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by Lorenzo Burlon and Montserrat Vilalta-Bufí

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TECHNICAL PROGRESS, RETRAINING COST AND EARLY RETIREMENT

by Lorenzo Burlon* and Montserrat Vilalta-Bufí**

Abstract

Technological progress affects early retirement in two opposing ways. On the one hand, it increases real wages and thus produces an incentive to postpone retirement. On the other hand, it erodes workers' skills, making early retirement more likely. Using the Health and Retirement Study surveys, we re-examine the effect of technical progress on early retirement, finding that when the technical change is small the erosion effect dominates, but when it is large the wage effect dominates. Our results imply that retraining cost is a strongly concave function with respect to technical progress.

JEL Classification: J24, J26, O33.
Keywords: technical progress, retraining, retirement.

Contents

1. Introduction ... 5
2. The model ... 7
3. Data and regression analysis ... 12
   3.1 Empirical results ... 13
   3.2 Comparison with Bartel and Sicherman (1993) ... 15
   3.3 Comparison with Ahituv and Zeira (2011) ... 16
4. Conclusion ... 17
References ... 19
A Appendix: data ... 22
B Appendix: figures and tables ... 23

* Bank of Italy, Directorate General for Economics, Statistics and Research.

** Department of Economic Theory and CREB, University of Barcelona

1 Introduction[1]

Life expectancy in the US has risen to around 80 years for males and 83 years for females. Moreover, above 70% of old age individuals feel in good health.[2] Yet, the labor participation rate for individuals between 50 and 64 years old remains below 70% for males and 60% for females, and the percentage of employed people within this age range is 45% and 33%, respectively (see Figure 1). Hence, there is a non-negligible fraction of individuals that exit the labor force well before they are 65. We refer to the exit from the labor market of elderly individuals under the age of 65 as early retirement.[3] Early retirement decisions influence the economic dependency ratio of a country.[4] Since policies aimed at decreasing the economic dependency ratio are highly desirable in the context of an aging population, it is important to understand the determinants of early retirement. In this paper we shed light on this issue.

The literature has highlighted several explanations for the evolution of early retirement in the last decades (see Maestas and Zissimopoulos [2010] for a review). Some examples are changes in the Social Security programs and pension plans (Atalay and Barrett [2014], Coile and Gruber [2007], Crawford and Lilien [1981], Blau [1994], Blundell et al. [2002], Rust and Phelan [1997], Ferreira and dos Santos [2013]), changes in the age and skill composition of the labor force (Blau and Goodstein [2010]), changes in leisure consumption

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[2]See OECD [2013].

[3]Although private or public pension schemes provided by different institutional contexts play a prominent role in shaping the dynamics of early retirement, they do not affect its definition. An individual can exit the labor market even in the absence of a pension scheme or without fulfilling the criteria to access potential pension benefits.

[4]The economic dependency ratio is the share of the number of pensioners and unemployed relative to the number of people in employment.

choices (Kopecky [2011]), or the rise of the dual-earner family and the tendency of couples to retire around the same time (Gustman and Steinmeier [2000], Maestas [2001], Coile [2004]).

We focus on the effect of technological change on early retirement. Bartel and Sicherman [1993] and Ahituv and Zeira [2011] highlight how technological progress can contribute to early retirement. Bartel and Sicherman [1993] find that workers in industries with high technological change retire later than workers in industries with low technical change. They argue that industries that experience high technological change provide on-the-job training along the whole working life, which incentivizes workers to retire later in order to recoup the returns on their training. They also find that unexpected shocks in technology increase the probability of early retirement due to the consequent erosion effect on individuals' skills. Ahituv and Zeira [2011] are the first to identify the wage and erosion effects of technical change on early retirement. They develop a general equilibrium model where wages equalize across sectors. Then, aggregate technical change is responsible for a general wage increase that might reduce early retirement (wage effect), while the sector-specific technical change is associated to the erosion effect. We reexamine the effect of technological progress on early retirement by considering a two period model where wages do not equalize across sectors. Then, total sector technical change implies both a wage and an erosion effect. The shape of the relationship between technical change and early retirement depends on the retraining cost function.

To test the main implications of the model we use the RAND Health and Retirement Study (HRS) data,[5] a survey that follows around 30000 adult individuals for 10 biannual waves between 1992 and 2010, with retrospective information on their job history. We merge this data with BEA aggregate data on labor productivity levels and their growth rates between 1948 and 2010. We associate to each individual the technical progress to which he was subject during his whole working life, and check how this technical change affects the probability to retire early. We find that the effect of technical change on the probability of early retirement depends on whether the productivity growth in the sectors where the individuals work is relatively high or low. More precisely, there exists a

[5]The RAND HRS Data file is an easy to use longitudinal data set based on the HRS data. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration. RAND [August 2013]

threshold technical change above which early retirement depends negatively on technical change, and below which it depends positively on technical change. This implies a strongly concave retraining function.

The policy implications of this study are two-fold. On the one hand, it predicts sectoral differences in the response of older workers to technical change. On the other hand, the finding that the retraining cost function is concave could help in the design of retraining programs to favor the permanence of the elderly in the labor force.

Our work is complementary to the literature that studies the effect of a growingly elderly labor force on productivity. Sala-i-Martin [1996] proposes a model where, due to a positive externality in the average stock of human capital, it is socially optimal to encourage retirement when the difference between the skill level of the young and that of the old is large enough. This points to a reverse causality between early retirement and productivity. For example, Meyer [2011] finds that firms with a younger workforce benefit from a larger rate of technology adoption. There is also some evidence that the age composition of the labor force has an aggregate effect on productivity (Feyrer [2007], Werding [2008]). Since we consider technical changes that occur during the whole working life of individuals and, thus, before the individual early retirement decisions, our results are robust to this issue.

The paper is organized as follows. In Section 2 we present the model and derive its main implications. In Section 3 we test empirically the implications of the model and compare our results with the previous literature, namely, Bartel and Sicherman [1993] and Ahituv and Zeira [2011]. Section 4 draws the final conclusions. All figures and tables are in the Appendix.

2 The model

Consider a two-period economy. All individuals work in the first period, and choose whether to work or retire early in the second period. Each period lasts 1 unit of time. In the second period, however, there is an amount Z of mandatory retirement, and only $L = 1 - Z$ units of time are available for working. For simplicity, we assume that individuals consume only in the second period.

