Technical Progress and Early Retirement

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Abstract

This paper claims that technical progress induces early retirement of older workers. Technical progress erodes technology specific human capital. Since older workers have shorter career horizons, there is less incentive for them or for their employers to invest in learning how to use the new technologies. Consequently, they are more likely to stop working. We call this effect the *erosion effect*. Since technical progress also raises wages in the economy as a whole and since technical progress is positively correlated across sectors, this presents an opposite effect of technical progress, which we call the *wage effect*. Using individual and sector data, we separate the two effects and find support for our theory.

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Technical Progress and Early Retirement

1. Introduction

The number of workers who quit working before they reach the formal age of retirement is surprisingly high. In 2005 the average labor force participation rate in OECD countries of men in ages 55-64 was 65.5 percent, while the labor force participation rate for men in ages 25-54 was 92.1 percent. Furthermore, it is quite a recent phenomenon. Labor participation rates for US men in ages 55-64 dropped from 86.7 percent in 1948 to 62.6 percent in 1996, recovering slightly to 68.7 percent in 2004. Early retirement is usually attributed to bad health, wealth, and to incentives by generous retirement plans like social security. This paper offers an additional explanation to early retirement: erosion of human capital by technical progress.

Technical progress changes continuously the way we produce goods and services. It introduces new goods, new machines and equipment, and new production methods. Simultaneously it creates new professions and destroys old ones. New technologies frequently make some existing human capital obsolete, while creating demand for new types of human capital. This paper proposes that human capital erosion by technical progress also reduces labor of older workers. It affects older workers more than younger ones, since their career horizon is much shorter. Hence it is less beneficial for them, or for their employers, to invest in learning the new technologies. The paper models this idea theoretically, examines its implications and finds significant empirical support for it, using micro US data.

The theoretical model describes a growing economy with many sectors. Each sector uses a specific technology, which requires specific human capital. Individuals learn and acquire technology-specific professions when young and then work using these technologies. Then new innovations arrive, replacing existing technologies while requiring workers to learn how to use these new technologies, via retraining. While younger workers learn the new technologies, many older workers choose not to learn, and retire early. Thus, technical progress raises the probability of early retirement. We call this the *erosion effect* of technical progress. Note that while in the model the worker decides on early retirement, in real life the decision is often made by the employer, who prefers not to retrain an older worker. The worker becomes unemployed and usually retires after some futile search for a new job. The basic result is the same.

But the model also enables us to consider the result of the positive correlation between rates of technical progress across sectors, which is implied by the data. This creates an opposite effect of technical progress, which we call the *wage effect*. In a period of high technical progress in all or most sectors, wages rise in the economy. As a result older workers tend to work more and delay retirement. The model shows that as a result, the average economy-wide rate of technical progress has an ambiguous effect on early retirement, because the erosion effect and wage effect work in opposite directions, while the sector component of technical progress has an unambiguous positive effect on early retirement, since it reflects only the erosion effect.

The empirical cross-sector prediction of the model is examined by US data on the labor status of a sample of men over the age of 50 from the Health and Retirement Study (HRS), which also includes information on job histories. This information is merged with sector productivity growth data, measured by Jorgensen (2000), which represents technical progress. We test how working status is affected by the sector specific component of technical progress, which we measure by the sector's rate of TFP growth minus the aggregate TFP growth. We find that the coefficient of the sector specific component of technical change on the probability of not working by older men is positive, while it is insignificant for younger workers. We also examine the possibility that this result is biased due to reverse causality, which might occur if sectors differ by lay-offs of older workers, and if the less productive workers are laid-off. We test an implication of this possibility and reject it. We also test the theory using an alternative measure of technical change, the ratio of equipment capital to labor, and the results are similar.

This paper is related to two different literatures, one on early retirement and the other on the effects of technical change on labor markets. The literature on early retirement has mostly focused on wealth, health and on greater financial incentives to retire.[1] The first paper that suggested that technical progress and early retirement are strongly related through erosion of human capital is Bartel and Sicherman (1993), from here on BS. Our paper follows this insight, but differs significantly in identifying the wage effect. We show that by not differentiating between the erosion effect and the wage effect, the test in BS is not well specified and leads to some wrong interpretations.[2] Our main contribution to this literature is therefore the general equilibrium theoretical model, which leads us to identify the wage effect.[3] This theoretical model leads us to use variables that can better differentiate between the wage and the erosion effects.

The paper is also related to recent research on the effect of technical progress on the labor market. Some papers in the new growth literature, like Aghion and Howitt (1994), Helpman and Trajtenberg (1998), Hornstein and Krusell (1996), and Galor and Moav (2000), have claimed that technical progress might reduce employment due to costs of learning new technologies. This paper shows that this effect is stronger for older workers, whose career horizon is short.[4]

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[1] See for example Stock and Wise (1990), Diamond and Gruber (1999), Costa (1998), Gruber and Wise (1997) and Gustman and Steinmeier (2000).

[2] Clearly, our disagreements with Bartel and Sicherman (1993) do not affect our admiration for their pioneering contribution on the erosion effect. The differences between the two papers are detailed in Sections 5.2 and 6.3.

[3] Our model is related to Boucekkine et al (2002), who discuss economic growth and retirement, but have no erosion of human capital and to Chari and Hopenhayn (1991), who analyze erosion of technology-specific human capital, but without retirement. Our model has both.

[4] Friedberg (2003) also points at the relationship between technology and age through use of computers.

The paper is organized as follows. Section 2 presents the basic model of technical progress, training and retirement. Section 3 describes the equilibrium and discusses the effects of technical progress on early retirement. Section 4 explains the empirical tests. Section 5 presents the basic empirical results on the effect of technical progress across sectors. Section 6 presents additional empirical tests and Section 7 concludes. The Appendix contains mathematical proofs, a theoretical discussion of BS, and more detailed empirical results.

2. The Model

Consider a small open economy in a world with one final good. The final good is produced by a continuum of intermediate goods $i \in [0, 1]$. The production of the final good is described by the following Cobb-Douglas production function:[5]

(1) $$\ln Y_t = \int_0^1 \ln X_{i,t} \, di ,$$

where Y_t is output of the final good, and $X_{i,t}$ are inputs of the intermediate goods. Time is discrete. The intermediate goods are produced by labor with fixed marginal productivity. A worker who uses the latest available technology in period t and works one unit of time produces an amount $a_{i,t}$ of the intermediate good i. The technology is not freely available, as it requires training and learning. Using a technology is therefore a specific profession.

We next describe technical progress. Each period new technologies of producing intermediate goods, which replace the old technologies, arrive exogenously. The new technologies in t become known in the beginning of the period and they change productivity:

(2) $$a_{i,t} = a_{i,t-1} b_{i,t} .$$

Technical change in sectors is assumed to be non-negative and bounded: $1 \leq b_{i,t} \leq B$. The lower bound is of course the case of no technical progress, while the upper bound B can be assumed to be 2.[6] The sector's rate of technical progress is therefore ln $b_{i,t}$.

We next assume that the rates of technical progress are correlated across sectors in each period. This assumption is reasonable since many new technologies are quite general and spread across sectors. It is also supported by the data, as shown below in Subsection 5.2. Formally, assume that the sector's rate of technical progress can be decomposed into an aggregate component g_t and a sector-specific component $s_{i,t}$ in the following way:

(3) $$\ln b_{i,t} = g_t + s_{i,t}.$$

Assume that the average rate of technical progress g_t is i.i.d. with a positive expectation g and the sector specific component $s_{i,t}$ is a white noise, independent both over time and across sectors. To ensure that the rate of technical progress in a sector is non-negative, assume that $s_{i,t} \geq -g_t$.

Individuals live two periods each in overlapping generations. Population is fixed and each generation consists of a mass of size 1. In first period of life each person acquires a profession i and supplies 1 unit of labor. The real life equivalent of this 1 unit of labor is around 30 years, from the age of 25, after acquiring a profession, to the age of 55, which is when workers are considered "older." In second period of life a person supplies only L units of labor, where $L < 1$, since some time Z is devoted to mandatory retirement. Since L describes the time to retirement, this career horizon in second period is decreasing with age. The older the worker, the shorter is L. If workers are considered older from age 55, then L can be equivalent to 10 years.

[5] It is easy to verify that the Cobb-Douglas production function is not necessary to any of the results below and they can be reached by using other constant returns to scale production functions, like CES.

[6] If a time period is between 25 to 30 years, this is an average annual upper bound of 3% on technical change, which we measure by TFP growth in a sector, as explained below. The fastest TFP growth in 1975-1996 was Agriculture, Forestry and Fishery that grew by an average of 2% annually. Thus, this upper bound is reasonable.

