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Technical Progress, Sorting, and Early Retirement

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Abstract

Technological progress has been shown to affect early retirement via two opposite forces. On the one hand, it increases real wages and, therefore, creates incentives to delay retirement. On the other hand, it causes an erosion of workers' skills, which raises the probability of early retirement. We reexamine the effect of technological progress on early retirement by taking into account that, at the beginning of their working life, individuals sort into sectors according to their ability level. This gives us two main results: 1) for small (large) technical changes the wage (erosion) effect dominates, and 2) the more able individuals resist better the erosion effect.

Resum

El progrés tecnològic afecta a la jubilació anticipada a través de dues forces oposades. Per una banda, augmenta el salari real i, per tant, crea incentius per posposar la jubilació. Per altra banda, causa l'erosió de les habilitats dels treballadors, el qual augmenta la probabilitat de jubilació anticipada. En aquest article reexaminem l'efecte del progrés tecnològic en la jubilació anticipada tenint en compte que, al principi de la vida laboral, els individus es distribueixen en diferents sectors segons la seva habilitat. Obtenim dos resultats principals: 1) per petits (grans) canvis tecnològics, l'efecte salari (erosió) domina, i 2) els individus més capaços resisteixen millor l'efecte erosió.

JEL Codes: J24, J26, O15 y O33

Keywords: Early retirement, technological progress, ability sorting, sectoral sorting

1 Introduction

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.[1] 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 stop working well before their formal retirement age. We refer to this phenomenon as early retirement. Early retirement decisions influence the economic dependency ratio of a country.[2] 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 (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 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 due to its erosion effect on individual's skills. In particular, 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. Ahituv and Zeira [2011],

[1] See OECD [2013].

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

instead, propose to estimate the erosion effect by distinguishing between aggregate and sector-specific rates of technical change. According to their model, the former is responsible for a general wage increase that might reduce early retirement, while the latter is associated to the erosion effect. We reexamine the effect of technological progress on early retirement by taking into account that individuals are heterogeneous at the beginning of their working life and sort into sectors according to their ability level.

We build on the previous work of Ahituv and Zeira [2011] and show that early retirement depends not only on the speed of technical change -the erosion and wage effects already found in the previous literature- but also on its interaction with the skill level of individuals -what we call the sorting effect-. We construct a simple model with ex-ante heterogeneous agents that choose in which sector to work when young and whether to retire early when old. The sectoral skill distribution in equilibrium is a product of the technological level of the sectors. Individuals with a high skill level sort into sectors with a relatively high productivity, while low-tech sectors attract low skill individuals. This sorting implies that individuals in more productive sectors are also more able to retrain and resist the erosion effect on their human capital exerted by the technical progress. Hence, the model predicts that the probability of early retirement depends on the technical change in the sector where the individuals work but also on the technical level at the time when individuals entered the labor market.

We employ our model to inform our empirical analysis. We use RAND Health and Retirement Study (HRS) data,[3] 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 productivity levels and their growth rates between 1948 and 2010. We find that 1) there exists sorting by skills across sectors with different technical level, 2) the probability of early retirement depends on whether the productivity growth in the sectors where the individuals work is relatively high or low, and 3) the sorting effect matters to explain early retirement.

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, it

[3]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 [December 2011]

suggests that the implications for retirement behaviors of retraining programs to favor the permanence of the elderly in the labor force depend crucially on the skill composition of the sector in which they work and on the pace of technical progress.

Our work is related 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 arguably qualitatively robust to this issue.

The paper is organized as follows. In Section 2 we present the set-up of the model. In Section 3 we solve the model and derive its main implications. In Section 4 we test empirically the implications of the model and compare our results with the previous literature, namely, Ahituv and Zeira [2011]. Section 5 draws the final conclusions. All proofs, figures, and tables are in the Appendix.

2 The model

We construct a small open economy on the basis of Ahituv and Zeira [2011]. On the production side, a unique consumption good is produced using a continuum of intermediate sectors. We normalize the mass of intermediate sectors to 1. The production Y_t of the consumption good at time t is the aggregation of sector-specific intermediate goods, that is,

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

where X_{it} is the output of sector i. Within each sector, a continuum of perfectly competitive firms employs capital and efficiency units of labor to realize production X_{it}, that is,

$$X_{it} = F(K_{it}, H_{it}) = H_{it} f(k_{it}), \tag{2}$$

where K_{it} is the quantity of capital in sector i, H_{it} measures the efficiency units of labor in sector i, $k_{it} \equiv K_{it}/H_{it}$ is the ratio of capital to efficiency units of labor, and the function f is the intensive form of the real-valued function F, which is strictly increasing and concave in both arguments, is homogeneous of degree one, and satisfies the Inada conditions. Under perfect competition, each firm chooses the optimal level of capital and efficiency units of labor in order to maximize profits, taking as given the price of capital r_{it} and the price per efficiency unit of labor w_{it}. Thus, the inverse demand functions for the two factors of production in sector i are

$$r_{it} = f'(k_{it}) \tag{3}$$

for capital and

$$w_{it} = f(k_{it}) - f'(k_{it})k_{it}, \tag{4}$$

for efficiency units of labor. Both prices are functions of the ratio k_{it}. We assume that the world rental rate is constant at the level $\bar{r}$. Since firms operate in a small open economy, they can borrow and lend without restrictions in the international capital markets. Hence, $r_{it} = \bar{r}$ for every i and for every t. As a consequence, the optimal ratio k_{it} is constant at $k_{it} = \bar{k}$ and therefore the price w_{it} of the efficiency units of capital is fixed at $w_{it} = \bar{w} = f(\bar{k}) - f'(\bar{k})\bar{k}$ for every i and for every t.[4]

The productivity -the efficiency units per unit of labor- in sector i at time t corresponds to the technical level a_{it} available in sector i at time t. This technical level evolves according to

$$a_{it} = a_{it-1}b_{it},$$

where b_{it} is the technical change in sector i. We assume that the technical change in every sector is non-negative and bounded for every t, that is, $1 \leq b_{it} \leq B$. Sector i's rate of technical change is therefore $\ln(b_{i,t}) = \ln(a_{it}) - \ln(a_{it-1})$.

Assumption 1. *The technical change is iid over time and across sectors with expectation* $b > 0$.

On the consumers side, each generation consists of a continuum of individuals of mass 1. Individuals live for two periods and are ex-ante heterogeneous in their inability to learn

[4] See Galor and Tsiddon [1997] for a similar framework.

f, which is distributed over the support set $[0, F]$. The lower f, the more able to learn the individual. 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. Consider an individual born in period $t-1$. In the first period of her life, each individual observes her ability f and the distribution of technical levels across sectors $\{a_{it-1}\}_i$, and decides the sector i where to work. Access to sector i requires a training time $\psi(a_{it-1}, f)$. We will refer henceforth to ψ as the entry function, and we denote ψ_j and ψ_{jj} the first and second partial derivatives with respect to argument $j = 1, 2$. The function ψ is strictly increasing and convex in both arguments. The higher the technical level a_{it-1} of the sector and/or the inability f of the individual, the more time the individual of type f that chooses to access sector i has to spend in training. We assume that $\psi_{12} \geq 0$.[5] Each individual divides her time in the first period between training and working, so that her supply of units of labor -her hours worked- in the first period is $(1 - \psi(a_{it-1}, f))$. Each individual then works and earns the wage income when young

$$W^{Y}_{t-1} \equiv \bar{w} a_{it-1}(1 - \psi(a_{it-1}, f)), \tag{5}$$

where $\bar{w}$ is the constant price per efficiency unit of labor as defined above, a_{it-1} is the efficiency units per hour worked -the technical level of the individual-, and $(1-\psi(a_{it-1}, f))$ is the individual supply of hours. Moreover, the individual chooses the optimal amount m_{t-1} of savings to pass to the second period. In the second period of life each individual has to choose among two possibilities. She can either retrain to the new technical level a_{it} of her sector and work, or retire early, supply no units of labor, and earn no wage income.[6] If she chooses to retrain and work, she supplies $L - \phi(b_{it}, f)$ units of labor, where $\phi(b_{it}, f)$ is the time spent in updating her 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 $j = 1, 2$. The function ϕ is strictly increasing

[5] The assumption $\psi_{12} \geq 0$ means that the marginal cost of reaching each level of knowledge a_{it-1} is non-decreasing with f. This assumption could be relaxed without changing significatively the results. We introduce it to simplify the analysis.

[6] 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, she prefers to retrain once she decides to work. The loss of generality is minimal, so we neglect this option for simplicity.

and convex in both arguments. Similarly to the entry function, we assume that $\phi_{12} \geq 0$. The wage income when old is

$$W_t^o \equiv \bar{w} a_{it} \left[L - \phi \left(b_{it}, f \right) \right], \tag{6}$$

where the productivity of the labor supply is a_{it}.[7]

An individual of type f derives utility from consumption in the first and second period, and from retirement if she retires early. Individuals have different preferences for retirement. We assume that the preference h for early retirement is distributed over the interval $[0, H]$ where $H \in \mathbb{R}_+$, and that h is independent from the learning inability f. Individuals know their type f from birth, and only their taste h for retirement remains unknown until the second period of life.[8] Hence, their ex-ante lifetime utility $U_{t-1}(a_{t-1}, f)$ does not depend on h but does depend on f. Individuals are perfectly rational and maximize their ex-ante lifetime utility based on their expectations in period $t-1$. The utility of an individual of type f that chooses to work in sector i is

$$U_{t-1}(a_{it-1}, f) \equiv u(c_{t-1}^y) + E\left[u(c_t^o) + \mathbb{1} v(h) \right], \tag{7}$$

where c_{t-1}^y is consumption when young, c_t^o is consumption when old, $\mathbb{1}$ is an indicator function that takes value $\mathbb{1} = 1$ if the individual retires early and $\mathbb{1} = 0$ if she does not, and $E[\cdot]$ is the expectation operator. We assume that the functions u and v are linear. This simplifies the model considerably but maintains intact its main insights on the sorting of individuals into different sectors and the probability of early retirement.

