A1.2
Cumulative percentages of retirement transition by age

Retirement Age	Cumulative %	Retirement age	Cumulative %
47	0.1	61	27.0
48	0.2	62	40.8
49	0.4	63	52.7
50	0.5	64	64.7
51	0.7	65	76.9
52	1.3	66	87.2
53	1.8	67	91.3
54	2.7	68	94.9
55	4.4	69	96.3
56	6.2	70	97.8
57	8.0	71	98.6
58	10.6	72	99.3
59	14.7	73	99.6
60	19.6	74	99.9
		76	100

Retirement age is the age on which individuals retire for the first time. Observations were censored after the first retirement or until they dropped out of the survey. In total 2591 transitions into retirement are observed. Retirement transition takes place when workers state to be retired for the first time (main activity in last week before survey). Observations were censored after the first retirement or until they dropped out of the survey.

Variable definitions

Retirement	Retirement transition dummy. The variable is coded 0 if workers remain employed and coded 1 if workers retire. The variable is based on the question concerning the major activity during the survey week. Workers who answered to be retired are assigned the code 1. Observations for each individual are censored after the first retirement or until they dropped out of the survey.
Gradual technological change	Mean annual rate in technological change by industry over the 10-year period before period t. The variable is based on the KLEM dataset of Jorgenson, Gollop and Fraumeni (1987) and is measured as the rate of change in productivity that is not accounted for by growth in the quantity and quality of physical and human capital.
Technological shocks	Unexpected change in the industry rate of technological change. This variable is based on the KLEM dataset of Jorgenson, Gollop and Fraumeni (1987) and measures the deviation of technological change from the mean annual industrial rate of technological change divided by the standard deviation of all technological change observations by industry over the 10-year period before period t.
Firm-specific training	Firm specific training history. The variable is a dummy, based on the asked NLSOM question in 1966 on who sponsored the longest vocational training program. It concerns training participation during the working life of workers until 1966. The variable is an indicator for firm-specific training history and equals 1 if a worker replied that he had ever received company-sponsored training and still benefits from this training in his present work.
General training	General training history. The variable is a dummy, based on the asked NLSOM question in 1966 on who sponsored the longest vocational training program. It concerns training participation during the working life of workers until 1966. The variable is an indicator for general training history and equals 1 if a worker replied that he had ever received other forms of training than company sponsored training and still benefits from this training in his present work.
Race	Race dummy. Race coded 1 if non-white.
Marital Status	Marital status dummy. The variable is coded 1 if workers replied to be married (spouse may be present or absent during interview) and coded 0 if workers are divorced, separated, not-married or widowed.
Years of Schooling	Years of schooling. The years of schooling variable refers to the total number of years of schooling of individuals in 1966. After 1966, no information is available on the years of schooling of individuals. It is assumed that the number of years of schooling remains the same since 1966.
Tenure	Tenure. Job tenure is measured using answers on two types of questions. For 1967, 1968, and 1971, answers to 'tenure on current or last job' questions were used. For the other years, we constructed our tenure variable by using answers to 'year started working on current or last job' questions. By subtracting the age of workers in the year that they started working on their current or last job from the age of workers when interviews were held, we calculated tenure rates.

Health limitations	Health limitations. The 'health limitations' variable is a lagged dummy variable that is constructed from answers to questions on the limitations of health on the working situation. The variable is coded 1 if health limits work and coded 0 if health does not limit work. In non-interview years, we assume that individuals have the same health as in the adjacent year.
If government employee	If government employee. This dummy variable is coded 1 if workers work for the government and 0 if not.
Age	Age. This variable measures the age of respondents in 1966.
Commitment to work	Commitment to work. This dummy variable is based on the asked question in 1966 if respondents would stop or continue working, if they got enough money to live comfortably. The variable is coded 1 if workers replied to continue to work and 0 if they replied that they would stop working.
Unemployment	Unemployment rates. Unemployment rates of the United States, measured for the civilian noninstitutional population of 16 years. Source: BLS Household Annual Averages data.
Gradual output growth	Mean annual rate in output growth by industry over the 10-year period before period t. The variable is based on the KLEM dataset of Jorgenson, Gollop and Fraumeni (1987).
Output shock	Unexpected change in the industry rate of output. This variable is based on the KLEM dataset of Jorgenson, Gollop and Fraumeni (1987) and measures the deviation of output from the mean annual industrial rate of output growth divided by the standard deviation of all output observations by industry over the 10-year period before period t.
Log lagged wage	Wage. This wage variable measures self-reported net yearly wages for each individual. The variable is top coded on 50,000 dollar. All individuals who reported incomes under 100 dollar are removed from the sample.