In the first period, each individual works in one sector s, which is exogenously assigned,[6] and receives a salary a_s, which is the sector labor productivity. In the second period, each sector receives a technical change b_s, which is iid across sectors, non-negative and bounded, that is, $1 \leq b_s \leq B$. Therefore, the labor productivity of a sector s increases to $a_s b_s$. Then the individual has to choose among two possibilities. He can either retrain to the new productivity level $b_s a_s$ of his sector and work, or retire early, supply no units of labor, and earn no wage income.[7]

Individuals are heterogeneous in their ability to learn f, which is distributed over the support set $[0, F]$. The higher f, the more able to learn the individual. If he chooses to retrain and work, he supplies $L - \phi(b_s, f)$ units of labor, where $\phi(b_s, f)$ is the time spent in updating his knowledge to the new productivity level. We will refer henceforth to ϕ as the retraining function, and we denote ϕ_j and ϕ_{jj} the first and second partial derivatives with respect to argument $j = 1, 2$. We assume $\phi_1 > 0$ and $\phi_2 < 0$, that is, the higher the technical change or the lower the ability to learn, the more time the individual has to spend in retraining. The wage income in the second period is then

$$W_{is} \equiv b_s a_s \left[L - \phi\left(b_s, f\right)\right], \tag{1}$$

where the productivity of the labor supply is $b_s a_s$.

An individual derives utility from consumption in the second period, and from retirement if he retires early. Individuals have different preferences for retirement. We assume that they receive a preference shock h for early retirement, where h is uniformly distributed over the interval $[0, H]$ and independent from the learning ability f. Individuals are perfectly rational and maximize their ex-ante lifetime utility based on their expectations. The utility of an individual i is

$$U_i \equiv E\left[u(c_i) + \mathbb{1} v(h)\right], \tag{2}$$

where c_i is consumption in second period, $\mathbb{1}$ is an indicator function that takes value $\mathbb{1} = 1$ if the individual retires early and $\mathbb{1} = 0$ if he does not, and $E[\cdot]$ is the expectation operator. We assume that the function u is strictly increasing and concave. Moreover,

[6] The choice of the sector could be endogeneized without changing the main implication of the model.

[7] As in Ahituv and Zeira [2011], we could add the possibility for workers to work without retraining. This option could be easily ruled out by a condition on the parameter space which ensures that even if the least able individual works in the sector with the highest technical change, he prefers to retrain once he decides to work. The loss of generality is minimal, so we ignore this option for simplicity.

the function v is strictly increasing and convex, and tends to infinity as h approaches its upper bound H. In this way we make sure that for a high enough preference for early retirement the individual will retire for sure.

The problem of the individual can be written as

$$\max\{u(W_{is} + a_s), u(a_s) + v(h)\}, \tag{3}$$

where a_s are the savings from the first period of life that are consumed in the second period. Individuals retire early if the utility from retiring $u(a_s) + v(h)$ is higher than the utility from working $u(W_{is} + a_s)$, that is, if

$$h > v^{-1} \left(u \left(b_s a_s \left[L - \phi \left(b_s, f \right) \right] + a_s \right) - u(a_s) \right), \tag{4}$$

where v^{-1} is the inverse function of v. Since the function v is strictly increasing and convex and has an asymptote in H, its inverse function v^{-1} is strictly increasing and concave, and has H as upper bound. Since the preference for early retirement h is uniformly distributed over $[0, H]$, the probability P_{is} of early retirement for an individual i in sector s is

$$P_{is} = 1 - \frac{v^{-1} \left(u \left(b_s a_s \left[L - \phi \left(b_s, f \right) \right] + a_s \right) - u(a_s) \right)}{H},$$

where actual retirement depends on the realization of the random variable h.[8] Early retirement is more likely whenever the period of obligatory retirement is large (small L), the learning ability is low (small f) or the initial sector productivity is large (large a_s). A larger a_s implies a lower probability of early retirement due to the concavity of u. Moreover, the more concave the utility function, the smaller the gap between $u \left(b_s a_s \left[L - \phi \left(b_s, f \right) \right] + a_s \right)$ and $u(a_s)$ and the larger the probability of early retirement.

Technical change b_s has an ambiguous effect on the probability of early retirement. On the one hand, a larger technical change increases the productivity of the retrained worker and creates therefore incentives to delay retirement (wage effect). On the other hand, it requires a longer retraining time and favors therefore higher rates of early retirement

[8] If h was a fixed parameter, early retirement would still depend of the learning ability and the assigned sector. However, the choice of early retirement net of the technical change would be deterministic. Thus, we could not define a probability of early retirement by integrating over the unobserved individual characteristics which we currently model as a preference shock.

(erosion effect).[9] The functional derivative of P_{is} with respect to b_s illustrates these two key insights, since

$$\frac{\mathrm{d}P_{is}}{\mathrm{d}b_s} = \underbrace{\frac{\partial P_{is}}{\partial\left[b_s a_s\right]}\frac{\partial\left[b_s a_s\right]}{\partial b_s}}_{\text{Wage effect}} + \underbrace{\frac{\partial P_{is}}{\partial\left[L-\phi(b_s,f)\right]}\frac{\partial\left[L-\phi(b_s,f)\right]}{\partial b_s}}_{\text{Erosion effect}},$$

where

$$\frac{\partial P_{is}}{\partial\left[b_s a_s\right]}\frac{\partial\left[b_s a_s\right]}{\partial b_s} = -\frac{1}{H}v^{-1'}(\cdot)u^{'}(\cdot)a_s\left[L-\phi\left(b_s,f\right)\right] < 0,$$

and

$$\frac{\partial P_{is}}{\partial\left[L-\phi(b_s,f)\right]}\frac{\partial\left[L-\phi(b_s,f)\right]}{\partial b_s} = \frac{1}{H}v^{-1'}(\cdot)u^{'}(\cdot)a_s b_s\phi_1\left(b_s,f\right) > 0.$$

While the wage effect tends to make individuals eschew early retirement, the erosion effect pushes them into it. The overall effect of technical change on a given individual depends on the balance between these two countervailing forces. In order to formalize under which circumstances each effect prevails, we define

$$\Phi(b_s,f) \equiv L-\phi\left(b_s,f\right)-b_s\phi_1\left(b_s,f\right), \tag{5}$$

and we state the following proposition.

Proposition 1. *Suppose that*

$$RRA \equiv -\frac{\phi_{11}\left(b_s,f\right)b_s}{\phi_1\left(b_s,f\right)} \tag{6}$$

is constant for every $b_s \in [1,B]$.