3 Equilibrium

At the beginning of her first period, an individual of type f chooses optimally the sector i where to work and the level of savings m_{t-1}. In the second period the individual chooses between retraining and working, or retiring early without working. We solve first for the second period problem. Given that the utility is assumed linear in consumption, the

[7]Note that if the individual decides to retrain, it must be that $L - \phi(b_{it}, f) \geq 0$.

[8]The preference for early retirement is unknown in the first period because it may depend on health status, family situation, and other issues difficult to predict when one is young. This assumption does not affect the main results of the paper.

problem can be written as

$$\max\{W_t^o + (1+\bar{r})m_{t-1}, (1+\bar{r})m_{t-1} + h\}. \tag{8}$$

At the beginning of the second period, individuals observe their taste h for early retirement and the technical change b_{it} in the sector they selected the period before. An individual decides to retire early if the utility from early retirement is higher than the utility from working, that is, if her taste for retirement is higher than the wage when old W_t^o,

$$h > W_t^o = \bar{w}a_{it}\left[L - \phi\left(b_{it}, f\right)\right]. \tag{9}$$

Early retirement is more likely whenever obligatory retirement is large (small L) and wage per efficiency unit of labor is low (small $\bar{w}$). Moreover, early retirement depends on the chosen sector in two ways. First, the probability of early retirement decreases with the initial labor productivity a_{it-1}.[9] In this way, the choice of the sector in the first period influences the early retirement. Second, the technical change b_{it} 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 (wage effect). On the other hand, the worker devotes more time to retraining, reducing her labor supply in the second period (erosion effect).[10]

Let us solve now for the first period problem. Given that the utility is linear in consumption, the optimal choice for savings is indetermined and the problem boils down to choosing the sector where to work. In the first period, each individual observes her type f and the distribution of productivity across sectors $\{a_{it-1}\}_i$. The choice of the sector depends on the wage when young W_{t-1}^y and the expected wage when old $E_{t-1}\left[W_t^o\right]$. If Assumption 1 holds, then the choice of the sector does not depend on the future technical

[9]Recall that $a_{it} = a_{it-1}b_{it}$.

[10]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 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 case, intermediate goods are perfect substitutes and individuals differ from the very first period. If individuals know their ability level already in the first period, the distinction between aggregate and sector-specific technical change does not help anymore in disentangling between the wage effect and the erosion effect.

change b_{it} but rather exclusively on a_{it-1}. Hence, the utility $U_{t-1}(a_{it-1}, f)$ of an individual of type f described in (7) depends on i only in terms of the initial level of productivity a_{it-1} of the sector that the individual chooses. Therefore, there will be a sorting of individuals into sectors according to their ability level.

Let us order the sectors at $t-1$ according to their technical level a_{it-1}, so that if $a_{it-1} > a_{jt-1}$ then $i > j$. Maximizing the lifetime utility with respect to i is equivalent to maximize the same lifetime utility with respect to $\{a_{it-1}\}_{i\in[0,1]}$, that is, to choose the technical level a_{it-1} in the set of available technologies at $t-1$ that maximizes the lifetime utility. Thus, we can write the first period problem as

$$\max_{\{a_{it-1}\}_{i\in[0,1]}} W^y_{t-1} - m_{t-1} + E_{t-1}\left[\max\{W^o_t + (1+\bar{r})m_{t-1}, (1+\bar{r})m_{t-1} + h\}\right]. \qquad (10)$$

Proposition 1. *Suppose that Assumption 1 holds. Then, the technical level a^*_{it-1} of the optimal sector for an individual i of type f is unique. Moreover, there exists a decreasing function $a_{t-1}(f)$ such that $a^*_{it-1} = a_{t-1}(f)$ for every i and for every f.*

This proposition states that each individual of type f chooses a unique sector i among those whose technical levels are available at time $t-1$. Moreover, individuals with high skill choose relatively high-productivity sectors, and individuals with low skill choose relatively low-productivity sectors. The function $a_{t-1}(f)$ represents the sorting of different individual types across sectors. Although all individuals of the same type choose the same sector, this does not imply that all individuals working in the same sector have the same skill level.[11] Proposition 1 implies that sectors differ in their skill composition, that is, high skill individuals are more likely in high productivity sectors and low skill individuals are more likely in low productivity sectors.

Following Proposition 1, the wage when young in equilibrium is a function of the type f, that is,

$$\left(W^y_{t-1}\right)^* = \bar{w}a_{t-1}(f)(1-\psi(a_{t-1}(f), f)),$$

for every f. Moreover, the wage when old in equilibrium is

$$(W^o_t)^* = \bar{w}b_{it}a_{t-1}(f)\left[L - \phi(b_{it}, f)\right],$$

[11]This depends on the initial distribution of productivities across sectors, which is not necessarily a continuous increasing function.

which depends on both the type f but also on the productivity growth b_{it}. According to the condition for early retirement in (9), an individual of type f in sector i at time t retires early if and only if

$$h > \bar{w} b_{it} a_{t-1}(f) \left[L - \phi(b_{it}, f) \right], \tag{11}$$

where $h \in [0, H]$.

We can distinguish two main forces that drive the decision on early retirement. On the one hand, the wage effect depends on the initial productivity level and the technical change of the chosen sector, and increases the incentives of working further. On the other hand, the erosion effect is determined by the retraining costs, and pushes individuals to retire early. The retraining costs depend on the technical change of the sector and the individual inability to learn. The decision of individuals of type f to go to a sector with productivity $a_{t-1}(f)$ introduces a sorting effect on top of the wage effect. In other words, the strength of the wage effect depends on the sector choice and therefore on the individual learning inability.

Condition (11) implies that if $(W_t^o)^* > H$ the individual keeps working with probability 1. If instead $(W_t^o)^* \in [0, H]$, then the probability $P_{it}(f)$ of early retirement of an individual of type f in sector i at time t is

$$P_{it}(f) = 1 - \frac{(W_t^o)^*}{H} = 1 - \frac{\bar{w} b_{it} a_{t-1}(f) \left[L - \phi(b_{it}, f) \right]}{H}.$$

Proposition 2. *Suppose Assumption 1 holds. Then, there exists a unique decreasing function $\bar{b}(f)$ that satisfies*

$$L - \phi(\bar{b}(f), f) - \phi_1(\bar{b}(f), f)\bar{b}(f) = 0, \tag{12}$$

such that

i) $\dfrac{dP_{it}(f)}{db_{it}} < 0$ *if* $b_{it} < \bar{b}(f)$ *and*

ii) $\dfrac{dP_{it}(f)}{db_{it}} > 0$ *if* $b_{it} > \bar{b}(f)$.

For low rates of technical change, the wage effect dominates and the probability of early retirement decreases with b_{it}. In contrast, when technical change in the sector is large, the erosion effect dominates and the probability of early retirement increases. Moreover, the threshold that distinguishes between small and large shocks depends on the inability level of the individual. Less skilled individuals suffer a relatively larger erosion effect than more skilled individuals.

Proposition 3. *Suppose Assumption 1 holds. Then,* $\dfrac{\partial P_{it}(f)}{\partial f} > 0$ *for any* b_{it}*.*

The probability of early retirement increases with the individual inability to learn, so those sectors that attracted more able individuals should experience less early retirement. The negative effect of inability on early retirement is due to both the lower wages for less able individuals and the more time needed to retrain in case of a technical change.

Proposition 4. *Suppose Assumption 1 holds. Then, there exists an* $\epsilon > 0$ *such that*

i) $\dfrac{\partial^2 P_{it}(f)}{\partial b_{it} \partial f} > 0$ *if* $b_{it} \leq \bar{b}(f) + \epsilon$ *and*

ii) $\dfrac{\partial^2 P_{it}(f)}{\partial b_{it} \partial f}$ *has an ambiguous sign if* $b_{it} > \bar{b}(f) + \epsilon$*,*

where $\bar{b}(f)$ *satisfies* (12).

The effect of a given technical change b_{it} on early retirement is larger for less able individuals as long as the shock is not too large. The ambiguous result for the case of large rates of technical change occurs because more able individuals have a larger time opportunity cost. They have to give up larger wages in order to retrain and this increases their total retraining costs.

4 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 30000 individuals followed in 10 biennial waves from 1992 to 2010. We have information about the labor status matched with personal characteristics and details on the job history of the respondents. We focus on individuals who are between 50 and 64 and were in the labour force two years earlier. Our sample covers more than 52000 observations of 14704 individuals. 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 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 decide 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 a panel of 10 periods and 14704 individuals distributed in 13 sectors.

The empirical strategy unfolds as follows. First, we document the sorting of workers of different skill levels -measured as years of education- in sectors with different initial productivity. Second, we regress the probability of not working in period t on 1) the change in productivity occurred since each individual started working, $\ln b_{it}$, 2) the individual (inverse of) skill level f, and 3) the interaction of the two. We control for personal characteristics such as gender, age, race, experience,[12] marital status, residence, and health status. Moreover, we run both pooled regressions with time dummies to capture aggregate conditions, and panel regressions with random effects. Third, we conduct the same exercise but separately for those individuals who experienced large (small) productivity shocks, where a large (small) productivity shock is defined as a growth rate of productivity above (below) the median for each level of education. Fourth, we add robustness checks regarding the sample size, different measures of productivity growth, and the identification of aggregate and sector-specific shocks.

