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The Cognitive Demands of Work and the Length of Working Life: The Case of Computerization*

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Abstract

This paper focuses on impact of computerization on the work and retirement decisions of the cohort of 51-61 year old individuals who entered the Health and Retirement Study in 1992 and have been followed for next 18 years through 2010. I use data on cognition and detailed occupations in the HRS linked to a measure of occupational computerization from the O*NET data assembled by the Bureau of Labor Statistics. Beginning with Autor et al. (2003), the labor economics literature suggests that advances in computers substitute for the tasks done by many middle-skilled workers and complement those done by high-skilled individuals. Advances in computer technology tend, therefore, to lower the productivity of the middle-skilled and raise the productivity of the high skilled. Older workers face a decision of whether to invest in keeping up with new technology, shifting to another occupation or exiting from full time work into partial or full retirement. I find strong evidence that women and many men retired earlier if they are in computer-intensive occupations while, for other men it appears that computerization does not have a significant effect on retirement. Higher cognition and being in a high wage occupation appears to partially offset retirement incentives of computerization.

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1. Introduction

Variations in the rewards to work during the past century in the United States have been explained as the outcome of the "The Race between Education and Technology" by Goldin and Katz (2008). Skill-biased technological change has continually raised the relative demands for more skilled workers which, in turn, has increased the derived demand for human capital investments via increased levels of formal education and on-the-job training. During much of the 20th century, Goldin and Katz argue that the rise in demand for skilled labor was accompanied by an even more rapid increase in the supply of more educated workers resulting in compression of wage differentials across education groups before World War Two. After the war, there was a long period during which the distribution of wages remained remarkably stable, suggesting that the race between the supply and demand for skills of all levels was a dead heat. This period of stability ended in the late 1970s with the beginning of a persistent widening in the wage distribution that continues to the present. For example, college graduates, who earned about 50 percent more than high school graduates on average in 1979, earned almost twice as much by 2008 (Acemoglu and Autor, 2011).

Economists have long argued that a major reason that technological change is skill biased lies in complementarity between new forms of physical capital and the skills needed for workers to learn to utilize capital effectively. (See Berman, Bound, and Griliches ,1994, for an early contribution.) More recent literature, surveyed by Acemoglu and Autor (2011), suggests that a more nuanced view is needed of the relationship between the cognitive abilities and skills of workers and the tasks they perform in order to understand how new technologies affect their productivity and employment. This literature documents major changes in the distribution of workers and wages across occupations that have taken place over the last thirty years. There has been a growing polarization of the occupational skill distribution created by a relative decline in the number of people in middle skilled—and middle class—occupations relative both to people in highest skilled occupations and those in the lowest skilled occupations (Autor et al., 2006). This shift in the distribution of occupational employment has been accompanied by a "hollowing out" of the wage distribution such that wage growth of those in middle skilled occupations has fallen far behind workers in the highest skilled occupations and somewhat behind workers in the least skilled occupations.

One important explanation for occupational polarization focuses on the impact of computerization on the tasks that workers perform in different occupations. In particular, Autor, et al. (2003) argue that occupations can be viewed as bundles of tasks and that a worker's capacity to carry out these tasks depends on the worker's cognitive and physical capabilities. They go on to argue that computerization has been complementary to the tasks carried out by highly skilled professional, technical and managerial workers. The productivity of these workers depends on their fluid intelligence, imagination and the advanced skills and knowledge they have gained from formal education and on-the-job experience in combination with other capital, labor and organizational resources provided by their employer. Computerization amplifies the productivity of such people by enabling them to carry out a wide range of complex tasks quickly and efficiently that previously were extremely tedious and time consuming or not possible at all. In contrast, Autor et al. (2003) argue that computers can substitute for the tasks that are carried out by people in middle skilled occupations, such as book keeping, if they involve routine tasks which can alternatively be carried out by instructions contained in a computer program. Given the trillion-fold decline in the cost per calculation and in computer memory, the range of tasks that are sufficiently routine to be computerized has grown at an accelerating rate since computers were introduced commercially in the 1960s. In contrast, Autor et al. points out that computers cannot (yet) substitute for the required tasks in many low skilled service sector jobs, such as a night watchman or janitor, in which vision, pattern recognition, judgment and physical actions are combined. Thus, the heterogeneous impact of computerization on the demand for labor in different occupations is a major reason for job polarization and the emergence of a U-shaped distribution of real wage growth.[1]

To my knowledge, the literature on the growing inequality of wages and the polarization of the job market has not addressed the implications of these changes for the labor market and retirement behavior of older workers. While changes in technology and the occupational distribution of the labor force have reduced the physical demands of work for most workers, the cognitive demands of work have greatly increased for much of the labor force. The goal of this paper is to explore the implications of the cognitive demands of work for the length of working life that individuals choose using extremely rich and, as yet, largely untapped data on cognition and detailed occupations in the HRS linked to a detailed characterization of these occupations by O*NET (formerly Dictionary of Occupational Titles) project of the Bureau of Labor Statistics. Although these data would allow for a much broader investigation of the cognitive demands of work and length of working life, in this paper I focus on the single dimension of computerization.