- *If $\Phi(1,f) \geq 0$ and $\Phi(B,f) \geq 0$, then $\frac{dP_i}{db_s} \leq 0$ for every $b_s \in [1,B]$.*
- *If $\Phi(1,f) \leq 0$ and $\Phi(B,f) \leq 0$, then $\frac{dP_i}{db_s} \geq 0$ for every $b_s \in [1,B]$.*
- *If $\Phi(1,f) \times \Phi(B,f) < 0$, then there exists a unique value $\bar{b} \in [1,B]$ such that*

[9] In contrast to Ahituv and Zeira [2011], the wage effect in our model is affected by the sector-specific technical change. In Ahituv and Zeira [2011] the wage effect corresponds only to the aggregate growth rate of technology since all individuals are equal in the first period and wages equalize across sectors through prices of intermediate goods. Consequently, they distinguish between aggregate and sector-specific technical change to identify the wage and the erosion effect. In our stylized model we allow for wage differentials across sectors. Hence, the distinction between aggregate and sector-specific technical change does not help to disentangle the wage and the erosion effect.

$$i) \text{ if } RRA > 2, \text{ then } \frac{dP_i}{db_s} > 0 \text{ for } b_s < \bar{b} \text{ and } \frac{dP_i}{db_s} < 0 \text{ for } b_s > \bar{b},$$
$$ii) \text{ if } RRA < 2, \text{ then } \frac{dP_i}{db_s} < 0 \text{ for } b_s < \bar{b} \text{ and } \frac{dP_i}{db_s} > 0 \text{ for } b_s > \bar{b}.$$

Proof. Consider the first derivative of P_i with respect to b_s, that is,

$$\frac{\partial P_i}{\partial b_s} = -\frac{1}{H} v^{-1'}(\cdot) u^{'}(\cdot) a_s \left[L - \phi\left(b_s, f\right) - b_s \phi_1\left(b_s, f\right)\right].$$

The sign of the first derivative $\frac{\partial P_i}{\partial b_s}$ is the opposite sign to $\Phi(b_s, f)$. Since RRA is constant, the function Φ is monotonically either strictly increasing or strictly decreasing. Thus, if both bounds $\Phi(1, f)$ and $\Phi(B, f)$ are either positive or negative, the intermediate values of $\Phi(b_s, f)$ for $b_s \in (1, B)$ are also all either positive or negative, respectively. If instead the upper and lower bounds for $\Phi(b_s, f)$ have opposite signs, then the function $\Phi(b_s, f)$ switches sign once b_s passes a certain threshold $\bar{b}$. Since Φ is either strictly increasing or strictly decreasing, the threshold $\bar{b}$ is unique. If $RRA > 2$, the function Φ is strictly increasing for every b_s. If $RRA < 2$, the function Φ is strictly decreasing. Hence, if $RRA > 2$ then $\Phi(b_s, f) < 0$ for $b_s < \bar{b}$ and $\Phi(b_s, f) > 0$ for $b_s > \bar{b}$, while if $RRA < 2$ then $\Phi(b_s, f) > 0$ for $b_s < \bar{b}$ and $\Phi(b_s, f) < 0$ for $b_s > \bar{b}$. □

Depending on the structure of the retraining costs, the probability of early retirement can be either a monotone or a non-monotone function of technical change. In the former case, the balance tilts systematically in favor of the erosion or the wage effect as the technical change becomes larger. If the wage effect dominates already over the erosion effect for low rates of technical change and higher rates simply enlarge the gap, then the probability of early retirement is monotonically decreasing with respect to technical change. If instead the erosion effect dominates for low rates and higher rates move further in the same direction, the probability is monotonically increasing. A necessary condition for non-monotonicity is that at least at the boundaries of the support set of b_s the balance between marginal increases of erosion and wage effects is reversed. If the concavity level of the retraining cost function is large enough ($RRA > 2$), the probability of early retirement is an inverse-U-shape function of technical change (erosion effect dominates for low levels of technical change only).[10] In contrast, when the concavity level of the retraining cost

[10]The condition is reminiscent of a high Arrow-Pratt-De Finetti coefficient of relative risk aversion for the retraining fuction ϕ.

function is not large enough ($RRA < 2$) or the function is even convex, the probability of early retirement is a U-shape function of technical change (erosion effect dominates for large levels of technical change only). The empirical question is to document whether these non-monotonic effects of technical change on early retirement behavior exist and, if that is the case, characterize their shape. This allows us to infer information on the retraining cost function. We also characterize which levels of technical change are more or less likely to be endured by the aging population.

To sum up, the total change in probability of early retirement due to technical change is the sum of wage and erosion effects. Technical change decreases the probability of early retirement if the wage effect is large enough relative to the erosion effect. Which effect is larger depends on the exact shape of the retraining function. If the retraining function is concave and has enough curvature, for low rates of technical change the erosion effect dominates and for high rates the wage effect dominates. The opposite happens if the retraining function is either convex or concave with not enough curvature. The exploration of the effects of technical change on the probability of early retirement remains an eminently empirical question, which we tackle in the following section.

3 Data and Regression Analysis

We use the RAND HRS dataset, which consists of a national panel survey of individuals collected for the study of retirement and health among the elderly in the United States. The RAND HRS contains information about around 37000 individuals followed in 10 biennial waves from 1992 to 2010. We have information about the labor status, personal characteristics and details on the job history of the respondents. We focus on males who are between 49 and 65 and were in the labor force two years earlier. This reduces our sample to 18726 observations of 5724 individuals.[11] We measure the probability of early retirement with the variable 'Not in the labor force', which takes value equal 1 when the individual was neither working nor actively looking for a job, 0 otherwise. We then merge the RAND HRS data with the aggregate data of the Bureau of Economic Analysis (BEA). The aggregate data reports value added and employment levels for different NAICS-code disaggregations of the sectoral composition of the US economy, spanning from 1948 to

[11] We exclude wave 1 because it does not include information on pension.

2010. We aggregate the NAICS codes so as to reconstruct the US Census sectors used in the RAND HRS dataset. In this way we obtain the individual productivity -measured as value added per worker- in the sector where each individual decides to work and the change in productivity occurred between the start and the end of the working life. We report in the Appendix the details on how we merge the two datasets and the construction of the productivity variable. The final result is an unbalanced panel of 9 periods and 5724 individuals distributed in 13 sectors. Table 1 reports the summary statistics of the variables. Table 2 shows the distribution of the individuals in the sample per labor status and age group for waves 2, 6 and 10.