4.1 Individual sorting in different sectors

Proposition 1 predicts that individuals with high skills choose high productivity sectors, while individuals with low skills choose low productivity sectors. In order to check whether this sorting by abilities occurs, we compute the correlation between the productivity level of sectors at entry and the education level of individuals. Table 3 reports this measure for each wave and for the whole sample. We obtain a positive and significant overall correlation of above 0.18, which suggests the sorting process occurs. Our model allows also that within each sector there might be more skill groups, and that the likelihood of

[12]We define experience as the number of years that the individual spent working.

finding the whole span of skills decreases with the technical level. Figure 2 shows that the higher the entry productivity in the sector, the lower the probability of finding low-education individuals in that sector. Figure 3 compares across time the sector averages of the productivity at entry with the sector averages of education, which confirms the intuition behind the sorting process. The higher the average productivity at entry, the higher the average skill level, both across sectors and over time.[13]

4.2 Baseline regressions

We regress the probability $P_{it}(f)$ of notworking for an individual of type f in sector i at period t on 1) the growth rate $(a_{it}-a_{it-1})/a_{it-1} \approx \ln b_{it}$ of productivity since the individual started working, 2) the inability level $f \equiv 17 - e$, where e is the years of education, and its quadratic form, and 3) the interaction between the productivity growth rate and the inability level. We first present the pooled regression in Table 4, with controls for personal characteristics and time dummies. Second, we report the results for the panel regression with random effects in Table 5.[14] In both regressions we compare the model (first column) without sorting effect, that is, without the interaction between inability and productivity growth, with the model (second column) with sorting effect. Moreover, we present an alternative model (third column) with additional controls. In particular we introduce whether the spouse is working, the wealth status, and the possibility that the individual has some pension plan from the current or previous job.[15] Standard errors are clustered at the sector-wave-inability level in the pooled regression, and at the sector-inability level in the panel regression.

[13]There is one notable exception. The Finance/Insurance/Real Estate sector experienced an increase in the average skill level over time associated with a decrease in the productivity level at entry. These dynamics appear in the waves between 2002 and 2006. Considering that on average individuals interviewed in those waves entered the labor market around 1970, this suggests that something peculiar must have happened in the Finance/Insurance/Real Estate labor market in those years.

[14]In Table 16 we compare the marginal effects computed from a probit model with the coefficients of the linear probability model. As results are very similar, we use the linear probability model unless otherwise specified.

[15]We do not introduce these controls in all the analyses because, on the one hand, they reduce the sample size by around 20% and, on the other hand, the main results are not qualitatively sensitive to their inclusion.

The effect of the productivity growth is negative for all the specifications (albeit insignificant in some cases), implying that individuals in sectors with higher technological change are on average less likely to retire early. As Bartel and Sicherman [1993] argue, this result could be a consequence of these sectors providing more on-the-job training to their workers, which incentivizes them to retire later. In terms of the distinction between wage and erosion effects described in Ahituv and Zeira [2011], this result implies that the wage effect slightly dominates the erosion effect. In other words, the wage increase due to technological change compensates on average for the retraining costs. If we read these results through the lens of Proposition 2, they suggest that on average the productivity growth is low enough ($b_{it} < \bar{b}(f)$) to let the wage effect dominate. This is consistent with the positive sign of the interaction term (see Proposition 4), which means that the higher the inability level the larger the positive effect of productivity growth on early retirement. The inability variable has the expected sign, although the quadratic form has a negative coefficient and the overall sign is therefore negative for high levels of inability (less than 6 years of education).

We find that individuals delay the decision on retirement if the spouse still works, 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. The wealthier the individual, the higher the likelihood of retirement. Moreover, if an individual has any pension plan from current or previous job, she is more likely to retire early, as the opportunity cost of working is higher (see Blundell et al. [2002] for similar results). 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.

4.3 Large and small shocks

In order to test our model we have to distinguish individuals who receive large shocks from individuals who receive small shocks. The model predicts a negative (positive) coefficient of technical change when shocks are small (large). Moreover, the interaction term is supposed to affect positively the likelihood of early retirement for small shocks. We define large (small) shock as a level of b_{it} which is above (below) the median of the distribution of b_{it}'s for each level of education.[16] In Table 6 we present the results for the pooled regression with time dummies, while in Table 7 we present the results for the panel regression with random effects.[17] In the first column we report the results for the overall sample, while in the second and third column we present the same exercise but separately for the individuals affected by large shocks and individuals affected by small shocks.

The large shocks have a positive effect on the probability of early retirement alone and a negative effect through the interaction term. Hence, the erosion effect seems to exceed the wage effect in the case of large shocks as predicted. Moreover, the negative interaction occurs because a higher wage increases the opportunity cost of retraining for more able individuals strongly enough to convince them to retire early. The small shocks instead make the wage effect dominate, as the largely negative coefficient on the productivity growth suggests. Nevertheless, for small shocks the interaction term has a positive coefficient, as predicted in Proposition 4. In other words, a higher inability level alleviates the negative wage effect, as the wage does not increase enough to justify the high tranining costs that a low skill individual has to bear to keep working. The coefficient on the interaction term for small shocks suggests that for high levels of inability (less than 6 years of education) individuals retire earlier because the shock is relatively large for them and the erosion effect dominates.

4.4 Robustness checks

We conduct three robustness checks for the main empirical analysis of our model. First, we perform the analysis for men only because the steady increasing participation rate of women may contribute in unclear ways to the results. Second, we consider an alternative measure of productivity growth. Third, we isolate sector-specific from aggregate productivity growth in order to compare our results to the ones in Ahituv and Zeira [2011]. For each of these checks, we report the results for both the pooled and the panel random

[16]We try different thresholds for the definition of large shocks and the results hold for different intermediate levels (from the 40th percentile to the 65th).

[17]Similarly to what we do for the baseline regressions, in Table 17 we report the marginal effects computed from a probit model. As results are very similar to the linear probability model, we use the latter hereinafter.

effects regressions distinguishing between small and large productivity shocks.

Table 8 and Table 9 report the results for men only. Both qualitatively and quantitatively the exercises confirm the results in the full sample.

In Table 10 and Table 11 we use the productivity growth occurred in the five years prior to the interview year instead of the growth since the year in which each individual entered the labor market. We then divide between small and large shocks as before, but using the median of the 5-year growth per inability type. This alternative measure of productivity growth provides similar results.[18]

The distinction between sector-specific shocks and aggregate shocks allows for a comparison with Ahituv and Zeira [2011]. Table 12 and Table 14 compare the set-up of Ahituv and Zeira [2011] (first column) with a set-up that includes also interaction terms of both sector-specific and aggregate productivity growth with inability. According to Ahituv and Zeira [2011], the effect of sector-specific shocks reveals the erosion effect while the effect of aggregate shocks takes into account both erosion and wage effects. Hence, the coefficient on sector-specific shocks should be positive while the coefficient on the aggregate shocks could have any sign. In the original paper, the growth rates are computed only over the five years prior to the interview date, so that there cannot be any variation in growth rates among individuals that work in the same sector. Hence, the measure of aggregate growth is perfectly collinear with the time dummies, which are used as a proxy of aggregate growth. Our measure of productivity growth instead accomodates for different years of entry in the labor market, so that there is variation across individuals within the same sector. Hence, we can separate time dummies and aggregate growth rates in our regression. Our exercise in the first column of Table 12 and Table 14 yields a largely negative effect of aggregate growth on the probability of early retirement, which suggests that the wage effect is quantitatively more important than the erosion effect. More importantly, we obtain a positive coefficient of the sector-specific technical change, which implies an erosion effect of productivity growth as in Ahituv and Zeira [2011]. The inclusion of interaction terms does not alter these results. In Table 13 and Table 15 we check whether the results of Ahituv and Zeira [2011] hold separately for large and small shocks. For large shocks the effect of a sector-specific shock is positive and the effect of

[18] The differences in magnitude of the coefficients are partly due to different scales in the growth rates.

an aggregate shock is negative, as in the original set-up. Nevertheless, for small shocks the effect of a sector-specific shock is negative, contrary to what Ahituv and Zeira [2011] predict and in accordance to what our model delivers.

5 Conclusion

We explore the role of technical change on early retirement decisions. Our contribution departs from previous literature in assuming initially heterogeneous individuals in terms of their (in)ability to learn. This assumption has important implications for the explanation of how technical change affects early retirement. Our model predicts that workers in sectors with an initially high productivity level are more able and can resist larger erosion of productivity shocks than workers in sectors with initially low productivity levels. Moreover, when productivity shocks are small, the increase in wage (wage effect) dominates the increase in the cost of retraining (erosion effect). Thus, the probability of retirement depends negatively on these shocks. In contrast, when productivity shocks are large, the erosion effect dominates and individuals are more likely to retire early.

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 role of different technological paces on the trend in early retirement, taking into account the different effects of small and large productivity shocks found in this paper.

