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TECHNICAL PROGRESS AND EARLY RETIREMENT*

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This article examines the effect of sector technical change on early retirement and identifies two opposing effects. One is caused by the need to learn the new technologies. As older workers have shorter career horizons, they gain less from such learning and retire earlier. This is the *erosion effect*. The second effect is opposite. Since technologies are positively correlated across sectors and since aggregate technical change raises aggregate wages, sector technical change is negatively related to early retirement. This is the *wage effect*. Using individual and sector data, we separate the two effects and find empirical support for the theory.

The number of workers who quit working before they reach the formal age of retirement is surprisingly high. In 2005 the average labour force participation rate in OECD countries of men in ages 55–64 was 65.5%, while the labour force participation rate for men in ages 25–54 was 92.1%. Furthermore, it is quite a recent phenomenon. Labour participation rates for US men in ages 55–64 dropped from 86.7% in 1948 to 62.6% in 1996, recovering slightly to 68.7% in 2004. Early retirement is usually attributed to bad health, wealth and to generous retirement plans. This article 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 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 article proposes that human capital erosion by technical change also reduces labour 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 article 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. When new innovations arrive, they replace the existing technologies, while requiring workers to learn how to use the new technologies. While younger workers

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learn these 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 in the model the worker decides on early retirement, while in real life the decision is often made by the employer, who prefers not to train 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 reveals an additional opposite relation between sector technical change and early retirement, which is implied by the fact that rates of technical progress across sectors are positively correlated. As a result sector technical change and the aggregate technical change are correlated as well. But since aggregate technical change raises aggregate wages, which induces older workers to delay retirement, it creates an opposite relation between technical change and early retirement, which we call the *wage effect*. Hence, the overall observed relation between the sector rate of technical change and early retirement could be ambiguous. Thus, in order to identify the erosion effect empirically, we test the relation between early retirement and net sector specific technical change, namely the part of sector technical change which is not correlated with aggregate technical change. This is our main empirical test.

The empirical tests use US data on the labour 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 over time, measured by Jorgensen (2000). We test how working status is affected by the sector-specific component of technical progress and find that its effect on the probability of not working by older men is positive, while it is lower 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. We test an implication of this possibility and reject it.

The article is related to two different literatures, one on early retirement and the other on the effect of technical change on labour markets. The literature on early retirement has mostly focused on wealth, health and on greater financial incentives to retire.[1] The first article that suggested that technical progress and early retirement are strongly related through erosion of human capital is Bartel and Sicherman (1993), from hereon BS. Our article follows this insight, but differs significantly in identifying the wage effect. We show that without acknowledging this effect the BS test is mis-specified and leads to some wrong interpretations.[2] Our main contribution to this literature is therefore the general equilibrium theoretical model, which uncovers the wage effect and thus helps us to empirically isolate the erosion effect.[3]

The article is also related to recent research on the effect of technical progress on the labour market. Some articles in the new growth literature, like Aghion and Howitt (1994), Helpman and Trajtenberg (1998), Hornstein and Krusell (1996) and Galor

[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 articles are detailed in Section 5.2.

[3] Our model is related to Boucekkine *et al.* (2002), who discuss economic growth and retirement, but without erosion of human capital, and to Chari and Hopenhayn (1991), who analyse erosion of technology-specific human capital but without retirement.

and Moav (2000), have claimed that technical progress might reduce employment due to costs of learning new technologies. This article shows that this effect is stronger for older workers, whose career horizon is short.[4]

The article is organised as follows. Section 1 presents the basic model of technical progress, training and retirement. Section 2 describes the equilibrium and discusses the effects of technical progress on early retirement. Section 3 explains the empirical tests. Section 4 presents the basic empirical results on the effect of technical progress across sectors. Section 5 presents additional empirical tests and Section 6 concludes. The Appendix contains mathematical proofs and more detailed empirical results.

1. 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]

$$\ln Y_t = \int_0^1 \ln X_{i,t} \, \mathrm{d}i, \tag{1}$$

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 labour 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.

Next we 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:

$$a_{i,t} = a_{i,t-1} b_{i,t}. \tag{2}$$

Technical change in each sector is non-negative and bounded: $1 \leq b_{i,t} \leq B$. The lower bound is of course the case of no technical change. The sector's rate of technical change is therefore $\ln(b_{i,t})$.

Next assume that the rates of technical change are correlated across sectors in each period. This assumption is reasonable since many new technologies are quite general and affect many sectors. It is also supported by the data, as shown below in Sub-section 4.2. Formally, assume that a sector's rate of technical change can be decomposed into an aggregate component g_t and a sector-specific component $s_{i,t}$ in the following way:

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

Assume that the average rate of technical change 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

4 Friedberg (2003) also points at a relationship between technology and age through the use of computers.
5 It is easy to verify that the results below can be reached by using a more general CES production function.

across sectors. To ensure that the rate of technical change 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 his first period of life each person acquires a profession i and supplies 1 unit of labour. In his second period of life a person supplies only L units of labour, where $L < 1$, since some time Z is devoted to mandatory retirement. Hence, L describes the time to retirement, or the career horizon.

A worker in his second period of life can use the previous technology and supply L units of labour, or he can retrain and learn the new technology but this requires time. Retraining time depends both on the size of technical change in the sector $b_{i,t}$ and on f, which measures individual learning inability, and is uniformly distributed on $[0, F]$, where 0 fits the fastest learning worker and F is the slowest to learn. The required retraining time is equal to:

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

Assume that retraining time is increasing and convex in technical change, namely $\varphi_b > 0$ and $\varphi_{bb} > 0$, and assume that retraining time is zero if there is no technical change: $\varphi(f, 1) = 0$. The assumption that retraining time increases with the size of technical change leads to the erosion effect. A retraining worker supplies $L - \varphi(f, b_{i,t})$ units of labour in his second period of life. For analytical convenience assume that part time work is spread uniformly throughout the period.[6]

Retraining time is bounded by $\varphi(F, B)$, namely by the slowest worker at the largest technical change. We next add the following simplifying restriction:

$$\varphi(F, B) < L\left(1 - \frac{1}{B}\right). \tag{5}$$

It can be shown that this assumption does not change any of the main results, and it is quite realistic. It holds if the maximum retraining time is below half of L, the working period of the old, and if the upper bound for technical progress B is around 2.[7]