The empirical strategy unfolds as follows. First, we regress the probability of not being in the labor force in period t on the change in productivity occurred since each individual started working, $\ln b_{st}$, and its square, $(\ln b_{st})^2$. The probability model leads to the following specification:

$$P_{it} = \frac{e^{\alpha+\beta_1 \ln b_{st}+\beta_2(\ln b_{st})^2+\gamma X_i st}}{1 + e^{\alpha+\beta_1 \ln b_{st}+\beta_2(\ln b_{st})^2+\gamma X_i st}}. \tag{7}$$

where X_{ist} are controls that include personal characteristics such as age, race, years of education, sector experience, marital status, region of residence, health status, wealth, cohort and sector dummies, whether the spouse is working, and whether the respondent has health insurance or pension. We expect both β_1 and β_2 significant if the relationship between technical change and early retirement is quadratic. The signs of these coefficients will reveal the shape of the retraining cost function.

We run pooled logit, panel logit random effects, and survival models. Second, we perform several robustness checks. We use changes in TFP instead of labor productivity using Jorgenson et al. [2012] data. We also check the probability of not working (instead of not being in the labor force). Further, we examine that results are not driven by outliers neither by the Great Recession period. Finally, we compare our results to the previous literature, namely, Bartel and Sicherman [1993] and Ahituv and Zeira [2011].

3.1 Empirical results

We first present the main regressions in Table 3. Column (1) shows the results from a pooled logit estimation, column (2) from a logit with survey weights, column (3) from a panel logit with random effects, and column (4) a survival model.[12] The effect of productivity growth is quadratic for all the specifications. The implied relationship between productivity change and the probability of early retirement is an inverse-U shape, as it can be seen in Figure 2.

The rest of covariates affect early retirement as previously found in the literature. We find that individuals delay the decision on retirement if the spouse is still working, in line with Baker and Benjamin [1999], Blau [1998], and Coile [2004], among other papers. The effect of the wealth status confirms another channel of the early retirement decision, although it is not always significant. In general, the wealthier the individual, the higher the likelihood of retirement (see Brown et al. [2010]). Moreover, if an individual has a government health insurance plan, he is more likely to retire early, while having an employer health insurance incentivates you to work longer. We obtain that having a pension reduces the probability of early retirement. While the opportunity cost of working is higher in this case (see Blundell et al. [2002]), if pension benefits increase with tenure, it may reduce probability of early retirement. We also find that a bad health status makes the individual more likely to retire early as in Ferreira and dos Santos [2013] and French [2005], among others. Sector experience has a negative effect on early retirement. This may be due to a selection effect, as individuals that have been longer in the labor market are those more likely to keep working. The impact of the years of education is either negative or not significant, which is consistent with what Ahituv and Zeira [2011] find.[13] In the panel random effects model, all coefficients increase their value significantly and the coefficient of the years of education becomes statistically significant. In the survival model the coefficients are closer to the pooled logit results and the years of education are again significant.

In Table 4 we estimate the benchmark model for each wave separately. In this way, we can use the survey weights provided by RAND HRS for each wave. The inverse-U shape between technical change and early retirement is confirmed in all waves, although

[12] We estimate a random effects model rather than a fixed effects because most variation is between individuals. The survival model is a pooled complementary log-log model.

[13] Results do not change if we use years of education standardized by cohorts.

coefficients are not always significant.[14]

We perform some robustness checks in Table 5. In column (1) we use an alternative measure of technical change. Instead of labor productivity growth, we compute the TFP change in the sector.[15] In column (2) we change the dependent variable. Instead of measuring if the individual is not in the labor force, we use whether he is not working, which treats unemployed individuals as early retired. Column (3) reports the estimation when the productivity change is winsorized to make sure that the results are not driven by extreme values of technical change. Finally in column (4) we exclude the waves from years 2008 and 2010. These are years of deep economic recession and individuals' retirement decisions might be differently driven. In all these robustness checks results hold.

3.2 Comparison with Bartel and Sicherman (1993)

Bartel and Sicherman [1993] (BS hereinafter) argue that workers in sectors with large technical change will retire later if these sectors are also those that provide more on-the-job training. They also argue that unexpected technical change will induce older workers to retire early. They use the 1966-83 National Longitudinal Surveys of Older Men to test these hypotheses. They measure technical change as the mean rate in the sector over the previous 10 years, while the unexpected change is measured as the unanticipated deviation from the mean. Although their results are not always statistically significant, they are consistent with their hypotheses.

Table 6 reports the result of similar regressions to the ones in BS and we compare them to our results. Our measure of technical change refers to the whole working life, as above. The unexpected change is computed as the technical change over the previous 5 years. Column (1) corroborates the results in BS. Productivity growth is negatively related to early retirement. In column (2) we introduce the unexpected shock. Although insignificant, the coefficient is positive. In columns (3) and (4) we introduce the quadratic specification

[14] We do not report the results for waves 9 and 10 as they have missing standard errors because of stratum with single sampling unit. In any case, the coefficients have the expected sign.

[15] TFP data is taken from United States World KLEMS (Jorgenson et al. [2012]). Computations are done similarly to the labor productivity growth. The correspondence between the KLEMS and the HRS sectors is not as clean as with the labor productivity measure. For this reason, the latter measure is preferred.

of both measures of technical change. Results reveal that unexpected technical change is not important to explain early retirement when we control for total productivity growth. Moreover, the inverse-U shape between technical change and early retirement remains intact. In column (4) we test whether the unexpected shock alone also presents a quadratic relationship with early retirement. It turns out that the unexpected shock has only an erosion effect as predicted in BS.

As mentioned above, the inverse-U shape between technical progress and early retirement indicates that the retraining cost function is strongly concave. This would be consistent with the hypothesis in BS as long as those sectors with larger productivity changes provide more on-the-job training to their workers and this reduces their marginal cost of retraining.

3.3 Comparison with Ahituv and Zeira (2011)

Ahituv and Zeira [2011] (AZ hereinafter) are the first to introduce the distinction between wage and erosion effects of technical change on early retirement. They develop a general equilibrium model where wages grow at the aggregate technical change rate, while the skill depreciation depends on aggregate and sector specific technical change. Therefore, they propose to estimate the erosion effect by distinguishing between aggregate technical change and sector-specific technical change. While aggregate technical change leads to both wage and erosion effect, the sector specific technical change causes only erosion of skills.