A worker in the second period of life can work using the previous technology and supply L units of labor. Alternatively, he can retrain and learn the new technology, but retraining requires time. This time depends both on the size of the technological innovation and on individual ability, which is idiosyncratic. Formally, f is a measure of individual learning inability, which is uniformly distributed on [0, F], where 0 is the worker who first learns the new technology and F is the slowest to learn. Retraining time is described by the function φ:

(4) $$\varphi(f, b_{i,t}).$$

Assume that retraining time is increasing and convex in technical change, namely $\varphi_b > 0$ and $\varphi_{bb} > 0$. If there is no technical change, retraining time is zero: $\varphi(f, 1) = 0$. The assumption that retraining time depends positively on the size of technical change is crucial to this paper, as it drives the erosion effect. A retraining worker supplies $L - \varphi(f, b_{i,t})$ units of labor in second period of life. For analytical convenience assume that part time work is spread uniformly throughout the period.[7] Retraining time is bounded by $\varphi(F, B)$, which is retraining time for the slowest worker and the largest technical change. A realistic value for this upper bound can be 2 years at most. Since L is equivalent to 10 years we get the following assumption:

(5) $$\varphi(F, B) < \frac{L}{5}.$$

A worker can also retire early in second period of life, earn no income, but enjoy utility from retirement. This utility differs across individuals as well, as it depends on age, health, and other individual parameters.[8] Formally, the utility function is

(6) $$U = u(c_1) + \mathrm{E}v(c_2, h).$$

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[7] This assumption is made to fit the idiosyncratic labor supply to a framework of discrete time.

[8] Interestingly, Ashenfelter and Card (2001) find that the elimination of compulsory retirement for professors has caused them to retire at different ages. This shows that retirement preferences are heterogeneous.

c_1 denotes consumption when young, c_2 consumption when old, and h is individual preference for early retirement. It is uniformly distributed between 0 and H, it is independent of f and equals 0 if there is no preference to retirement. If the individual does not retire early, $h = 0$ as well. The functions u and v are increasing and concave in consumption. The expectation operator is with respect to the unknowns in second period of life, which are the second period wages, technical progress in the sector, and also the individual parameters, namely second period effort of learning f and utility from early retirement h. We assume that the worker does not know them in first period, and they are revealed in second period of life only.

As mentioned above, the economy is small and open. We assume that the final good is fully traded, while labor and intermediate goods are non-traded. Capital is fully mobile and is traded at the world interest rate.[9] For simplicity assume that the world interest rate is 0. Markets are assumed to be perfectly competitive and expectations are rational. In order to simplify the analysis we further assume that there is no insurance for employment risk.

3. Equilibrium

3.1. Wages and Income

Let the final good be the numeraire. Due to Cobb-Douglas production (1), demand for intermediate good i in period t is described by:

(7) $$p_{i,t} = \frac{\partial Y_t}{\partial X_{i,t}} = \frac{Y_t}{X_{i,t}}.$$

The young choose professions in the beginning of period to maximize income, knowing which technologies will be used and hence what prices will prevail. Choice of sectors by the young

[9] Note that individuals only lend in this economy. Borrowers are from abroad and not modeled. It is easy though to add borrowers to the model, either as government or as firms.

equates incomes $p_{i,t}a_{i,t}$ across sectors, through adjustments of $X_{i,t}$.[10] Denote the common real income of the young across sectors by w_t and call it the wage rate:

(8) $$w_t = p_{i,t}a_{i,t} \quad \text{for all } i.$$

We next calculate this equilibrium real wage. First, note that (7) and (8) yield:

(9) $$X_{i,t} = \frac{Y_t}{p_{i,t}} = a_{i,t}\frac{Y_t}{w_t}.$$

Substitute (9) in (1) and get:

(10) $$\ln w_t = \int_0^1 \ln a_{i,t}\, di.$$

Hence, wage is equal to average total factor productivity (TFP). The rate of change of wages is

(11) $$\ln w_t - \ln w_{t-1} = \int_0^1 \ln b_{i,t}\, di = g_t.$$

Since labor is the only factor of production, the rate of change of wages is equal to the average rate of technical progress across sectors, namely to the growth rate of aggregate TFP.

To describe workers' incomes in second period of life note that prices of intermediate goods are the same for all producers, young and old. Hence, an old worker who retrains earns the same wage as the young, w_t. A worker who does not retrain faces competition from younger workers with a better technology and earns only $a_{i,t-1}p_{i,t} = w_t / b_{i,t}$. Thus, wages of old workers trapped in their previous professions are lower than wages of young or of old who retrain and are negatively related to sector technical progress. Intuitively, technical progress in a sector increases productivity, but not wages, due to entry of young workers. Since supply of the good increases, the price falls and the income of non-training old workers in the sector falls as well.

[10] Workers care about the future t+1 wages as well, but these expected wages are equal across sectors because future wages will be equalized across sectors by the next generation.

3.2. Decisions in Second Period of Life

In this model a person faces three decisions: choice of profession and allocation of income to consumption and saving when young, and in the second period of life choice between retiring, retraining, and using the old technology. We first study choice in second period of life. Let m_{t-1} denote savings by a worker born in t-1. Utility in second period of life if the worker retrains is

$$v\left[m_{t-1} + w_t L - w_t \varphi(f, b_{i,t}), 0\right]. \tag{12}$$

Utility in second period if the worker does not retrain and uses the old technology is

$$v(m_{t-1} + w_t L / b_{i,t}, 0). \tag{13}$$

Finally, utility if the worker decides to retire early, in the beginning of second period, is

$$v(m_{t-1}, h). \tag{14}$$

Compare first retraining to working in the old technology. Technical change reduces income of worker if he does not retrain due to competition by the young, but also if he retrains due to retraining time. A worker compares these two costs and retrains if (12) exceeds (13):

$$\varphi(f, b_{i,t}) \leq L\left(1 - \frac{1}{b_{i,t}}\right). \tag{15}$$

Note that the two sides are zero at $b_{i,t} = 1$, but the required retraining time at the LHS is convex in $b_{i,t}$, while the RHS of (15) is concave in $b_{i,t}$. Hence, if condition (15) holds at the upper bound of technical progress B and F, it holds everywhere. Applying (5) we get that at B the RHS, which is $L/2$, is larger than the LHS. Hence, condition (15) holds for all values of f and b.[11]

We next examine the decision whether to retrain and work or to retire early. A worker retires early in the second period of life if (14) exceeds (12), namely if:

[11] Note that even if (5) is not assumed, the main result of the paper on the erosion effect holds and is even stronger, since wages of workers who do not retrain, w_t/b, are lower and that raises the possibility of early retirement.

(16) $$v\left[m_{t-1}+w_t(L-\varphi(f,b_{i,t})),0\right]<v(m_{t-1},h).$$

Since this decision depends on past saving, we need to describe how saving is determined.

3.3. Saving Decision in First Period of Life

Following the results of the previous sub-section, a worker born in period t-1 chooses the amount of saving m_{t-1} that maximizes the following expected utility:

(17) $$\begin{aligned} &u(w_{t-1}-m_{t-1})+\underset{w_t,b_{i,t},f,h}{\mathrm{E}}\max\left\{v\left[m_{t-1}+w_t[L-\varphi(f,b_{i,t})],0\right],v(m_{t-1},h)\right\}= \\ &=u(w_{t-1}-m_{t-1})+\underset{g_t,b_{i,t},f,h}{\mathrm{E}}\max\left\{v\left[m_{t-1}+w_{t-1}e^{g_t}[L-\varphi(f,b_{i,t})],0\right],v(m_{t-1},h)\right\}. \end{aligned}$$

It is clear from this maximization that optimal savings m_{t-1} depend on previous wage w_{t-1}, on L, F and on H. Clearly, increasing F and H adds probabilities of retirement and thus increases savings, while L has an opposite effect. Denote the saving function by m, so:

$$m_{t-1}=m(w_{t-1},L,F,H).$$

3.4. Work or Early Retirement

Substituting m in (16) we get that a worker retires if:

(18) $$v\left[m(w_{t-1},L,F,H),h\right]>v\left\{m(w_{t-1},L,F,H)+w_{t-1}e^{g_t}[L-\varphi(f,b_{i,t})],0\right\}.$$

Equality in (18) defines a function h, which is the border between working and retiring:

(19) $$h=h(f,w_{t-1},b_{i,t},g_t,L,F,H).$$

In case that there is no equality in (18), h is set at H. It always exceeds 0, as can be seen in (18).

