Technical Progress and Early Retirement

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Abstract

This paper claims that technical progress induces early retirement of older workers. It presents a model where human capital is technology specific, so that technical progress erodes some existing human capital. This affects mostly older workers, who have a smaller incentive to learn the new technology, since their career horizon is shorter. Hence, their labor supply declines. We find strong support to this erosion effect in HRS data, which shows that labor of older workers is negatively related to technical progress in their sectors. Unlike the effect across sectors, the model is ambiguous about the aggregate effect of technical progress on labor supply of older workers. While in sectors with many innovations it falls due to the erosion effect, in other sectors it increases due to higher wages. To examine which effect dominates we run a time series test using US data and find that the effect of average technical progress on aggregate labor force participation by the old is negative. Namely, the erosion effect dominates.

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1. Introduction

Many workers retire before they reach the formal age of retirement. This has become a widespread phenomenon in modern economies. For example, 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 it was 93.1 percent. Furthermore, this phenomenon is quite recent, as early retirement increased significantly in recent decades. Thus, labor participation rates of US men in ages 55-64 dropped from 86.7 percent in 1948 to 62.6 percent in 1996. Former attempts to explain early retirement focused mainly on two explanations. The first is health problems of older workers, and the second is the incentive created by generous retirement plans and benefits, like social security. The latter argument also helps to explain why early retirement increased so dramatically over the last 50 years. This paper offers a third explanation to early retirement, which is the erosion of human capital due to technical progress.

Technical progress changes continuously the way we produce. It introduces new goods, new machines, and new production methods. Simultaneously it creates new professions and destroys old ones. Hence, 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 force participation of older workers. The reason why such technical progress has an effect on older rather than on younger workers is because their career horizon is much shorter, and hence it is less beneficial for them to invest in learning the new technologies. The paper models this idea theoretically and then tests its implications using both micro and macro US data and finds strong support for it.

We present the main idea with 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 in first period of life and work using these technologies in second and third periods of life. Meanwhile new innovations arrive and replace existing technologies. The new technologies are more productive, but require learning. Hence, reaction to new innovations differs by age. While younger workers learn the new more productive professions, older workers do not learn, since their career horizon is much shorter. Hence, they stick to less productive technologies and their income falls due to competition with the young. As a result they reduce their labor supply and retire earlier. Furthermore, if the rate of technical progress in the sector is higher, their income falls by more and they retire earlier. Note, that the decision to retire early may be the worker's own decision as in the model, or the decision of the employer, who prefers not to retrain an older worker. The basic result is the same.

The model has two main empirical implications. The first implication is that labor supply of older workers should be negatively correlated with the rate of technical progress across sectors, as described above. The second implication is on the time-series effect of the average rate of technical progress on aggregate labor supply of older workers. Here the model is more ambiguous. On the one hand, during periods of rapid technical progress, more sectors have high technical progress and in these sectors older workers retire earlier. We call this negative effect of technical progress the '*erosion effect*'. But on the other hand, wages rise in periods of high technical progress and that has a positive effect on labor supply of older workers, which we call the '*wage effect*.' The model shows that under fairly plausible conditions the erosion effect dominates.

The paper next turns to empirically test the predictions of the model using US data. We first test the cross sector prediction of the model by looking at labor decisions of men over

50 and how these decisions are affected by technical progress in their respective sectors. The data on individual labor decisions is from the Health and Retirement Study (HRS), which also includes information on job histories. We merge this information with data on productivity growth in sectors, as measured by Jorgensen (2000), after making some adjustments in order to isolate technical progress from the productivity data. We find that the coefficient of sector TFP growth on the probability that men over 50 will not work is positive. Furthermore, we show that the positive effect of sector TFP growth on not working is stronger for production workers than for other workers. This finding supports our hypothesis that technical progress affects employment through erosion of technology specific human capital.

We next turn to examine the relationship between the average rate of technical progress and the aggregate labor supply of older workers over time. This test is important, since it enables us to empirically compare the two opposite effects: the erosion effect and the wage effect. Since TFP growth rates reflect both technical progress and other temporary shocks we use the Blanchard and Quah (1989) Structural VAR method to differentiate between these two shocks. Our analysis shows that the effect of technical progress on labor force participation of men above 55 is indeed negative. Hence, the erosion effect dominates the wage effect.

There is vast literature, which tries to explain why so many older workers retire early and why their number has increased so much over recent decades. As mentioned above, this literature focuses mostly on health and on social institutions such as Social Security, pension funds and health insurance. Prominent recent papers in this line of research are Diamond and Gruber (1999), Costa (1998), Gruber and Wise (1997) and Gustman and Steinmeier (2000).[1] While we agree that these explanations account for much of the secular decline in labor participation rates of older workers, we focus instead on fluctuations of these rates around trend. We show that these fluctuations, both across sectors and over time, are negatively related to technical progress. Furthermore, we show that some of the secular decline of labor force participation rate over the last decades can be explained by the high rates of technical progress in this period.

There is not much literature that relates technical progress to employment of older workers. Some recent empirical studies have shown that technological innovations tend to be followed by short-run reduction in overall employment. A recent example is Gali (1999), who also cites other papers with similar results. Closer to our paper is Peracchi and Welch (1994), who analyze the decline in labor participation rates of older men and raise the possibility that older unskilled workers were pushed out of the labor force as a result of technological advances. Much closer to ours is a paper by Bartel and Sicherman (1993), who examine the relationship between technical progress and labor supply of older workers across sectors. Our paper extends their work in three important directions: first, by embedding the empirical analysis in a theoretical model, which reveals the different roles of the erosion effect and the wage effect. Second, by testing the aggregate effect of technical progress over time, in order to examine which effect dominates. Third, our cross-section test differs from theirs quite significantly, as it uses a different data set and it also adds the important test of the separate effect of technical progress on production and non-production workers. Another recent paper that examines the correlation between technology and early retirement is Friedberg (1999), who shows that older workers tend to use computers less than younger workers, probably due to a shorter career horizon.

