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 some existing technology specific human capital. Since older workers have shorter career horizons, there is smaller incentive for them or for their employers to invest in learning how to use the new technology. Consequently, they are more likely to stop working. Using individual data, we find support for this *erosion effect,* as early retirement is positively correlated to the sector's rate of technical progress. At the aggregate level, the effect of technical progress on labor supply of older workers is mixed. It falls in innovating sectors due to the above *erosion effect*, but it increases in other sectors due to higher wages. This is the *wage effect*. US time series aggregate data demonstrate that the overall effect of technical progress on aggregate labor force participation of the old is negative. Namely, the *erosion effect* dominates.

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1. Introduction

The number of workers who quit working before they reach the formal age of retirement is surprisingly high in modern economies. In 1996 the average labor force participation rate in OECD countries of men in ages 55-64 was 63.6 percent, while labor force participation rate for men in ages 25-54 was 93.1 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. Early retirement is usually attributed to bad health, and to wealth, intensified by generous retirement plans like social security. This paper offers a third 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 always make some existing human capital obsolete, while creating demand for new types of human capital. This paper claims that as a result, technical progress 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 new technologies. The paper models this idea theoretically, examines its implications and tests them, using both micro and macro US data, and finds significant support for it.

The main idea is presented in a simple growth model where production is organized in 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. Meanwhile, new innovations arrive and replace existing technologies. The new technologies are more productive, but require learning. While all young workers learn to use the new and more productive technologies, some older workers do not learn, since their career horizon is much shorter. Those who do not learn can either stick to the less productive technologies, in which case they have lower income due to competition from the young in their sector, or retire early. Thus, technical progress raises the probability of early retirement. Note that while this paper models the decision to retire early as a worker's decision, for reasons of tractability, in real life it is many times a decision made by the employer, who prefers not to retrain an older worker on the job. If the worker becomes unemployed at old age, he usually retires after some futile search for a new job. The basic result is the same.

The theoretical model is important beyond the basic idea, as it helps in forming the empirical tests of how technical progress affects early retirement, and especially it helps in forming a test of the reverse causality hypothesis. Most importantly, the theoretical model leads us to the above distinction between the erosion effect and the wage effect at the aggregate level. That also leads to the aggregate empirical test. So, while one of our tests is similar to that of Bartel and Sicherman (1993), who also examine the relationship between technical progress and labor supply of older workers across sectors, our approach is different, as it is based on an analytical model that leads to many additional tests.

One main empirical implication of the model is therefore that the probability of being out of work for older workers should be positively correlated with the rate of technical progress across sectors. The model also analyzes the aggregate effect of technical progress on participation by older workers in the economy as a whole and shows that this aggregate effect is ambiguous. On one hand, during periods of rapid technical progress, more sectors have new technologies and in these sectors more old workers retire. This is called the *erosion effect*, as it reflects erosion of human capital. On the other hand, wages rise in periods of high technical progress and that has a positive effect on labor supply of older workers in other sectors. This is the *wage effect*. Clearly, the two effects are opposing.

The paper examines the empirical predictions of the model using US data. We first examine the effect of sector technical progress on the labor status of individual men over the age of 50. The data on individual labor decisions are 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), after some adjustments. We find that the coefficient of sector TFP growth on the probability that older men do not work is positive. 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 such a possibility and reject it.

We next study the aggregate effect of technical progress. We examine the relationship between the average rate of technical progress in the US and the aggregate labor supply of older workers over time. This test compares the two opposite effects: the *erosion effect* and the *wage effect*. Since aggregate TFP growth rates reflect both technical progress and temporary shocks we use the Blanchard and Quah (1989) Structural VAR methodology to identify the two shocks. Our test shows that the effect of technical progress on labor force participation of men over 55 is indeed negative. Hence, the *erosion effect* dominates the *wage effect*.

This paper is most closely related to two different lines of research. One is research on early retirement of old workers and its explanations, and the other is research on the effects of technical progress on the labor market. Most of the literature on early retirement focuses on wealth, which has increased in recent decades due to economic growth and to institutions such as

Social Security and pension funds. Such explanations appear in Stock and Wise (1990), Diamond and Gruber (1999), Costa (1998), Gruber and Wise (1997) and Gustman and Steinmeier (2000).[1] This paper suggests that the erosion effect of technical progress is an additional explanation to early retirement. This idea has been previously mentioned by Peracchi and Welch (1994), but this paper develops the idea further and presents it in a full general equilibrium theoretical model.[2]

The paper is also related to the literature on the effects of technical progress on labor markets. A number of recent theoretical papers, such as Aghion and Howitt (1994), Helpman and Trajtenberg (1998), Hornstein and Krusell (1996), and Galor and Moav (2000), claim that technical progress reduces employment due to costs of learning new technologies. This paper shows that this effect is stronger for older workers, whose career horizon is short. There are also some recent empirical papers, which study the effect of technical progress on the labor market, and find that technological innovations are followed by short-run unemployment. This is shown in Gali (1999) and in many other papers that he cites. Our paper is highly relevant to these papers, since it shows that the effect they find is due mainly to the negative effect on employment of older workers, and it does not hold for younger workers.[3] Thus our tests suggest a very different interpretation to these findings.

The paper is organized as follows. Section 2 presents the basic model of technical progress, training and retirement. Section 3 describes the equilibrium, finds various effects that cause early retirement, focusing on the effect of technical progress. Section 4 describes the

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[1] A theoretical analysis of how social security affects retirement appears already in Feldstein (1974).

[2] Two theoretical papers are related to our model. Boucekkine et al (2002) discusses economic growth and retirement, but has no erosion of human capital. Chari and Hopenhayn (1991) describe a model with erosion of technology-specific human capital, but without retirement. Our model combines the two approaches together.

[3] Another recent paper that points at the relationship between technology and age is Friedberg (1999), who shows that older workers use computers less than younger workers.

empirical implications of the model, Section 5 presents and evaluates the empirical results on the effect of technical progress across sectors, Section 6 reports the aggregate results, and the last section concludes.

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:

$$(1) \qquad \log y_t = \int_0^1 \log x_{i,t} \, di ,$$

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 available technology in period t produces an amount $a_{i,t}$ of the intermediate good i in a unit of time. This technology is not freely available, as it requires training and learning. Using a technology is therefore a specific profession for which workers need to train.

We next describe technical progress. Each period new technologies of producing intermediate goods, which replace the old technologies, arrive exogenously. These new technologies are more productive, namely:

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

We assume that $1 \le b_{i,t} \le 2$. The lower bound is of course the case of no technical progress, while the upper bound is fairly reasonable. The sector's rate of technical progress is log $b_{i,t}$. The new technologies for time t become known in the beginning of the period. The rate of technical progress log $b_{i,t}$ is independent and identically distributed over time.