A worker can also retire early in second period of life and earn no income. Assume that workers derive utility from consumption in first and in second period of life and from retirement, if they retire early. The utility from retirement is assumed to differ across individuals, as it depends on age, health and taste. The individual preference for early retirement is represented by h, which is assumed to be uniformly distributed over the population on $[0, H]$, where 0 is the case of no preference for early retirement and H is maximum preference for retirement. It is also assumed that f and h are independent of each other. Formally, the utility function of a worker is

$$U = u(c_1) + \mathrm{E}[u(c_2) + Iv(h)], \tag{6}$$

c_1 is consumption when young, c_2 is consumption when old and I is an indicator, equal to 1 if he retires early and to 0 if not. The functions u and v are increasing and

[6] This simplifying assumption is made to fit the idiosyncratic labour supply to a framework of discrete time.
[7] If the time period is 30 years, this is translated to an average annual upper bound of 3% on technical change in a sector. Note that the fastest TFP growth in 1975–96 was in Agriculture, Forestry and Fishery that grew by an average of 2% annually. Thus, this upper bound is quite realistic.

concave and $v(0) = 0$, so that a worker who does not retire has the same utility as a worker with no preference for retirement.

The expectation operator is with respect to the unknowns in second period of life: second period wages, sector technical change, and the individual parameters f and h. We assume that these personal characteristics are unknown at first period of life and are realised by the worker only in second period of life, when he confronts the need to retrain and the decision over retirement. Thus, workers born in period t are similar at that time, but differ in period $t+1$, when they are identified by pairs (f, h) in the set $[0, F] \times [0, H]$.

As mentioned above, the economy is small and open. Assume that the final good is fully traded, while labour and intermediate goods are non-traded. Capital is fully mobile and is traded at the world interest rate.[8] For simplicity assume that the world interest rate is 0. Markets are perfectly competitive and expectations are rational. To simplify the analysis assume that employment risk or labour related risks are not insured.

2. Equilibrium

2.1. *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:

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

The young choose professions in the beginning of the period to maximise income, knowing which technologies will be used and hence what prices will prevail. Choice of sectors by the young equates incomes $p_{i,t}\ a_{i,t}$ across sectors, through adjustments of $X_{i,t}$.[9] Denote the common real income of the young across sectors by w_t and call it the wage rate:

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

We next calculate this equilibrium real wage. If we substitute the demand and supply conditions (7) and (8) in the production function (1) we get:

$$\ln w_t = \int_0^1 \ln a_{i,t}\ \mathrm{d}i. \tag{9}$$

Hence, the wage is equal to the average total factor productivity (TFP) across sectors, as labour is the only factor of production. The rate of change of wages is equal to the aggregate TFP growth:

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

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

$$\ln w_t - \ln w_{t-1} = \int_0^1 \ln b_{i,t} \, \mathrm{d}i = g_t. \tag{10}$$

To find workers' incomes in the second period of life note that the prices of intermediate goods are the same for all producers, young and old. Hence, an old worker who retrains earns the same wage per unit of time as the young, w_t. A worker who does not retrain faces competition from younger workers with a better technology and earns only $a_{i,t-1}\, p_{i,t} = w_t/b_{i,t}$. Wages of old workers trapped in their previous professions are therefore lower than wages of young or of retraining old 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. Increased supply of the good lowers its price and with it the income of non-training old workers in the sector.

2.2. *Decisions in the Second Period of Life*

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

$$u[m_{t-1} + w_t L - w_t \varphi(f, b_{i,t})]. \tag{11}$$

If the worker does not retrain and uses the old technology his second period utility is

$$u(m_{t-1} + w_t L / b_{i,t}). \tag{12}$$

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

$$u(m_{t-1}) + v(h). \tag{13}$$

Compare first retraining to keeping the old technology. Technical change reduces income of a 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 (11) exceeds (12), namely if:

$$\varphi(f, b_{i,t}) \leq L\left(1 - \frac{1}{b_{i,t}}\right). \tag{14}$$

Note that the two sides of (14) are equal to zero at $b_{i,t} = 1$ but the required retraining time at the LHS is convex in $b_{i,t}$, while the RHS is concave in $b_{i,t}$. Hence, if condition (14) holds at the upper bounds B and F, it holds everywhere. Thus, (5) implies that (14) holds for all values of f and b.[10]

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 (13) exceeds (11), namely if:

[10] Even if (5) is not assumed, the main result of the article 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.

$$u\{m_{t-1} + w_t[L - \varphi(f, b_{i,t})]\} < u(m_{t-1}) + v(h). \tag{15}$$

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

2.3. *Saving Decision in the 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 maximises the following expected utility:

$$\begin{aligned} &u(w_{t-1} - m_{t-1}) + \underset{w_t, b_{i,t}, f, h}{\mathrm{E}} \max(u\{m_{t-1} + w_t[L - \varphi(f, b_{i,t})]\}, u(m_{t-1}) + v(h)) \\ &\quad = u(w_{t-1} - m_{t-1}) + \underset{g_t, b_{i,t}, f, h}{\mathrm{E}} \max(u\{m_{t-1} + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\}, u(m_{t-1}) + v(h)). \end{aligned} \tag{16}$$

It is clear from this maximisation that optimal savings $m_{t\text{-}1}$ depend on previous wage w_{t-1}, on L, F and on H only. Denote the saving function by m, so:

$$m_{t-1} = m(w_{t-1}, L, F, H). \tag{17}$$

2.4. *Work or Early Retirement*

Substituting m in (15) we get that a worker retires if:

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

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

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

When there is no equality in (18), h is set at H. The function h is therefore everywhere positive.

LEMMA 1. *The function h satisfies*: $h_f < 0, h_b < 0, h_g > 0, h_F < 0, h_H < 0$ *and* $h_L > 0$.

Proof. In the Appendix.