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A Appendix: Proofs

Proof of Proposition 1. Consider the problem in (10). The First Order Condition (FOC) of this problem is

$$\psi(a^*_{it-1}, f) + \psi_1(a^*_{it-1}, f)a^*_{it-1} - 1 - E\left[b_{it}\left(L - \phi(b_{it}, f)\right)\right] = 0,$$

for each f.[19] By the implicit function theorem we obtain that

$$\frac{\partial a_{t-1}(f)}{\partial f} = -\frac{\psi_2(a_{it-1}, f) + \psi_{12}(a_{it-1}, f)a_{it-1} + E\left[b_{it}\phi_2(b_{it}, f)\right]}{2\psi_1(a_{it-1}, f) + \psi_{11}(a_{it-1}, f)a_{it-1}},$$

which is negative under the assumption that ψ is increasing and convex in both arguments and $\psi_{12} \geq 0$.[20] □

Proof of Proposition 2. Consider first the derivative of $P_{it}(f)$ with respect to b_{it}, that is,

$$\frac{\partial P_{it}(f)}{\partial b_{it}} = -\frac{\bar{w}a_{t-1}(f)}{H}\left(L - \phi(b_{it}, f) - \phi_1(b_{it}, f)b_{it}\right).$$

Since the retraining function ϕ is strictly increasing and convex, $\Phi(b_{it}, f) \equiv L - \phi(b_{it}, f) - \phi_1(b_{it}, f)b_{it}$ is positive for any $b_{it} < \bar{b}(f)$, where $\bar{b}(f)$ satisfies $\Phi(\bar{b}, f) = 0$, and negative for any $b_{it} > \bar{b}(f)$. Hence,

$$\frac{\partial P_{it}(f)}{\partial b_{it}} < 0 \text{ if } b_{it} < \bar{b}(f),$$

and

$$\frac{\partial P_{it}(f)}{\partial b_{it}} \geq 0 \text{ if } b_{it} \geq \bar{b}(f).$$

Moreover, since $\Phi(b_{it}, f)$ is decreasing in f because $\phi_2 > 0$ and $\phi_{12} \geq 0$, $\bar{b}(f)$ is also decreasing in f. □

Proof of Proposition 3. Consider the derivative of $P_{it}(f)$ with respect to f, that is,

$$\frac{\partial P_{it}(f)}{\partial f} = -\frac{\bar{w}b_{it}}{H}\left[\frac{\partial a_{t-1}(f)}{\partial f}\left(L - \phi(b_{it}, f)\right) - a_{t-1}(f)\phi_2(b_{it}, f)\right].$$

Since the function $a_{t-1}(f)$ is decreasing in f by Proposition 1, we have that

$$\frac{\partial P_{it}(f)}{\partial f} > 0$$

for any b_{it}. □

Proof of Proposition 4. Consider the cross derivative of $P_{it}(f)$ with respect to b_{it} and f, that is,

$$\frac{\partial^2 P_{it}(f)}{\partial b_{it}\partial f} = -\frac{\bar{w}}{H}\left[\frac{\partial a_{t-1}(f)}{\partial f}\Phi(b_{it}, f) + a_{t-1}(f)\Phi_2(b_{it}, f)\right],$$

[19] To be precise, we call $a_{t-1}(f)$ the solution of (10) if the feasible set were $\mathbb{R}_+$. Given that $\{a_{it-1}\}_{i\in[0,1]} \subseteq \mathbb{R}_+$, the actual solution a^*_{it-1} is simply the closest element in $\{a_{it-1}\}_{i\in[0,1]}$ to $a_{t-1}(f)$, for every f. In case of two such elements in $\{a_{it-1}\}_{i\in[0,1]}$, suppose we take the lowest of the two.

[20] Again, to be precise the approximate mapping between a^*_{it-1} and $a_{t-1}(f)$ implies that if $f > f'$ where $a^*_{it-1} = a_{t-1}(f)$ and $a^*_{jt-1} = a_{t-1}(f')$, then $a^*_{it-1} \leq a^*_{jt-1}$.

where $\Phi(b_{it}, f)$ is defined as above. The cross derivative is positive if

$$\frac{\partial a_{t-1}(f)}{\partial f}\Phi(b_{it}, f) < -a_{t-1}(f)\Phi_2(b_{it}, f).$$

Since $\Phi_2(b_{it}, f) = -\phi_2(b_{it}, f) - \phi_{12}(b_{it}, f)b_{it} < 0$, the right-hand side of the inequality is always positive. Moreover, the left-hand side is non-positive for any $b_{it} \leq \bar{b}(f)$ since then $\Phi \geq 0$. Therefore, the inequality is satisfied whenever $b_{it} \geq \bar{b}(f)$.

Moreover, the left hand side is increasing in b_{it}. Therefore, there exists some $\epsilon > 0$ such that the inequality is satisfied for values of $b_{it} < \bar{b}(f) + \epsilon$. For larger values of b_{it} results are ambiguous.

To sum up, $\frac{\partial^2 P_{it}(f)}{\partial b_{it}\partial f} > 0$ if $b_{it} < \bar{b}(f) + \epsilon$ for some $\epsilon > 0$, and $\frac{\partial^2 P_{it}(f)}{\partial b_{it}\partial f}$ has an ambiguous sign otherwise. □

B 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 her working life, and how many years she spent working. We then substract this duration from the year in which she 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. 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.[21] In this way we have the initial productivity a_{it-1} in the sector i where individuals decided to start working and we can compute also the growth rate $\frac{a_{it} - a_{it-1}}{a_{it-1}} \approx \ln b_{it}$ of productivity from the year they started working to the year they stopped. The aggregation of sectors is done as indicated in Table 1. For the comparison with Ahituv and Zeira [2011], we compute aggregate productivity growth as the average across sectors for each time span. Then, we obtain the sector-specific productivity growth by substracting the aggregate from the sectoral productivity growth defined above.

[21]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).

C Appendix: Figures and Tables

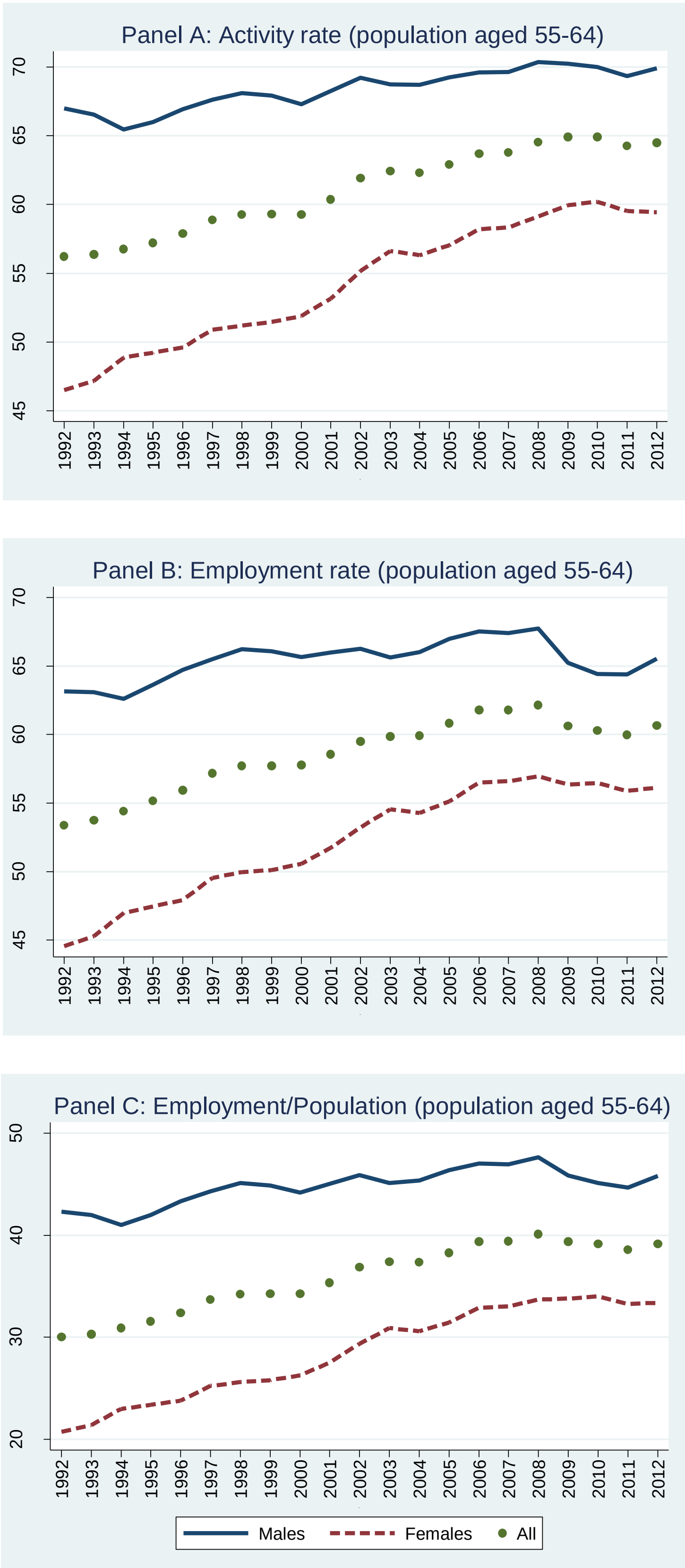

Figure 1: Data from OECD.Stat. Data refers to individuals aged 55-64 in the US.

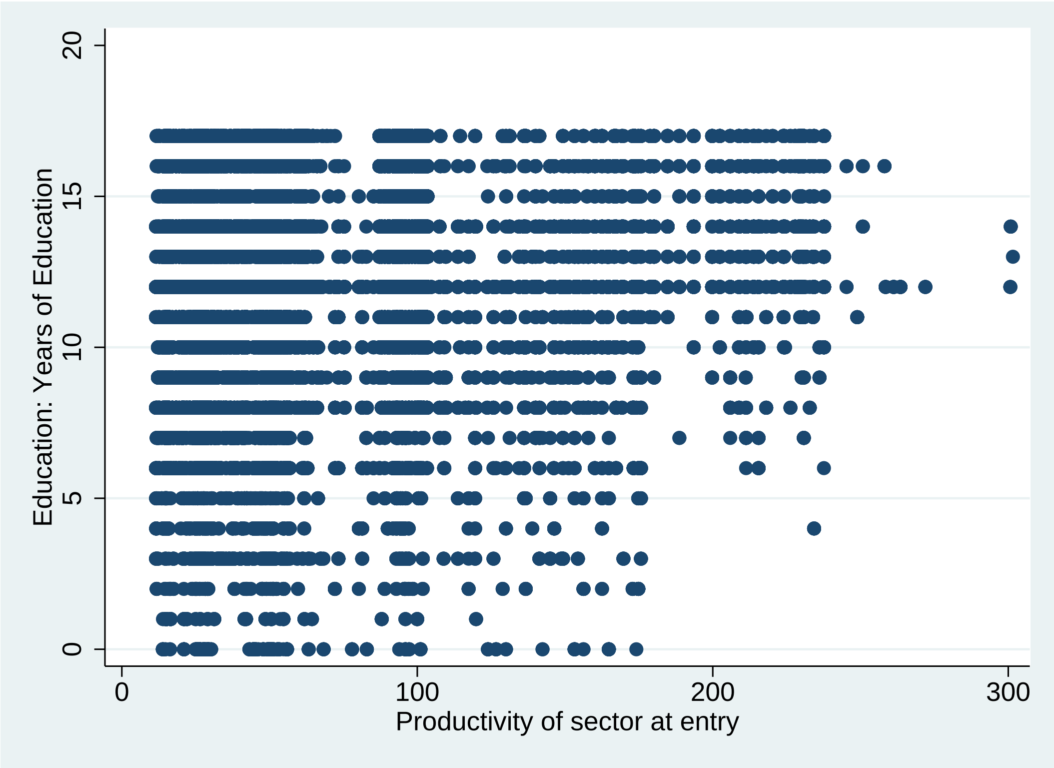

Figure 2: Individual sorting. Sources: RAND HRS and BEA. Each data point is an individual. On the vertical axis we have the years of education from the RAND HRS data. For illustrative purposes, we focus on the 2006 wave. On the horizontal axis we report the productivity -value added per worker from the BEA data- of the sector where individuals work computed at the time when individuals entered the labor market. The graph does not change significantly for other waves.