Lemma 1: The function h satisfies: $h_f<0,\ h_b<0,\ h_g>0,\ h_F<0,\ h_H<0\ and\ h_L>0$. The effect of w_{t-1} is ambiguous, due to an income effect through saving and a substitution effect through second period wages.

Proof: In the Appendix.

According to Lemma 1 the effect of sector technical progress b on early retirement is positive, since it increases retraining costs. This is the *erosion effect*. The effect of aggregate technical progress g is opposite, since it raises income from work. We call it the *wage effect*. The decision of workers in the second period of life is presented in Figure 1, where workers are distributed between 0 and H on the h axis and between 0 and F on the f axis. The negatively sloped curve is the function h, which divides the rectangle to W on the left, where workers retrain and continue to work, and to R on the right, where workers retire early.

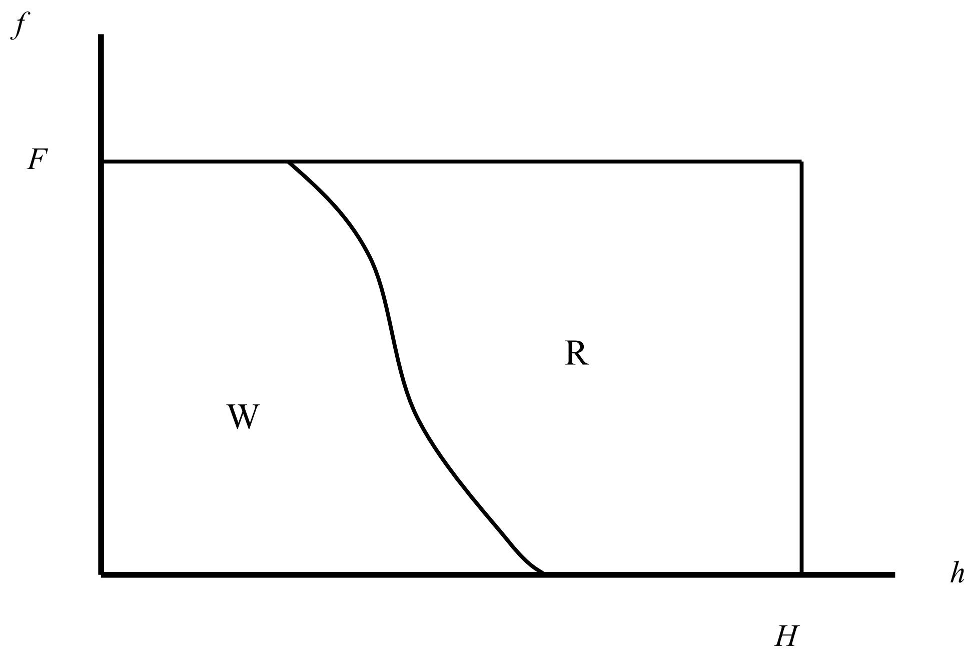

Figure 1

3.5. The Probability of Not Working

The probabilities of working and of early retirement are the areas of W and R in Figure 1, divided by *FH*, respectively. Note that the area of W is always positive, since *h* always exceeds 0. Calculating the probability that workers in sector *i* in time *t* retire early yields:

$$(20) \qquad P_{i,t} = 1 - \frac{\int_0^F h(f, w_{t-1}, b_{i,t}, g_t, L, F, H)df}{FH}.$$

This probability depends on various variables. The main variable of interest is the sector's rate of technical progress. A rise in $b_{i,t}$ shifts the curve in Figure 1 to the left and increases the area of early retirement. Hence, the probability of early retirement rises. This is the erosion effect of technical progress. The second important variable is the aggregate rate of technical change g_t, which has a negative effect on retirement, since higher wages induce older workers to work. Since g_t is positively correlated with $b_{i,t}$, we differentiate between the aggregate and the sector specific rates of technical progress by substituting (3) in (20) and get:

$$(21) \qquad P_{i,t} = 1 - \frac{\int_0^F h(f, w_{t-1}, g_t + s_{i,t}, g_t, L, F, H)df}{FH}.$$

It follows from (21) that the effect of the sector specific technical change *s* on early retirement is positive. This is the erosion effect. The overall effect of aggregate technical change *g* is ambiguous, as it involves the opposing erosion and wage effects. Note that equation (21) is more suitable for empirical estimation than (20), since its variables are independent. Thus only equation (21) can fully and accurately reveal the erosion effect.

Proposition 1: Denote the function of the probability of early retirement described in (21) by *P*: $P_{i,t} = P(w_{t-1}, s_{i,t}, g_t, L, F, H)$. This function satisfies: $P_s > 0, P_L < 0,\ P_F > 0, P_H > 0$, while the effect of g is ambiguous. The effect of the level of wages w_{t-1} is ambiguous as well, due to the conflicting income and substitution effects.

Proof: In the Appendix.

We next examine a specific utility function for which the effect of wages w_{t-1} on the probability of retirement becomes zero, as the income and substitution effect fully cancel one another. This of course does not change any of the other results, as they are obtained for a general specification of utility. It only abstracts from the long run effect of growth on early retirement, which is not the focus of this paper anyway. Assume that utility is described by the following logarithmic utility:

(22) $$U = u(c_1) + Ev(c_2, h) = \ln c_1 + E[\ln c_2 + \ln(1+h)].$$

The following Lemma shows that in this case wages have no effect on early retirement.

Lemma 2: Under (22) the probability of early retirement is $P_{i,t} = P(s_{i,t}, g_t, L, F, H)$, where the effects of the various variables and parameters are the same as in Proposition 1.

Proof: In the Appendix.

3.6. The Effect of Age

We next discuss the effect of age on the decision to retire. On the one hand younger workers have a longer career horizon L, so that even if they need to retrain the same time as older workers, they expect to enjoy this investment for a longer time and thus have a greater incentive to retrain. This is shown in Proposition 1, where L has a negative effect on the probability of early retirement. But on the other hand, younger workers can gain more from retirement, since they retire for a longer time. This is reflected in the positive effect of H on the probability of retirement in Proposition 1. These are the two opposite effects of age on early retirement.

To analyze these opposing effects we specify the model further. First we use the utility function (22). Second, we assume that H is proportional to the expected life horizon, which is $L + Z$, where Z is expected mandatory retirement: $H = d(L + Z)$. Note that the proportionality parameter d reflects the preference of leisure over consumption. This assumption implies that reducing age, namely increasing L, raises the career horizon L proportionally more than the retirement horizon H. This leads to the following result.

Lemma 3: If (22) holds and if $H = d(L + Z)$, the probability to retire early increases with age. If d is sufficiently low (d = .43), the probability of early retirement falls to zero already at the age of 50.

Proof: In the Appendix.

3.7. The Effect of Sector Technical Progress on Wages

In this subsection we analyze the effect of the sector's rate of technical progress on the average wage of older workers who keep working. We are interested in this effect for an empirical test in Subsection 6.1. Clearly the wages of workers who do not retire is reduced with technical progress, since they have to devote more time to retraining and their effective labor time is reduced. The average wage of these workers is described by the following calculation, with the overall pay to older workers in the nominator and their number multiplied by an old worker's labor supply L is in the denominator:

(23) $$w_t \frac{\int_0^F [1-h(f,w_{t-1},b_{i,t},g_t,L,F,H)][L-\varphi(f,b_{i,t})]df}{L\int_0^F [1-h(f,w_{t-1},b_{i,t},g_t,L,F,H)]df}.$$

It can be shown that sector technical progress $b_{i,t}$, or the sector specific technical progress $s_{i,t}$, has a negative effect on this average wage. Note that if $b_{i,t}$ is equal to 1, if there is no technical change in the sector, the average wage is w_t. If technical change in the sector is maximal, $b_{i,t} = 2$, the average wage is much above $.8w_t$, due to condition (5), and due to convexity of φ. Hence, the effect of technical change on the average wage is negative, but cannot be too big.

4. Empirical Implications of the Model

In order to examine whether our theory is supported by the data we conduct a series of tests of empirical implications of the model, using available US data. We start by estimating a simple Probit model, where the dependent variable is 'not working,' on a sample of men of age 50-64. To check robustness of the results, we estimate alternative specifications, such as adding more dependent variables, utilizing only sub-groups of the sample, and estimating a random effect model. These attempts isolate the various effects of sector-specific technical progress on the supply of labor by older men. While these tests are discussed in Section 5, Section 6 contains additional tests, like a test of the reverse causality hypothesis, a test that compares our results with those of BS, and a test that uses an alternative measure of technical change.