The decision of workers in second period of life is presented in Figure 1, where workers are distributed on $[0, F] \times [0, H]$. The negatively sloped curve is the function h, which divides the rectangle into W on the left, those who retrain and work, and R, those who retire early. Note that higher sector technical change $b_{i,t}$ shifts the curve to the left and increases early retirement in the sector. This is the *erosion effect* of technical change. If aggregate technical change g_t increases, the curve shifts to the right and that reduces early retirement. Since we assume that $b_{i,t}$ and g_t are positively related, this creates an additional effect of the sector technical change $b_{i,t}$ on early retirement, this time negative, which we call the *wage effect*. The empirical implication of these two effects is the following. As long as we compare workers in the same period of time, namely with the same g_t, the effect of sector technical change on early retirement

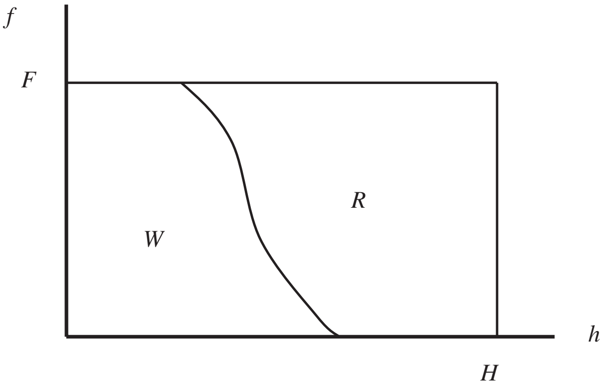

Fig. 1. *Working and Retirement*

reflects only the erosion effect and is clearly increasing early retirement. But if we compare workers across sectors over a number of periods of time, the effect of sector technical change no longer reflects only the erosion effect but also the opposite wage effect. Hence, in that case we need to empirically differentiate between the aggregate and the sector specific rates of technical change.

Note that the effect of the wage level w_{t-1} on h is ambiguous, due to a negative income effect through saving and a positive substitution effect through second period wages. It can be shown that if constant relative risk aversion is 1, when utility from consumption is logarithmic, these income and substitution effects cancel one another and retirement is independent of w_{t-1}.[11] It can also be shown that if relative risk aversion is higher, wages have a negative effect on retirement, while if relative risk aversion is lower, wages affect retirement positively. Hence, the effect of w_{t-1} on h is indeed ambiguous. Hence, the benefit of using the logarithmic utility function is that it makes early retirement independent of the growing level of productivity.

2.5. *The Probability of Early Retirement*

The probabilities of working and of early retirement are the areas of W and R in Figure 1, normalised by FH, respectively. Note that the area of W is always positive, since h is always positive. Calculating the probability that workers in sector i at time t retire early, $P_{i,t}$, yields:

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

We of course focus mainly on the sector's rate of technical progress. As shown in Sub-section 2.4 in the analysis of Figure 1, a rise in $b_{i,t}$ increases the probability of early

[11] If utility from consumption is logarithmic first period savings m are proportional to w_{t-1}. Then showing that h does not depend on w_{t-1} follows easily.

retirement and this is the erosion effect. A rise in the aggregate rate of technical change g_t reduces the probability of early retirement, as shown in Figure 1. Since g_t is positively correlated with $b_{i,t}$, sector technical change has also an opposite negative effect on the probability of early retirement, which is the wage effect. Hence if we measure the effect of sector technical change on early retirement over more than one period of time, it is misleading to use $b_{i,t}$. In order to isolate the erosion effect we differentiate between the aggregate and the sector specific rates of technical change by substituting (3) in (20). We get:

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

It follows from (21) that the effect of the sector specific technical change s on early retirement is positive as it fully reflects the erosion effect. The overall effect of aggregate technical change g is ambiguous, as it involves the opposing erosion and wage effects. Clearly, (21) is more suitable for empirical estimation than (20), since its variables are independent. Thus only (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. *Then*: $P_{i,t} = P(w_{t-1}, s_{i,t}, g_t, L, F, H)$. *This function satisfies:* $P_s > 0, P_L < 0, P_F > 0, P_H > 0$, *while the effect of* g *is ambiguous.*

Proof. In the Appendix.

2.6. *The Effect of Sector Technical Progress on Wages*

We next examine 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 in order to use it in Sub-section 5.1 to test the possibility of the reverse causality argument. The average wage of older workers who do not retire is described by the following equation, where the overall pay to workers who keep working in the set W in Figure 1 is divided by the overall number of workers in this set:

$$w_t = \frac{\int_0^F h(f, w_{t-1}, b_{i,t}, g_t, L, F, H)[L - \varphi(f, b_{i,t})]\mathrm{d}f}{L\int_0^F h(f, w_{t-1}, b_{i,t}, g_t, L, F, H)\mathrm{d}f}. \tag{22}$$

Clearly the overall pay of a worker in the set W is negatively related to technical change, since his training time increases with it, so his effective labour time is reduced. Hence, sector technical change lowers the wage of each worker in area W, which reduces the average pay. But area W also shrinks as its border shifts to the left and the workers who quit are those whose earnings are the lowest. That raises the average wage. It can be shown that despite the two opposing effects the average wage declines as a result of sector technical change but not by much.

3. Empirical Implications of the Model

In order to examine if our theory is supported by the data we test the empirical implications of the model using US survey data from a sample of men over the age of 50. Our main empirical test is an estimation of a reduced-form specification of (21), which describes the probability of early retirement of older workers as a function of the sector component of the rate of technical progress $s_{i,t}$, of aggregate technical change g_t, of the past wage w_{t-1} and of the parameters L, F, and H. Actually we do not include the variable g_t in the estimation but control for it by time dummies. We also do not include in the estimation the past wage level w_{t-1}, both since our time period is relatively short and also because the effect of this variable is ambiguous, as shown above.

We estimate the following Probit regression:

$$Z_{j,t} = \mathbf{I}_{j,t}\boldsymbol{\gamma} + \mathbf{S}_{j,t}\boldsymbol{\delta} + \boldsymbol{\varepsilon}_{j,t}, \tag{23}$$

where j runs over individuals, t is the year of the survey, and $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are vectors of parameters to be estimated. The dependent variable $Z_{j,t}$ is indicator for early retirement. The explanatory variables are divided to two: a vector $\mathbf{I}_{j,t}$ of individual time-varying and time-invariant characteristics and a vector $\mathbf{S}_{j,t}$ of indicators of the performance of the sector in which the individual held his *last main job*. This variable is defined as the most recent job, in which the worker has stayed for at least 5 years. We next discuss the empirical counterparts of the variables in the theoretical model in more detail, beginning with the dependent variable, the probability of early retirement.