This paper is also related to another line of research, which emphasizes the costs associated with technical progress, as in Helpman and Trajtenberg (1998), Aghion and Howitt (1994), and Hornstein and Krusell (1996). This paper describes one such specific cost, namely

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

the erosion of some human capital of workers, and the resulting early retirement of those workers, who are too old to adjust to the new technologies.

The paper is organized as follows. Section 2 presents the basic model of technical progress, investment in human capital and retirement. Section 3 describes the equilibrium and Section 4 discusses the cross-section and aggregate effects of technical progress on labor supply of older workers. Section 5 discusses how the theory is taken to the data. Section 6 presents the cross-section empirical analysis, while Section 7 reports the time-series aggregate results. Section 8 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) $$\log y_t = \log z_t + \int_0^1 \log x_{i,t}\, di \,,$$

where y_t is output of the final good, $x_{i,t}$ are inputs of the intermediate goods, and z_t are random variables, which are i.i.d., with expectation z. We show below that z_t is the transitory part of productivity, in addition to technical progress. Time is assumed to be discrete.

The intermediate goods are produced by labor with fixed marginal productivity. The available technology in period t for production of the intermediate good i, enables each worker to produce an amount $a_{i,t}$ in one unit of time. This technology is not freely available to workers, but is acquired by training and learning. Using a technology is therefore a specific profession, for which the individual needs to train before she produces.

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

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

where $b_{i,t}$? 1. Note that the new technologies become operative in period t, but must be known already in period t-1 for workers to learn them. The sector's rate of technical progress is, therefore, log $b_{i,t}$. We assume that log $b_{i,t}$ is not correlated over time and is identically distributed. But we also assume that the rates of technical progress are correlated across sectors in each period. Namely, there are periods of rapid aggregate technical progress, where log $b_{i,t}$ is high in many sectors, and periods of low average technical progress, where many sectors grow slowly. This assumption is necessary if we want the average rate of technical progress to change over time, and is also supported by our US data. The average rate of technical progress is

(3) $$g_t = E_i \log b_{i,t} = \int_0^1 \log b_{i,t} di .$$

Due to the above assumptions the aggregate rate g_t is i.i.d. We denote its expectation by g >0. The assumption that rates of technical progress are correlated across sectors means that they are also positively correlated with the average g_t.

Individuals in this economy live three periods each in overlapping generations. They go from young to grownup and then to old. Population is fixed and each generation consists of a mass of individuals of size 1. In first period of life each individual studies and acquires a profession. In second period of life a grownup individual works 1 unit of time in the profession acquired when young. The individual can instead to go to school when grownup and retrain in another profession instead of working. In third period of life the old supplies only l units of labor, where: 0 ? l ? 1, namely she can retire early, as she has disutility from labor in that period of life. For analytical convenience we assume that whenever the individual works part time, this time is spread uniformly throughout the period. For tractability we also assume that individuals consume in third period of life only. The utility function of each individual is therefore from consumption and leisure when old:

(4) $$u = \log c + \alpha \log(1 - l),$$

where c is consumption when old and $\alpha > 0$.[2] The main decisions facing the individual are, therefore, for which profession to train when young, whether to work when grownup or retrain, and how much labor to supply when old.

As mentioned above, the economy is small and open. We assume that the final good is fully traded, while the various types of labor and the intermediate goods are non-traded. Capital is fully mobile and the world interest rate is equal to r.[3] 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 to employment risk.

3. Equilibrium Conditions

The young in the economy choose professions based on their expectations for the future. They already know which new technologies will be used in next period and hence they know the output levels in next period as well. The demand for intermediate good i in period t is given by:

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

due to Cobb-Douglas production function (1). Prices of all goods are in terms of the final good, which serves as a numeraire. When the young choose sectors in period t-1, they equate

[2]More general utility functions can be used and the main results remain unchanged.
[3]Note that individuals only lend in this economy. Since borrowers are abroad we do not model them, but they could be easily added to the model, either as governments or as firms.

expected income across all sectors in period t, namely they equate $p_{i,t}a_{i,t}$ across sectors.[4] This equalization is achieved by changes in $x_{i,t}$ as sectors are chosen. Denote the common income 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 the 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 in (1) and get:

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

Hence, the level of wages is the sum of transitory productivity and the average state of technology. The rate of change of wages, is therefore equal to

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

Note that when labor is the only factor of production, the rate of change of wages is equal to the rate of change of productivity, namely to total factor productivity (TFP) growth. Equation (9) shows that TFP growth fluctuates over time, with an average rate of growth g. Furthermore, TFP growth can be decomposed into two components: technical progress g_t and changes in transitory productivity z_t.

In the second period of life, the grownup has to decide whether to work in the profession acquired when young or whether to retrain. To make this decision a forward-looking grownup has first to consider the wage expected when old and how it is affected by technical progress in his sector. We therefore turn next to analyze optimal behavior of the old and only then return to grownups.

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[4]Clearly, workers care about future wages in period t+1 as well, but these are equalized across sectors by the

Consider an old worker, who has earned income I when grownup and who faces a wage w per unit of time when old. Below we specify precisely the values of I and w. An old worker maximizes

(10) $$\log[I(1+r)+wl]+\alpha\log(1-l)$$

in order to determine the optimal labor supply in third period of life. The first order condition leads to

(11) $$l=\frac{1}{1+\alpha}-\frac{\alpha(1+r)}{1+\alpha}\frac{I}{w}.$$

This is labor supply as long as the first order condition holds. A corner solution of l=0 emerges if $w/I<\alpha(1+r)$. Hence $\alpha I(1+r)$ is the reservation wage. Therefore, labor supply of an old worker depends on the ratio of current wage to past income. Note that labor supply depends positively on wages, as the substitution effect dominates the income effect. Substituting (11) in (10) we get that optimal utility is

(12) $$u=\log w+\log\left[1+\frac{I}{w}(1+r)\right]+\alpha\log\alpha-(1+\alpha)\log(1+\alpha).$$

We next turn to determine the equilibrium wage of old w and past earnings from second period of life I for those who are old in period t and have been grownups in t-1. Past income I is either $w_{t-1,}$ if the old has worked as grownup, or 0, if he has retrained when grownup. In order to determine the wage of old in period t note that due to competition in the intermediate goods markets, the price of each such good is the same across all workers, grownup as old. Hence, old workers face competition from younger workers, who use a new more productive technology and charge a lower price. As a result, the income or wage of such workers, who use the former technology, is:

next generation. The anticipated effect of new technologies on wages of older workers is independent of sector.