We next add some structural assumptions on the correlation between rates of technical progress across sectors. These structural assumptions are used only in the macroeconomic part of the analysis. We assume that the rates of technical progress are correlated across sectors in each period. Namely, when technical progress is high, it is high in many sectors. This assumption is also supported by the data.[4] Formally we assume that the sector's rate of technical progress can be decomposed into an aggregate component g_t and a sector component in the following way:

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

According to the assumptions above the average rate of technical progress g_t is an i.i.d. process with a positive expectation g and the sector relative component $s_{i,t}$ is a white noise, independent both over time and across sectors. In order to ensure that the rate of technical progress in a sector is non-negative, we assume that $s_{i,t} \geq -1$.

Individuals live two periods each in overlapping generations. Population is fixed and each generation is a mass of size 1. In first period of life each person acquires a profession i and supplies 1 unit of labor. In second period of life a person can either supply L units of labor in the former technology, where L<1, or retrain and learn the new technology but work less, or retire. To retrain the worker uses f time, where f is a personal measure of effort of retraining. Hence, he supplies only $L - f$ units of labor in second period of life.[5] For analytical convenience assume that part time work is spread uniformly throughout the period. The personal measure of effort f differs across individuals and is assumed to be uniformly distributed between 0 and F, where $L/2 < F < L$. This distribution reflects many things: level of education, quality of training system, supply of on-the-job training, etc. If the worker retires he has no income in the second

[4] This assumption reflects the fact that many technological innovations are quite general and spread across sectors.
[5] In principle the learning time should depend on the size of the innovation as well, namely on $b_{i,t}$. This addition to the model does not change the main results and is not included here to simplify the exposition only.

period of life, but he enjoys utility from retirement, which also differs across individuals.[6] For tractability we assume that individuals consume in the second period of life only. Formally, the utility function is

(4) $$u = \log c + \delta \log(1+h),$$

where c is consumption when old, δ is 1 if the worker retires and 0 if not, and $\log h$ is utility from retirement, which is individual. We assume that h is uniformly distributed between 0 and H, and is independent of f. An individual therefore faces two decisions during lifetime. When young he chooses a profession. When old he chooses between one of the three mutually exclusive options: retire, retrain and work with the new technology, or work with the old technology.

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 the world interest rate is equal to r.[7] 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

The young choose professions according to expected income. They know which technologies will be used and hence they know output and price levels as well. Due to Cobb-Douglas production (1), demand for intermediate good i in period t is described by:

[6] 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.
[7] 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 a government or as firms.

(5) $$p_{i,t} = \frac{\partial y_t}{\partial x_{i,t}} = \frac{y_t}{x_{i,t}}.$$

Prices of all goods are in terms of the final good, the numeraire. Choice of sectors by the young equates expected incomes $p_{i,t}a_{i,t}$ across sectors, through adjustments of $x_{i,t}$.[8] Denote the common real income of the young across sectors by w_t and call it the wage rate:

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

We next calculate this equilibrium real wage. First, note that (5) and (6) yield:

(7) $$x_{i,t} = \frac{y_t}{p_{i,t}} = a_{i,t}\frac{y_t}{w_t}.$$

Substitute (7) in (1) and get:

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

Hence, the wage is equal to the average state of technology. The rate of change of wages is

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

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, which in this model is equal to the growth rate of total factor productivity (TFP).

We next describe workers' incomes in the second period of life. Note first that due to homogeneity the price of each intermediate good is the same for all producers, young and old. Hence, the wage rate of an old worker who retrains is the same as that of the young, w_t. A worker who does not retrain faces competition from younger workers with a better technology and earns

[8] Workers care about the future t+1 wages as well, but these expected wages are equal across sectors for two reasons. First, future ex-post wages will be equalized across sectors by the next generation. Second, expected effect of new technologies on workers' incomes is equal, since technical progress is independent of sector.

only $a_{i,t-1}p_{i,t} = w_t / b_{i,t}$. Thus, wages of old workers trapped in their former professions are lower than wages of young or of old who retrain. Furthermore, wages of these workers are negatively related to sector technical progress. The intuition behind this result is as follows. Technical progress increases productivity in a sector, which does not lead to higher wages in the sector, due to labor mobility of young workers, but it increases entry of young workers to the sector. Hence, supply of the intermediate good increases, and its relative price falls. This reduces the income of old workers in this sector who do not retrain.

3.2. Early Retirement, Retraining or Business as Usual

We next turn to analyze decisions in the second period of life. An older worker chooses between three alternatives: retrain, not retrain but work, and retire. Utility if the worker retrains is

(10) $$\log\left[w_{t-1}(1+r) + w_t(L-f)\right].$$

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

(11) $$\log\left[w_{t-1}(1+r) + L\frac{w_t}{b_{i,t}}\right].$$

Utility if retires is

(12) $$\log\left[w_{t-1}(1+r)\right] + \log(1+h) = \log\left[w_{t-1}(1+r)(1+h)\right].$$

Comparing utilities leads to the worker's choice. He prefers to retrain if:

(13) $$f \le L\left(1 - \frac{1}{b_{i,t}}\right) = L\frac{b_{i,t}-1}{b_{i,t}}.$$

The RHS of (13) is bounded by *L*/2 and hence is bounded by *F*. Clearly retraining rises with *L*, the length of career horizon, as it affects the incentive to retrain. This is why our model of human capital erosion applies mainly to older workers with low *L*. The conditions for staying in work and not retiring are the following. If (13) holds, the worker retrains and works if:

(14) $$h \le \frac{1}{1+r}\frac{w_t}{w_{t-1}}(L-f)\,.$$

If (13) does not hold the worker does not retrain but keeps working if:

(15) $$h \le \frac{1}{1+r}\frac{w_t}{w_{t-1}}\frac{L}{b_{i,t}}\ .$$

The decision of older workers is presented in Figure 1, in which workers are distributed between 0 and *H* on the *h* axis and between 0 and *F* on the *f* axis. Lines I, II and III divide them according to their choices. Line I is defined by equality in (13). Workers below it retrain and workers above it do not. Line II is defined by equality in (14) and line III is defined by equality in (15), and they divide workers between retirement and work. The three lines meet at the same point. Workers in area A, above I and to the left of III, use the old technology. Workers in area B, below I and to the left of II, retrain, and workers in area C, to the right of II and III, retire. The probabilities of these three choices are the areas A, B, and C, divided by *FH*, respectively.

[Insert Figure 1 here]

Note that according to our above assumptions all three areas in Figure 1 are positive, and so are the probabilities of all three outcomes, if *H* is sufficiently large. The main qualitative results of the model hold even if *H* or *F* is smaller, though the size of the effect of technical progress might change.

3.3. The Probability of Working in Old Age

According to Figure 1, the probability that workers stop working is

(16) $$P_{i,t} = 1 - \frac{L}{HF(1+r)}\frac{w_t}{w_{t-1}}\left[\frac{F}{b_{i,t}} + \frac{L}{2}\left(1-\frac{1}{b_{i,t}}\right)^2\right].$$

This probability depends on various variables. The most important one is of course the sector's rate of technical progress, which is our main variable of interest. A rise in $b_{i,t}$ shifts line I up and line III to the left, leaving line II unchanged. As a result area B of retraining increases, area A of no retraining decreases, and area C of early retirement increases. Hence, the probability of not working or of early retirement rises. This can be shown by direct derivation of (16) as well.