[1] "Offshorability" is another determinant of changes in occupation-specific labor demand that has received considerable attention in the literature. The basic idea is that certain tasks (e.g., physical labor or handling hotel reservations over the telephone) can be shifted to an off-shore location while others (e.g., barbering or construction) cannot. (See, e.g., Firpo, et al. ,2011, for an analysis of how occupational wages vary with respect to both "offshorability" and "routinizability" and other characteristics. We focus only on computerization in this paper.

This paper studies the impact of computerization on the original HRS cohort that was born in 1931-1941 and entered the HRS in 1992 when cohort members were 51-61 years of age.[2] They were in their 20s at the beginning of the 1960s when mainframe computers began to be introduced into the economy; in their 30s in the 1970s when the spread of mainframes and minicomputers vastly extended the range of economically significant computer applications; and in their 40s when personal computers were introduced in the 1980s and computers began to spread to home as well as business. Thus, members of the HRS cohort made their educational and early occupational choices before the introduction of computers. To the extent that they learned to use computers in their work, they did so on-the-job. If they failed to learn computer skills in occupations that demanded them, they may have switched occupations during their careers, with their places being taken by younger, more computer savvy workers. This historical period also coincided with the growth of female labor force participation with an increasing proportion of women pursuing sustained labor market careers and making substantial investments in on-the-job training. Computerization has had a particularly large effect on the technologies used in many female-dominated occupations in office work, health services and other services. In this paper, I analyze the implications of computerization separately for men and women.

However, I have not yet utilized all the data that is available in the HRS that can be used to study the differential impact of computerization across cohorts and genders on the length of working life. Also, other than measures of computer use, I have not yet attempted to utilize the rich data from the HRS and O*NET that characterize skills, tasks, cognitive abilities and

[2] Comparisons of the impact of computerization on the length of working life of the 1992 cohort with younger cohorts that entered the HRS in 1998, 2004 and 2010 await future research. The value of cross-cohort analysis is currently limited by the small size of the 1998 cohort; the impact of the Great Recession on the 2004 cohort and fact that they are only 57-62 by 2010 and, of course, by the fact that only baseline information at ages 51-56 is currently available for the 2010 cohort.

personality traits that are useful in different occupations and possessed to different degrees by HRS respondents. Finally, it should be noted that the HRS introduced several new measures of cognitive ability in 2010 that will eventually further enrich our understanding of the interplay between the cognitive demands of work and the length of working life. In short, the current paper should be regarded as an initial foray into a longer term research agenda and my findings should be viewed as tentative.

As a brief summary of the main results, I find strong evidence that members of the 1992 HRS cohort who are in computer-intensive occupations tend to retire earlier and somewhat weaker evidence that persons with higher cognitive ability tend to retire later, controlling for marital status, gender, education and health and baseline earnings. However, other things equal, those in high wage occupations tend to retire later. There are dramatic gender differences in the effect of computerization on retirement behavior. Being in a computer-intensive occupation creates a strong incentive for women at all ages from their mid-50s onward to exit the labor force and enter into partial or full retirement earlier than women in other occupations.

The age pattern for men of the effects of computerization is more complex. Before reaching eligibility for Social Security claiming at age 62, the work disincentive associated with computerization for men follows a similar profile to that of women, but is even stronger. After age 62, however, the disincentive falls abruptly to insignificance. Following Autor, et al. (2003), I hypothesize that this pattern may be generated by two distinct groups of men. One group is in occupations in which computers substitute for the tasks these men. For these men, the returns to additional investment in human capital in late career are low and, therefore, they have incentives to retire earlier than men in less computer-intensive occupations. The other group consists of men with skills that are complemented by computers. Their productivity is raised advances in computer technology and, if they continue to maintain their skills, they have incentives to continue working longer. The detailed occupational data in HRS linked with the broad range of occupational characteristics from O*NET would allow a deeper exploration of this hypothesis and its further implications in a future version of this paper.