(13) $$a_{i,t-1}p_{i,t} = \frac{a_{i,t-1}w_t}{a_{i,t}} = \frac{w_t}{b_{i,t}}.$$

The old workers earn lower wages, as they are trapped in their sector. Hence, older workers who continue to work face different wages across sectors. Note that their income is lower the higher technical progress in the sector is. Hence, workers who do not retrain and hold an outdated technology face wage erosion when old. This is the reason why workers in sectors with a higher rate of technical progress tend to retire earlier, which is the main result of the paper, as discussed below.

We next turn to examine the decision of grownups whether to work in their professions or retrain. Consider a grownup worker, who realizes that a new technology in his sector will significantly reduce his income in the next period, as shown in (13). He then can go to school again, in order to earn more when old. But such a policy is of course costly, as the worker loses income in second period of life. Note that this cost does not deter young individuals, since they plan to use the new technology for a longer period of time. The grownup worker can use it only during a much shorter period and hence is less likely to make the necessary investment. The key element of the model used here is therefore the finite life horizon or career horizon of workers.[5] The returns from investment in human capital are accrued over a finite period of time, and when this period of time is short enough this investment is not profitable.

Consider a grownup in period t-1, who faces the choice whether to work or retrain. The technologies to be used in period t are already known with certainty. If the worker does not retrain, his income when grownup is $I = w_{t-1}$, and future income when old is $w_t/b_{i,t}$. If the worker retrains, income when grownup is zero, but future income when old is w_t. Calculating

[5]Hence, the OLG model is used here for introducing finite career horizons rather than trade frictions.

utilities in the two cases according to equation (12) yields that utility difference between working when grownup and retraining is

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

Using equation (9), which describes the wage ratio w_t/w_{t-1}, we get from (14) that the grownup works and does not retrain if:

(15) $$\frac{1}{b_{i,t}}+\frac{z_{t-1}}{z_t}e^{-g_t}(1+r)\geq 1.$$

The LHS of equation (15) is a sum of two components, each of which is close to 1 on average. Hence, if the variables do not fluctuate too much this condition should be satisfied. We therefore add the following assumption:

<u>Assumption 1:</u> The variables $b_{i,t}$ and z_t are bounded and satisfy condition (15) for all *i* and *t*.

We next add assumption 1 to the model. As shown above, under this assumption grownups do not return to school to learn the new technology and prefer to work instead, even if they lose income in third period of life. We have therefore proven:

<u>Lemma 1</u>: If assumption 1 holds, grownups work and do not retrain in second period of life.

Lemma 1 therefore completes the characterization of equilibrium in the economy. Young workers choose a profession, work in this profession when grownup and continue to work when old, even when income from this profession is reduced. They work less when they are old and their labor supply depends on the rate of technical progress. In the next section we examine precisely how.

4. The Effect of Technical Progress on Labor Participation

We next analyze labor supply by the old. From Section 3 we deduce that an old worker in period t has worked and earned w_{t-1} in period t-1, works in period t in sector i with an outdated technology, and earns $w_t/b_{i,t}$. Hence labor supply of an old worker in period t and sector i is:

(16) $$l_{i,t} = \frac{1}{1+\alpha} - \frac{\alpha(1+r)}{1+\alpha}\frac{w_{t-1}}{w_t}b_{i,t} = \frac{1}{1+\alpha} - \frac{\alpha(1+r)}{1+\alpha}\frac{z_{t-1}}{z_t}e^{-g_t+\log b_{i,t}}.$$

Note that labor supply is negatively related to log $b_{i,t}$. This means that in sectors with high rates of technical progress the supply of labor by the old is low. This is the first main result of the paper and is formally stated in Proposition 1.

Proposition 1: The labor supply of old workers is negatively related to the rate of technical progress in their sector.

We next turn to analyze the effect of technical progress on the aggregate labor supply of older workers. When we think about the aggregate economy we no longer consider the rates of technical progress in individual sectors but rather focus on the average rate of technical progress g_t. From equation (16) we see, that the average rate of technical progress g_t has two opposite effects on the labor supply of old workers. First, there is a positive effect through the aggregate wage w_t: the higher the average rate of technical progress, the higher the wage rate and hence the larger the supply of labor. We call this the *wage effect*. The second effect is due to the positive correlation between the sector's rate of technical progress log $b_{i,t}$ and the average rate of technical progress, which is assumed above. A higher g_t raises the sector's rate of technical progress and thus reduces labor supply of the old due to erosion of human capital. We call this the *erosion effect* and it is a negative effect. The two effects apply not only to individual labor supply, as shown in (16), but also to aggregate labor supply of old workers. A high rate of technical progress brings new innovations with high productivity to some sectors on the one hand, but on the other hand it raises the aggregate real wage. The erosion effect reduces labor supply by old in the progressive sectors, while the wage effect tends to increase labor supplied by old in other sectors. We next examine the relative weights of the two effects more formally.

The aggregate labor supply of older workers in the economy in period t is:

(17) $$L_{t,O} = \int_0^1 n_{i,t} l_{i,t} di,$$

where $n_{i,t}$ is the number of old workers in sector i, which has been determined in period t-1. Note that the integral of $n_{i,t}$ across sectors is equal to 1 since all the old work some of the time. Substituting (16) in (17) we get:

(18) $$L_{t,O} = \frac{1}{1+\alpha} - \frac{\alpha(1+r)}{1+\alpha} \frac{z_{t-1}}{z_t} \int_0^1 n_{i,t} e^{-g_t + \log b_{i,t}} di.$$

In this equation we clearly see the two effects of average technical progress g_t on labor supply by the old, namely the direct wage effect through g_t and the erosion effect through log $b_{i,t}$. The two effects work in opposite directions. Proposition 2 shows that under plausible conditions the erosion effect dominates.

Proposition 2: The effect of aggregate technical progress on labor participation by the old tends to be negative if the variability of technical progress across sectors rises with the average rate of technical progress.