The probability of early retirement depends not only on the sector rate of technical progress, but on the aggregate rate as well, through the general wage effect w_t / w_{t-1}. This effect is negative, and we return to it in section 3.5. Equation (16) also tells us also how the other parameters *F*, *H*, *L* and *r* affect the probabilities of work and of retirement. The maximum training costs *F* has a positive effect on not working. Intuitively, higher retraining costs reduce the incentive to retrain and to stay in the labor market. The maximum utility from retirement *H* also has a positive effect on early retirement, clearly. *L* has a negative effect on early retirement. Intuitively, the longer the work horizon of older workers, the more they gain from working and from retraining, and the less they tend to retire. The effect of interest rate *r* on early retirement is positive. Intuitively, wealth accumulation increases consumption of leisure and thus increases early retirement.

We therefore summarize the above by the following function *P*, which rephrases (16). The probability of not working in sector *i* in time *t* is

(17) $$P_{i,t} = P(L, F, H, r, g_t, b_{i,t}) .$$

As shown above: $P_L < 0,\ P_F > 0, P_H > 0, P_r > 0, P_g < 0, P_b > 0$.

3.4. 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. The reason we are interested in this effect is its use in the empirical analysis in Section 5. The effect of sector technical progress on wages of workers who do not retire is mixed. On one hand, technical progress lowers wages of workers who do not retrain, but on the other hand, it reduces their number relative to those who retrain, which raises the average. Hence, the overall effect of technical progress on the average wage is ambiguous.

In our specific model the average wage of workers who continue to work is:

$$w_t \frac{b_{i,t}^3 + (2F/L-3)b_{i,t} + 2}{b_{i,t}^3 + (2F/L-2)b_{i,t}^2 + b_{i,t}}. \tag{18}$$

If the sector has no technical progress and $b_{i,t} = 1$, the average wage equals w_t. As $b_{i,t}$ increases, the average wage falls and then rises again. If, for example, $F = L/2$, then the average returns to w_t again at $b_{i,t} = 2$. This is shown in Figure 2. Hence, the two effects tend to cancel one another, so that the overall effect of technical progress on the average wage is ambiguous and small, being close to zero. This result plays an important role in the empirical analysis in Section 5.

[Insert Figure 2 here]

3.5. The Aggregate Effect of Technical Progress

We next turn to the effect of aggregate technical progress on labor supply of older workers in the whole economy. From the above discussion we learn that the average rate of technical progress g_t has two opposite effects on early retirement. First, there is a negative *wage effect*, since g_t raises wages, which increases labor supply of older workers in all sectors. This is shown by $P_g < 0$ in equation (17). The second effect comes from the positive correlation between the average and the sectors' rates of technical progress. A higher g_t is correlated with higher sector technical progress $b_{i,t}$ and thus with more early retirement and less labor supply in the innovating sectors. This is the positive *erosion effect*. The two effects are seen in the following aggregate probability of not working:

$$P_t = \int_0^1 n_{i,t} P_{i,t} di = 1 - \frac{L}{FH(1+r)} e^{g_t} \int_0^1 n_{i,t} \left[\frac{F}{b_{i,t}} + \frac{L}{2}\left(1 - \frac{1}{b_{i,t}}\right)^2 \right] di. \tag{19}$$

The numbers $n_{i,t}$ are the sector shares in employment of this generation. The direct negative effect of g_t is the wage effect. The positive effect of g_t through $b_{i,t}$ is the erosion effect.

In order to get a better understanding of the interaction between the two effects, we use the decomposition of sector technical progress to the aggregate and idiosyncratic components (3). Substituting in equation (19) we get after some manipulation:

$$P_t = 1 - \frac{L}{FH(1+r)} \int_0^1 n_{i,t} \left[(F-L)e^{-g_t s_{i,t}} + \frac{L}{2} e^{g_t} + \frac{L}{2} e^{-g_t - 2g_t s_{i,t}} \right] di. \tag{20}$$

To examine which effect is stronger under this specification, the wage effect or the erosion effect, we calculate the derivative of (20) with respect to the average rate of technical progress g_t. This derivative is

$$\frac{\partial P_t}{\partial g_t} = \frac{L}{FH(1+r)} \left[(L-F)\int_0^1 (-s_{i,t}) e^{-g_t s_{i,t}} n_{i,t} di - \frac{L}{2} e^{g_t} \left(1 - \int_0^1 n_{i,t} (1+2s_{i,t}) e^{-2g_t - 2g_t s_{i,t}} di \right) \right]. \tag{21}$$

Examination of this derivative shows that its sign is ambiguous and depends mainly on F. In Section 6 we take this issue to the US data. We examine the effect of the average rate of technical progress on the rate of labor participation by old, which is precisely $1-P_t$, to see which effect is stronger, the positive wage effect or the negative erosion effect.

4. Testing the Empirical Implications of the Model

We conduct a series of tests of the empirical implications of our theory, using available US data. We start by estimating a simple Probit model, where the dependent variable is 'not working' on a sample of men age 50-64. To check the robustness of the results, we estimate alternative specifications, such as using alternative 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. To test for reverse causality, we also look at estimates from wage regressions. Finally, we use aggregate US data to examine the time-series relationship between the average rate of technical progress and the aggregate labor participation rate of men age 55-64, using a "structural" VAR model.

In Section 5 we present estimates of a reduced-form specification of equation (16), according to which the probability of early retirement of older workers depends on the rate of technical progress in their sector $\log b_{i,t}$, and on the parameters L, F, H, and r. Therefore, we estimate a Probit panel regression over three periods of the HRS data set, of the form

$$Z_{j,t} = I_{j,t}\gamma + S_{j,t}\delta + \varepsilon_{j,t}, \tag{22}$$

where 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 theoretical model variables, beginning with the dependent variable, the probability of early retirement.

Finding empirical counterparts to the decisions of older workers in the model poses two main problems. The first is that we do not observe on-the-job training, which is the prevalent form of retraining. Thus, our data do not distinguish between retraining and keeping the old technology. Hence, our estimation lumps these two states together into one state. The second problem is that while in our model workers decide when to quit, in reality and in the data a worker can be fired as well.[9] We therefore use the fact that the data contain more information on

[9] See Appendix, Table A1 for the distribution of reasons for leaving a job.

not working statuses, and in addition to 'not working', we also estimate equation (22) with unemployment and retirement as alternative dependent variables.[10] 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 drop from the labor force permanently.

The main explanatory variable in this test is the sector's rate of technical progress, $\log b_{i,t}$. Of course, this variable is not directly observed. We use instead the rate of growth of total factor productivity (TFP) per sector. Although it has been found by Bartel and Sicherman (1993) to be a good measure of technical progress, it has some problems. The main problem is that it reflects not only technical progress, but also other shocks that affect utilization. This problem is dealt in a number of ways. First, we subtract aggregate TFP growth from sector TFP growth to eliminate aggregate demand shocks. Second, we average TFP growth rates over periods of 5 years. Third, we add sector output growth to the estimation to control for sector-specific demand shocks.