Unlike the model, in which the decision of quitting is made by the worker, in reality and in the data workers can also be fired.[12] We therefore use the information contained in the data on working status and estimate (21) with 'not working', 'unemployed', 'disabled' and 'retired' 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 labour force permanently.

The main explanatory variable in our tests is the sector component of the rate of technical progress, $s_{i,t}$. We use the rate of growth of total factor productivity (TFP) per sector as a measure for the sector's technical change ln $b_{i,t}$.[14] Since TFP growth reflects not only technical change but also utilisation, we average it over periods of 5 years. We

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

[13] A multinomial logit model with disjoint states (working, unemployed, disabled and retired) yields similar results.

[14] We also tried other measures for technical change instead of TFP growth. Bartel and Sicherman (1999) analyse such alternative measures and show that they all yield similar results with respect to younger workers. Most of the measures they use, however, fit only industrial sectors, while in our data most sectors are not industrial. We therefore used instead the rate of growth of the ratio of equipment capital to labour, assuming that new technologies are embodied in new machines. We find, using data from BEA (2007) that this measure yields similar results to those reported below.

then subtract the aggregate TFP growth rate from each sector to obtain a measure for $s_{i,t}$, the sector specific technical progress.

The other parameters of (21) are approximated by personal characteristics that appear in the data. Thus, age is a good inverse indicator for the length of work horizon, L. Health is an inverse indicator for the maximum utility from 'not-working' H, and education is an inverse indicator for F, 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. This is the same as estimating (15), where data on m_{t-1} are available. Since these are past savings, they can be considered to be empirically exogenous. Both wealth and pension status are expected to have a positive effect on early retirement.

4. The Main Empirical Tests

4.1. *The Personal Data*

Our 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 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 labour-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 of output and total factor productivity (TFP) for 35 economic sectors, from 1970 to 1996.

Table 1 presents labour status shares across the three interviews, for three 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: 20% in this group, compared with less than 5% for men 40–45 years old, as in Katz and Murphy (1992). The share of not-working increases steadily over age and reaches 50% in the older group. There are several reasons for not working. Note that retirement becomes the major status among non-working men only

Table 1
Work Status by Years and Age (%)

	1992			1994			1996		
	50–54	55–59	60–64	50–54	55–59	60–64	50–54	55–59	60–64
In the Labour 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 Labour 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

Note. Data source is employment section of HRS, waves 1–3 (1992–6).

after age 60. While only 11% to 14% are retired at 55–59, more than 35% are retired at age 60–64.

Contrary to retirement, unemployment rates decrease with age according to Table 1. Interestingly, these rates are much lower than the overall unemployment rates in the US at the time (7.5% in 1992 and 5.4% in 1996). A transition matrix analysis shows that most unemployed are retired by the next interview, suggesting that unemployment is a transitional state between work and retirement. Interestingly, the share of disabled tends to increase over time, suggesting that this is a form of retirement as well. A possible explanation is that while employed workers keep working even with health problems, once they are fired and cannot find a job, they declare themselves disabled. In the empirical analysis the aggregate 'not-working' is the main dependent variable but the determinants of unemployed, disabled and retired are estimated as well.

Most 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 are more recent. Since they might also be correlated with sector, we add them only to one regression to check robustness.

4.2. *The Sector Data*

The sector variables ($\mathbf{S}_{j,t}$) are related to the last main job, which is defined in Section 3. The 14 sectors reported in the HRS data are matched to the relevant sectors in the 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.

The Jorgensen data reveal a strong correlation between sector TFP growth and the average TFP growth across sectors. The correlation for the whole period 1960–96 is 0.2918. The correlation is high also in each sub-period. Hence, this justifies the main assumption in the theoretical model, that sectors' technical change is correlated across sectors. This assumption leads to the wage effect of technical progress. We also examine the persistence over time of TFP growth and find that the average has strong persistence but individual sectors' TFP growth rates do not show high persistence over time. In AR(1) and AR(2) regressions for all sectors together the lag coefficients are very small and insignificant.

The empirical counterpart of the sector's specific rate of technical change $s_{i,t}$ is a variable called 'net TFP growth,' which is calculated in three stages. We first calculate 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*.[15] We then calculate the aggregate TFP growth, denoted *MTFPG*, by averaging *TFPG* over all sectors. Finally, we subtract the aggregate rate from the sector TFP growth to get net TFP growth: $NTFPG = TFPG - MTFPG$. This is the main sector variable in our analysis. The net TFP growth rate differs significantly across sectors and over time. The sector output growth, which is also calculated as an average over the same 5 years, is denoted *XG*.

[15] These five years end on average two years prior to the survey year, since job loss happens prior to interview.

Table 2

The Effect of Sector NTFPG on Probability of Early Retirement

		Marginal effect on probability of being:			
	Model	Not-Working	Unemployed	Retired	Disabled
1)	Basic Model	1.61	0.45	0.49	0.80
		(0.78)**	(0.15)***	(0.44)	(0.19)***
2)	With Wealth, Union and Pension	0.86	0.37	0.14	0.48
		(0.81)	(0.14)***	(0.45)	(0.13)***
3)	Age 50–60	1.22	0.58	0.04	0.84
		(0.72)*	(0.23)***	(0.37)	(0.23)***
4)	Random-Effect Model	3.13	0.55	0.54	1.26
		(1.67)***	(0.19)***	(0.85)	(0.34)***
5)	Non-Production Workers	1.17	0.62	0.49	0.60
		(0.58)**	(0.16)***	(0.40)	(0.13)***
6)	Production Workers	2.30	0.14	0.47	1.20
		(1.67)	(0.34)	(0.80)	(0.49)***
7)	With Output Growth	1.58	0.46	0.52	0.80
		(0.77)**	(0.14)***	(0.40)	(0.18)***
Means of Dependent Variables		0.329	0.042	0.175	0.094

Notes. Standard errors in parentheses. Significance at 10%, 5% and 1% is denoted by *, ** and *** respectively. The standard errors in all regressions except (4) are clustered at sectors and years. The number of observations in models 1, 2, 3 and 7 is 13,471, 9,490 in model 4, 8,280 in model 5 and 5,191 in model 6. Full regression results of models 1 and 2 for not working and unemployed are presented in Table A2.