They merge the first three waves of the HRS survey with TFP data from US KLEM data. Their measure of technical progress is the TFP growth rate averaged over periods of 5 years. Then, they subtract the aggregate technical progress to this variable to measure the sector-specific technical change. They find a significant positive effect of the sector-specific technical growth on early retirement as predicted by their model.

We focus on the effect of technical change that occurs during the whole working life. We can however check whether their conclusions hold in our framework. In Table 7 we compare the predictions in AZ with those in our model. To do so we measure the sector-specific technical change (net shock) by subtracting the aggregate change to total sector technical change. Columns (1) and (2) report the effect of technical change in early retirement, separating between net and aggregate shock. We use the measure that refers to the change in the last 5 years of the working life to keep our analysis as close as possible to theirs. In column (1) we estimate the same equation as in AZ. Moreover, we use the first 3 waves of the HRS, the TFP change measure of technical change and the same dependent variable as in AZ (whether the individual is not working). The net shock has a positive effect on early retirement as AZ predict, although it is insignificant.[16] Column (2) follows the main specification of the previous sections using the last 5 years measure of technical change in terms of TFP change. The coefficient of the net shock is again positive, although not significant. Therefore, we obtain weak support for the AZ predictions. Columns (3), (4) and (5) present the estimation with the quadratic form of technical change. When we use technical change in the last 5 years of the working life, we do not obtain any coefficient significant (column (3)). Columns (4) and (5) use the working-life measure of technical change. We obtain that sector-specific technical change follows the same inverse-U shape relationship as we found for the total sector technical change.

To sum up, we find that when considering technical change that occured during the whole working life, both sector-specific and aggregate technical change cause erosion and wage effect.

4 Conclusion

We explore the role of technical change on early retirement decisions. Our contribution departs from previous literature in considering the technical change that each individual was subject to during his whole working life. Our model predicts that when productivity shocks are small, the cost of retraining (erosion effect) dominates the increase in wage (wage effect). Thus, the probability of retirement depends positively on these shocks. In contrast, when productivity shocks are large, the wage effect dominates and individuals are less likely to retire early. These results are consistent with the retraining cost function being strongly concave, a characteristic compatible with on-the-job training and life-long

[16] This may be due to different classification of those individuals that report being partly retired as retired or working part-time, the different measure of TFP change, different sector aggregations or differences between the RAND HRS and the HRS surveys.

learning. This result might be of interest to better design retraining programs for elderly workers.

Although the trend for early retirement has been decreasing in the last two decades, it is still very common in the US and most OECD countries. Further research could explore the mechanisms behind the apparent concavity of the retraining cost function, such as on-the-job training and life-long learning. Additionally, one might study how different technological paces affect early retirement.

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A Appendix: Data

We merge RAND HRS and BEA data in the following way. From the RAND HRS, we know in which sector each individual worked most of his working life, and how many years he spent working. We then subtract this duration from the year in which he stops working and compute in which year the respondent entered the labor market. From the BEA data, we compute the value added per worker in each sector and year and use this ratio as our measure of productivity.[17] We then associate to each individual the productivity when they entered the labor market and the productivity when they stopped working for the sector where they spent most of their working life.[18] In this way we have the initial productivity a_s in the sector s where individuals start working and we can compute also the growth rate $\frac{b_s a_s - a_s}{a_s} \approx \ln b_s$ of productivity from the year they started working to the year they stopped. The aggregation of sectors is done as indicated in Table 8. For the comparison with Ahituv and Zeira [2011], we also compute aggregate productivity growth for each time span using total value added per worker. Then, we obtain the sector-specific productivity growth by subtracting the aggregate from the sectoral productivity growth defined above. We compute also the productivity growth rate of the last 5 years in the sector, which we identify as an unexpected technical change. For robustness analysis, analogous measures of TFP change are computed using Jorgenson et al. [2012] data.

[17]We use the value added in millions of chained (2005) dollars.

[18]There are individuals who migrate between sectors across time but we assign them the sector where they spent most of their working life. In any case, their number is negligible (less than 5% of the sample).