The other parameters of equation (16) 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 utility from 'not-working' H, and the inverse of education is an indicator for F, which describes the effort required to learn new technologies. The interest rate r, affects early retirement through accumulation of past wealth. Luckily, our data contains information on personal accumulated wealth as well as on pension funds. Both wealth and pension status are expected to have a positive effect on retirement.

The sector empirical analysis contains not only tests of equation (16) but tests of equation (18) as well, namely of how the average wage of the older workers, who continue to work, is related to the sector's rate of technical progress. This test examines the possibility of reverse

[10] We also estimate a multinomial logit model with the three disjoint states working, unemployed and retried. In general, this model yields similar results to the Probit regression. To save space, we do not present them.

causality, namely that sectors with high rates of early retirement are more efficient, because they can get rid of less productive old workers, and have a higher rate of TFP growth as a result. This reverse causality hypothesis implies that wages of old workers in more productive sectors should be higher, contrary to the prediction of equation (18), that the effect of sector TFP growth on wages of old workers is ambiguous. This issue is also examined with the cross section data set.

The empirical work concludes with a structural VAR estimation of equation (20). This is done by using time-series aggregate data on technical progress and on labor participation of older workers in the US. We use these data to test which effect has been stronger in the post World War II period, the erosion effect or the wage effect. In this test we further improve the identification of technical progress by breaking up aggregate TFP growth into permanent and temporary shocks and by identifying the permanent shocks with technical progress.

5. The Effects of Technical Progress across Sectors

5.1. The Data

The main data source that we use is the first three interviews (1992, 1994, and 1996) of the Health and Retirement Study (HRS), which contains detailed micro information on a large group of individuals of age 50 and above. The HRS gathered information on their jobs and career histories during 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 merge the HRS with Jorgenson's (2000) data set that measures output, input factors, and Total Factor Productivity (TFP) for 35 economic sectors, from 1970 to 1996.

Table 1 presents labor status shares across the three interviews, for three separate age groups: 50-54, 55-59, and 60-64. The results in Table 1 confirm that non-working is quite common for men in their early fifties (20% compared with less than 5% for men 40-45 years old) and increases steadily to over 50% in the older group. The reasons for not working are very heterogonous.[11] Note that retirement becomes the major status among the non-working men only after age 60, whereas in the 55-60 group between 11 to 14 percent are retired, while 15-16 percent are unemployed or disabled. The share of retirement climbs to more than 35 percent for men in the 60-64 group, while the combined share of the other three not-working groups decreases to about 12 percent.

[Insert Table 1 here]

Contrary to retirement rates, unemployment rates decrease with age, from 5.1 percent in the younger age group to 2.3 percent in the older age group. Interestingly, these figures are much lower than the overall unemployment rates in the US at that time (7.5 percent in 1992 and 5.4 percent 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, combined with the fact that the share of disabled workers seems to be unaffected by age and by economic variables, leads us to focus on 'not-working' as the main indicator of early retirement. In addition, we also estimate the determinants of unemployment, and of official retirement.

Most of the covariates in the vector $I_{j,t}$ have been determined many years prior to the survey and can be considered to be exogenous to the decision of working or not. Such variables are age, race, immigration status, marital status and education. Other covariates, like pension

[11] See Table A1 in the Appendix on reasons for not working in the first HRS interview.

status, union membership, and accumulated net wealth have also been determined in the past but might be affected by more recent decisions. Since these variables 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 profession in last main job, whether it has been a production or non-production profession.[12] This variable is added to some of the regressions to test for interaction with technical progress.

The sector variables ($S_{j,t}$) are related to the last main job. We match the sector reported in the HRS, which has 14 sectors, to the relevant sectors in the Jorgensen data set, which has 35 sectors. The main variable we use is a proxy for the sector's rate of technical progress, which is derived from the rate of TFP growth. Since TFP growth is not identical to technical progress, as discussed in Section 4, we use some manipulation. We use the average rate of TFP growth in the sector during the 5 years prior to the relevant year of survey and subtract from it the average rate of TFP growth for all sectors during this period. The TFP growth rate differs significantly across sectors and over time.[13] Since TFP growth might reflect demand changes in addition to technical progress, we add to most regressions sector output growth as an additional explanatory variable in order to control for such demand effects.

5.2. Labor Status Regressions

Table 2 and Table A2 present the main results of this test. Table 2 focuses on the effects of TFP growth on labor status, while Table A2 reports the effects of the entire control variables from six 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 is not transparent from the coefficient estimates in Table A2. Thus, column 1 of Table 2

[12] 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.

reports the effect of a one percentage-point increase in TFP growth on the absolute probability of 'not working'. It therefore reports exactly the empirical equivalent of the model derivative of equation (16), calculated by using the normal density at the sample means. Formally:

$$\delta^* = \frac{\partial P_{labor \quad status}}{\partial (TFP\ growth)} = \phi(\bar{I}\hat{\gamma} + \bar{S}\hat{\delta})\hat{\delta}_{TFP\ growth}\,, \tag{23}$$

where ϕ is the normal density. Columns 2 and 3 report comparable estimates for two subgroups of 'not-working', namely 'unemployed' and 'retired,' giving us a profound view on the entire process of exiting from the labor force by old workers.

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

[Insert Table 2 here]

The effect of 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 compelling evidence to support our main hypothesis, that technical progress *pushes* many older workers in these industries out of work, mainly to unemployment.

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[13] In 1992, the sector TFP growth ranged from –0.1% to 4% (mining), with an average of 0.6% and standard error of 1.3%. In 1996, the leading sector was agriculture with 2%, the average was 0.2%, and the standard error 1.1%.

The magnitudes of these effects are quite significant, as a one-percent increase in TFP decreases the probability of employment by about 1.58 percentage-points in the basic model.

A more detailed examination of the results yields some further 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 a possible correlation between the wealth variables and sector, if sectors with better wage and pension conditions have higher rates of technical progress as well. But even with these variables added, the effect of TFP growth on 'not working' is still negative, which points to robustness.

Not surprisingly, the erosion effect is weaker when we restrict the sample to younger men in ages 50-60. Indeed, the effect of technical progress on early retirement is even not significant for this group. However, the positive effect on unemployment is even stronger than the effect for the full sample. We take advantage of the panel structure of the data and run a random-effect model (Model 5) to check for robustness and find that even when controlling for unobserved individual effects, the main results of the model remain unchanged.

Models 6 and 7 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, production workers are expected to suffer more from erosion of human capital related to sector specific 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 effect.

Column 2 in Table 2 presents similar effects on 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 with the exception of the younger group, which happens to be more sensitive to technical growth than older workers. 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 official retirement responds with a delay, which we are unable to identify its length with our regression analysis.