Our main empirical test is therefore an estimation of a reduced-form specification of equation (21), which describes the probability of retirement of older workers as a function of the sector component of the rate of technical progress $s_{i,t}$ and of the parameters L, F, and H. We do not include the variable g_t in the estimation since it is correlated with the time dummy in the panel regression. We also do not add the past wage level w_{t-1}, since it is basically similar for the periods of the panel, which span only a few years.

Formally we estimate the following Probit panel regression over three periods of the HRS data set:

$$Z_{j,t} = I_{j,t}\gamma + S_{j,t}\delta + \varepsilon_{j,t}, \tag{24}$$

where j runs over individuals, and γ and δ are vectors of parameters to be estimated. The dependent variable $Z_{j,t}$ is indicator for 'not working.' The explanatory variables are divided to two: a vector $I_{j,t}$ of personal time-varying and time-invariant characteristics, and a vector $S_{j,t}$ of indicators of the performance of the sector in which the individual held his *last main job*. We define the variable *last main job* as the most recent job, in which the worker has stayed for at least 5 years, and it is set anew each survey year. We next discuss in more detail the empirical counterparts of the variables in the theoretical model, beginning with the dependent variable, the probability of early retirement.

The main problem in finding empirical counterparts to the decision of older workers is that unlike the model, in which the decision of quitting is made by the worker, in reality and in the data a worker can also be fired.[12] We therefore use the fact that the data contain more information on not working statuses, and in addition to 'not working', we also estimate equation (21) with unemployment and retirement as alternative dependent variables.[13] Our data show that being unemployed is often a first stage in a process of leaving work, as laid-off older workers first search for a job, despair after some time and then drop from the labor force permanently.

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[12] See Table A1 in the Appendix for the distribution of reasons for leaving a job.

[13] We have also estimated a multinomial logit model with the three disjoint states of working, unemployed and retried. This model yields similar results to the Probit regression. To save space, we do not present them.

The main explanatory variable in our tests is the sector component of the rate of technical progress, $s_{i,t}$. Of course, this variable is not directly observed. We calculate it from the rate of growth of total factor productivity per sector, which we use as a measure for the sector rate of technical progress ln $b_{i,t}$. Although it was found in another paper by Bartel and Sicherman (1999) to be a good measure of technical progress, it has some problems nonetheless. The main one is that it reflects not only technical change, but also utilization. We deal with this problem in a number of ways. First, we average TFP growth rates over periods of 5 years, and second we add to some regressions sector output growth, to control for sector-specific demand shocks.[14]

The other parameters of equation (21) are approximated by personal characteristics that are observed in the data. Thus, age is a good indicator for the length of work horizon, *L*. Health is an indicator for the maximum utility from 'not-working' *H*, and the inverse of education is an indicator for *F*, which is related to the effort required to learn new technologies. Luckily, our data contain information on personal accumulated wealth and on pension funds as well. Hence, although these variables are endogenous in our theoretical model, data availability enables us to control for them as well.[15] Since these are past savings, they can be considered to be exogenous. Also, due to capital markets imperfections these variables are more exogenous in reality than in the model. Both wealth and pension status are expected to have a positive effect on retirement.

5. The Main Empirical Tests

5.1. The Personal Data

The main data sources are the first three interviews (1992, 1994, and 1996) of the Health and Retirement Study (HRS), which contain detailed information on a large group of individuals of

[14] This method is used in BS as well.

age 50 and above. The HRS contains information on their job and career histories in the 10 years prior to the 1992 interview. In the regression analysis, we restrict ourselves to men who were between 50 and 64 in the years of interviews, and who were in the labor-force two years prior to the present interview date, ending up with 13,471 observations of 5,217 individuals. We then merge the HRS data with Jorgenson's (2000) data set of output and total factor productivity (TFP) for 35 economic sectors, from 1970 to 1996.

Table 1: Work Status by Years and Age (Percents)

	1992			1994			1996		
	50-54	**55-59**	**60-64**	**50-54**	**55-59**	**60-64**	**50-54**	**55-59**	**60-64**
In the Labor Force									
Working	80.1	70.0	48.9	79.7	72.1	49.1	81.8	73.9	49.7
Unemployed	5.5	5.6	2.4	5.5	5.0	2.9	1.3	4.2	1.6
Out of the Labor Force									
Disabled	8.7	10.4	8.8	10.6	11.6	11.8	9.3	10.8	10.2
Retired	5.5	13.8	39.8	3.8	11.2	35.9	5.0	11.0	38.5
Other	0.2	0.2	0.1	0.4	0.1	0.3	0.2	0.1	0.0
No. of Observations	1,811	2,451	1,053	837	2,320	1,394	77	2,164	1,599

Data Source: Employment section of HRS, waves 1-3 (1992-1996)

Table 1 presents labor status shares across the three interviews, for three separate age groups: 50-54, 55-59, and 60-64. Table 1 confirms that not-working is quite common for men already in their early fifties: it is 20% in this group, compared with less than 5% for men 40-45

[15] This is equivalent to estimation of equation (16), where data on m_{t-1} is available. The results should be similar.

years old, as shown in Katz and Murphy (1992). The share of not-working increases steadily over time and reaches more than 50% in the older group. The reasons for not working are heterogonous.[16] Note that retirement becomes the major status among non-working men only after age 60. While only 11% to 14% are retired in age 55-59, more than 35% are in age 60-64.

Contrary to retirement, unemployment rates decrease with age in Table 1. Interestingly, these rates are much lower than the overall unemployment rates in the US at that time (7.5% in 1992 and 5.4% in 1996). Using transition matrix analysis, we find that most unemployed older workers are retired by the next interview, suggesting that unemployment is a transitional state between work and retirement. This result, and the fact that the share of disabled workers is unaffected by the explanatory variables, leads us to focus on 'not-working' as a main dependent variable. In addition, we also estimate the determinants of unemployment and of retirement.

Most of the variables in the vector $I_{j,t}$, such as age, race, immigration status, marital status and education, were determined many years prior to the survey and can be considered to be exogenous. Other variables, like pension status, union membership, and accumulated net wealth were also determined in the past, but might be more recent. Since they might also be correlated with sector, we add them only to some of the regressions to check robustness. Another variable in $I_{j,t}$ is whether profession in last main job has been a production or non-production.[17] This variable is used in some regressions to test for possible interaction with technical progress.

5.2. The Sector Data

The sector variables ($S_{j,t}$) are related to the last main job, which is defined in Section 4. We match the sector reported in the HRS, which has 14 sectors, to the relevant sectors in the

[16] Table A1 in the Appendix describes reasons for not working in the first HRS interview.

Jorgensen data set, which has 35 sectors. It is important to stress that this matching does not lose much information, since the sectors lost in the aggregation are fairly small. This is demonstrated in Table A2 in the Appendix.

We also examine correlations across sectors and over time of rates of TFP growth in the Jorgensen data. We find a strong correlation between the sector TFP growth and the average TFP growth across sectors. The correlation for the whole period 1960-1996 is 0.2918. The correlation is high also in each sub-period. Hence, these results justify the assumption made in the theoretical model, that sectors' technical change is correlated across sectors. This is the assumption that leads to the wage effect of technical progress. We also examine the correlation between the sector TFP growth and the sector average TFP growth over the years and find that it is positive as well, but smaller, 0.1980.

We next examine the persistence over time of TFP growth for sector specific and for the average TFP growth rates. We find that the average has strong persistence. The AR(1) coefficient is very significant and equal to 0.219. Testing for AR(2) we find that the two first lags are significant, where the first lag coefficient is 0.275 and the second lag is -0.218. Unlike the average TFP growth, the individual sectors' TFP growth rates do not show high persistence over time. In AR(1) regressions for randomly selected 4 sectors we found that in all but one the coefficient was insignificant. In AR(1) and AR(2) regressions for all sectors together the lag coefficients are very small and insignificant.[18] These findings cast some doubt on one of the main assumptions of BS, namely that a sector's past TFP growth rates are a predictor to the sector's future TFP growth. This point is further discussed in Section 6.2.

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[17] The professions we classify as production are: farming, forestry, fishing, mechanics and repair, construction, trade, extractors, machine operators, handlers and health services. The non-production professions are: managerial, high professional, sales, clerical, administrative, various services and members of armed forces.