B Appendix: Figures and Tables

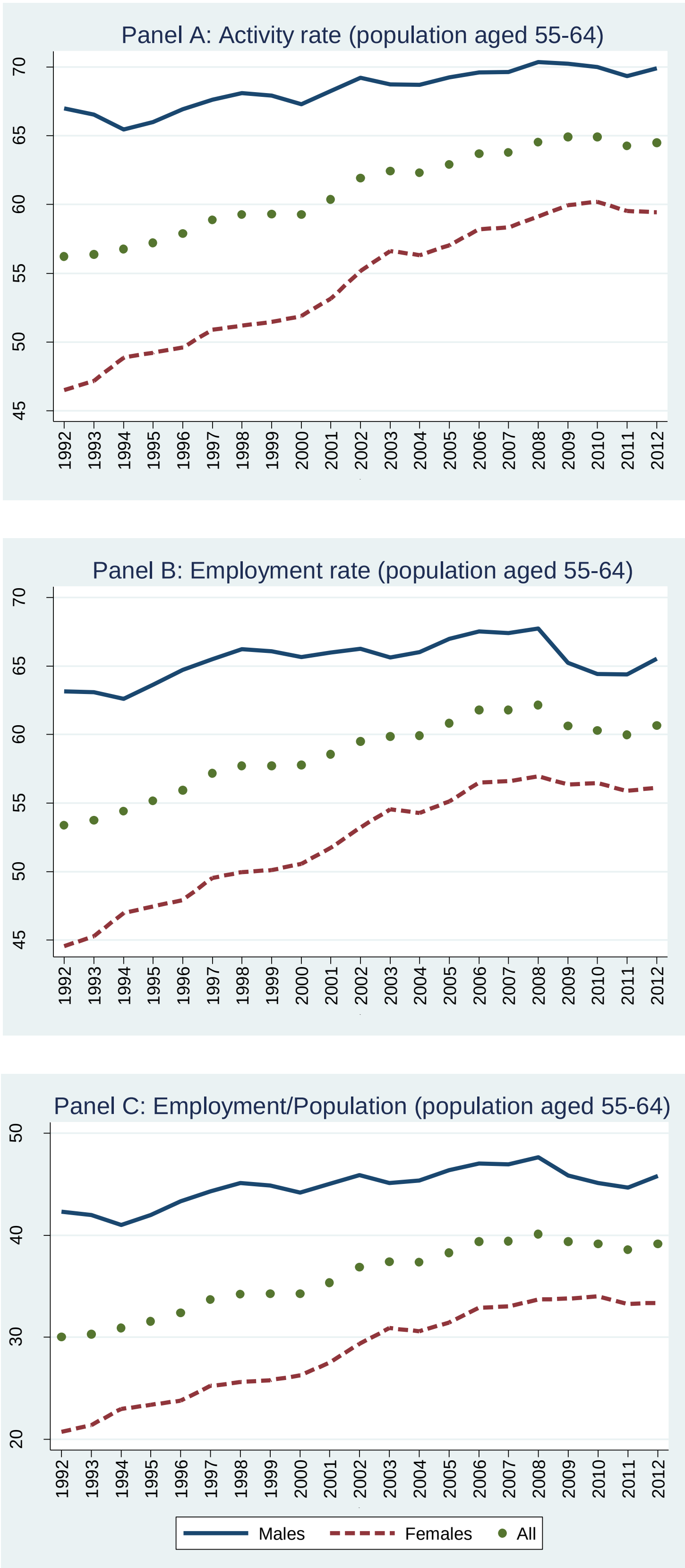

Figure 1: Data from OECD.Stat. Data refers to individuals aged 55-64 in the US.

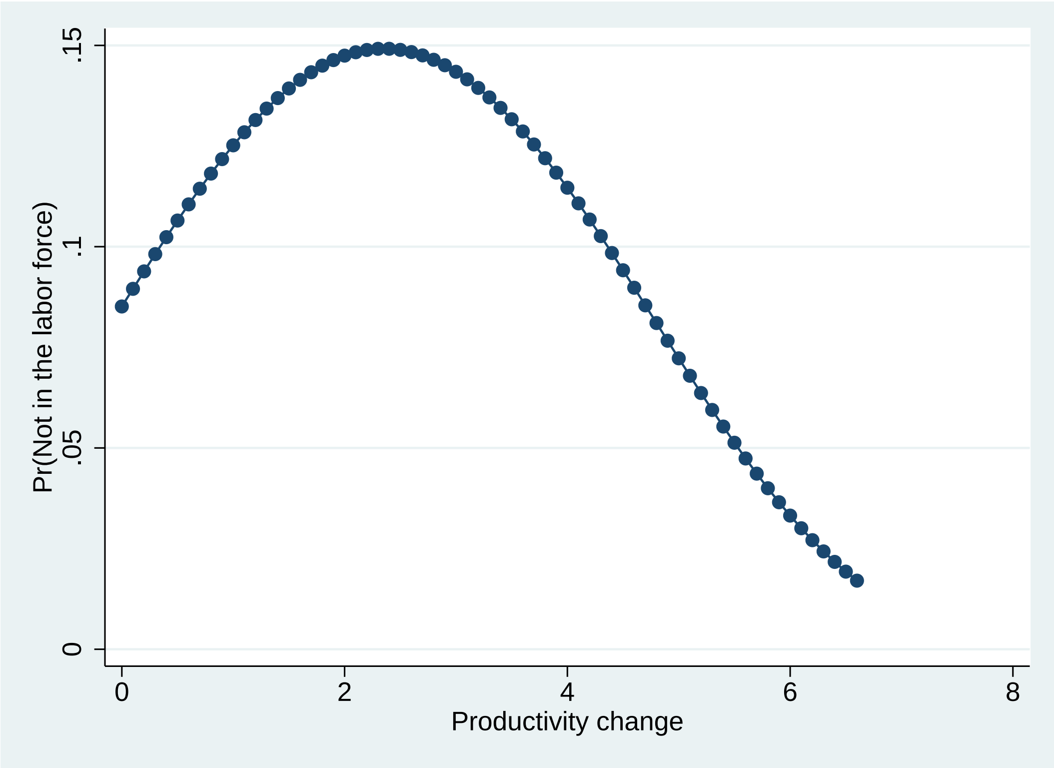

Figure 2: Predicted probability of early retirement based on a probit regression identical to the pooled estimation reported in Table 3.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Not in the labor force	0.15	0.35	0	1
Not working	0.17	0.38	0	1
Labor productivity change	1.20	1.43	-0.48	6.59
Aggregate technical change	0.54	0.16	-0.16	0.91
Sector specific technical change	0.66	1.39	-1.22	5.83
TFP change	1.21	0.90	-0.94	5.35
Age	57.82	3.62	50	64
Years of education	12.99	3.18	0	17
Sector Experience	37.28	8.41	0	51
African-American	0.12	0.33	0	1
Hispanic	0.11	0.31	0	1
Immigrant	0.11	0.31	0	1
Married	0.82	0.38	0	1
Bad health	2.51	1.06	1	5
Spouse working	0.52	0.50	0	1
Employer health insurance	0.79	0.40	0	1
Government health insurance	0.07	0.25	0	1
Wealth (winsorized)	0.04	0.06	-0.01	0.50
Pension	0.60	0.49	0	1
Region: Mid-West	0.26	0.44	0	1
Region: South	0.40	0.49	0	1
Region: West	0.19	0.39	0	1
Region: North-East	0.16	0.36	0	1
Agriculture, Forestry and Fishing	0.04	0.20	0	1
Mining and Construction	0.11	0.31	0	1
Manufacturing: Non-durable	0.09	0.29	0	1
Manufacturing: Durable	0.17	0.37	0	1
Transportation	0.10	0.30	0	1
Wholesale	0.05	0.23	0	1
Retail	0.08	0.27	0	1
Finance, Insurance, Real Estate	0.05	0.22	0	1
Business, Repair Services	0.06	0.23	0	1
Personal Services	0.02	0.13	0	1
Entertainment, recreation	0.01	0.10	0	1
Professional and related services	0.14	0.35	0	1
Public administration	0.08	0.26	0	1
Observations		18726		

Table 2: Summary statistics. Labor status by age group for waves 2, 6 and 10, survey weights used.