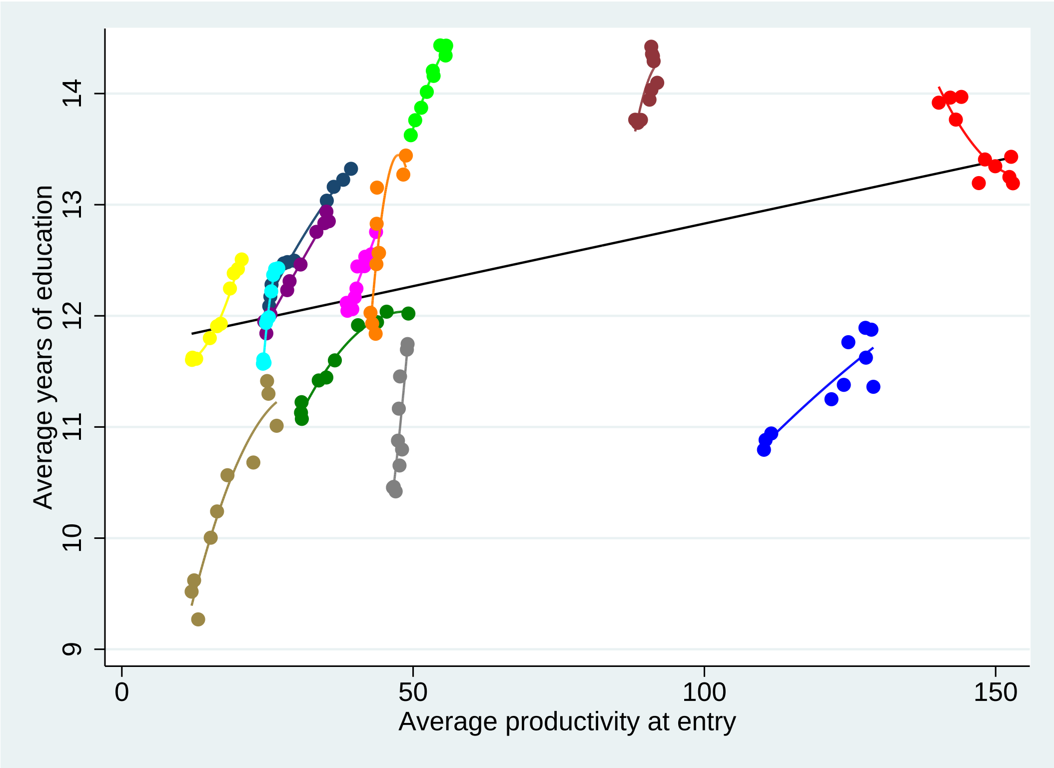

Figure 3: Average sorting across sectors and time. Sources: RAND HRS and BEA. Each data point represents a sector-wave pair. On the vertical axis we show the average years of education of individuals that work in a given sector as reported in a certain wave of the RAND HRS data. On the horizontal axis we have the productivity -value added per worker from the BEA data- of the sector where individuals work computed at the time when individuals entered the labor market, and averaged across all individuals in the same sector and wave. Different colors refer to different sectors. Different data points of the same color represent different waves for the same sector. The curved and colored lines represent polynomial fits within sectors. The solid black line is a linear regression across all data points. Agric/Forest/Fish (1) is brown, Mining and Constr (2) is blue, Mnfg: Non-durable (3) is green, Mnfg: Durable (4) is yellow, Transportation (5) is navy, Wholesale (6) is purple, Retail (7) is cyan, Finan/Ins/RealEst (8) is red, Busns/Repair Svcs (9) is magenta, Personal Services (10) is gray, Entertn/Recreatn (11) is orange, Prof/Related Svcs (12) is maroon, and Public Administration (13) is lime. We report the correspondance between HRS/Census codes and BEA codes in Table 1.

Table 1: Sectoral aggregation

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

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Not-Working	0.234	0.423	0	1	52310
Productivity growth	0.837	1.103	-0.199	5.096	52310
Inability	4.147	2.947	0	17	52310
Experience	32.475	10.359	0	51	52310
Dummy for Male	0.443	0.497	0	1	52310
Age	57.217	3.836	50	64	52310
Age squared	3288.485	438.962	2500	4096	52310
African-American	0.157	0.363	0	1	52310
Hispanic	0.081	0.273	0	1	52310
Foreign-born	0.101	0.301	0	1	52310
Married	0.738	0.44	0	1	52310
Region: Midwest	0.253	0.435	0	1	52310
Region: South	0.41	0.492	0	1	52310
Region: West	0.169	0.375	0	1	52310
Bad health	2.546	1.092	1	5	52310
Year 1994	0.123	0.328	0	1	52310
Year 1996	0.115	0.318	0	1	52310
Year 1998	0.129	0.335	0	1	52310
Year 2000	0.107	0.309	0	1	52310
Year 2002	0.089	0.284	0	1	52310
Year 2004	0.106	0.308	0	1	52310
Year 2006	0.079	0.269	0	1	52310
Year 2008	0.065	0.247	0	1	52310
Year 2010	0.05	0.219	0	1	52310
Spouse working	0.455	0.498	0	1	50837
Net Wealth	275242.946	397996.731	-29700	3034308.75	51330
Pension	0.649	0.477	0	1	42488

Table 3: Pair-wise correlation between productivity at entry and years of education

Variables	Education: Years of Education
Productivity of sector at entry (All waves)	0.183***
Productivity of sector at entry (Wave 1)	0.167***
Productivity of sector at entry (Wave 2)	0.179***
Productivity of sector at entry (Wave 3)	0.179***
Productivity of sector at entry (Wave 4)	0.181***
Productivity of sector at entry (Wave 5)	0.182***
Productivity of sector at entry (Wave 6)	0.183***
Productivity of sector at entry (Wave 7)	0.171***
Productivity of sector at entry (Wave 8)	0.183***
Productivity of sector at entry (Wave 9)	0.179***
Productivity of sector at entry (Wave 10)	0.158***

Table 4: Baseline regression: Pooled

	No sorting		Baseline		Extended	
Productivity growth	-0.001	(0.002)	-0.005	(0.003)	-0.008***	(0.002)
Inability	0.011***	(0.002)	0.011***	(0.002)	0.003**	(0.001)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.000***	(0.000)
Growth*Inability			0.001	(0.001)	0.001***	(0.000)
Experience	-0.009***	(0.000)	-0.009***	(0.000)	-0.002***	(0.000)
Male	0.012***	(0.004)	0.013***	(0.004)	0.026***	(0.003)
Age	-0.280***	(0.014)	-0.280***	(0.014)	-0.234***	(0.012)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.002***	(0.000)
African-American	0.002	(0.006)	0.002	(0.006)	0.002	(0.004)
Hispanic	-0.031***	(0.007)	-0.031***	(0.007)	-0.003	(0.005)
Foreign-born	-0.055***	(0.006)	-0.055***	(0.006)	-0.024***	(0.004)
Married	0.004	(0.004)	0.004	(0.004)	0.015***	(0.004)
Region: Midwest	-0.005	(0.005)	-0.005	(0.005)	0.001	(0.004)
Region: South	0.011**	(0.005)	0.011**	(0.005)	-0.002	(0.003)
Region: West	0.024***	(0.006)	0.024***	(0.006)	0.004	(0.004)
Bad health	0.081***	(0.002)	0.081***	(0.002)	0.023***	(0.002)
Year 1994	0.025***	(0.009)	0.025***	(0.009)	0.041***	(0.004)
Year 1996	0.068***	(0.011)	0.068***	(0.011)	0.056***	(0.006)
Year 1998	0.043***	(0.009)	0.043***	(0.009)	0.043***	(0.006)
Year 2000	0.042***	(0.010)	0.042***	(0.010)	0.037***	(0.005)
Year 2002	0.089***	(0.010)	0.089***	(0.010)	0.047***	(0.008)
Year 2004	0.056***	(0.008)	0.056***	(0.008)	0.031***	(0.006)
Year 2006	0.051***	(0.009)	0.052***	(0.009)	0.028***	(0.007)
Year 2008	0.050***	(0.010)	0.050***	(0.010)	0.013**	(0.007)
Year 2010	0.060***	(0.013)	0.060***	(0.013)	0.009	(0.009)
Spouse working					-0.046***	(0.003)
Wealth					0.000***	(0.000)
Pension					0.094***	(0.003)
Constant	7.424***	(0.394)	7.420***	(0.394)	6.197***	(0.322)
Adj.R-squared	0.171		0.171		0.135	
Observations	52310		52310		40562	