Proof: This is a standard result of the Jensen Inequality. Note first that

$$\int_0^1 n_{i,t} e^{-g_t + \log b_{i,t}} di$$

is a convex combination of a convex function of $\log b_{i,t} - g_t$. Note also that the same convex combination of $\log b_{i,t} - g_t$ is approximately equal to 0, since $n_{i,t}$ are approximately equal to 1 (it can be shown that effective labor inputs are equal across sectors). If g_t increases, the variability of $\log b_{i,t} - g_t$ increases as well, but its average remains approximately 0. Hence, a convex combination of a convex function of $\log b_{i,t} - g_t$ increases. Hence, the effect on labor supply of older workers is negative.

Q.E.D.

Proposition 2 claims that the erosion effect dominates if the variability of technical progress increases with average technical progress. This assumption is quite plausible. For example, in each period there are sectors, which do not experience technical progress and hence the bottom of the distribution is 0. In such a case increasing the average rate of technical progress is likely to raise variability. But the result of Proposition 2 still depends on other specific assumptions, like logarithmic utility functions, etc. Hence, the issue of which effect dominates - the erosion effect or the wage effect – is not fully solved by Proposition 2. This is why we think that the issue should be taken to the data and be examined empirically.

5. Taking the Model to the Data

Our model describes how technical progress erodes the human capital related to former technologies, which are replaced by new ones. This erosion affects mostly older workers, who have less incentive to learn new technologies, since their career horizon is short. As a result our model predicts that older workers will supply less labor when technical progress is high. More specifically, our model has two main empirical implications, which are tested below. The first implication is across sectors. Older workers in sectors with high rate of technical progress work less, or retire earlier. We intend to test this implication by using individual data on older workers and their sectors. The second implication is aggregate and is thus examined over time. Our model predicts that aggregate technical progress has two opposite effects on labor of older workers. The erosion effect is negative while the wage effect is positive. Our model shows that it is more likely that the negative erosion effect dominates. To test this claim we examine the relationship between average rates of technical progress and aggregate participation rates of older workers in the US over time.

We wish to explain why the two empirical tests, namely both the cross-section one and the time-series one, are important. The cross-section test is of course important in order to show that the effect described in this paper does exist in the data. We use this test not only to examine whether the sector technical progress leads to less labor by older workers, but also to try and test what is the mechanism that generates this effect. We do it by testing the effect of technical progress separately for production and non-production workers. But the time-series test is important as well for two main reasons. First, it interesting in itself to see how technical progress affects the aggregate labor participation of older workers. Second, this test serves as an additional test for how strong is the erosion of human capital due to technical progress. As our theoretical model shows, the erosion effect and the wage effect work in opposite directions. The time-series test is expected to tell us which effect is stronger.

Before we turn to describe the empirical tests in detail in the following sections, we discuss some of the problems of translating the model into reality. The first is related to the issue of who decides on early retirement: the worker himself or the employer. In our model labor is the only factor of production and there are no firms or employers. In reality the decision to stop working is often made by the employer, who fires a worker, or by the market, if the business is closed. We overlook this distinction between decision-makers in our analysis, since we focus on the decision itself. The identity of the decision-maker depends on institutional aspects. If wages are flexible or if workers finance their own training, it is more likely that they would decide to retire, as in the model. If on the contrary wages are rigid, or if training for the new technology is done on the job, it is the employer that decides to fire older workers and train younger workers instead. The economic decision in both cases is essentially the same. Table A1 in the Appendix presents the various reasons for leaving a job for men in our data set (HRS). It shows indeed that there are various reasons for leaving a job, like closing of business, laying off, family reasons, etc. Note that 47 percent of those who do not work left job to retire.

This paper therefore looks at the decision to quit working at an old age regardless of who makes the decision. But the issue of who makes the decision affects how we translate the model to the data. What is described in the model as reducing labor supply of fits the state of not working in data, either due to early retirement, or unemployment, or other forms of not working. In order to gain better understanding on the effect of technical progress we test it in our cross sector analysis on all three categories: not working, unemployed and retired. In the aggregate analysis we test the effect technical progress on labor participation rates of older workers, namely we look at those who remain in the labor force only. This includes older workers who are unemployed, and hence does not fully capture the number of older workers who stay on the job, our main variable of interest. This reflects data limitations, but is justified by the assumption that the dynamics of labor participation rates are fairly similar to those of employment rates. This assumption is also supported by individual data, which show that among older workers there are many more retired than unemployed.

Another problem that arises in testing the model is the measurement of the rate of technical progress. This variable is not directly observed in sectors or in the aggregate. We use instead measures of productivity growth. But these measures include in addition to the rate of technical progress also other shocks to productivity, due to utilization, reallocation, etc. These additional shocks are even modeled in our theoretical model by the variable z. We try to deal with this problem of measuring technical progress by use of TFP data in a number of ways, which are described in detail in the next two sections. Although there are never ideal solutions, we believe that we go a long way in isolating the rate of technical progress from the productivity data.

6. Technical Progress and Early Retirement across Sectors in the US

This section explores the empirical relation between technical progress and working status of older workers across sectors in the US. The theoretical model implies that labor supply of older workers should be negatively correlated with the rate of technical progress in their sector. In our empirical analysis we expect to find that individuals in their 50s or early 60s are less likely to work, if their sectors have experienced fast technical changes in previous periods, and are more likely to be either unemployed or fully retired. Furthermore, we expect to find that this effect is stronger for production workers than for non-production workers, since their jobs are more technology specific.

In our analysis we merge data on individuals with data on sectors. Before presenting the estimation and the results we briefly describe the data. Our individual data source is the Health and Retirement Study (HRS). This data set contains detailed information on a large group of individuals of age 50 and above, who were interviewed in 1992, 1994 and 1996. The data also include details on their job and career histories in the 10 years prior to the first interview in 1992. We restrict ourselves to men who were between the age of 50 to 65 in the years of interviews and end up with 13,471 observations of 5,217 individuals. Our data source for sectors is Jorgenson's measures of output, factors, and total factor productivity growth for 35 economic sectors, which is taken from Jorgenson (2000).