Wave 2 (1994)		**Age group**		
Labor status	**50-54**	**55-59**	**60-64**	**Total**
Working FT	85.3%	80.7%	67.9%	79.2%
Working PT	4.7%	5.3%	6.1%	5.3%
Unemployed	2.9%	2.7%	3.2%	2.8%
Retired	5.2%	9.5%	20.8%	10.8%
Disabled	1.6%	1.1%	1.8%	1.4%
Not in labor force	0.4%	0.7%	0.2%	0.5%

Wave 6 (2002)		**Age group**		
Labor status	**50-54**	**55-59**	**60-64**	**Total**
Working FT	83.2%	82.2%	67.2%	76.6%
Working PT	8.2%	4.2%	7.1%	5.5%
Unemployed	2.4%	4.1%	2.1%	3.3%
Retired	6.2%	8.0%	22.3%	13.2%
Disabled	0.0%	0.7%	1.1%	0.8%
Not in labor force	0.0%	0.9%	0.2%	0.6%

Wave 10 (2010)		**Age group**		
Labor status	**50-54**	**55-59**	**60-64**	**Total**
Working FT	85.1%	77.8%	69.3%	74.1%
Working PT	6.0%	4.8%	7.4%	6.1%
Unemployed	1.6%	7.0%	4.0%	5.3%
Retired	5.0%	8.9%	17.5%	12.8%
Disabled	2.5%	0.6%	1.4%	1.0%
Not in labor force	0.0%	1.0%	0.5%	0.7%

Notes: The sample includes only those males that were in the labor force the previous 2 years.

Table 3: Main results. Pooled logit, random effects and survival models

	(1) Pooled Logit	(2) Weighted logit	(3) Random effects	(4) Survival model
Productivity growth	0.496***	0.464***	1.141**	0.250**
	(0.150)	(0.169)	(0.510)	(0.126)
Product. Growth^2	-0.107***	-0.094***	-0.342***	-0.071***
	(0.029)	(0.030)	(0.077)	(0.025)
Years of education	-0.005	-0.013	-0.077*	-0.016**
	(0.010)	(0.016)	(0.046)	(0.008)
Sector experience	-0.008**	-0.008	-0.025*	-0.007**
	(0.003)	(0.006)	(0.013)	(0.003)
Married	0.066	0.192	-0.006	0.037
	(0.069)	(0.121)	(0.274)	(0.060)
Bad health	0.481***	0.413***	1.301***	0.377***
	(0.027)	(0.043)	(0.091)	(0.023)
Spouse working	-0.637***	-0.866***	-2.184***	-0.537***
	(0.053)	(0.086)	(0.206)	(0.047)
Emp. health ins.	-0.194***	-0.115	-1.796***	-0.144**
	(0.068)	(0.123)	(0.232)	(0.057)
Gov. health ins.	1.188***	1.095***	3.444***	0.936***
	(0.098)	(0.140)	(0.332)	(0.075)
Wealth	0.788*	1.205*	2.441	0.479
	(0.426)	(0.622)	(1.618)	(0.334)
Pension (dummy)	-1.046***	-1.299***	-4.394***	-0.868***
	(0.073)	(0.087)	(0.250)	(0.061)
Pseudo R-squared	0.220			
ρ			0.948	
σ_u			7.716	
Observations	18726	14515	18726	18726

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Standard errors in parenthesis (Clustered by sectors and waves in (1) and (4)).

Notes: All models include sector, region, age, cohort and race dummies, and aggregate unemployment rate.

Table 4: Main results. Logit per wave, weighted.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Wave 2	**Wave 3**	**Wave 4**	**Wave 5**	**Wave 6**	**Wave 7**	**Wave 8**
Product. growth	1.103*	0.594	0.801**	2.577***	1.038*	0.300	1.030**
	(0.576)	(0.453)	(0.384)	(0.673)	(0.523)	(0.409)	(0.408)
Product. Growth^2	-0.309**	-0.152	-0.229**	-0.637***	-0.302***	-0.158**	-0.220***
	(0.152)	(0.106)	(0.089)	(0.149)	(0.112)	(0.068)	(0.077)
Years of education	-0.000	-0.040*	-0.027	-0.055	-0.016	-0.012	0.023
	(0.025)	(0.024)	(0.031)	(0.035)	(0.035)	(0.033)	(0.044)
Sector experience	-0.012	-0.015*	-0.003	-0.017*	0.015	0.014	-0.004
	(0.010)	(0.008)	(0.009)	(0.010)	(0.012)	(0.012)	(0.012)
Married	-0.261	-0.135	0.634***	-0.225	0.273	-0.158	0.377
	(0.201)	(0.182)	(0.201)	(0.226)	(0.219)	(0.224)	(0.276)
Bad health	0.658***	0.512***	0.522***	0.537***	0.505***	0.420***	0.547***
	(0.083)	(0.073)	(0.087)	(0.069)	(0.099)	(0.090)	(0.096)
Spouse working	-0.750***	-0.618***	-0.632***	-0.416**	-0.959***	-0.677***	-0.846***
	(0.148)	(0.160)	(0.125)	(0.168)	(0.168)	(0.218)	(0.203)
Emp. health ins.	-0.232	-0.501***	-0.231	-0.448*	0.028	-0.322	-0.199
	(0.187)	(0.167)	(0.208)	(0.256)	(0.280)	(0.215)	(0.253)
Gov. health ins.	1.142***	1.296***	1.429***	1.065***	0.674	0.838**	0.788**
	(0.241)	(0.240)	(0.224)	(0.328)	(0.412)	(0.318)	(0.312)
Wealth	1.653	0.342	1.371	2.944**	-0.602	-2.250	1.150
	(1.505)	(1.409)	(1.412)	(1.256)	(1.303)	(1.421)	(1.247)
Pension (dummy)	-0.568***	-0.640***	-1.216***	-1.244***	-1.320***	-1.173***	-1.497***
	(0.182)	(0.191)	(0.140)	(0.190)	(0.201)	(0.187)	(0.199)
Observations	2971	2456	2814	2251	1702	2202	1763

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors in parenthesis.

Notes: All models include age, sector, region and race dummies.

Table 5: Robustness checks. Pooled logit.