Finally, while our primary interest is in the labor supply response to technical progress, we briefly summarize the estimated effects of the other control variables. Our findings, as reported in Table A2, conform with Costa (1998), Peracchi and Welch (1994) and Bartel and Sicherman (1993), despite the use of different data sets. Our results 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, while it does not have a significant effect on unemployment. We also find, as in other studies, that wealth and pension tend to lengthen work at the individual level, which contradicts our model. We can think of two possible explanations for this finding. One is that these variables capture some individual innate ability, which is related to retraining ability. The other explanation is that wealth and pension status are job and sector related and thus capture some sector characteristics.

5.3. Testing for Reverse Causalities

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 reorganization. Since firms tend to keep only the best workers, reorganization might increase productivity. This too can create a positive correlation between sector TFP growth and not working. To test this possibility we do two things, first, include sector output growth in the tests of labor status, as reported in Table 2, and second, test for the effect of sector TFP growth on wages of those who continue to work.

If higher productivity is caused by lay-offs, then early retirement and high TFP should also be positively correlated with reductions in demand and in output. As mentioned above, the sector's output growth is included in six of the models in Table 2. Comparing the estimation without output growth in Model 3 to the other models shows that the coefficient of TFP growth is almost unchanged, going up from 0.79 to 0.86. Furthermore, the correlation between sector's TFP growth and sector's output growth is almost zero. Thus, the alternative hypothesis that TFP growth is due to lay-off of older workers seems less likely.

The second and main test for reverse causality examines the effect of TFP growth on wages of workers who continue to work. Under the reverse hypothesis, remaining workers should have higher wages in sectors with more lay-offs, which get rid of unproductive workers. Hence, under reverse causality we expect a positive correlation between TFP growth and wages, while according to our erosion model this correlation is close to zero, as shown in Section 3.4.

[Insert Table 3 here]

Table 3 presents the regressions for four specifications of the wage equation. The main result of all 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. Interestingly, this effect on wages of old workers contrasts the strong positive effect of technical progress on wages of young workers, found by Bartel and Sicherman (1999) and others. Note, that the effect of sector output growth, which represents demand shifts, is not significant as well.

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 the main result is still unchanged. Note that the results in the selection equation are similar to those of Model 2 in Table A2. As our model predicts that retraining increases hourly wages of workers that choose to retrain, the results of the Heckman selection model suggest that retraining is not common within this sample of old workers.

The other results of the wage equations are in line with the standard literature. The positive coefficient of wealth supports our above hypothesis that this variable is correlated with innate individual ability. To conclude, the results of these tests demonstrate a rejection of the possibility of reverse causality and support the robustness of our results on the *erosion effect*.

6. The Effect of Aggregate Technical Progress in the US

This section examines the relationship between the average rate of technical progress and the aggregate rate of labor participation of older workers. While Section 5 provides cross sectional evidence on the erosion effect, this section examines how strong this erosion effect is in the economy as a whole, by weighing it against the wage effect. This is done by testing the relationship over time between the labor participation rate of older workers and the rate of technical progress. The main empirical problem we face is that, we do not directly observe technical progress but only Total Factor Productivity (TFP). The latter consists of two components: technical progress and transitory changes in productivity. In order to decompose the rate of total factor productivity growth between these two components, we apply the Blanchard and Quah (1989) method of Structural VAR.

Before applying the Structural VAR model, we present the data and discuss the relation between the two main variables, the rate of Growth of Total Factor Productivity (GTFP) and the rate of Growth of Labor Force Participation of Older workers (GLFPO). We calculate the series of GTFP by using Jorgenson (2000) and Jorgenson and Stiroh (1999) US annual data in 1948-1996, and construct the series of GLFPO for the same years by using data from the Bureau of Labor Statistics (2000). The series of GLFPO is calculated by taking logarithm changes of LFP rates of men between the ages 55-64. During the sample period, the index of TFP has increased from 0.89 to 1.34, at an average annual rate of 0.7 percent. Labor force participation of all working-age men (16-64) has decreased from 78.5 to 70.5 percent, and most of this decline is due to lower participation of older men, which has dropped from 86.7 percent to 62.6 percent.

[Insert Figures 3-A and 3-B here]

A simple analysis of the data reveals interesting relations between productivity changes and labor force participation rates. The correlation between GLFP for all working-age men (ages 16-64) and GTFP in the US from 1948 to 1996 is 0.3, while the same correlation for older men, between GLFPO and GTFP is only 0.04. These relations are also manifested in Figures 3-A and 3-B, which display series of annual changes of LFP of men of age 16-64, of men of age 55-64, and of GTFP. The figures show, similar to the simple unconditional correlation, that GLFP of all men and GTFP are positively correlated, while GLFPO and GTFP are not correlated.

We next turn to describe the Structural VAR model, which we use to decompose TFP growth to technical changes and to transitory changes. While the theoretical model assumes for simplicity that productivity is driven solely by technical progress, in reality it is also affected by other shocks, mostly demand driven. In the following empirical model we allow for such shocks and assume that they are temporary, while technology shocks are permanent. We therefore assume that the two observed variables, the rate of Growth of Total Factor Productivity (GTFP) and the rate of Growth of Labor Force Participation of Older workers (GLFPO) are both functions of two disturbances: ε_{1t} and ε_{2t}. The first disturbance reflects transitory changes in productivity, while the second is the rate of technical progress, namely g_t from the model. Hence, the joint dynamics of GTFP and GLFPO follow this stationary process:

(23) $$\begin{bmatrix} GTFP_t \\ GLFPO_t \end{bmatrix} = \begin{bmatrix} C_{11}(L)\ C_{12}(L) \\ C_{21}(L)\ C_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}.$$

The random variables ε_{1t} and ε_{2t} are assumed to be independent white-noise disturbances with constant variances, and the $C(L)$'s are polynomials in the lag operator L.

Since the model is stationary we can estimate a reduced form VAR representation of the form:

(24) $$\begin{bmatrix} GTFP_t \\ GLFPO_t \end{bmatrix} = \begin{bmatrix} A_{11}(L)\ A_{12}(L) \\ A_{21}(L)\ A_{22}(L) \end{bmatrix} \begin{bmatrix} GTFP_{t-1} \\ GLFPO_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix},$$

where $A(L)$ is the matrix of the coefficients estimated, and $e_{1\mathrm{t}}$ and $e_{2\mathrm{t}}$ are the VAR residuals. We then calculate the moving average representation of the VAR:

(25) $$\begin{bmatrix} GTFP_t \\ GLFPO_t \end{bmatrix} = \begin{bmatrix} B_{11}(L)\ B_{12}(L) \\ B_{21}(L)\ B_{22}(L) \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}.$$

In the next stage we use the Blanchard and Quah (1989) method to recover the ε's and the $C(L)$'s from this VAR estimation, by using the identifying restriction that only technical progress shocks have permanent effects on TFP, while transitory productivity shocks have temporary effects.

In order to use this method we first test the crucial assumption, that both variables are derived from stationary processes, by using the Dickey-Fuller test. We reject the null hypothesis of a unit root for each of the two variables (at 1-percent significance level), empirically motivating the VAR specification of equations (24) and (25). Then we estimate several specifications of lags, and find that the specification AR(2) fits the data better than others.[14] Using the restriction on the effect of the temporary coefficient on TFP we identify the ε's and the $C(L)$'s. This enables us to calculate the Impulse Response Functions of the two variables.