Using the data from both sources we estimate the following probit panel regression over all relevant workers and over the three years of survey, 1992, 1994 and 1996:

(19) $$Y_{i,t} = \gamma I_{i,t} + \delta S_{i,t} + \varepsilon_{i,t} \,.$$

The dependent variables $Y_{i,t}$ include the three labor status indicators: not working, retired, and unemployed. The explanatory variables are divided to individual variables $I_{i,t}$, and to sector variables for last main job $S_{i,t}$. We define the variable "last main job" in the following way. It is the most recent job, in which the worker has stayed for at least 5 years.[6] The choice of a 5 years period is determined by the questionnaire, but we find it reasonable for our goal as well. This variable of last main job is set for each year in the sample. It can therefore differ over time, but this is quite rare (5% of the sample).

We next describe the variables in the regression equation (19). We first look at the dependent variables, namely the various states in the labor market. Table 1 presents the descriptive statistics from our sample of these states at the three years of survey, and for two age groups: 55-60, and 61-64. The results of Table 1 verify that early retirement is quite common. Even in the 55-60 group, between 11 to 14 percent are retired and this rate climbs to more than 35 percent for men over 60. To the contrary, unemployment rates decrease with age (from 4.9 percent in 1992 to 2.3 percent in 1996), and have been much lower than overall unemployment rates (7.5 percent in 1992 and 5.4 percent in 1996). Furthermore, we find in the survey that most unemployed older workers are retired by the next interview. As for time effects, we see that retirement rates of the older subgroup do not vary much, but retirement rates of the younger subgroup and unemployment rates were higher during the recession of 1992. The rate of disabled workers is rather stable and seems not to be affected by economic

[6]Formally the "last main job" is determined in the following way: if the worker has stayed in current job for more than 5 years, this is "last main job." If not, it is the former job, which lasted more than 5 years, which is given by the questionnaire.

variables. This is why we restrict our attention in the empirical analysis to three labor states: working (or not working), unemployed, and retired.

[Insert Table 1 here]

The individual variables are of three types. The first consists of variables, which are either exogenous, or have been determined many years prior to the survey: age, race, immigration status, marital status, education and health. The second type of individual variables, which we add only to some of the regressions, consists of more endogenous variables like union membership, pension plan, and accumulated net wealth. Note that these last variables might also be correlated with the variable last main job or sector of last main job. The third individual variable is profession in last main job, or more precisely whether it is a production or non-production profession. We add this variable to some of the regressions to test for the interaction effect with technical progress.[7]

The sector variables relate to the sector of the last main job. We first 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 sector variable is a proxy for the sector's rate of technical progress, which we call "TFP growth", but is more elaborated and is constructed in the following way. We calculate the rate of TFP growth in the sector over the 5 years prior to the relevant year and subtract from it the average rate of TFP growth for all sectors during this period. We are aware that the TFP growth rate is not an ideal measure for technical progress, since it is affected by other changes in productivity, like utilization and reallocation, which are demand driven.[8] We cope with this problem in three ways. First, the use of averages over time

[7]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.

[8]Bartel and Sicherman (1999) compare six indicators that have been used by researchers as proxies for technical progress. They find the Jorgenson measure to be strongly correlated with the other measures: NBER TFP, investment in computers as a share of total investment, R&D as a share of net sales, patents, and share of scientists and engineers of total employees.

smoothes much of the temporary fluctuations, as in Bartel and Sicherman (1993, 1999). Second, by subtracting average TFP growth from the sector's rate we take out the aggregate cyclical effects and better isolate the sector specific productivity change. Third, we add to our regressions another sector variable, namely output growth in the sector during the same 5 years, which controls for changes in demand for that sector and for some changes in productivity, which are not due to technical progress.

Table 2 presents our main results by focusing only on the effects of TFP growth on the three dependent variables. Each variable is estimated in 7 different models, which amounts to 21 regressions. In all regressions we report the effect of a one percentage-point increase in TFP growth on the absolute probability of the relevant labor status. To give the reader a better insight on the other variables in the estimations, Table A2 in the Appendix presents all the coefficients from three of these regressions. The seven models estimated are the following. The basic model includes the basic exogenous individual variables and the sector variables, TFP growth and output growth. The second model adds three individual variables: wealth, union membership and pension fund membership. The third model excludes sector's output growth and the fourth focuses on younger men in ages 50-60 only. The fifth model adds random-effects to the estimation. The sixth and seventh models test the interaction of TFP growth with production and non-production workers.

[Insert Table 2 here]

The effects of TFP growth are positive in all 21 regressions but one. Moreover, it is significant in all regressions of "unemployed" (column 3), and in most of the non-employment models (column 1). We therefore conclude that this data supports our main hypothesis, that technical progress *pushes* many older workers in these industries out of work, to unemployment and later on to early retirement. The magnitudes of these effects are surprisingly large. For example, a one-percent increase in TFP decreases the probability of employment by 0.75-1.50 percent, dependent on the specification.

We next discuss the results in more detail. First, the effect of technical progress becomes weaker when we control for wealth, pension and union membership. This can be explained by the correlation of these variables with last sector. It is possible that sectors with better labor conditions and better pension plans, also have higher rates of technical progress. Thus early retirement could be related to technical progress through this channel as well. But even when controlling for these variables the effect of TFP growth is still positive, and this shows how robust our results are. Another result in Table 2 is that the effect of TFP growth on retirement is less significant than on unemployment or on working. Our explanation to that fits what we see in the data, namely that most older men who leave their work, first look for another job, and are therefore defined as unemployed, and only after some time decide to retire. Hence, unemployment is more sensitive to technical changes, while retirement responds to them with a delay. This is why the effect of these changes on retirement appears to be less significant in our tests.

We next run the basic model while restricting the sample to the younger men in the sample, in ages 50-60. According to our theory the effect of technical progress on this group should be smaller and less significant, since they face a longer career horizon. Indeed our estimation shows that this is the case. The effect of TFP growth on not working in these ages is positive, but smaller in size and insignificant. The effect on unemployment though is positive, large and significant. Another test we run to check robustness is the random-effect estimation. We find that even when controlling for unobserved individual effects, the main results of the model remain unchanged.