4.3. *Labour Status Regressions*

Table 2 and Table A2 present the main results of the labour status tests. Table 2 focuses on the effects of net TFP growth (*NTFPG*) on labour status, while Table A2 reports the effects of the entire set of control variables from four representative regressions. Given the nonlinearity of the Probit regression model, the quantitative magnitudes 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 labour status, calculated by using the normal density at the sample means, namely:

$$\delta * = \frac{\partial P_{labor\ status}}{\partial (NTFPG)} = \phi(\bar{\mathbf{I}}\hat{\boldsymbol{\gamma}} + \bar{\mathbf{S}}\hat{\boldsymbol{\delta}})\hat{\delta}_{NTFPG}, \qquad (24)$$

where φ is the normal density function. Table 2 reports the effect of net TFP growth on 'not working' and on its sub-categories 'unemployed,' 'retired' and 'disabled.' Thus Table 2 also gives us a detailed view on the entire process of exiting from the labour force by old workers.

For a robustness check, each column reports estimates from 7 different models. The *basic model* includes only the exogenous personal control variables and the sector net TFP growth (*NTFPG*). The second model adds three personal variables: wealth, union membership, and pension fund membership, which are not added to the other regressions. 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 that uses the panel structure of the data. The fifth and sixth regressions test if net TFP growth has different effects for production and non-production workers. The seventh regression adds sector output growth *XG* as an explanatory variable. All regressions, except for the random-effect model, cluster the standard errors on the sectors in different years, to adjust the standard errors for possible correlation within sectors and time.[16]

The effect of net TFP growth on 'not working', across the seven models, is always positive. It is significant in all models except when wealth, union and pension status are added, and for production workers. As described below the effect of net TFP growth is significant on most sub-categories of not working. This provides strong evidence in support of our main hypothesis, that technical change *pushes* older workers out of work. The magnitudes of these effects are quite significant, as a 1% increase in TFP growth reduces the probability of employment by about 1.6 percentage-points in the basic model. The size of the effect is even doubled in the random-effects regression.

From Table 2 we also learn that the effect of sector technical progress on 'not working' is stronger for older workers. The effect of *NTFPG* on not working becomes smaller and less significant when we restrict the sample to men in ages 50–60 in model 3. The effect of *NTFPG* on retirement in this group also becomes much smaller. We have also conducted a similar test for younger workers, of ages 27–36, in the same years, 1992–6, based on NLSY with 8,039 observations, and have found that the effect of *NTFPG* on work status of young workers is insignificant as well. Hence, the positive effect of technical progress on 'not working' seems to be much stronger and more significant for older workers. Note also that age has a separate positive effect on not working, as shown in Table A2.

The other results of Table 2 are interesting as well. First, the effect of technical progress on not working becomes weaker and insignificant when we control for wealth, pension and union membership in model 2 and the effects on other labour status is smaller too. One possible explanation can be that wealthier workers have higher ability and thus are more likely to retrain. Another explanation is that these variables are correlated with sectors, as workers in sectors with high rates of technical change might have better pensions and higher wealth. But even with these variables the effects of *NTFPG* on unemployed and disabled are still positive and significant, which points to robustness. Interestingly, controlling for unobserved individual effects in the random-effect regression in model 4 makes the results much stronger.

Models 5 and 6 provide some additional 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 change for production and non-production workers separately.[17] Production workers usually use more sector-specific technologies, while non-production workers tend to use more general technologies of management and services. Hence, the human capital of non-production workers is expected to suffer less erosion from sector specific new technologies. Indeed models 5 and 6 in Table 2 show that the effects of *NTFPG* on non-production workers are smaller

[16] Such a procedure is required when micro data is estimated on macro variables. See Moulton (1990).

[17] The professions classified 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.

than the effects on production workers.[18] Model 7 adds output growth to the basic regression to control for possible effect of demand on sector *TFPG*. As shown in Table 2, this addition has only a small effect on the results.

We next turn to the effects of *NTFPG* on the sub-categories of not-working: unemployed, retired and disabled. First note that in each of the 7 models in Table 2 the sum of these effects is approximately equal to the effect on 'not working.' The effect of *NTFPG* on unemployment is positive and even more significant than the effect on 'not working.' The effect of *NTFPG* on disability status is very significant and quite large in all 7 models, which supports our assumption above that disability is one of the main routes to early retirement. The effect of *NTFPG* on retirement is much weaker and is insignificant in all models. We think that it is a result of the above observation that full retirement follows some period of unemployment. As a result, retirement responds with a delay, which makes it harder to identify in our regression analysis.

The regressions in Table 2 examine the effect of *NTFPG* on labour status, as this variable measures the sector specific rate of technical change and is therefore the right variable to test the erosion effect, which indeed comes out strong and significant. Note that the importance of using this variable instead of the gross sector technical change, *TFPG*, cannot be fully assessed in our data set, as it spans a small number of years, when the aggregate TFP growth rate does not change much. Still, the importance of using *NTFPG* is demonstrated in Section 5.2, by the comparison with BS, as there TFP growth is taken over a longer period of 10 years.

Finally, while this article focuses mainly on technical change, the estimated effects of other control variables, as reported in Table A2, are in line with the estimates reported by 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 and bad health has a strong positive effect on early retirement. As in other studies we find that wealth and pension make people work longer, which contradicts our model and the general theory of the income effect on leisure. A possible explanation for this finding, that fits our model, can be that these variables capture individual innate talents, which are positively related to retraining ability.

5. Additional Empirical Tests

5.1. *Testing for Reverse Causality*

This Sub-section examines the possibility that the positive correlation 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 the best workers, such reorganisation might increase productivity. Hence, the positive correlation between sector TFP growth and not-working might be driven by such a mechanism as well. We examine this possibility empirically in two ways. First, we refer to the tests of labour status that include sector output growth, since changes in demand are usually correlated with lay-offs. As reported in model 7

[18] The coefficient of not working for production workers is insignificant but that can be a result of less unemployment among these workers and also a smaller size of this group.

in Table 2, the results are not affected significantly by including output growth in the regression. The second and main way in which we examine the possibility of such 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 older workers in sectors with higher TFP growth should be higher, since in sectors with more lay-offs, employers prefer to keep the more productive workers, which are also better paid. Hence, under the reverse causality hypothesis 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 2.6.