[Insert Figures 4-A and 4-B here]

Figures 4-A and 4-B display two representations of the dynamic responses of labor force participation of older workers to technical progress. Figure 4-A displays the Impulse Response Function of GLFPO to a unit change at period zero in ε_{2t}. In response to a positive technology shock of one percent, GLFPO experiences an immediate decrease of 0.6 percent. After two periods, the growth rate stabilizes and converges to zero after 6-7 periods. We therefore conclude that according to this test of US data, the erosion effect is strong and dominates the wage effect.

Interestingly recent studies have shown that technology shocks have a negative effect on employment in general, as shown by Gali (1999) and other studies he cites. We find that this effect holds mainly for older workers. We have run a similar SVAR test for workers in ages 16-64, and found a smaller and less persistent negative effect to technical progress on labor participation. Hence, our analysis can provide an explanation to the findings by Gali (1999) and others on the negative effect of technology shocks on employment.

According to our theoretical model the effect of technical progress on labor force participation of the old is temporary, so it explains fluctuations of labor force participation around trend, rather than the trend itself. But our empirical analysis shows that the effect of technical progress is quite persistent and lasts quite long. Figure 4-B illustrates this, by displaying the effect of a one-period one-percent shock of ε_2 in 1949 on the level of labor force

[14] The results of the VAR estimation are in Table A3 in the Appendix.

participation of men in ages 55-64 over the next 15 years. The upper line in the figure displays the actual rates, while the lower line displays the calculated series. The calculation includes an adjustment for annual entry of new men to the 55-64 years age group. Figure 4-B shows that the negative effect of the shock remains significant for many years and the two lines meet only after more than twenty years. A unit technology shock in 1949 would have reduced the 1955's LFP of men age 55-64 by 0.7 percentage points, by 0.5 in 1960, and by 0.3 percentage points in 1965. Thus, the negative effect of aggregate technology shocks on LFPO persists over a long period.[15]

The persistence of the effect of technical progress on labor force participation means that it can also serve as one of the explanations to the observed decline in LFP of older workers in recent decades, in addition to increased social security coverage, as Diamond and Gruber (1999) suggest. During the sample period, TFP increased by 45 percentage points, from 0.89 to 1.34, and LFP of older men decreased by 24 percentage points, from 86.7 to 62.6. Our results suggest that a sequence of positive technology shocks may have contributed to this decline.

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 in labor economics. We combine these two areas together by observing that technical progress has a substantial negative effect on labor participation rates of older workers, as it erodes technology-specific human capital mostly for older workers, who have a shorter career horizon. We describe the erosion effect by a simple

[15] Our calculation underestimates the negative effect of technical progress, as we assume that new entrants to the group of 55-64 years old are not affected by technical progress, while they might to some extent.

growth model and then test it across sectors in the US. We find that technical progress has a negative effect on employment of older workers.

At the aggregate level our model identifies an additional effect to the negative erosion effect, which is the positive wage effect. But using US data, we find that in the years 1950-1996 the erosion effect has dominated the wage effect, namely that years of high technical progress were characterized by reduced labor force participation of older workers. This means that the erosion of human capital in the innovating sectors has been stronger than the positive incentive to work by higher wages due to technical progress across the economy.

This paper therefore indicates that the erosion effect is potent and merits further research. Can we measure it by analyzing labor dynamics of workers across jobs and how related they are to technical progress? Can differences in educational and training systems explain international differences in labor participation? These and related questions are still waiting to be answered.