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

Table 5: Baseline regression: Panel Random Effects

	No sorting		Baseline		Extended	
Productivity growth	-0.006*	(0.003)	-0.014***	(0.005)	-0.015***	(0.004)
Inability	0.014***	(0.003)	0.013***	(0.004)	0.004	(0.003)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.001**	(0.000)
Growth*Inability			0.002*	(0.001)	0.002***	(0.001)
Experience	-0.011***	(0.000)	-0.011***	(0.000)	-0.004***	(0.000)
Male	0.019**	(0.009)	0.019**	(0.009)	0.047***	(0.008)
Age	-0.237***	(0.017)	-0.237***	(0.017)	-0.206***	(0.013)
Age squared	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)
African-American	0.010	(0.010)	0.009	(0.010)	0.002	(0.007)
Hispanic	-0.027**	(0.011)	-0.027**	(0.011)	-0.006	(0.008)
Foreign-born	-0.070***	(0.009)	-0.070***	(0.009)	-0.040***	(0.007)
Married	0.004	(0.006)	0.004	(0.006)	0.015**	(0.007)
Region: Midwest	-0.001	(0.009)	-0.001	(0.009)	0.002	(0.007)
Region: South	0.025***	(0.009)	0.025***	(0.009)	0.007	(0.005)
Region: West	0.035***	(0.010)	0.035***	(0.010)	0.009	(0.008)
Bad health	0.065***	(0.003)	0.065***	(0.003)	0.017***	(0.002)
Spouse working					-0.050***	(0.006)
Wealth					0.000***	(0.000)
Pension					0.081***	(0.005)
Constant	6.132***	(0.479)	6.127***	(0.480)	5.427***	(0.366)
R-squared-within	0.147		0.147		0.122	
R-squared-between	0.203		0.203		0.183	
R-squared-overall	0.163		0.163		0.122	
Observations	52310		52310		40562	

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

Table 6: Large and small shocks: Pooled

	All shocks		Large shocks		Small shocks	
Productivity growth	-0.005	(0.003)	0.012***	(0.004)	-0.299***	(0.094)
Inability	0.011***	(0.002)	0.021***	(0.003)	0.002	(0.003)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.000	(0.000)
Growth*Inability	0.001	(0.001)	-0.003***	(0.001)	0.027**	(0.012)
Experience	-0.009***	(0.000)	-0.008***	(0.000)	-0.010***	(0.000)
Male	0.013***	(0.004)	0.012**	(0.006)	0.008	(0.007)
Age	-0.280***	(0.014)	-0.277***	(0.020)	-0.285***	(0.018)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.003***	(0.000)
African-American	0.002	(0.006)	0.017**	(0.007)	-0.014*	(0.008)
Hispanic	-0.031***	(0.007)	-0.009	(0.011)	-0.056***	(0.010)
Foreign-born	-0.055***	(0.006)	-0.056***	(0.008)	-0.052***	(0.010)
Married	0.004	(0.004)	0.001	(0.005)	0.007	(0.006)
Region: Midwest	-0.005	(0.005)	-0.002	(0.008)	-0.011	(0.008)
Region: South	0.011**	(0.005)	0.001	(0.007)	0.019***	(0.007)
Region: West	0.024***	(0.006)	0.022***	(0.008)	0.023***	(0.009)
Bad health	0.081***	(0.002)	0.078***	(0.003)	0.084***	(0.003)
Year 1994	0.025***	(0.009)	0.010	(0.011)	0.033**	(0.014)
Year 1996	0.068***	(0.011)	0.055***	(0.015)	0.075***	(0.018)
Year 1998	0.043***	(0.009)	0.024*	(0.013)	0.068***	(0.014)
Year 2000	0.042***	(0.010)	0.031**	(0.014)	0.056***	(0.013)
Year 2002	0.089***	(0.010)	0.058***	(0.016)	0.134***	(0.020)
Year 2004	0.056***	(0.008)	0.036***	(0.012)	0.097***	(0.016)
Year 2006	0.052***	(0.009)	0.029**	(0.013)	0.102***	(0.016)
Year 2008	0.050***	(0.010)	0.031**	(0.014)	0.098***	(0.019)
Year 2010	0.060***	(0.013)	0.040**	(0.018)	0.116***	(0.023)
Constant	7.420***	(0.394)	7.321***	(0.559)	7.585***	(0.523)
Adj.R-squared	0.171		0.149		0.196	
Observations	52310		27452		24858	

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

Table 7: Large and small shocks: Panel Random Effects

	All shocks		Large shocks		Small shocks	
Productivity growth	-0.014***	(0.005)	0.005	(0.007)	-0.326***	(0.105)
Inability	0.013***	(0.004)	0.025***	(0.006)	0.009**	(0.004)
Inability squared	-0.001***	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)
Growth*Inability	0.002*	(0.001)	-0.002	(0.001)	0.025**	(0.012)
Experience	-0.011***	(0.000)	-0.010***	(0.001)	-0.011***	(0.000)
Male	0.019**	(0.009)	0.022**	(0.010)	0.006	(0.014)
Age	-0.237***	(0.017)	-0.250***	(0.023)	-0.236***	(0.017)
Age squared	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)
African-American	0.009	(0.010)	0.022*	(0.012)	-0.001	(0.012)
Hispanic	-0.027**	(0.011)	-0.010	(0.015)	-0.043***	(0.016)
Foreign-born	-0.070***	(0.009)	-0.069***	(0.012)	-0.066***	(0.015)
Married	0.004	(0.006)	0.004	(0.009)	0.004	(0.008)
Region: Midwest	-0.001	(0.009)	-0.001	(0.010)	-0.003	(0.013)
Region: South	0.025***	(0.009)	0.010	(0.010)	0.039***	(0.012)
Region: West	0.035***	(0.010)	0.032**	(0.013)	0.038**	(0.015)
Bad health	0.065***	(0.003)	0.064***	(0.004)	0.069***	(0.003)
Constant	6.127***	(0.480)	6.442***	(0.650)	6.064***	(0.467)
R-squared-within	0.147		0.154		0.154	
R-squared-between	0.203		0.156		0.221	
R-squared-overall	0.163		0.144		0.184	
Observations	52310		27452		24858	

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

Table 8: Robustness: Only men (pooled)

	All shocks		Large shocks		Small shocks	
Productivity growth	0.001	(0.004)	0.007	(0.005)	-0.162*	(0.089)
Inability	0.014***	(0.002)	0.019***	(0.004)	0.011***	(0.004)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.001**	(0.000)
Growth*Inability	-0.000	(0.001)	-0.002**	(0.001)	0.007	(0.012)
Experience	-0.010***	(0.000)	-0.010***	(0.001)	-0.010***	(0.001)
Age	-0.284***	(0.022)	-0.302***	(0.028)	-0.252***	(0.032)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.002***	(0.000)
African-American	0.004	(0.008)	0.012	(0.011)	-0.006	(0.012)
Hispanic	-0.034***	(0.011)	-0.012	(0.014)	-0.066***	(0.015)
Foreign-born	-0.085***	(0.009)	-0.090***	(0.011)	-0.080***	(0.014)
Married	-0.057***	(0.007)	-0.052***	(0.009)	-0.066***	(0.012)
Region: Midwest	-0.012	(0.008)	-0.005	(0.010)	-0.027**	(0.013)
Region: South	-0.005	(0.007)	-0.008	(0.009)	0.001	(0.011)
Region: West	0.002	(0.008)	0.001	(0.010)	0.004	(0.015)
Bad health	0.080***	(0.003)	0.078***	(0.004)	0.083***	(0.004)
Year 1994	0.024***	(0.009)	0.015	(0.012)	0.035**	(0.016)
Year 1996	0.048***	(0.011)	0.048***	(0.016)	0.043**	(0.018)
Year 1998	0.030***	(0.011)	0.020	(0.014)	0.046***	(0.016)
Year 2000	0.021*	(0.012)	0.027*	(0.016)	0.010	(0.016)
Year 2002	0.074***	(0.013)	0.052***	(0.019)	0.113***	(0.022)
Year 2004	0.032***	(0.011)	0.029**	(0.014)	0.040**	(0.016)
Year 2006	0.021*	(0.012)	0.007	(0.015)	0.063***	(0.022)
Year 2008	0.034**	(0.015)	0.033*	(0.018)	0.041	(0.029)
Year 2010	0.026	(0.019)	0.018	(0.026)	0.047**	(0.024)
Constant	7.619***	(0.620)	8.082***	(0.807)	6.746***	(0.899)
Adj.R-squared	0.172		0.159		0.197	
Observations	23197		14739		8458	

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

Table 9: Robustness: Only men (panel RE)

	All shocks		Large shocks		Small shocks	
Productivity growth	-0.008	(0.006)	0.001	(0.009)	-0.289**	(0.116)
Inability	0.018***	(0.005)	0.025***	(0.008)	0.017***	(0.006)
Inability squared	-0.001***	(0.000)	-0.001***	(0.001)	-0.001**	(0.001)
Growth*Inability	0.001	(0.001)	-0.001	(0.001)	0.018	(0.013)
Experience	-0.013***	(0.001)	-0.013***	(0.001)	-0.011***	(0.001)
Age	-0.244***	(0.026)	-0.270***	(0.030)	-0.211***	(0.031)
Age squared	0.002***	(0.000)	0.003***	(0.000)	0.002***	(0.000)
African-American	0.006	(0.013)	0.012	(0.018)	0.007	(0.018)
Hispanic	-0.033*	(0.018)	-0.013	(0.020)	-0.067***	(0.024)
Foreign-born	-0.104***	(0.012)	-0.111***	(0.015)	-0.095***	(0.017)
Married	-0.050***	(0.009)	-0.044***	(0.011)	-0.062***	(0.014)
Region: Midwest	-0.009	(0.013)	-0.000	(0.013)	-0.025	(0.021)
Region: South	0.005	(0.011)	-0.000	(0.014)	0.013	(0.018)
Region: West	0.009	(0.012)	0.012	(0.013)	0.007	(0.023)
Bad health	0.065***	(0.003)	0.065***	(0.004)	0.067***	(0.004)
Constant	6.403***	(0.739)	7.103***	(0.851)	5.479***	(0.865)
R-squared-within	0.160		0.170		0.152	
R-squared-between	0.206		0.172		0.235	
R-squared-overall	0.167		0.155		0.190	
Observations	23197		14739		8458	