Table 3 presents regression results for the effect of sector net TFP growth on wages for 4 specifications of the wage equation. The effects of all other variables are presented in Table A3 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 they are positive but in all cases the hypothesis that the coefficient is zero cannot be rejected. Note that we should be aware of the possibility of self-selection, as we test for the wages of those who chose to continue working. We control for self-selection using the Heckman procedure in model 4, and test for both wages of working and for the work status. The main result is still unchanged: the effect of net TFP growth on wages of workers who still work is not significant. Hence, the results of the tests reported in Table 3 indicate a rejection of the possibility of reverse causality.

5.2. *Comparison with Bartel and Sicherman*

There are naturally many differences between BS and our article but we think that the main difference is the wage effect, which is derived from our theoretical model and affects our empirical estimation. BS assume that expected technical change increases early on-the-job training and thus workers stay longer in their jobs, while 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, denoted by us $TFPG10_{i,t}$, and the unexpected part of technical change by a

Table 3
Effects on NTFPG on Wages of Those Who Stay Working

	1. Basic Model	2. Include Wealth Variables	3. Include Sector Dummies	4. Heckman Selection Model: Wage Equation	4. Heckman Selection Model: Status of Working
NTFPG	−0.641	−0.167	2.648	1.173	−2.26
	(1.178)	(1.055)	(3.041)	(0.856)	(0.955)**
R-squared	0.15	0.24	0.17	NA	NA
Observations	7,897	7,897	7,897	13,471	13,471

Notes. Standard errors in parentheses. Standard errors in all regressions except 4 are clustered by sectors and years. Significance at 10%, 5% and 1% is denoted by *, ** and *** respectively. Full results of these regressions are in Table A3.

variable called a shock to technology, defined as $TFPG_{i,t} - TFPG10_{i,t}$, normalised by the standard deviation. We denote it $SHCK_{i,t}$. 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 that BS ignore the wage effect. To show it we replicate in Table 4 the results of BS using our data and contrast them with our results. The regressions in Table 4 control for the same individual variables as in model 1 in Table 2.

Table 4 presents results of four different regression models for comparison. Model 1 regresses the probability of 'not working' on our variable *NTFPG*. Model 2 regresses the probability of 'not working' on the BS variables, *TFPG*10 and *SHCK*. As in BS the two variables are insignificant in our data as well, although the signs of the coefficients are opposite to those reported in BS. Since BS test the interaction between their variables and the 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 are significant while the BS variables are insignificant, except for the shock variable above age 61. Hence the main difference between our results and the BS results is not due to the different data set and to the different periods of time but to the choice of variables. We next examine what are the possible reasons for these differences.

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 (0.765)**			
*TFPG*10		0.696 (0.944)		
SHCK		−0.128 (0.555)		
NTFPG (Age 60−)			1.402 (0.787)*	
NTFPG (Age 61+)			1.924 (0.984)**	
*TFPG*10 (Age 60−)				0.737 (0.897)
SHCK (Age 60−)				0.425 (1.155)
*TFPG*10 (Age 61+)				0.389 (0.587)
SHCK (Age 61+)				−1.178 (0.509)**
No. of Individuals	5,217	5,217	5,217	5,217
No. of Person-Years	13,471	13,471	13,471	13,471

Notes. Standard errors are in parentheses and are clustered by sectors and years. Significance at 10%, 5% and 1% is denoted by *, ** and *** respectively. The other variables in the regressions are the same as in the basic model in Table A2.

We claim that the variable of average sector technical change over last ten years, does not measure well future expectations of technical change in the sector. In general, the BS variable of past sector technical change can capture two separate possible effects. One is the sector's all time average growth rate. The other is the aggregate technical change, since averaging sector growth rates over 10 years eliminates much of the sector specific technical change. Since the aggregate rate of technical change is persistent, as reported in Sub-section 4.2, it is correlated with current aggregate technical change. To examine this possibility we calculated the correlations between the sector variable $TFPG10_{i,t}$ and two variables, the current mean technical change over all sectors and the net sector technical change, *NTFPG*. We find that the correlation between *TFPG*10 and the mean technical change is 0.2311, while the correlation with 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.

Therefore, *TFPG*10 captures both the sector's long run rate of technical change and the aggregate rate of technical change. The first variable has a positive effect on early retirement, due to the erosion effect, while the second has a negative effect on early retirement, due to the wage effect. The combination of these two opposing effects can explain the insignificance results both with respect to *TFPG*10 and with respect to SHCK, which is defined by use of *TFPG*10. Hence, our article extends BS by taking into consideration the wage effect, both theoretically and empirically.

6. Conclusions

This article 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 labour participation of older workers. We combine these two areas together by observing that sector technical progress has a substantial negative effect on labour supply of older workers, as it erodes technology-specific human capital mostly for older workers, who have a shorter career horizon.

But technical progress also 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 sector technical progress has two opposite correlations with 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. This variable is calculated by deducting the aggregate rate of technical progress from the sector rate of technical progress. We find, using US data, that it increases unemployment, disability and early retirement, as our model predicts.

Hence, technical change, which benefits many in the economy, by increasing productivity and income of many workers, might also cause losses to some of the older workers, who find it too late in their work career to adjust to new technologies. Understanding this issue can help us in forming relevant social policies. Our research also points at some possible future research extensions. One of these 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 this cost of technical change.

Appendix A

Proof of Lemma 1

The function h is defined by:

$$u(m) + v(h) = u\{m + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\}. \tag{25}$$

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

To analyse the effects of the other variables note that:

$$\frac{dh}{dm} = \frac{u'\{m + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\} - u'(m)}{v'(h)} < 0.$$

Hence, due to diminishing marginal utility, m has a negative effect on h. Intuitively, higher savings reduce the benefits of future income and thus increase the propensity to retire. From (16) it follows that the first order condition that determines savings is:

$$\begin{aligned} u'(w_{t-1} - m_{t-1}) &= \frac{d}{dm_{t-1}} \mathrm{E}\max(u\{m_{t-1} + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\}, \\ u(m_{t-1}) + v(h)) &= \mathrm{E}_{R^c} u'\{m_{t-1} + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\} + \mathrm{E}_R u'(m_{t-1}), \end{aligned} \tag{26}$$

where R is the set of retirement:

$$R = \{(f, h, w, b, g, m) | u(m) + v(h) \geq u\{m + we^g[L - \varphi(f, b)]\}\}.$$

Increasing H increases the set R without changing the marginal utility of consumption in each case. Due to diminishing marginal utility:

$$u'\{m + w_{t-1}e^{g_t}[L - \varphi(f, b_{i,t})]\} < u'(m_{t-1}).$$

Hence, increasing the set R raises the expectation and so raises the RHS of (26). This proves that $dm/dH > 0$ and as a result $h_H < 0$.