The sector's output growth is included in the model to control for efficiency effects, which are not technological. For example, in times of declining demand firms tend to lay off workers, usually the least productive ones, and this tends to increase TFP. This mechanism also leads to a positive correlation between TFP growth and reduced work by older men. We add sector's output growth to control for such effects. When we exclude this variable from the estimation we see that it has a small effect, as the effect of TFP growth is almost unchanged.

We consider the test for separate effect of technical progress for production and non-production workers to be very important, since it can support our claim that the mechanism through which technical progress affects labor of older workers is through erosion of human capital. If the effect of TFP growth is larger for more technical workers, who use specific technologies, it supports our erosion model. Comparing production workers to non-production workers in the sixth and seventh models in Table 2 has mixed results. The effect on the decision not to work is stronger and more significant for production workers. However, the effect on unemployment is stronger for non-production workers. One possible explanation for this is that the list of professions reported in the survey is not detailed enough, and we intend to look at this issue in future research.

Finally, we turn a bit away from the main focus of our research to some of the other regression results.[9] Comparing our results on the individual variables with pervious studies of Costa (1998), Peracchi and Welch (1994) and Bartel and Sicherman (1993) shows that despite the use of different data sets, the signs on common variables (age, race, residence, etc.) are in general similar. For example, we find that minorities' men have higher unemployment rates. We also find that schooling is important in reducing unemployment at older age, but that a college degree does not have any additional effect. Another result, which is in line with the literature, is that bad health has a strong negative effect on labor participation. Surprisingly, however, it does not have significant effect on unemployment. One possible explanation is

[9]Some of the results of the detailed regressions appear in Table A2 in the Appendix. All other results can be obtained upon request.

that older men with health problems do not tend to search for job opportunities. Another result is that workers, who have invested more in pension plans or other forms of savings, tend to stay longer in work. This result contradicts our theoretical model. We can think of two possible explanations for that. One is that these variables capture some innate ability. The other is that they capture some specific job and sector characteristics, as explained above.

7. 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 6 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. For that we need to test the relationship over time between the labor participation rate of older workers and the rate of technical progress. The main problem in empirically testing this hypothesis is that, we do not directly observe data on technical progress but only Total Factor Productivity (TFP). The latter consists of two components: technical progress, which is g_t in the model, and transitory changes in productivity, which are z_t in the model. 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 available data and the main relationships between the variables. We present 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 (age 16-64) has decreased from 78.5 to 70.5 percent, where most of this decline is due to reduction in participation of older men, which has dropped from 86.7 percent to 62.6 percent.

[Insert Figures 1-A and 1-B here]

A simple analysis of the data reveals interesting relationships between labor force participation rates and productivity changes. 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, namely between GLFPO and GTFP is only 0.04. These relationships are also manifested in Figures 1-A and 1-B, which display series of annual changes of LFP of men of age 16-64, of men 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. This probably reflects the wage effect, which is especially strong for young workers.

We next turn to describe the Structural VAR model, which we use to decompose productivity growth to technical changes and to transitory changes. Assume, as in the theoretical model, that the two observed variables, namely 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 is the rate of transitory changes in productivity and is similar to z_t / z_{t-1} in the theoretical model. The second disturbance is the rate of technical progress, and is similar to g_t from the model. Hence, the joint process followed by GTFP and GLFPO follows the following stationary process:

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

where 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:

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

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

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

The next stage is to use the Blanchard and Quah (1989) method to recover the ε's and the C(L)'s from this VAR estimation, and this is done by using the identifying restriction that only technical progress shocks have a permanent effect on total factor productivity, while transitory productivity shocks have a temporary effect.

In order to use this method we first test the crucial assumption, that both variables originate 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 (20) and (22). Second, we estimate several specifications of lags, and find that the specification AR(2) fits the data better than others.[10] We then use the restriction on the effect of the temporary coefficient on TFP and identify the ε's and the C(L)'s. This enables us to calculate the Impulse Response Functions of the two variables.

[Insert Figures 2-A and 2-B here]

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

Figures 2-A and 2-B display two representations of the dynamic responses of labor force participation of older workers to technical progress. Figure 2-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 slowly and converges to zero after 6-7 periods. We therefore see that according to this empirical test the erosion effect is strong enough and it dominates the wage effect. Hence, the US data we employ supports the result of Proposition 2, that positive technological shocks reduce aggregate labor participation rates of older workers.[11] It is important to note that we ran a similar SVAR test for all workers, in ages 16-64, and found a smaller and less persistent negative effect to technical progress on labor participation.

Our theoretical model predicts that technical progress reduces labor force participation of the old temporarily, where the relevant unit of time is half the length of a career. Indeed, our empirical analysis suggests that technical progress lowers labor force participation for a fairly long period of time. Figure 2-B illustrates this result, by displaying the effect of a one-period one-percent shock of ε_2 in 1949 on the level of labor force participation of men in ages 55-64 during 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 entry of new men to the 55-64 age group every year. Figure 2-B shows that the shock has an immediate negative effect and in the following years LFPO continues to remain lower by almost the same size and the two lines meet only after more than twenty years. For example, a unit technology shock in 1949 would have reduced the 1955's LFP of men age 55-64 by 0.7 percentage points (from 84.2 to 83.5), by 0.5 in 1960, and by 0.3 percentage points in 1965

[11] It is interesting to note that some recent studies on business cycles have found that technological shocks have a negative effect on employment in general. Recent examples are Baumol and Wolff (1996) and Gali (1999), who

(from 81.9 to 81.6). Thus, the negative effect of aggregate technology shocks on LFPO withstood for a long period.[12]

This result might add an explanation to the observed decline in LFP of older workers in recent decades, in addition to the explanation of increased social security coverage, as in Diamond and Gruber (1999). 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 in LFP of men ages 55-64.

8. Conclusions

This paper combines together two distinct lines of research from two different areas in economics. One area is the study of technical progress, which is usually related to the study of economic growth and productivity, and the other area is labor participation of older workers, which is an important issue in labor economics. We combine these two areas together by showing that technical progress has a substantial negative effect on labor participation rates of older workers, as it has an erosion effect on technology-specific human capital of such workers. We describe this effect by a simple growth model with finite career horizons and then test for this effect across sectors in the US, where we find indeed that technical progress reduces labor of older workers.