Since rates of technical change are correlated across sectors, as shown above, we introduce a new variable, called 'net TFP growth,' to capture the sector's specific rate of technical progress $s_{i,t}$. To derive this variable we use the average rate of TFP growth in the sector during the 5 years prior to the relevant year of survey, which we denote by TFPG.[19] These averages are presented in Table A2 in the Appendix. We then calculate the aggregate TFP growth, denoted MTFPG, by averaging TFPG over all sectors, and then subtract it from the sector TFP growth to get net TFP growth: NTFPG = TFPG – MTFPG. This variable, the empirical counterpart of $s_{i,t}$, is the main sector variable in the analysis. The net TFP growth rate differs significantly across sectors and over time, as implied by Table A2. The sector output growth, which is also calculated as an average over the same 5 years, is denoted XG.

5.3. Labor Status Regressions

Table 2 and Table A3 present the main results of the labor status tests. Table 2 focuses on the effects of net TFP growth on labor status, while Table A3 reports the effects of the entire set of control variables from four representative regressions. Given the nonlinear form of the conditional expectation function associated with the Probit regression model, the quantitative magnitude of the effects of technical progress are not transparent from the coefficient estimates. Thus, Table 2 reports the effect of a one percentage-point increase in net TFP growth on the absolute probability of the labor status, calculated by using the normal density at the sample means, namely:

(25) $$\delta^* = \frac{\partial P_{labor \quad status}}{\partial (NTFPG)} = \phi(\bar{I}\hat{\gamma} + \bar{S}\hat{\delta})\hat{\delta}_{NTFPG},,$$

[18] In the AR(1) regression the lag coefficient is 0.02 and its t-value is 0.71. In the AR(2) regression the lag coefficients are 0.02 for the first lag, with t-value 0.67, and 0.04 for the second lag, with t-value 1.43.

[19] Actually the five years begin two years prior to the survey year, since job loss happens on average two years prior to interview.

where ϕ is the normal density function. Column 1 reports the effect of NTFPG on 'not working', Columns 2 on 'unemployed,' and column 3 on 'retired,' giving us a detailed view on the entire process of exiting from the labor force by old workers.

Table 2: The Effect of Sector Net TFP Growth on the Probability of Early Retirement

	Marginal effect on probability of:		
Model	**Not-Working**	**Unemployed**	**Retired**
1) Basic Model	**1.61** **(0.35)**	**0.45** **(0.12)**	**0.49** **(0.26)**
2) With Wealth, Union and Pension	**0.86** **(0.35)**	**0.37** **(0.11)**	0.13 (0.26)
3) Age 50-60	0.62 (0.36)	**0.47** **(0.15)**	-0.16 (0.23)
4) Random-Effect Model	**0.84** **(0.28)**	**0.41** **(0.15)**	0.18 (0.21)
5) Non-Production Workers	0.54 (0.45)	0.29 (0.17)	-0.12 (0.41)
6) Production Workers	**2.32** **(0.54)**	**0.31** **(0.16)**	0.54 (0.41)
7) With Output Growth	**1.58** **(0.35)**	**0.46** **(0.12)**	**0.52** **(0.27)**
Means of Dependent Variables	0.329	0.042	0.175

Notes:

1) Standard errors in parentheses. Significant coefficients, at 5% level, are in bold.

2) The number of observations in models 1, 2, 4 and 7 is 13,471; in model 3 is 9,490; in model 5 is 8,280; and in model 6 is 5,191.

For robustness check, each column reports estimates from 7 different specifications. The *basic model* includes the exogenous personal control variables and the sector variable net TFP growth (NTFPG). The second model adds three more personal variables: wealth, union membership, and pension fund membership (we include these three variables also in Models 3-6). The third model focuses on younger men in ages 50-60 only, to examine the effect of age. The fourth is a random-effects model. The fifth and sixth regressions test if net TFP growth has different effects on early retirement for production and for non-production workers. The seventh regression adds output growth (XG) to the explanatory variables of the basic model to control for possible demand changes that might be part of NTFPG.

The effect of net TFP growth on 'not working', across the seven models, is always positive. Furthermore, as we explain below, the differences in the magnitude of the effect (and the level of significance) provide strong evidence in support of our main hypothesis, that technical progress *pushes* many older workers in these sectors out of work, mainly to unemployment. The magnitudes of these effects are quite significant, as a one percent increase in TFP reduces the probability of employment by about 1.6 percentage-points in the basic model.

We claim that this effect of sector technical progress on 'not working' is limited to older workers. First, age has a positive effect on not working and unemployment given the quadratic function of the effect of age in the regressions in Table A3. Second, the erosion effect is weaker when we restrict the sample to men in ages 50-60 in model 3. Indeed, the effect of NTFPG on not-working becomes even insignificant for this group. Third, we conduct a similar test for younger workers, of ages 27-36, in the same years, 1992-1996, based on NLSY with 8,039 observations. The results of this test are presented in the Appendix in Table A4. The effect of

NTFPG on work status of young workers is insignificant. Hence, the positive effect of technical progress on ‘not working’ seems to hold for older workers only.

A more detailed examination of the results yields some more interesting conclusions. First, the effect of technical progress becomes weaker when we control for wealth, pension, and union membership in model 2. One possible explanation can be that wealthier workers have higher ability and thus are more likely to retrain. Another explanation is that there is a possible correlation between the wealth and sector variables, if sectors with high rates of technical progress have better wage and pension conditions as well. But even with these variables added, the effect of net TFP growth on ‘not working’ is still positive, which points to robustness. In model 4 we take advantage of the panel structure of the data and run a random-effect regression to check for robustness and find that even when controlling for unobserved individual effects, the main results of the model remain unchanged.

Models 5 and 6 provide more support to our hypothesis that the positive correlation between not working and technical progress is driven by erosion of human capital. These models test the effects of technical progress on production and non-production workers separately. Production workers usually use the more specific technologies of the sector, while non-production workers tend to use more general technologies of management and services. Hence, the human capital of production workers is expected to suffer more erosion from sector specific new technologies. The empirical results support it, as the effect on non-production workers is not significant, while the effect on production workers is stronger than the average.

Model 7 adds output growth to the basic regression to control for the possibility that some of the TFP growth reflects changes in demand. Adding this variable leads to very similar results, as shown in Table 2. We deal more with this possibility in Subsection 6.1. Column 2 in

Table 2 presents similar effects for unemployment. The magnitudes are lower than for 'not-working', but the significance level is higher. In general, the changes across the models are similar to those in the first column The effect of TFP growth on retirement is weaker, and except for the *basic model* is not significant. This fits the above observation that quite commonly unemployment is a first stage in becoming retired. Hence, unemployment is sensitive to technical change, while full retirement responds with a delay, which we are unable to fully identify in our regression analysis.

Finally, while this paper focuses mainly on technical progress, note that the estimated effects of other control variables, as reported in Table A3, are in line with those of Costa (1998), Peracchi and Welch (1994) and others, despite the different data sets. The results also fit most of the model predictions. Schooling has a negative effect on unemployment and on early retirement and bad health has a strong positive effect on early retirement. We also find, as in other studies, that wealth and pension tend to lengthen work at the individual level, which contradicts the theory in general and not only our model. One possible explanation for this finding is that these variables might capture some individual innate ability, which is related to retraining ability.

6. Additional Empirical Tests

6.1. Testing for Reverse Causality

This sub-section examines the possibility that the positive correlation found between sector TFP growth and retirement is due to reverse causality. This might occur if sectors differ by how many old workers they lay-off during declines in demand. Since firms prefer to keep only the best workers, reorganization might increase productivity. Such a mechanism can also create a positive correlation between sector TFP growth and not-working. We cope with this possibility in two ways. First, we include sector output growth in the test of labor status, since changes in demand are usually correlated with lay-offs. As reported in Table 2, the results are not affected significantly by including output growth in the regression. The second and main way we check the possibility of reverse causality is by testing the effect of sector TFP growth on wages of those who continue to work.

The reverse causality hypothesis implies that wages of old workers in sectors with higher TFP growth should be higher, since in sectors with more lay-offs, employers get rid of the less productive workers. Hence, under reverse causality we expect to find a positive correlation between TFP growth and wages across sectors, while according to our erosion model this correlation should be weakly negative, as shown in Section 3.7.