Note that if F increases it adds higher values of f to the distribution. That increases R but reduces consumption over R^c, its complement, and thus increases the marginal utility on the set R^c. Since the change has no effect on marginal utility of consumption in R, both effects increase the expectation and raise RHS of (26). Hence: $dm/dF > 0$, which proves that $h_F < 0$.

Increasing L has both a direct positive effect through (25) and an indirect effect through saving m. As for indirect effect, increasing L reduces R and reduces the marginal utility of consumption over the set R^c. Both clearly reduce the expected marginal utility of consumption and thus reduce the RHS of (26), which reduces m_{t-1}. 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 concludes the proof of the Lemma.

Appendix B

Proof of Proposition 1

The effects of $s_{i,t}$ and of L on $P_{i,t}$ follow immediately from applying Lemma 1 to (21). Since h_H is negative and the integral in (21) is divided by FH, the overall effect of H is positive. The effect of F on $P_{i,t}$ is analysed by use of Figure 1. A higher F reduces h, through its positive effect on savings, so the curve h shifts to the left, which increases $P_{i,t}$. A higher F also shifts the top of the rectangle upward. Since the curve h is downward sloping, this increases the area to its right relative to the rectangle. Hence, the rise in F increases $P_{i,t}$ through these two channels.

Finally we show that the effect of g_t on $P_{i,t}$ is ambiguous. The ambiguity arises from the positive effect of g and the negative effect of b. To show that the overall effect can be either positive or negative consider this case: utility from consumption is $u(c) = \ln c$, utility from retirement is $v(h) = \ln(1 + h)$, and the cost of retraining is: $\varphi(f, b) = \alpha f(b - 1)^2$. Under this specification the function h is:

$$h = \frac{w_{t-1}}{m_{t-1}} e^{g_t}[L - \alpha f(b-1)^2] = \frac{1}{M(L,F,H)} e^{g}[L - \alpha f(b-1)^2]. \tag{27}$$

The function M is savings per unit of income, as savings are proportional to income under the logarithmic utility function: $m_{t-1} = w_{t-1}M(L, F, H)$. Hence, (27) implies that (time subscripts are deleted):

$$P = 1 - \frac{1}{HM(L,F,H)} e^{g}[L - \frac{\alpha F}{2}(e^{g}e^{s} - 1)^2]. \tag{28}$$

Calculating the derivative of (28) with respect to g yields that its sign is positive if:

$$\frac{L}{\alpha F} < (b-1)\left(\frac{b-1}{2} + e^{s}\right). \tag{29}$$

Note that condition (5) implies that: $(L/\alpha F) \geq (b-1)b$. It can be easily shown that (29) holds if e^{s} is sufficiently large, but it does not hold if it is sufficiently small. This concludes the proof of the Proposition.

Appendix C

Additional Tables

Table A1

Reasons Respondents Left Previous Job (%)

	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 are: '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)?' etc.

Table A2

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
	(0.785)**	(0.810)	(0.153)***	(0.142)***
Age	−0.326	−0.316	0.050	0.048
	(0.042)***	(0.044)***	(0.014)***	(0.013)***
Age-squared	0.003	0.003	−0.0005	−0.0004
	(0.000)***	(0.000)***	(0.0001)***	(0.0001)***
African American	0.074	0.069	0.011	0.007
	(0.013)***	(0.014)***	(0.005)**	(0.004)*
Hispanic	0.007	−0.006	0.013	0.008
	(0.020)	0.021)	(0.008)	(0.007)
Foreign Born	−0.082	−0.096	0.019	0.015
	(0.016)***	(0.013)***	(0.008)***	(0.007)**
Currently Married	−0.104	−0.075	−0.030	−0.021
	(0.012)***	(0.012)***	(0.005)***	(0.004)***
Years of Schooling	−0.002	0.002	−0.002	−0.002
	(0.003)	(0.003)	(0.001)***	(0.001)***
College Degree	−0.022	−0.014	−0.002	0.002
	(0.018)	(0.019)	(0.005)	(0.005)
Regions: Central	−0.039	−0.044	−0.016	−0.016
	(0.014)***	(0.015)***	(0.004)***	(0.004)***
S-E	−0.028	−0.046	−0.008	−0.010
	(0.013)**	(0.012)***	(0.004)*	(0.003)***
Pacific	0.018	0.007	−0.005	−0.004
	(0.016)	(0.014)	(0.005)	(0.005)
Bad Health	0.345	0.302	−0.002	−0.007
	(0.012)***	(0.013)***	(0.004)	(0.003)**
Year 1994	0.019	0.005	0.010	0.009
	(0.023)	(0.024)	(0.004)***	(0.004)**
Year 1992	0.016	−0.019	0.009	0.006
	(0.030)	(0.028)	(0.005)**	(0.005)
Union Member		0.006		0.006
		(0.021)		(0.007)
Pension Plan		−0.273		−0.030
		(0.030)***		(0.005)***
Total Net Wealth		−9. E-8		−3. E-8
		(1. E-8)***		(1. E-8)***
Observations	13,471	13,471	13,471	13,471

Notes. Standard errors are in parentheses are clustered by sectors and years. Significance at 10%, 5% and 1% is denoted by *, ** and *** respectively. The number of observations is 13,471.