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

Table 10: Robustness: 5-year productivity growth (pooled)

	All shocks		Large shocks		Small shocks	
Growth (5y)	-0.137***	(0.043)	0.061	(0.064)	-0.416*	(0.236)
Inability	0.012***	(0.002)	0.032***	(0.006)	-0.000	(0.005)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.000	(0.000)
Growth (5y)*Inability	0.003	(0.007)	-0.059***	(0.012)	0.095***	(0.030)
Experience	-0.009***	(0.000)	-0.008***	(0.000)	-0.010***	(0.000)
Male	0.015***	(0.004)	0.025***	(0.006)	-0.003	(0.009)
Age	-0.285***	(0.013)	-0.298***	(0.018)	-0.264***	(0.020)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.003***	(0.000)
African-American	0.002	(0.005)	0.002	(0.008)	-0.005	(0.008)
Hispanic	-0.031***	(0.007)	-0.017	(0.010)	-0.043***	(0.011)
Foreign-born	-0.054***	(0.006)	-0.046***	(0.008)	-0.062***	(0.010)
Married	0.002	(0.004)	-0.008	(0.005)	0.014**	(0.006)
Region: Midwest	-0.001	(0.005)	0.003	(0.007)	-0.009	(0.008)
Region: South	0.011**	(0.005)	0.005	(0.006)	0.015*	(0.008)
Region: West	0.024***	(0.006)	0.032***	(0.008)	0.014	(0.009)
Bad health	0.081***	(0.002)	0.076***	(0.003)	0.085***	(0.003)
Year 1994	0.022**	(0.009)	0.067***	(0.013)	-0.029	(0.028)
Year 1996	0.063***	(0.011)	0.125***	(0.016)	0.003	(0.029)
Year 1998	0.038***	(0.010)	0.071**	(0.030)	0.025	(0.038)
Year 2000	0.040***	(0.010)	0.067***	(0.022)	0.045	(0.032)
Year 2002	0.085***	(0.011)	0.107***	(0.019)	0.112***	(0.034)
Year 2004	0.051***	(0.009)	0.091***	(0.018)	0.042	(0.041)
Year 2006	0.045***	(0.010)	0.143***	(0.023)	-0.046	(0.031)
Year 2008	0.037***	(0.010)	0.172***	(0.027)	-0.055*	(0.029)
Year 2010	0.051***	(0.013)	0.220***	(0.033)	-0.047	(0.029)
Constant	7.571***	(0.379)	7.866***	(0.511)	7.009***	(0.572)
Adj.R-squared	0.170		0.174		0.184	
Observations	54384		29611		24773	

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

Table 11: Robustness: 5-year productivity growth (panel RE)

	All shocks		Large shocks		Small shocks	
Growth (5y)	-0.159***	(0.057)	0.053	(0.055)	-0.895***	(0.284)
Inability	0.014***	(0.003)	0.020***	(0.006)	0.008	(0.005)
Inability squared	-0.001***	(0.000)	-0.001*	(0.000)	-0.000	(0.000)
Growth (5y)*Inability	0.004	(0.009)	-0.028***	(0.010)	0.121***	(0.038)
Experience	-0.011***	(0.000)	-0.010***	(0.000)	-0.011***	(0.001)
Male	0.022**	(0.009)	0.019*	(0.012)	0.013	(0.012)
Age	-0.244***	(0.016)	-0.266***	(0.020)	-0.249***	(0.023)
Age squared	0.002***	(0.000)	0.003***	(0.000)	0.002***	(0.000)
African-American	0.011	(0.009)	0.008	(0.012)	0.006	(0.010)
Hispanic	-0.027**	(0.011)	-0.010	(0.015)	-0.046***	(0.013)
Foreign-born	-0.069***	(0.009)	-0.050***	(0.011)	-0.069***	(0.014)
Married	0.003	(0.006)	-0.008	(0.008)	0.012	(0.008)
Region: Midwest	0.002	(0.009)	0.008	(0.009)	-0.007	(0.014)
Region: South	0.025***	(0.009)	0.017*	(0.009)	0.023**	(0.011)
Region: West	0.036***	(0.010)	0.042***	(0.009)	0.017	(0.015)
Bad health	0.064***	(0.003)	0.066***	(0.003)	0.066***	(0.003)
Constant	6.328***	(0.454)	6.895***	(0.558)	6.506***	(0.638)
R-squared-within	0.147		0.153		0.134	
R-squared-between	0.200		0.172		0.191	
R-squared-overall	0.163		0.158		0.171	
Observations	54384		29611		24773	

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

Table 12: Robustness: Net and aggregate productivity growth I (pooled)

	No sorting		Sorting	
Net growth	0.006***	(0.002)	0.001	(0.003)
Aggregate growth	-0.727***	(0.021)	-0.714***	(0.023)
Inability	0.015***	(0.002)	0.019***	(0.003)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)
Net growth*Inability			0.001**	(0.001)
Aggr growth*Inability			-0.003*	(0.002)
Male	0.018***	(0.004)	0.018***	(0.004)
Age	-0.298***	(0.013)	-0.298***	(0.013)
Age squared	0.003***	(0.000)	0.003***	(0.000)
Experience	0.014***	(0.001)	0.014***	(0.001)
African-American	-0.005	(0.005)	-0.006	(0.005)
Hispanic	-0.029***	(0.007)	-0.030***	(0.007)
Foreign-born	-0.053***	(0.006)	-0.052***	(0.006)
Married	0.003	(0.004)	0.003	(0.004)
Region: Midwest	-0.008	(0.005)	-0.008	(0.005)
Region: South	0.010*	(0.005)	0.009*	(0.005)
Region: West	0.028***	(0.006)	0.027***	(0.006)
Bad health	0.077***	(0.002)	0.077***	(0.002)
Year 1994	0.028***	(0.009)	0.028***	(0.009)
Year 1996	0.042***	(0.010)	0.042***	(0.011)
Year 1998	0.054***	(0.009)	0.054***	(0.009)
Year 2000	0.092***	(0.010)	0.093***	(0.010)
Year 2002	0.158***	(0.010)	0.158***	(0.010)
Year 2004	0.203***	(0.009)	0.204***	(0.009)
Year 2006	0.198***	(0.009)	0.198***	(0.009)
Year 2008	0.182***	(0.010)	0.182***	(0.010)
Year 2010	0.234***	(0.012)	0.234***	(0.013)
Constant	7.633***	(0.372)	7.632***	(0.372)
Adj.R-squared	0.212		0.212	
Observations	52309		52309	

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

Cluster-robust standard errors in parenthesis.

Table 13: Robustness: Net and aggregate productivity growth II (pooled)

	No sorting		Large shocks		Small shocks	
Net growth	0.006***	(0.002)	0.010***	(0.004)	-0.218***	(0.079)
Aggregate growth	-0.727***	(0.021)	-0.753***	(0.036)	-0.895***	(0.080)
Inability	0.015***	(0.002)	0.021***	(0.004)	0.015***	(0.005)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Net growth*Inability			-0.001	(0.001)	0.024**	(0.011)
Aggr growth*Inability			-0.002	(0.003)	0.018*	(0.011)
Male	0.018***	(0.004)	0.009	(0.005)	0.023***	(0.007)
Age	-0.298***	(0.013)	-0.305***	(0.019)	-0.291***	(0.017)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.003***	(0.000)
Experience	0.014***	(0.001)	0.017***	(0.001)	0.012***	(0.001)
African-American	-0.005	(0.005)	0.004	(0.007)	-0.017**	(0.008)
Hispanic	-0.029***	(0.007)	-0.006	(0.011)	-0.054***	(0.010)
Foreign-born	-0.053***	(0.006)	-0.053***	(0.008)	-0.049***	(0.009)
Married	0.003	(0.004)	0.002	(0.005)	0.003	(0.006)
Region: Midwest	-0.008	(0.005)	-0.008	(0.008)	-0.008	(0.008)
Region: South	0.010*	(0.005)	0.001	(0.007)	0.017**	(0.007)
Region: West	0.028***	(0.006)	0.022***	(0.008)	0.030***	(0.009)
Bad health	0.077***	(0.002)	0.073***	(0.003)	0.079***	(0.003)
Year 1994	0.028***	(0.009)	0.018*	(0.011)	0.035***	(0.013)
Year 1996	0.042***	(0.010)	0.021	(0.014)	0.056***	(0.018)
Year 1998	0.054***	(0.009)	0.035***	(0.012)	0.076***	(0.014)
Year 2000	0.092***	(0.010)	0.089***	(0.014)	0.100***	(0.014)
Year 2002	0.158***	(0.010)	0.137***	(0.014)	0.186***	(0.016)
Year 2004	0.203***	(0.009)	0.197***	(0.012)	0.225***	(0.015)
Year 2006	0.198***	(0.009)	0.187***	(0.013)	0.230***	(0.015)
Year 2008	0.182***	(0.010)	0.171***	(0.014)	0.213***	(0.018)
Year 2010	0.234***	(0.012)	0.220***	(0.018)	0.274***	(0.020)
Constant	7.633***	(0.372)	7.738***	(0.529)	7.478***	(0.494)
Adj.R-squared	0.212		0.195		0.229	
Observations	52309		26474		25835	