Table 3: Coefficient Estimates for the Wage Equations

	1. Basic Model	**2. Include Wealth Variables**	**3. Include Sector Dummies**	**4. Heckman Selection Model**	
				Wage Equation	**Status of Working**
NTFPG	-0.641	-0.167	2.648	1.173	**-2.26**
	(0.801)	(0.762)	(3.107)	(0.856)	**(0.955)**
R-square	0.15	0.24	0.17	NA	NA
Observations	7,897	7,897	7,897	13,471	13,471

Notes: standard errors in parentheses. Significant coefficients, at 5% level, are in bold.
Data Source: HRS, waves 1-3 (1992-1996)

Table 3 presents the regression results for sector net TFP growth on wages for four specifications of the wage equation. The effects of all other variables are presented in Table A5 in the Appendix. The main result of these regressions is that the effect of TFP growth on wages is not significant. In two specifications the coefficients are negative and in the other two are positive, but in all cases we are unable to reject the hypothesis that the coefficient is zero. Note that in this analysis we should be aware of the possibility of self-selection, as we test for the wages of those who have chosen to continue working. We control for self-selection using the Heckman procedure in Model 4, and test for both wages of working and work status. The main result is still unchanged: the effect of net TFP growth on wages of workers who still work is not significant. To conclude, the results of the tests reported in Table 3 demonstrate a rejection of the possibility of reverse causality and support the robustness of our results on the *erosion effect*.

6.2. Comparison with Bartel and Sicherman (1993)

To compare our results with those of BS note that they differentiate between the effects of expected and unexpected technical change in each sector. They assume that expected technical change increases early on-the-job training and thus workers stay longer in their jobs, namely it reduces early retirement. The unexpected technical change erodes human capital and thus increases early retirement. They measure the expected part of technical change by the previous ten years average rate of TFP growth, which we denote by $TFPG10_{i,t}$. They measure the unexpected part of technical change by a variable they call a shock to technology, which is defined by $TFPG_{i,t} – TFPG10_{i,t}$, normalized by the standard deviation. We denote it by $SHCK_{i,t}$. They find that the unexpected part of technical change has a negative effect on working, while the expected part has a positive effect on working, though both are insignificant (except above age 65). We claim that the main reason for these insignificant results is ignoring the wage effect. Acknowledging this effect enables us to better interpret the results and to choose variables that are better suited to identify the erosion effect. To show this we replicate in Table 4 the results of BS using our data and contrast them with our results.[20]

[20] Table 4 contains only the coefficients of the variables which are relevant for the comparison.

Table 4: Comparison with BS

	Not-Working			
	Model 1 -AZ Basic	Model 2 – BS Basic	Model 3 – AZ with Age	Model 4- BS with Age
NTFPG	**1.579**			
	(0.353)			
TFPG10		0.696		
		(0.408)		
SHCK		-0.128		
		(0.193)		
NTFPG (Age 60-)			**1.402**	
			(0.428)	
NTFPG (Age 61+)			**1.924**	
			(0.589)	
TFPG10 (Age 60-)				0.737
				(0.480)
SHCK (Age 60-)				0.425
				(0.665)
TFPG10 (Age 61+)				0.389
				(0.233)
SHCK (Age 61+)				**-1.178**
				(0.333)
No. of Individuals	5,217	5,217	5,217	5,217
No. of Person-Years	13,471	13,471	13,471	13,471

*Note:*1) standard errors are in parentheses. Significant coefficients, at 5% level, are in bold.
2)The other variables in the regressions are as in A3.

Table 4 presents results of four different regression models for comparison. Model 1 is the regression of the probability of not working using our variable NTFPG. Model 2 is the regression of the probability of not working on the BS variables, TFPG10 and SHCK. As in BS the two variables are insignificant in our data as well, although the signs of the coefficients are opposite. Since BS test the interaction between their variables and age groups we do the same for our variables in model 3 and for the BS variables in model 4. The results are still similar, since our variables come out significant while the BS variables are not significantly different than zero, except for the shock above age 61. Hence the main difference between our results and the

BS results is not due to the different data set and to different period of time, but due to the choice of variables. We next examine what are the possible reasons for these differences.

We claim that the variable which BS use, namely past average rates of sector technical change over ten years, does not measure well future expectations of technical change in the sector. This follows already Section 5.2 where it is shown that there is very weak persistence over time in sector TFP growth rates. Actually, this variable of past sector technical change can capture two separate possible effects. One possibility is the sector's all time average growth rate. Another possibility is that averaging sector growth rates over 10 years eliminates much of the sector specific technical change, but leaves the aggregate rate of technical change, due to its strong persistence, as shown in Section 5.2. Hence, it could be that past technical change reflects to some extent the future aggregate wage effect. To examine this possibility we calculated the correlations in Jorgensen's data between the BS variable of past technical change $TFPG10_{i,t}$ and two variables, the average technical change over all sectors in period t and the net current sector technical change, namely TFPG minus the mean. We found that the correlation between the BS variable and the average technical change is 0.2311, while the correlation between the BS variable and the net current sector technical change is only 0.0477. Hence, the BS variable reflects the aggregate technical change much more than the expected sector technical change.

Hence, the BS variable of the average over the past ten years of TFP growth captures both the sector's long run rate of technical change and also the aggregate rate of technical change. The first variable has a positive effect on early retirement, as both expected and unexpected technical change require retraining, as shown in Appendix II. The second element reflected in the BS variable, the aggregate technical change, has a negative effect on early retirement, due to the wage effect. The combination of these two effects explains why the results of BS, both in their data and in ours, come out insignificant. Hence, the BS variables do not sufficiently separate the aggregate and sector specific rates of technical change. Our paper extends their seminal work both in introducing a formal theoretical model, which analyzes the various effects of technical change on early retirement, and also in empirically testing these effects by an improved set of variables, that are implied by the model and that separate the erosion and wage effects from one another.

6.3. An Alternative Measure of Technical Change

Finally we examine the possibility of another measure of technical progress in addition to TFP growth. In another paper Bartel and Sicherman (1999) explore the issue of alternative measures of technical change and find out that most measures yield similar results with respect to the wages of young workers. The alternative measures that they use are investment in computers, use of patents, percentage of engineers, and investment in R&D. We chose not to use these alternative measures because they fit mostly the industrial sectors and the Bartel and Sicherman (1999) deals with industries only, while most of our sectors are not industrial. We therefore turned to another measure of technical change, which is the ratio of equipment capital to labor in each sector. This measure reflects the assumption that implementing new technologies usually involves using new equipment, or new machines. Our source of data on capital stocks in the US is the BEA (2007). We calculate this alternative measure of technical change in a similar way to our calculations of TFP growth. We calculate for each sector the average rate of growth of the ratio of equipment capital to labor in the previous 5 years and then calculate the net rate of growth. We denote this variable by NEQKLG. The main results of the estimation of the model using this variable are summarized in Table 5.

Table 5: The Effect of Sector Net Equipment Capital to Labor Growth on the Probability of Early Retirement

	Marginal effect on probability of being:		
Model	**Not-Working**	**Unemployed**	**Retired**
1) Basic Model	0.06 (0.17)	-0.03 (0.06)	**0.16** **(0.12)**
2) With Wealth, Union and Pension	**0.41** **(0.17)**	-0.02 (0.05)	**0.33** **(0.11)**
3) With Output Growth	0.21 (0.16)	-0.06 (0.07)	**0.33** **(0.12)**
Means of Dependent Variables	0.329	0.042	0.175

Notes:

1) Standard errors in parentheses. Significant coefficients, at 5% level, are in bold.

Table 5 shows that NEQKLG has a positive effect on not working and on retirement, but a mixed effect on unemployment, though insignificant. The effect of the variable on retirement is significant in all three models, and the effect on not-working is significant when the financial variables are controlled for. We can therefore claim that using this alternative measure of technical change supports the main claim of the paper.

7. Conclusions

This paper combines two distinct lines of research from two different areas in economics. One is the study of technical progress, which is usually related to economic growth and productivity, and the other is labor participation of older workers. We combine these two areas together by observing that technical progress has a substantial negative effect on labor supply of older workers, as it erodes technology-specific human capital mostly for older workers, who have a shorter career horizon.

But technical progress has an opposite effect on workers in other sectors, since it raises wages on average and thus increases the incentive to remain at work. Since technical progress across sectors is positively correlated, it means that technical progress has two opposite effects on early retirement, the positive erosion effect and the negative wage effect. In order to distinguish between the two effects empirically we test how the working status of older workers is affected by the sector specific component of technical progress in each sector, which is derived by deducting the aggregate rate of technical progress from the sector rate of technical progress. We find, using US data, that it increases unemployment and early retirement, as our model predicts.

Hence, technical change, which benefits many in the economy, by increasing productivity in general and income of many workers, might also cause losses to others in the economy, in our case to older workers, who find it too late in their work career to adjust to the new technologies. Understanding this issue can help us in many ways, among them in forming more efficient social policies. A possible extension of our paper is to try to directly estimate the retraining time of workers and how it is related to technical change. This can give us a better assessment of the potential costs of technical progress.