When analyzing the aggregate effect of technical progress on labor participation of older workers our model identifies two opposite effects: a negative effect due to the erosion of technology specific human capital and a positive effect due to higher wages in times of technical progress. Using US data, we find that in the years 1950-1996 the erosion effect has

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also cites similar results by Blanchard (1989), Blanchard and Quah (1989), and Cooley and Dwyer (1995).

dominated the wage effect, namely that years of high technical progress were characterized by reduced labor force participation of older workers.

The paper presents a contribution both to the literature of technical progress and to the literature of labor market performance of older workers. Technical progress has been mainly discussed as the most important driving force of global economic growth in the recent two centuries, but there has been less discussion of the costs involved in technical progress. This paper describes one such specific cost, namely erosion of technology-specific human capital, and its negative effect on labor force participation. The vast literature on labor force participation of older workers has focused mainly on issues of health, pensions, social security, health insurance and similar institutions. This paper adds another important variable to this list: technical progress. It describes this effect in a theoretical model and tests it empirically both across sectors and over time. Our empirical analysis is limited to US data only and it could be interesting to expand it to other countries as well.

As we stress in the paper, the erosion of technology-specific human capital affects mostly older workers, since their career horizon is shorter than that of younger workers. But if the cost of retraining, namely of learning the new technology, could be reduced, that would also reduce the negative effect of technical progress on older workers. Hence, the effect we describe in the paper depends crucially on the ability of the educational or training system to supply retraining for new technologies. This opens interesting topics for future research. Can differences in educational and training systems explain international differences in the reaction of labor to new technologies? Do institutional arrangements of retraining, on the job or out of job, have an effect on labor force fluctuations? Are there policy implications?

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[12]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 probably are to some extent.

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Table 1: Work Status by Years and Age

	1992		1994		1996	
	Age 55-60	Above 60	Age 55-60	Above 60	Age 55-60	Above 60
In the Labor Force						
Working	70.0	48.9	72.1	49.1	73.9	49.7
Unemployed	5.6	2.4	5.0	2.9	4.2	1.6
Out of the Labor Force						
Disabled	10.4	8.8	11.6	11.8	10.8	10.2
Retired	13.8	39.8	11.2	35.9	11.0	38.5
Other	0.2	0.1	0.1	0.3	0.1	0.0
No. of Observations	2,451	1,053	2,320	1,394	2,164	1,599

Table 2: Effects of TFP Growth on Non-Work Status

	Model	Not-Working	Retired	Unemployed
	Mean of Dependent Var.	0.329	0.175	0.042
		Effects of TFP growth on the probabilities to be:		
	Model	**Not-Working**	**Retired**	**Unemployed**
1)	**Basic Model**	1.58***	0.52**	0.46***
2)	**With Wealth, Union and Pension**	0.75**	0.14	0.38***
3)	**Without Output Growth**	0.83**	0.13	0.36***
4)	**Age 50-60**	0.53	-0.12	0.49***
5)	**Random-Effect Model**	1.26***	0.42	0.61***
6)	**Non-Production Workers**	1.16**	0.49	0.52***
7)	**Production Workers**	2.19***	0.56**	0.37**

Notes:

1) "*" Denotes significant at 10% level; "**" Denotes significant at 5% level; and "***" Denotes significant at 1% level.

2) The models of retirement do not include men that have been working in the public sector.

3) The effects dF/dX are calculated based on probit model estimates, and are evaluated at the sample means.

4) Appendix A2 reports all the coefficients in the regressions of "Unemployed", models 1, 2 and 5.

Table A1: Reasons Respondent Left Previous Job (percent)

	People not working in 1992				People working in 1992			
	Age 50-54	**Age 55-60**	**Above 60**	**All**	**Age 50-54**	**Age 55-60**	**Above 60**	**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 question: "Why did you leave this employer? (Did the business close, were you laid off or let go, did you find a better job, did you leave to take care of family members, or what?)".

Table A2: Probit Estimates of the Probabilities to be Unemployed

	Model 1	Model 2	Model 5
Age	0.650	0.669	0.973
	(0.171)	(0.173)	(0.239)
Age-square	-0.006	-0.006	-0.009
	(0.001)	(0.001)	(0.002)
African American	0.134	0.098	0.142
	(0.055)	(0.056)	(0.086)
Hispanic	0.157	0.117	0.171
	(0.076)	(0.077)	(0.119)
Foreign Born	0.205	0.184	0.250
	(0.068)	(0.068)	(0.106)
Currently Married	-0.320	-0.264	-0.304
	(0.048)	(0.049)	(0.073)
Years of Schooling	-0.029	-0.021	-0.027
	(0.007)	(0.008)	(0.012)
College Degree	-0.016	0.037	0.053
	(0.066)	(0.067)	(0.103)
Regions:			
Central	-0.229	-0.244	-0.340
	(0.065)	(0.066)	(0.102)
South-East	-0.101	-0.135	-0.168
	(0.055)	(0.057	(0.088)
Pacific	-0.071	-0.063	-0.092
	(0.068)	(0.069)	(0.107)
Bad Health	-0.022	-0.101	-0.109
	(0.049)	(0.050)	(0.070)
Year 1994	0.115	0.109	0.137
	(0.054)	(0.055)	(0.069)
Year 1992	0.145	0.114	0.161
	(0.055)	(0.056)	(0.073)
Union Member		0.085	0.123
		(0.066)	(0.100)
Pension Plan		-0.430	-0.564
		(0.054)	(0.084)
Total Net Wealth		-4.132	-5.563
		(0.084)	(1.262)
Sector TFP Growth	6.071	5.478	8.009
	(1.580)	(1.596)	(2.413)
Sector Output Growth	-5.244	-4.566	-6.146
	(1.357)	(1.365)	(2.031)
Constant	-18.758	-19.102	-27.832
	(4.927)	(4.986)	(6.912)
Log-Likelihood Function	-2,208	-2,156	-2,075
No. of Individuals	5,217	5,217	5,217
No. of Person-Years	13,471	13,471	13,471

Note: standard errors 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).