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Figures

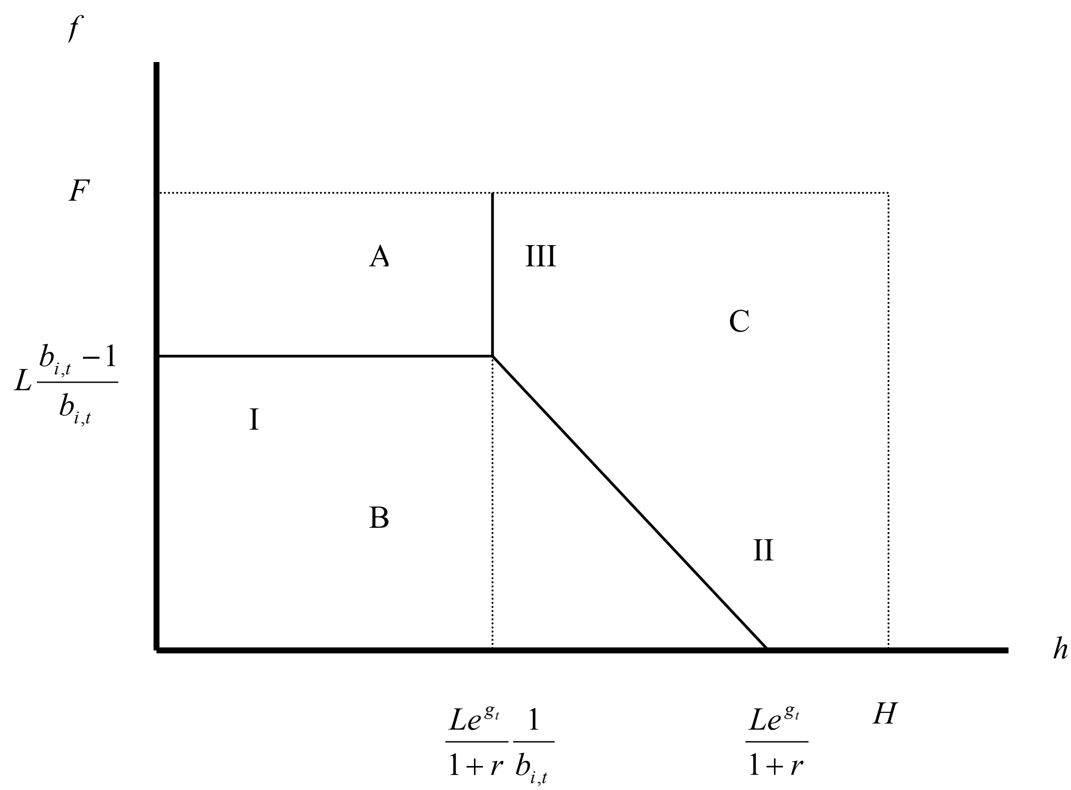

Figure 1

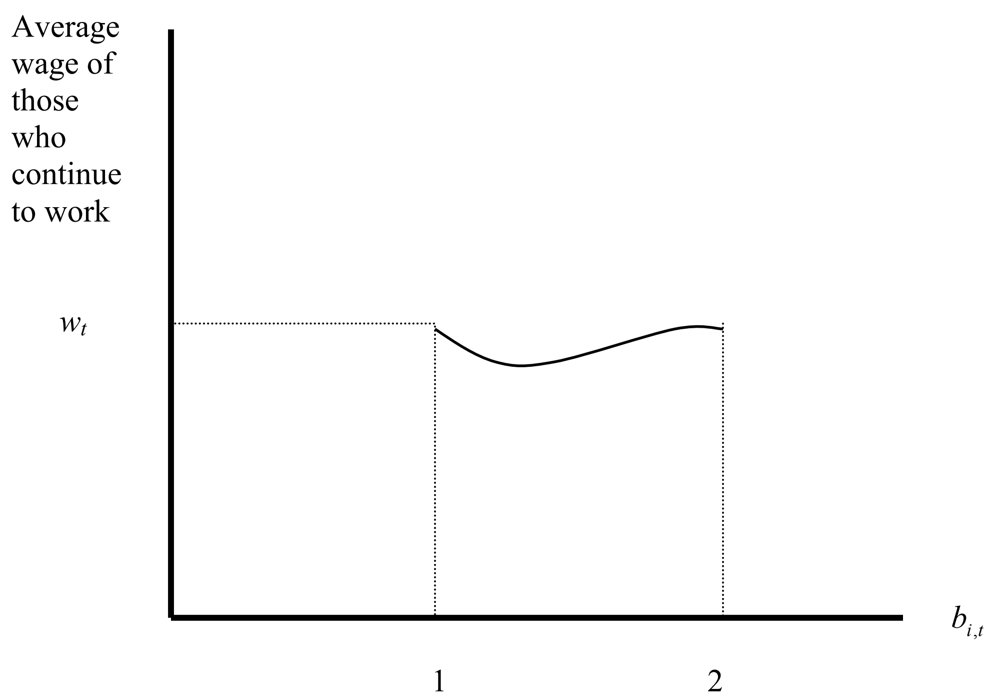

Figure 2

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

	Model	Marginal effect on the probability of: Not-Working	Unemployed	Retired
1)	Basic Model	**1.58**	**0.46**	**0.52**
		(0.35)	**(0.12)**	**(0.27)**
2)	With Wealth, Union and Pension	**0.79**	**0.39**	0.15
		(0.35)	**(0.11)**	(0.26)
3)	Without Output Growth	**0.86**	**0.37**	0.13
		(0.35)	**(0.11)**	(0.26)
4)	Age 50-60	0.57	**0.50**	-0.12
		(0.37)	**(0.15)**	(0.23)
5)	Random-Effect Model	**0.82**	**0.39**	0.16
		(0.28)	**(0.16)**	(0.22)
6)	Non-Production Workers	0.54	0.29	-0.12
		(0.45)	(0.17)	(0.41)
7)	Production Workers	**1.14**	**0.46**	0.33
		(0.54)	**(0.14)**	(0.32)
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 calculation were done using the Probit parameters estimated for Equation 21. The formula used to calculate the effect of a 1 percentage-point increase in TFP growth on the probability to be in non-labor status I is

$$\delta_i^* = \phi(\bullet)\delta_i ,$$

where we use the normal density, and the effects are evaluated at the sample means.

3) Appendix A2 reports the full set of coefficients for the Probit regressions of "Not-Working" and "Unemployed", models 1, 2 and 5.

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

Table 3: Coefficient Estimates for Ln Wage Equations

	1. Basic Model	2. Include Wealth Variables	3. Include Sector Dummies	4. Heckman Selection Model Wage Equation	Selection on Working
Sector TFP Growth	-0.641	-0.167	2.648	1.173	-2.26
	(0.801)	(0.762)	(3.107)	(0.856)	(0.955)*
Sector Output Growth	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	-0.12	-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
		(0.020)**			(0.026)**
Total 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 at 5% level; ** significant at 1% level
Data Source: HRS, waves 1-3 (1992-1996)

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: Probit Estimates for Table 2

	Not-Working			Unemployed		
	Model 1	Model 2	Model 5	Model 1	Model 2	Model 5
Sector TFP Growth	4.486	2.189	4.964	6.071	5.478	8.009
	(1.003)	(1.03)	(2.124)	(1.580)	(1.596)	(2.413)
Sector Output Growth	1.907	3.354	5.064	-5.244	-4.566	-6.146
	(0.869)	(0.887)	(1.746)	(1.357)	(1.365)	(2.031)
Age	-0.927	-0.922	-1.511	0.650	0.672	0.971
	(0.096)	(0.099)	(0.163)	(0.171)	(0.173)	(0.239)
Age-square	0.009	0.009	0.014	-0.006	-0.006	-0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
African American	(0.201)	0.194	0.370	0.134	0.098	0.142
	(0.035)	(0.037)	(0.082)	(0.055)	(0.056)	(0.086)
Hispanic	0.016	-0.019	0.006	0.157	0.117	0.171
	(0.053)	(0.054)	(0.12)	(0.076)	(0.077)	(0.119)
Foreign Born	0.244	-0.298	-0.518	0.205	0.184	0.250
	(0.048)	(0.05)	(0.11)	(0.068)	(0.068)	(0.106)
Currently Married	0.282	-0.215	-0.285	-0.320	-0.264	-0.304
	(0.033)	(0.034)	(0.067)	(0.048)	(0.049)	(0.073)
Years of Schooling	0.006	0.005	-0.002	-0.029	-0.021	-0.027
	(0.005)	(0.005)	(0.012)	(0.007)	(0.008)	(0.012)
College Degree	0.067	-0.058	-0.101	-0.016	0.037	0.053
	(0.039)	(0.04)	(0.09)	(0.066)	(0.067)	(0.103)
Regions:						
Central	0.111	-0.128	-0.218	-0.229	-0.244	-0.340
	(0.038)	(0.04)	(0.088)	(0.065)	(0.066)	(0.102)
South-East	0.078	-0.134	-0.207	-0.101	-0.135	-0.168
	(0.035)	(0.036)	(0.08)	(0.055)	(0.057	(0.088)
Pacific	0.054	0.019	-0.001	-0.071	-0.063	-0.092
	(0.042)	(0.044)	(0.097)	(0.068)	(0.069)	(0.107)
Bad Health	0.921	0.819	1.074	-0.022	-0.101	-0.109
	(0.029)	(0.03)	(0.055)	(0.049)	(0.050)	(0.070)
Year 1994	0.057	0.018	-0.015	0.115	0.109	0.137
	(0.031)	(0.032)	(0.044)	(0.054)	(0.055)	(0.069)
Year 1992	0.034	-0.079	-0.147	0.145	0.114	0.161
	(0.032)	(0.033)	(0.051)	(0.055)	(0.056)	(0.073)
Union Member		0.014	0.017		0.085	0.123
		(0.04)	(0.087)		(0.066)	(0.100)
Pension Plan		-0.840	-1.450		-0.430	-0.564
		(0.032)	(0.075)		(0.054)	(0.084)
Total Net Wealth		-0.018	-0.035		-4.132	-5.563
		(0.003)	(0.001)		(0.084)	(1.262)
Constant	23.537	23.935	37.283	-18.758	-19.102	-27.832
	(2.795)	(2.901)	(4.754)	(4.927)	(4.986)	(6.912)
Log-Likelihood Function	-7,218	-6,721	-5,997	-2,208	-2,156	-2,075
No. of Individuals	5,217	5,217	5,217	5,217	5,217	5,217
No. of Person-Years	13,471	13,471	13,471	13,471	13,471	13,471

Note: standard errors are in parentheses

Appendix A3: Estimates of Bivariate VAR for TFP Growth and LFP of men 55-64 (U.S. Data)

	GTFP	GLFPO
Panel A: Growth of TFP (GTFP)		
T-1	0.113	-0.528**
	(0.143)	(0.198)
T-2	0.239*	0.004
	(0.133)	(0.195)
Panel B: Growth of Labor Force Participation of Men 55-64 (GLFPO)		
T-1	0.263**	0.646**
	(0.098)	(0.136)
T-2	-0.215**	-0.015
	(0.091)	(0.134)

Notes: Standard errors are shown in parentheses. Significance is indicated by one asterisk (10-percent level), or two asterisks (5-percent level).