Annex 2

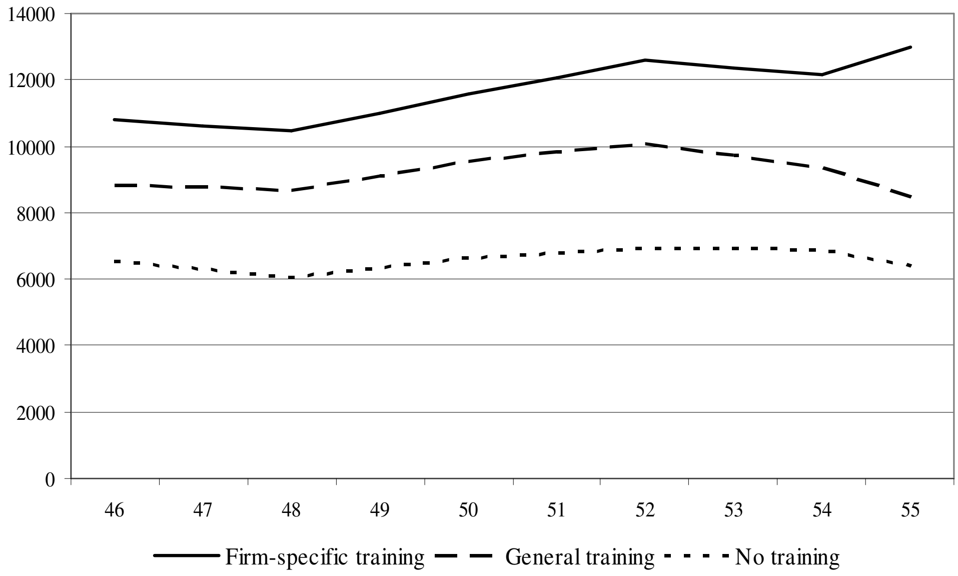
Table A2.1
OLS Regression results: Tenure and training
(robust standard errors in parentheses)

Dependent variable: Tenure	**(1)**	**(2)**
Constant	-81.724	-78.597
	(7.774)***	(7.709)***
Firm-specific training	1.379	1.598
	(.424)***	(.421)***
General training	-.615	-.472
	(.215)***	(.218)***
Gradual technological change	.087	.153
	(.078)	(.078)**
Technological shocks	.027	.041
	(.058)	(.058)
Race	1.893	2.075
	(.200)***	(.203)***
Marital status	1.311	1.118
	(.257)***	(.255)***
Years of schooling	-.067	-.084
	(.026)**	(.029)***
Health limitations	-.430	-.383
	(.197)**	(.194)**
If government employee	-1.108	-.879
	(.207)***	(.214)***
Age	1.436	1.361
	(.275)***	(.272)***
Age2	-.010	-.009
	(.002)***	(.002)***
Log wage	5.464	5.271
	(.1287)***	(.133)***
Year dummy variables	included	included
Occupatation dummy variables		included
Adjusted R-square	.132	.152
Observations	17,837	17,837

$*** < 0.01,\ ** < 0.05,\ * < 0.10.$

Figure 1

Earning profiles by type of training



Earning profiles of men aged 46 in 1967. Earnings in US dollars (deflated). Source: NLSOM