	(1)	(2)	(3)	(4)
	TFP	**Notworking**	**Winsorized**	**Waves 1994-2006**
Productivity growth	0.741***	0.456***	0.506***	0.652***
	(0.144)	(0.130)	(0.150)	(0.169)
Product. Growth^2	-0.119***	-0.091***	-0.110***	-0.155***
	(0.023)	(0.026)	(0.029)	(0.032)
Years of education	-0.006	0.008	-0.005	-0.006
	(0.010)	(0.010)	(0.010)	(0.011)
Sector experience	-0.019***	-0.014***	-0.008***	-0.007**
	(0.004)	(0.003)	(0.003)	(0.004)
Married	0.058	0.058	0.066	0.045
	(0.069)	(0.061)	(0.069)	(0.078)
Bad health	0.486***	0.435***	0.482***	0.488***
	(0.026)	(0.024)	(0.027)	(0.030)
Spouse working	-0.638***	-0.564***	-0.636***	-0.625***
	(0.053)	(0.048)	(0.053)	(0.058)
Emp. health ins.	-0.182***	-0.353***	-0.194***	-0.266***
	(0.067)	(0.059)	(0.068)	(0.067)
Gov. health ins.	1.196***	0.993***	1.188***	1.191***
	(0.097)	(0.096)	(0.098)	(0.104)
Wealth	0.797*	-0.035	0.782*	0.440
	(0.424)	(0.396)	(0.426)	(0.467)
Pension (dummy)	-1.043***	-1.283***	-1.046***	-0.963***
	(0.074)	(0.068)	(0.073)	(0.074)
Pseudo R-squared	0.221	0.210	0.220	0.224
Observations	18726	18726	18726	16198

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Cluster-robust standard errors in parenthesis.

Notes: All models include sector, region, age, cohort and race dummies, and aggregate unemployment rate.

Table 6: Comparison to Bartel & Sicherman. Pooled logit.

	(1)	(2)	(3)	(4)
	BS	**BS**	**Last 5 years**	**Last 5 years**
Productivity growth	-0.097*	-0.123***	0.450***	
	(0.050)	(0.046)	(0.141)	
Product. Growth^2			-0.101***	
			(0.028)	
Product. Growth (5y)		0.663	1.102	1.476*
		(0.598)	(0.875)	(0.892)
Product. Growth^2 (5y)			-1.473	-3.369
			(2.748)	(2.740)
Years of education	-0.005	-0.005	-0.005	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)
Sector experience	-0.004	-0.004	-0.008**	-0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Married	0.064	0.064	0.066	0.065
	(0.068)	(0.068)	(0.069)	(0.069)
Bad health	0.484***	0.484***	0.482***	0.485***
	(0.026)	(0.026)	(0.027)	(0.026)
Spouse working	-0.631***	-0.631***	-0.637***	-0.633***
	(0.053)	(0.053)	(0.053)	(0.053)
Emp. health ins.	-0.187***	-0.188***	-0.195***	-0.187***
	(0.068)	(0.067)	(0.068)	(0.067)
Gov. health ins.	1.187***	1.187***	1.189***	1.188***
	(0.098)	(0.098)	(0.098)	(0.098)
Wealth	0.819*	0.818*	0.790*	0.830**
	(0.423)	(0.422)	(0.424)	(0.422)
Pension (dummy)	-1.038***	-1.036***	-1.045***	-1.039***
	(0.073)	(0.073)	(0.073)	(0.073)
Pseudo R-squared	0.218	0.219	0.221	0.219
Observations	18726	18726	18726	18726

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Cluster-robust standard errors in parenthesis.

Notes: All models include sector, region, age, cohort and race dummies, and aggregate unemployment rate.

Table 7: Comparison to Ahituv & Zeira. Pooled logit.

	Replication AZ		**Quadratic form**		
	(1)	(2)	(3)	(4)	(5)
	TFP, last 5y	**TFP, last 5y**	**LP, last 5y**	**TFP**	**LP**
Net shock	0.056	0.125	1.035	0.273**	0.441***
	(0.420)	(0.315)	(0.647)	(0.126)	(0.133)
Net shock^2			-4.694	-0.115***	-0.111***
			(2.953)	(0.036)	(0.031)
Aggregate shock		1.891	187.954	1.405***	4.771***
		(1.490)	(125.693)	(0.331)	(0.731)
Aggregate shock^2			-1219.506	-0.185	-5.703***
			(814.988)	(0.258)	(0.694)
Married	-0.481***	0.069	0.074	0.050	0.069
	(0.091)	(0.068)	(0.069)	(0.068)	(0.068)
Years of education	-0.012	-0.004	-0.004	-0.007	-0.016*
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Bad health	0.485***	0.486***	0.483***	0.486***	0.479***
	(0.037)	(0.026)	(0.027)	(0.027)	(0.027)
Sector experience		-0.007***	-0.007***	-0.030***	0.005
		(0.003)	(0.003)	(0.004)	(0.005)
Spouse working		-0.633***	-0.640***	-0.645***	-0.634***
		(0.054)	(0.053)	(0.054)	(0.053)
Emp. health ins.		-0.191***	-0.188***	-0.186***	-0.206***
		(0.068)	(0.069)	(0.067)	(0.068)
Gov. health ins.		1.189***	1.187***	1.194***	1.208***
		(0.098)	(0.098)	(0.098)	(0.098)
Wealth		0.842**	0.768*	0.794*	0.602
		(0.420)	(0.421)	(0.426)	(0.434)
Pension (dummy)		-1.043***	-1.043***	-1.047***	-1.075***
		(0.073)	(0.073)	(0.074)	(0.073)
Pseudo R-squared	0.118	0.220	0.223	0.223	0.226
Observations	10182	18726	18726	18726	18726

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Cluster-robust standard errors in parenthesis.

Notes: Column (1) includes age, age squared, region, wave, and race dummies, and observations from waves 1 to 3 only. Columns (2) to (5) include sector, region, age, cohort and race dummies, and aggregate unemployment rate.

Table 8: Sectoral aggregation as in HRS.

HRS sector	**NAICS codes**
01.Agric/Forest/Fish	11
02.Mining and Constr	21, 23
03.Mnfg: Non-durable	31, 32 (except 321 and 327)
04.Mnfg: Durable	33, 321, 327
05.Transportation	22, 48, 49 (except 491), 51
06.Wholesale	42
07.Retail	44, 45
08.Finance, Insurance, and Real Estate	52, 53
09.Busns/Repair Svcs	54, 55, 56
10.Personal Services	72, 81
11.Entertn/Recreatn	71
12.Prof/Related Svcs	6
13.Public Administration	NA (includes 491)

Table 9: Sectoral aggregation to compute TFP change.

HRS sector	**31 ISIC rev 3 industries**
01.Agric/Forest/Fish	A,B
02.Mining and Constr	C,F
03.Mnfg: Non-durable	15-25
04.Mnfg: Durable	26-37
05.Transportation	E,60-64
06.Wholesale	50-51
07.Retail	52
08.Finance, Insurance, and Real Estate	J, 70
09.Busns/Repair Svcs	71-74
10.Personal Services	H
11.Entertn/Recreatn	O
12.Prof/Related Svcs	M,N
13.Public Administration	L

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