Table A3

Coefficient Estimates for the Wage Equations

Variable	1. Basic Model	2. Include Wealth Variables	3. Include Sector Dummies	4. Heckman Selection Model: Wage Equation	4. Heckman Selection Model: Status of Working
NTFPG	−0.641	−0.167	2.648	1.173	−2.26
	(1.178)	(1.055)	(3.041)	(0.856)	(0.955)**
XG	0.918	−0.625	−0.689	1.259	−4.478
	(0.864)	(0.813)	(1.903)	(0.682)*	(0.815)***
Age	0.238	0.170	0.217	−0.209	0.749
	(0.094)**	(0.091)*	(0.094)**	(0.081)***	(0.092)***
Age-squared	−0.002	−0.002	−0.002	0.002	−0.007
	(0.001)***	(0.001)**	(0.001)**	(0.001)***	(0.001)***
African American	−0.106	−0.080	−0.106	−0.072	−0.126
	(0.029)***	(0.027)***	(0.029)***	(0.031)**	(0.034)***
Hispanic	−0.120	−0.049	−0.111	−0.129	0.043
	(0.027)***	(0.025)*	(0.026)***	(0.0439)***	(0.050)
Foreign Born	−0.013	0.028	0.009	−0.094	0.274
	(0.039)	(0.036)	(0.037)	(0.037)***	(0.045)***
Currently Married	0.161	0.090	0.156	0.089	0.090
	(0.024)***	(0.024)***	(0.024)***	(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
	(0.023)***	(0.022)***	(0.024)***	(0.031)***	(0.037)
Regions:					
Central	−0.084	−0.054	−0.073	−0.120	0.145
	(0.040)**	(0.034)	(0.036)*	(0.031)***	(0.037)***
South-East	−0.175	−0.095	−0.166	−0.161	0.102
	(0.025)***	(0.024)***	(0.025)***	(0.028)***	(0.033)***
Pacific	−0.086	−0.066	−0.071	−0.066	0.034
	(0.034)**	(0.036)*	(0.033)**	(0.035)*	(0.041)
Bad Health	−0.213	−0.163	−0.208	−0.105	−0.592
	(0.034)***	(0.029)***	(0.032)***	(0.030)***	(0.030)***
Year 1994	−0.002	−0.021	−0.003	0.013	−0.070
	(0.038)	(0.029)	(0.020)	(0.026)	(0.030)**
Year 1992	−0.095	−0.115	−0.084	−0.191	0.192
	(0.038)**	(0.030)***	(0.023)***	(0.026)***	(0.031)***
Union Member		0.045			0.086
		(0.021)**			(0.031)***
Pension Plan		0.429			0.701
		(.025)***			(0.026)***
Net Wealth		55 E-8			50 E-8
		(4 E-8)***			(3 E-8)***
Constant	3.153	4.923	3.433	15.594	−19.743
	(2.694)	(2.620)*	(2.701)	(2.343)***	(2.684)***
R-squared	0.15	0.24	0.17	NA	NA
Observations	7,897	7,897	7,897	13,471	13,471

Notes. Standard errors in parentheses and except for (4) are clustered by sectors and years. Significance at 10%, 5% and 1% is denoted by *, ** and *** respectively.

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References

Aghion, P. and Howitt, P. (1994). 'Growth and unemployment', *Review of Economic Studies*, vol. 61(3), pp. 477–94.

Bartel, A.P. and Sicherman, N. (1993). 'Technological change and retirement', *Journal of Labour Economics*, vol. 11 (1), pp. 162–83.

Bartel, A.P. and Sicherman, N. (1999). 'Technological change and wages: an interindustry analysis', *Journal of Political Economy*, vol. 107 (2), pp. 285–325.

BEA, (2007). http://www.bea.gov/national/FA2004/details/index.html.

BLS, (2000). http://www.bls.gov/datahome.htm.

Boucekkine, R., De la Croix, D. and Licandro, O. (2002). 'Vintage human capital, demographic trends, and endogenous growth', *Journal of Economic Theory*, vol. 104 (2), pp. 340–75.

Chari, V.V. and Hopenhayn, H. (1991). 'Vintage human capital, growth, and the diffusion of new technology', *Journal of Political Economy*, vol. 99 (6), pp. 1142–65.

Costa, D.L. (1998). *The Evolution of Retirement: An American Economic History, 1880-1990*, Chicago and London: University of Chicago Press.

Diamond, P. and Gruber, J. (1999). 'Social security and retirement in the US', in (J. Gruber and D. Wise, eds), *Social Security and Retirement Around the World*, pp. 437–74, Chicago: University of Chicago Press.

Friedberg, L. (2003). 'The impact of technological change on older workers: evidence from data on computer use', *Industrial and Labor Relations Review*, vol. 56 (3), pp. 511–29.

Galor, O. and Moav, O. (2000). 'Ability biased technological transition, wage inequality and economic growth', *Quarterly Journal of Economics*, vol. 115 (2), pp. 469–97.

Gruber, J. and Wise, D. (1999). 'Social security programs and retirement around the world', in (S.W. Polachek, ed), *Research in Labor Economics*, vol. 18, pp. 1–40, Stamford, CN: JAI Press.

Gustman, A.L. and Steinmeier, T.L. (2000). 'Retirement outcomes in the health and retirement study', *Social Security Bulletin*, vol. 63 (4), pp. 57–71.

Helpman, E. and Trajtenberg, M. (1998). 'A time to sow and a time to reap: growth based on general purpose technologies', in (E. Helpman, ed.), *General Purpose Technologies and Economic Growth*, pp. 55–83. Cambridge, MA: MIT Press.

Hornstein, A. and Krussel, P. (1997). 'Technology improvements and productivity slowdowns: another crazy explanation?', *NBER Macroeconomic Annual*, vol. 11, pp. 209–59.

Jorgenson, D.W. (2000). http://www.economics.harvard.edu/faculty/jorgenson/data/.

Katz, L. and Murphy, K.M. (1992). 'Changes in relative wages, 1963-1987: supply and demand factors', *Quarterly Journal of Economics*, vol. 107 (1), pp. 35–78.

Moulton, B.R. (1990). 'An illustration of a pitfall in estimating the effects of aggregate variables on micro units', *Review of Economics and Statistics*, vol. 72 (2), pp. 334–8.

Peracchi, F. and Welch, F. (1994). 'Trends in labour force transitions of older men and women', *Journal of Labor Economics*, vol. 12 (2), pp. 210–42.

Stock, J. and Wise, D. (1990). 'Pensions, the option value of work, and retirement', *Econometrica*, vol. 58 (5), pp. 1151–80.