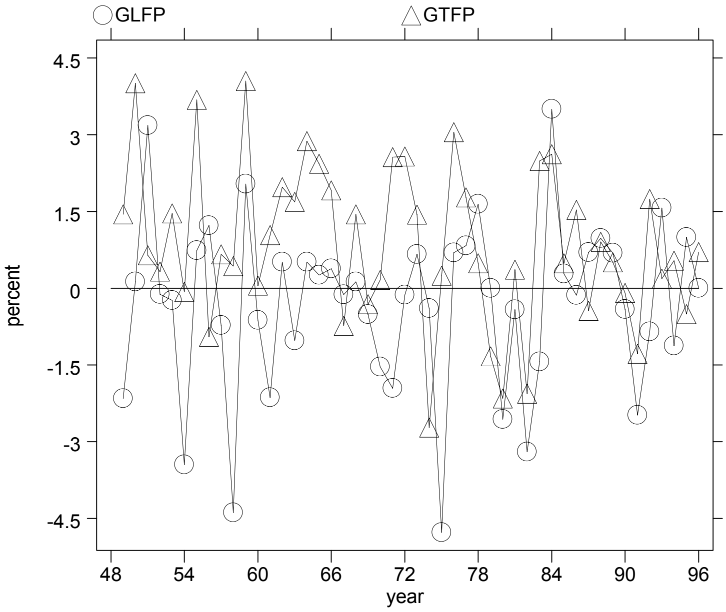

Figure 1-A

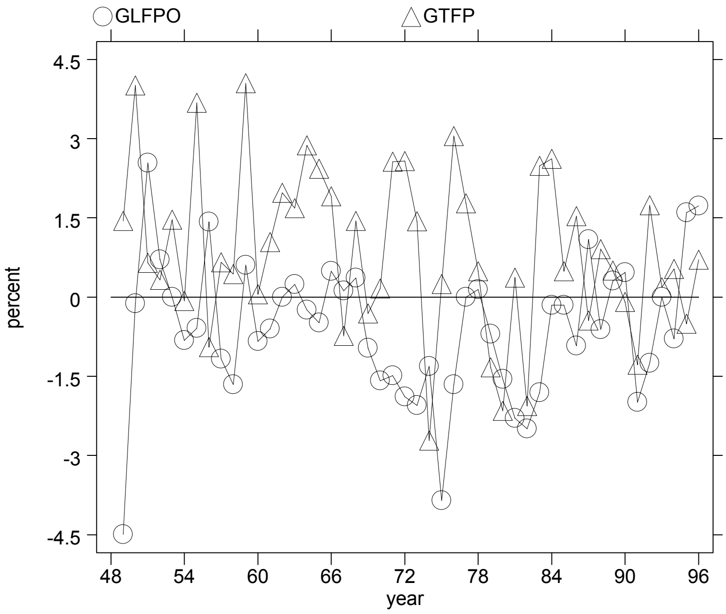

Figure 1-B

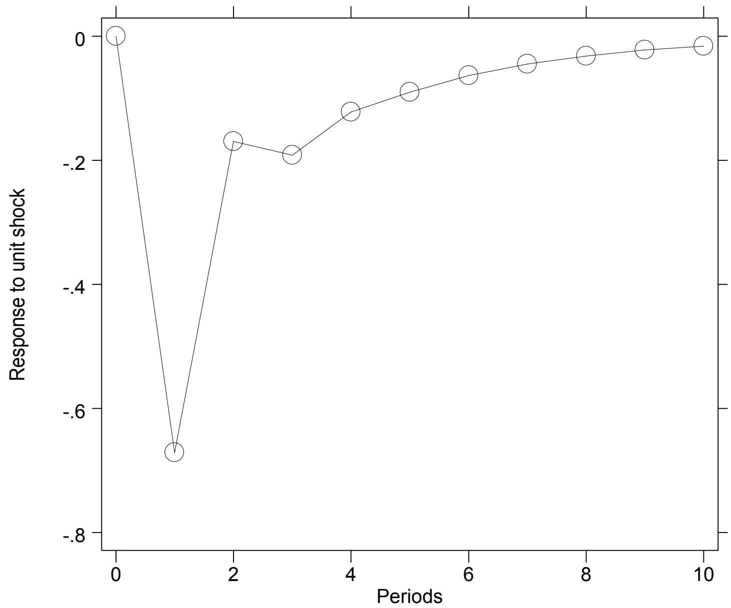

Figure 2-A

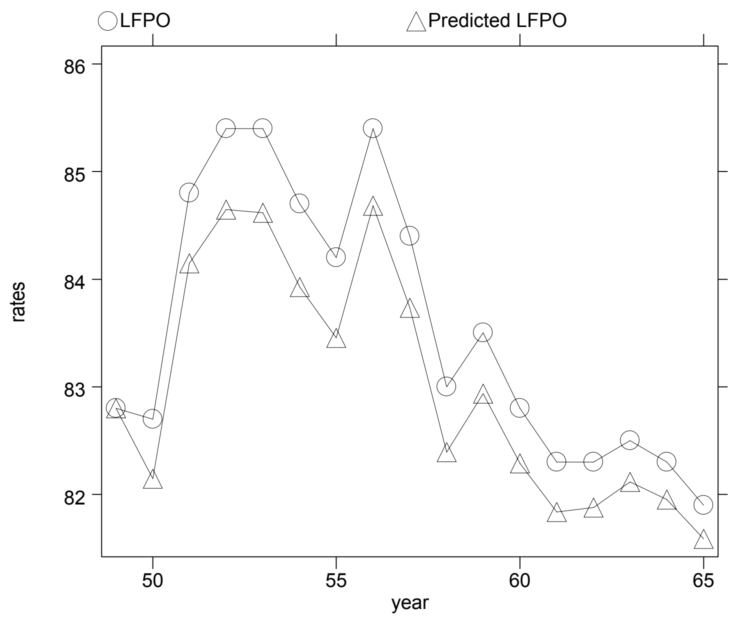

Figure 2-B