Appendix

I. Proofs

Proof of Lemma 1:

The function h is defined by:

(A.1) $$v(m,h) = v\left[m + w_{t-1}e^{g_t}\left(L - \varphi(f, b_{i,t})\right), 0\right]$$

Since v is increasing in h and since f and $b_{i,t}$ are increasing in φ we get that h depends negatively on f and $b_{i,t}$. Similarly h depends positively on g_t.

To analyze the effects of the other variables note that m has a negative effect on h since the marginal utility from consumption in the RHS is lower than the marginal utility of consumption in the LHS, due to diminishing marginal utility. Intuitively, higher savings make future work less beneficial, so they increase the propensity to retire. From equation (17) we get that the effect of F on saving is positive since a larger F reduces expected future income and thus increases future expected marginal utility from consumption. This increases savings and a larger m has a negative effect on h. This proves that $h_F < 0$. In a similar way it can be proven that h_H <0. Analyzing the effect of L is more complicated since it has a direct effect through (A.1) and an indirect effect through m. The direct effect is positive, as is clear from (A.1). As for indirect effect, (17) implies that a higher L reduces m, since second period income increases and thus reduces future expected marginal utility from consumption. Since m has a negative effect on h, the indirect effect of L on h is positive as well and hence $h_L > 0$. This proves the Lemma.

Proof of Proposition 1:

The effects of $s_{i,t}$, g_t and of L on $P_{i,t}$ follow immediately from applying Lemma 1 to equation (21). Since h_H is negative and the integral in (21) is divided by FH, the overall effect of H on $P_{i,t}$ is positive. For the effect of F on the probability of retirement return to Figure 1. A higher F

reduces h, so it shifts the curve in figure 1 to the left, which increases $P_{i,t}$. A higher F also shifts the top of the rectangle upward. Since the curve is downward sloping, this adds values of f with relatively lower values of h. Hence, it increases the area to the right of the curve relative to the rectangle. Hence the rise in F increases $P_{i,t}$ through both channels. This concludes the proof of Proposition 1.

<u>Proof of Lemma 2:</u>

Note that under specification (22) the expected utility (17) becomes:

$$\text{(A.2)}\ 2\ln w_{t-1} + \ln\left(1 - \frac{m_{t-1}}{w_{t-1}}\right) + \underset{g_t, b_{i,t}, f, h}{\mathrm{E}} \max\left\{\ln\left[\frac{m_{t-1}}{w_{t-1}} + e^{g_t}[L - \varphi(f, b_{i,t})]\right], \ln\left(\frac{m_{t-1}}{w_{t-1}}(1+h)\right)\right\}.$$

Clearly, the decision of the consumer is with respect to the share of saving in income only, since utility is homothetic and utility from retirement is multiplicative. Hence, savings m_{t-1} are proportional to wages: $m_{t-1} = w_{t-1}M(L, F, H)$ and the effect on the parameters is the same as in the general case.

Substituting in (18) we get that the condition to retire is:

$$\ln[w_{t-1}M(L,F,H)(1+h)] > \ln\{w_{t-1}M(L,F,H) + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\}.$$

This condition is therefore equivalent to:

$$\text{(A.3)} \qquad h > \frac{e^{g_t}\left(L - \varphi(f, b_{i,t})\right)}{M(L,F,H)}.$$

Hence, the function h does not depend in this case on the wage level, and so does the probability of early retirement. This concludes the proof of the Lemma.

<u>Proof of Lemma 3:</u>

With logarithmic utility the line between the areas of work and retirement is described by equality in (A.3). Since the saving rate M is always smaller than 1 and since $e^{g_t} \geq 1$ we get:

(A.4) $h \geq L - \varphi(f, b_{i,t}) \geq L - \varphi(F, B).$

Applying (A.4) to the calculation of the probability of retirement we get:

(A.5) $$P_{i,t} = 1 - \frac{\int_0^F hdf}{FH} \leq 1 - \frac{L - \varphi(F, B)}{H} = 1 - \frac{L - \varphi(F, B)}{d(L + Z)}.$$

Clearly, this bound on the probability is negatively related to L. Hence, younger workers will have a lower probability of early retirement.

Note that this bound is equal to zero if $L = \varphi(F, B) + d(L + Z)$. If Z is equivalent to 15 years, from 65 to 80, and if we follow our assumption that $\varphi(F, B)$ is equivalent to 2 years, then the bound will be zero for workers at the age of 50, namely with L equivalent to 15, if $d \leq 13/30 = .43$. Note that for d = .43 the bound on probability of retirement at the age of 55 rises from zero to .26.

We therefore conclude that if workers prefer consumption over leisure sufficiently, early retirement is very sensitive to age and falls significantly if workers are slightly younger. This concludes the proof of the Lemma.

II. Implications of Persistence of Technical Change

In this appendix we examine what happens if technical change is not correlated across sectors in each period, but rather correlated over time. In other words, some sectors have higher technical change on average than others. This case is studied here in order to examine the prediction of BS that such correlation might lead to less retirement in the sectors with faster technical change.

Assume that the model is the same as the benchmark model in the paper, except for equation (3). Instead assume that technical progress in a sector is correlated over time. Formally, technical change satisfies:

(A.6) $$\ln b_{i,t} = s_i + d_{i,t}.$$

The variable s_i is the sector's long-run average rate of technical change, while $d_{i,t}$ is its idiosyncratic component, and is independent across sectors and over time. Under this specification the wage rate in the economy satisfies:

(A.7) $$\ln w_t = \int_0^1 \ln a_{i,t}\, di = \int_0^1 \ln a_{i-1,t}\, di + \int_0^1 \ln b_{i,t}\, di = \ln w_{t-1} + s,$$

where s is the average long-run growth of all sectors: $s = \int_0^1 s_i\, di$.

The rest of the solution of this model is the same as in the benchmark model, except that the condition for retirement becomes:

(A.8) $$v[m(w_{t-1}, L, F, H), h] > v\{m(w_{t-1}, L, F, H) + w_{t-1} e^{s} [L - \varphi(f, e^{s_i} e^{d_{i,t}})], 0\}.$$

It follows from (A.8) that h depends negatively both on s_i and on $d_{i,t}$. Hence, the probability of early retirement depends positively on both variables. This is opposite to the prediction of BS that the sector long-run technical change reduces early retirement since workers expect higher wages in the future. The reason for the different result in the model is that if technical change in the sector is expected to be high in the future, the sector attracts more young workers and they mitigate the effect on wage. Hence, the erosion effect is more powerful and it increases early retirement.

III. Additional Tables

Table A1: Reasons Respondent Left Previous Job (percent)

	People not working in 1992				People working in 1992			
	50-54	**55-60**	**60-64**	**All**	**50-54**	**55-60**	**60-64**	**All**
Business Closed	13.0	13.4	5.6	10.6	21.2	25.2	27.8	24.0
Laid-Off or Let-Go	21.7	18.2	10.6	16.3	12.4	13.7	12.2	13.0
Family Reasons (health, moved...)	21.4	18.1	9.0	15.6	8.3	6.9	5.1	7.2
Better Job	9.0	7.3	6.4	7.3	29.4	24.8	25.1	26.7
Quit	11.4	6.8	5.6	7.3	23.9	21.2	16.4	21.6
Retired	23.4	36.3	62.8	42.7	4.7	8.2	13.4	7.6
No. of observations	299	659	500	1,458	900	1,088	335	2,323

Note: Sources are questions 3612-3619 in the Job History section of the HRS Wave 1. The questions: "Why did you leave this employer (Did the business close, were you laid off or let go, did you leave to take care of family members, did you find a better job, ... or what)"?