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

Table 14: Robustness: Net and aggregate productivity growth I (panel)

	No sorting		Sorting	
Net growth	0.007*	(0.003)	0.011**	(0.005)
Aggregate growth	-0.397***	(0.028)	-0.586***	(0.024)
Inability	0.002	(0.003)	0.011**	(0.005)
Inability squared	-0.000**	(0.000)	-0.001***	(0.000)
Net growth*Inability			0.001	(0.001)
Aggr growth*Inability			-0.001	(0.003)
Experience	0.009***	(0.001)	0.008***	(0.001)
Male	0.032***	(0.008)	0.000	(0.008)
Age	-0.238***	(0.013)	-0.271***	(0.015)
Age squared	0.002***	(0.000)	0.003***	(0.000)
African-American	0.001	(0.007)	0.008	(0.009)
Hispanic	0.008	(0.008)	-0.007	(0.011)
Foreign-born	-0.038***	(0.007)	-0.065***	(0.009)
Married	0.014**	(0.007)	0.002	(0.006)
Region: Midwest	0.001	(0.007)	0.000	(0.009)
Region: South	0.007	(0.005)	0.025***	(0.008)
Region: West	0.016**	(0.008)	0.044***	(0.010)
Bad health	0.019***	(0.002)	0.066***	(0.003)
Spouse working	-0.048***	(0.006)		
Wealth	0.000***	(0.000)		
Pension	0.071***	(0.004)		
Constant	6.104***	(0.350)	6.765***	(0.437)
R-squared-within	0.159		0.187	
R-squared-between	0.202		0.224	
R-squared-overall	0.144		0.184	
Observations	40562		52309	

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

Cluster-robust standard errors in parenthesis.

Table 15: Robustness: Net and aggregate productivity growth II (panel)

	No sorting		Large shocks		Small shocks	
Net growth	0.015***	(0.003)	0.019***	(0.006)	-0.139**	(0.057)
Aggregate growth	-0.588***	(0.020)	-0.581***	(0.037)	-0.693***	(0.057)
Inability	0.010***	(0.003)	0.006	(0.005)	0.019**	(0.008)
Inability squared	-0.001***	(0.000)	-0.001	(0.000)	-0.001**	(0.000)
Net growth*Inability			-0.000	(0.001)	0.008	(0.009)
Aggr growth*Inability			0.003	(0.004)	0.004	(0.008)
Experience	0.008***	(0.001)	0.008***	(0.001)	0.007***	(0.001)
Male	0.000	(0.008)	-0.009	(0.009)	0.008	(0.013)
Age	-0.271***	(0.015)	-0.292***	(0.022)	-0.261***	(0.015)
Age squared	0.003***	(0.000)	0.003***	(0.000)	0.003***	(0.000)
African-American	0.008	(0.009)	0.019	(0.012)	0.001	(0.012)
Hispanic	-0.006	(0.011)	0.017	(0.016)	-0.024	(0.015)
Foreign-born	-0.065***	(0.009)	-0.074***	(0.011)	-0.059***	(0.014)
Married	0.002	(0.006)	0.005	(0.009)	-0.001	(0.008)
Region: Midwest	0.000	(0.009)	-0.000	(0.011)	0.001	(0.012)
Region: South	0.025***	(0.008)	0.009	(0.010)	0.038***	(0.011)
Region: West	0.044***	(0.010)	0.037***	(0.013)	0.049***	(0.015)
Bad health	0.066***	(0.003)	0.065***	(0.004)	0.069***	(0.003)
Constant	6.766***	(0.439)	7.343***	(0.613)	6.448***	(0.423)
R-squared-within	0.187		0.192		0.187	
R-squared-between	0.224		0.185		0.237	
R-squared-overall	0.184		0.169		0.197	
Observations	52309		26474		25835	

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

Table 16: Baseline: Probit vs. Linear probability model (pooled)

	Probit		Mrg Effects		Linear Prob	
Productivity growth	-0.021*	(0.013)	-0.005*	(0.003)	-0.005	(0.003)
Inability	0.040***	(0.006)	0.010***	(0.002)	0.011***	(0.002)
Inability squared	-0.003***	(0.001)	-0.001***	(0.000)	-0.001***	(0.000)
Growth*Inability	0.004*	(0.002)	0.001*	(0.001)	0.001	(0.001)
Experience	-0.031***	(0.001)	-0.008***	(0.000)	-0.009***	(0.000)
Male	0.019	(0.017)	0.005	(0.004)	0.013***	(0.004)
Age	-0.790***	(0.052)	-0.203***	(0.013)	-0.280***	(0.014)
Age squared	0.008***	(0.000)	0.002***	(0.000)	0.003***	(0.000)
African-American	0.013	(0.020)	0.003	(0.005)	0.002	(0.006)
Hispanic	-0.105***	(0.028)	-0.027***	(0.007)	-0.031***	(0.007)
Foreign-born	-0.208***	(0.026)	-0.053***	(0.007)	-0.055***	(0.006)
Married	0.028*	(0.015)	0.007*	(0.004)	0.004	(0.004)
Region: Midwest	-0.018	(0.022)	-0.005	(0.006)	-0.005	(0.005)
Region: South	0.039*	(0.020)	0.010*	(0.005)	0.011**	(0.005)
Region: West	0.089***	(0.024)	0.023***	(0.006)	0.024***	(0.006)
Bad health	0.291***	(0.007)	0.075***	(0.002)	0.081***	(0.002)
Year 1994	0.111***	(0.037)	0.029***	(0.009)	0.025***	(0.009)
Year 1996	0.275***	(0.042)	0.071***	(0.011)	0.068***	(0.011)
Year 1998	0.184***	(0.039)	0.047***	(0.010)	0.043***	(0.009)
Year 2000	0.173***	(0.039)	0.045***	(0.010)	0.042***	(0.010)
Year 2002	0.345***	(0.039)	0.089***	(0.010)	0.089***	(0.010)
Year 2004	0.235***	(0.035)	0.060***	(0.009)	0.056***	(0.008)
Year 2006	0.204***	(0.039)	0.053***	(0.010)	0.052***	(0.009)
Year 2008	0.210***	(0.041)	0.054***	(0.011)	0.050***	(0.010)
Year 2010	0.250***	(0.048)	0.064***	(0.012)	0.060***	(0.013)
Constant	18.814***	(1.505)			7.420***	(0.394)
Adj.R-squared					0.171	
Psd.R-squared	0.157					
Observations	52310		52310		52310	

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

Table 17: Large and small shocks: Probit vs. Linear probability model (pooled)

	Large shocks				Small shocks			
	Probit Mrg Effects		Linear Prob		Probit Mrg Effects		Linear Prob	
Productivity growth	0.011**	(0.004)	0.012***	(0.004)	-0.273***	(0.089)	-0.299***	(0.094)
Inability	0.020***	(0.003)	0.021***	(0.003)	0.002	(0.003)	0.002	(0.003)
Inability squared	-0.001***	(0.000)	-0.001***	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Growth*Inability	-0.002***	(0.001)	-0.003***	(0.001)	0.025**	(0.011)	0.027**	(0.012)
Experience	-0.007***	(0.000)	-0.008***	(0.000)	-0.009***	(0.000)	-0.010***	(0.000)
Male	0.006	(0.005)	0.012**	(0.006)	-0.000	(0.007)	0.008	(0.007)
Age	-0.196***	(0.018)	-0.277***	(0.020)	-0.212***	(0.018)	-0.285***	(0.018)
Age squared	0.002***	(0.000)	0.003***	(0.000)	0.002***	(0.000)	0.003***	(0.000)
African-American	0.018***	(0.007)	0.017**	(0.007)	-0.013*	(0.007)	-0.014*	(0.008)
Hispanic	-0.005	(0.010)	-0.009	(0.011)	-0.054***	(0.010)	-0.056***	(0.010)
Foreign-born	-0.054***	(0.009)	-0.056***	(0.008)	-0.051***	(0.010)	-0.052***	(0.010)
Married	0.003	(0.005)	0.001	(0.005)	0.011*	(0.006)	0.007	(0.006)
Region: Midwest	-0.002	(0.008)	-0.002	(0.008)	-0.011	(0.008)	-0.011	(0.008)
Region: South	0.001	(0.007)	0.001	(0.007)	0.018**	(0.007)	0.019***	(0.007)
Region: West	0.021**	(0.008)	0.022***	(0.008)	0.022**	(0.009)	0.023***	(0.009)
Bad health	0.071***	(0.002)	0.078***	(0.003)	0.078***	(0.002)	0.084***	(0.003)
Year 1994	0.012	(0.013)	0.010	(0.011)	0.039**	(0.016)	0.033**	(0.014)
Year 1996	0.057***	(0.015)	0.055***	(0.015)	0.077***	(0.018)	0.075***	(0.018)
Year 1998	0.028**	(0.014)	0.024*	(0.013)	0.069***	(0.015)	0.068***	(0.014)
Year 2000	0.033**	(0.014)	0.031**	(0.014)	0.058***	(0.014)	0.056***	(0.013)
Year 2002	0.059***	(0.015)	0.058***	(0.016)	0.128***	(0.018)	0.134***	(0.020)
Year 2004	0.038***	(0.013)	0.036***	(0.012)	0.099***	(0.016)	0.097***	(0.016)
Year 2006	0.029**	(0.014)	0.029**	(0.013)	0.098***	(0.016)	0.102***	(0.016)
Year 2008	0.035**	(0.015)	0.031**	(0.014)	0.095***	(0.018)	0.098***	(0.019)
Year 2010	0.042**	(0.017)	0.040**	(0.018)	0.116***	(0.021)	0.116***	(0.023)
Constant			7.321***	(0.559)			7.585***	(0.523)
Adj.R-squared			0.149				0.196	
Observations	27452		27452		24858		24858	

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