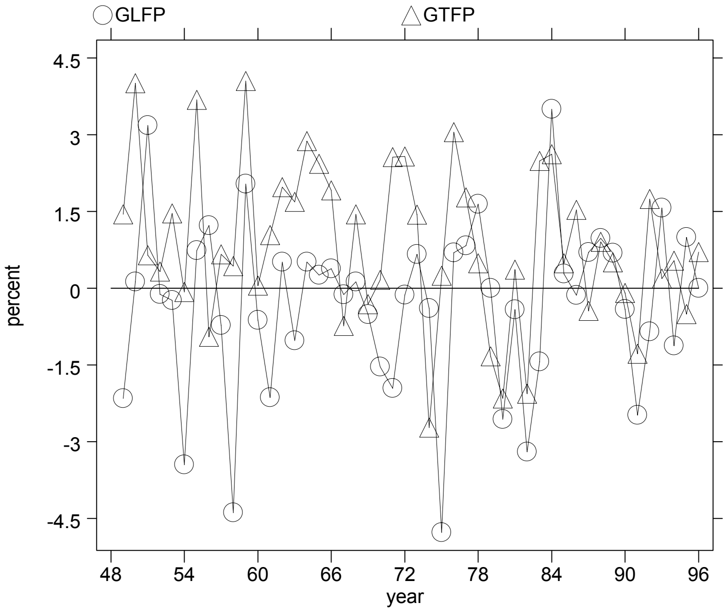

Figure 3-A

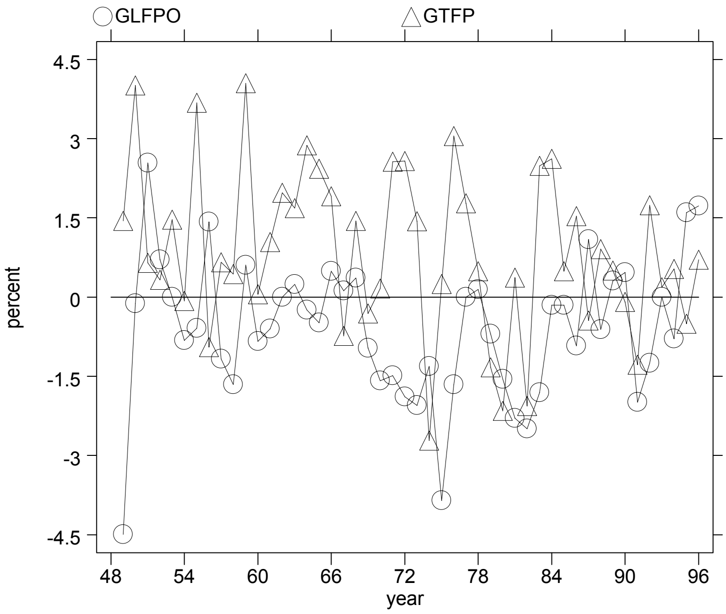

Figure 3-B

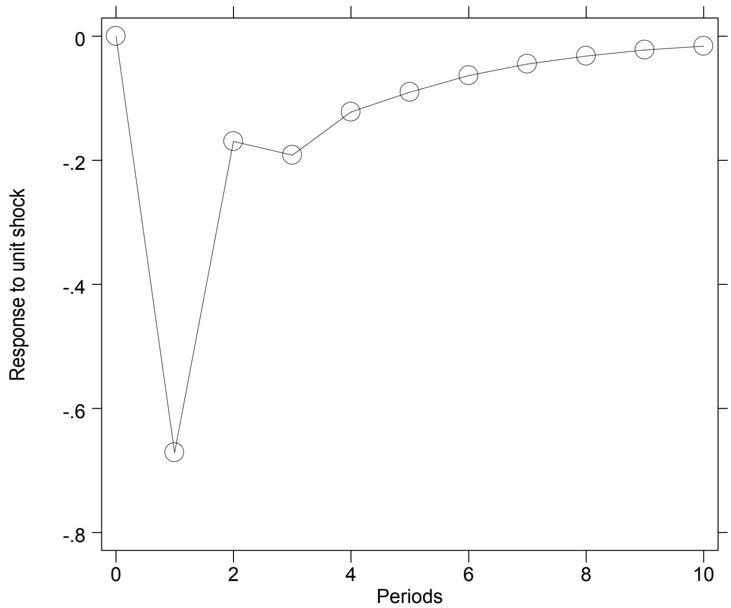

Figure 4-A

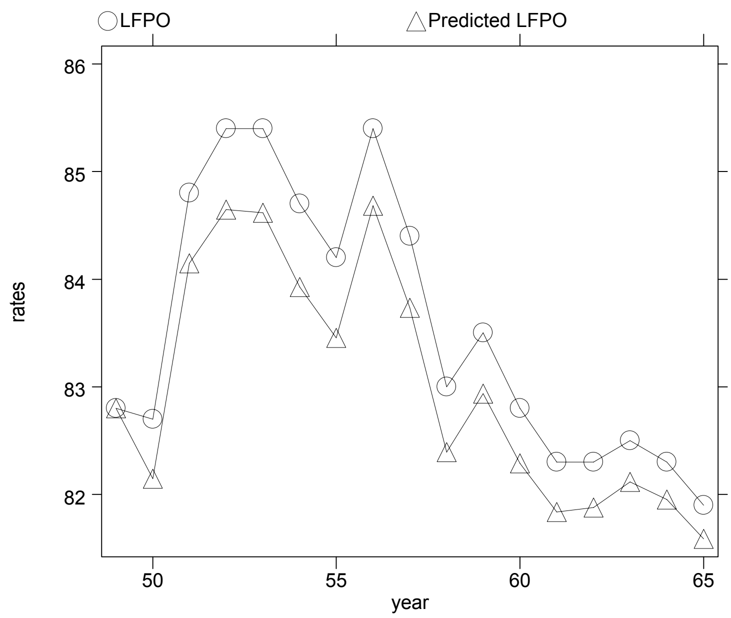

Figure 4-B