Table A2: 5 year Average of TFP Growth by Sectors and Years

	Sectors in HRS	Sectors' # in Jorgenson	Share of HRS Employment	TFP Growth 1992	TFP Growth 1994	TFP Growth 1996
1	Agriculture, Forestry, Fishing	1	5.54	2.30%	2.59%	2.18%
2	Mining and Construction	2-5	6.29	4.33%	3.90%	1.26%
3	Manufacturing: Non-durable	7-10, 15-18	8.46	0.23%	1.09%	1.26%
4	Manufacturing: Durable	11-14, 19-27	14.76	0.85%	0.89%	1.57%
5	Transportation	28	10.08	1.07%	0.96%	0.20%
6	Wholesale	32	5.44	0.84%	0.79%	0.94%
7	Retail	32	8.59	0.84%	0.79%	0.94%
8	Finance, Insurance, and Real Estate	33	5.51	-1.04%	-1.50%	-0.84%
9	Business and Repair Services	30-31	6.78	0.92%	-0.55%	-0.53%
10	Personal Services	34	1.80	-0.16%	-0.69%	-0.70%
11	Entertainment and Recreation	29	1.30	0.68%	1.26%	0.62%
12	Professional and Related Services	34	15.68	-0.16%	-0.69%	-0.70%
13	Public Administration	35	5.00	-0.78%	-1.15%	-0.50%
14	Construction	6	4.77	-0.67%	-1.19%	-1.49%
	Annual Average			0.66%	0.46%	0.30%
	Annual Standard Error			1.38%	1.54%	1.10%

Notes: The growth rates are in percents.
Data Source: Author's tabulation based on Jorgenson (2000).

Table A3: Marginal Effects for Table 2

	Not-Working		Unemployed	
	Model 1	Model 2	Model 1	Model 2
Net TFP Growth	1.607	0.863	0.451	0.374
	(0.353)**	(0.353)*	(0.122)**	(0.114)**
Age	-0.326	-0.316	0.05	0.048
	(0.034)**	(0.034)**	(0.013)**	(0.012)**
Age-square	0.003	0.003	0.001	0.001
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
African American	0.074	0.069	0.011	0.007
	(0.013)**	(0.013)**	(0.005)*	(.004)
Hispanic	0.007	-0.006	0.013	0.008
	(.019)	(.019)	(.007)	(.006)
Foreign Born	-0.082	-0.096	0.019	0.015
	(0.015)**	(0.014)**	(0.007)**	(0.006)*
Currently Married	-0.104	-0.075	-0.03	-0.021
	(0.012)**	(0.012)**	(0.005)**	(0.005)**
Years of Schooling	-0.002	0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.001)**	(0.001)**
College Degree	-0.022	-0.014	-0.002	0.002
Regions:	(0.013)	(0.014)	(0.005)	(0.005)
Central	-0.039	-0.044	-0.016	-0.016
	(0.013)**	(0.013)**	(0.004)**	(0.004)**
South-East	-0.028	-0.046	-0.008	-0.01
	(0.012)*	(0.012)**	(0.004)	(0.004)*
Pacific	0.018	0.007	-0.005	-0.004
	(0.015)	(0.015)	(0.005)	(0.005)
Bad Health	0.345	0.302	-0.002	-0.007
	(0.011)**	(0.011)**	(0.00)	(0.003)*
Year 1994	0.019	0.005	0.01	0.009
	(0.01)	(0.01)	(0.005)*	(0.004)*
Year 1992	0.016	-0.019	0.009	0.006
	(0.01)	(0.01)	(0.004)*	(0.004)
Union Member		0.006		0.006
		(0.01)		(0.01)
Pension Plan		-0.273		-0.03
		(0.009)**		(0.004)**
Total Net Wealth		0.001		0.001
		(0.000)**		(0.000)**
Observations	13,471	13,471	13,471	13,471

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%

Table A4: Probit Estimates of "Not-Working" with NLSY Data

	Model 1	Model 2		Model 1	Model 2
NTFPG	1.864	-0.141	**Currently Married**	**-0.232**	**-0.511**
	(3.363)	(2.462)		**(0.109)**	**(0.055)**
XG	1.020		**Years Married**	0.019	
	(1.708)			(0.014)	
Age	0.006	-0.159	**One or Two Child**	0.001	-0.079
	(0.289)	(0.253)		(0.070)	(0.057)
Age-square	0.003	0.003	**Three or more children**	**0.149**	0.049
	(0.005)	(0.004)		**(0.086)**	(0.070)
African American	**0.247**	**0.446**	**Resident in Urban area**	0.081	0.133
	(0.080)	**(0.065)**		(0.087)	(0.071)
Hispanic	0.160	**0.193**	**County Avg. Earnings**	-0.008	-0.011
	(0.090)	**(0.077)**		(0.010)	(0.008)
AFQT	-0.020	**-0.086**	**County Unempl. Rate**	-0.006	0.004
	(0.021)	**(0.017)**		(0.010)	(0.008)
Parents Income, 1979	1.541	-2.756	**Foreign Born**		-0.025
	(2.201)	(1.873)			(0.100)
Years of Schooling	**-0.054**	**-0.079**	**Year 1994**		0.051
	(0.016)	**(0.013)**			(0.069)
Work Experience	**-0.245**		**Year 1996**		0.064
	(0.028)				(0.085)
Work Expr.-square	-0.000		**Constant**	-1.598	1.859
	(0.002)			(4.533)	(3.986)

Note: standard errors are in parentheses. Significant coefficients, at 5% level, are in bold. The only difference between Model 1 and Model 2 is a number of independent variables.

Data Source: NLSY 1979, years 1992-1996. It includes 8,039 person-years observations from the nationally representative, non-military sample, ages 27-36.

Table A5: Coefficient Estimates for the Wage Equations

	1. Basic Model	2. Include Wealth Variables	3. Include Sector Dummies	4. Heckman Selection Model	
				Wage Equation	Status of Working
NTFPG	-0.641	-0.167	2.648	1.173	**-2.26**
	(0.801)	(0.762)	(3.107)	(0.856)	**(0.955)**
XG	0.918	-0.625	-0.689	1.259	**-4.478**
	(0.626)	(0.598)	(2.001)	(0.682)	**(0.815)**
Age	**0.238**	**0.169**	**0.217**	**-0.209**	**0.749**
	(0.076)	**(0.072)**	**(0.075)**	**(0.081)**	**(0.092)**
Age-square	**-0.002**	**-0.002**	**-0.002**	**0.002**	**-0.007**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
African American	**-0.106**	**-0.081**	**-0.106**	**-0.072**	**-0.126**
	(0.029)	**(0.027)**	**(0.028)**	**(0.031)**	**(0.034)**
Hispanic	**-0.120**	**-0.049**	**-0.111**	**-0.129**	**0.043**
	(0.041)	**(0.039)**	**(0.040)**	**(0.0439)**	**-0.05**
Foreign Born	-0.013	0.028	0.009	**-0.094**	**0.274**
	(0.034)	(0.032)	(0.034)	**(0.037)**	**(0.045)**
Currently Married	**0.161**	**0.089**	**0.156**	**0.089**	**0.09**
	(0.026)	**(0.024)**	**(0.026)**	**(0.028)**	**(0.032)**
Years of Schooling	**0.064**	**0.051**	**0.061**	**0.060**	**-0.012**
	(0.004)	**(0.004)**	**(0.004)**	**(0.005)**	**(0.005)**
College Degree	**0.168**	**0.124**	**0.162**	**0.159**	0.038
	(0.029)	**(0.028)**	**(0.029)**	**(0.031)**	-0.037
Regions:					
Central	**-0.084**	**-0.054**	**-0.073**	**-0.120**	**0.145**
	(0.028)	**(0.027)**	**(0.028)**	**(0.031)**	**(0.037)**
South-East	**-0.175**	**-0.095**	**-0.166**	**-0.161**	**0.102**
	(0.026)	**(0.025)**	**(0.026)**	**(0.028)**	**(0.033)**
Pacific	**-0.086**	-0.066	-0.071	-0.065	0.034
	(0.032)	(0.030)	(0.032)	(0.034)	-0.041
Bad Health	**-0.213**	**-0.163**	**-0.208**	**-0.104**	**-0.592**
	(0.028)	**(0.027)**	**(0.028)**	**(0.029)**	**(0.030)**
Year 1994	-0.002	-0.021	-0.003	0.013	**-0.07**
	(0.024)	(0.023)	(0.024)	(0.026)	**(0.029)**
Year 1992	**-0.095**	**-0.115**	**-0.084**	**-0.191**	**0.192**
	(0.024)	**(0.023)**	**(0.027)**	**(0.026)**	**(0.031)**
Union Member		**0.045**			**0.086**
		(0.022)			**-0.031**
Pension Plan		**0.429**			**0.701**
		(.020)			**(0.026)**
Net Wealth		**0.055**			**0.001**
		(0.002)			**(0.000)**
Constant	3.153	**4.923**	3.433	**15.593**	**-19.743**
	(2.176)	**(2.063)**	(2.153)	**(2.342)**	**(2.684)**
R-square	0.15	0.24	0.17	NA	NA
Observations	7,897	7,897	7,897	13,471	13,471

Notes: standard errors in parentheses. Significant coefficients, at 5% level, are in bold.

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