2. Theoretical Considerations

Economic theory suggests that the cognitive demands of work may affect the length of work life through several channels. Previous research suggests that highly able workers tend to be sorted into jobs that are more cognitively demanding, often in occupations that experience higher rates of technological change. In late career, workers in such jobs may require significant investment to maintain their skills or acquire new ones in the face of continued technological change that threatens to erode the value of their existing human capital. (See Bartel and Sicherman, 1993, and Ahituv and Zeira, 2010, for formal theoretical models.) While some of this investment may occur with formal training programs provided by the employer, it is likely that much of it will involve informal "learning by doing" by the worker along with help from co-workers. The cost of investment entails direct training costs, the opportunity costs to the firm from lost output of the worker and co-workers plus the disutility to the worker entailed in the effort to acquire new skills or minus the utility the worker enjoys from learning new things.

Holding the rate of technological change constant, the net benefit of making an investment to prevent the erosion of skills depends on the marginal effect of the investment on the worker's annual productivity and the number of years that the worker expects to remain on the job and thus will be able to capture the returns from the investment.[3] These investments are less costly for workers with greater fluid intelligence and, as discussed earlier, will tend to be higher the greater degree of complementarity between the worker's existing skills (i.e., crystallized intelligence) and the new technology. Since fluid intelligence, which reflects the worker's ability to think and reason in new situations, tends to decline with age, the cost of making investments to prevent the erosion of skills would be expected to increase with age.

Because the investment horizon shortens as retirement approaches, the net benefit of investing in the maintenance of one's human capital falls. At some point the net benefit becomes negative, the worker stops investing, and his or her skills begin to deteriorate and obsolesce. At the same time, the disutility of work may be increasing because of deteriorating health, employer policies toward older workers and other work and family-related issues. The declining benefits to investment in skills together with increasing disutility of labor create an incentive for workers to scale to shift to less demanding tasks, scale back work hours, change occupations or retire altogether. In addition, these factors may interact with policy variables such as the Social Security minimum claiming age that generates a large spike in retirement at age 62.

It is important to point out that the connection between age at retirement—that is, the length of the horizon before the end of working life—and decisions about human capital investment is endogenous. Consider two observationally similar men, A and B, of the same age in a given firm who both expect to retire at 65. Imagine that a new computer technology is introduced. Suppose that the two men differ in some unobservable characteristic that causes A

[3] For simplicity, I assume that new skills represent general human capital and there is a competitive labor market so that worker's wage is equal to his or her marginal product minus the (direct or opportunity) cost of human capital investment. Older workers may have considerable firm-specific human capital and, therefore, may incur substantial decreases in wages if they switch employers. The determination of wages and employment in this situation would involve aspects of worker-firm bargaining and long term explicit or implicit contracts that are beyond the scope of this paper to consider.

to choose not to invest in learning the new technology while B chooses to make the investment. Conditional on these choices, A will tend to retire earlier because his skills will deteriorate while B will work beyond age 65 because his marginal product of labor at age 65 will be higher than it would have been without the new technology. More generally, measured or unmeasured factors that encourage a worker to undertake investment in human capital at a given age will tend also to extend his desired length of working life.

Cognitive decline is one of the factors that might lead to early retirement, perhaps by decreasing a person's productivity directly or by reducing their incentive and ability to maintain their skills in the face of technological change. Conversely, several papers including Rohwedder and Willis (2010), Bonsang, et al. (2012) and Mazzona and Peracchi (2012) have found evidence that early retirement has a negative causal effect on cognitive ability where causality is established using instrumental variable methods to control for endogenous effects of cognition on retirement behavior. In particular, Rohwedder and Willis speculate that one of the mechanisms driving this relationship is an "on-the-job retirement" effect such that workers who face national policies that create strong incentives for early retirement have reduced incentives to maintain their skills and, because of reduced mental stimulation at work, tend to experience greater cognitive decline. In this paper, I use cognition as an explanatory variable in regressions on retirement without attempting to control for reverse causation. I do find that cognitive decline is associated with earlier retirement, but leave it for future research to disentangle the causal arrows.

3. Data

In this paper, I study the impact of computerization and cognition on retirement using extremely rich and, as yet, largely untapped data on detailed occupations in the HRS linked to a detailed characterization of these occupations by O*NET (formerly Dictionary of Occupational Titles) project of the Bureau of Labor Statistics. I focus the analysis on the original "HRS Cohort" of 51-61year olds (and their spouses), born between 1931 and 1941, who entered the HRS in 1992. The data are organized into a panel containing person-wave data from the respondent's year of entry 1992 through the most recently available wave in 2010. The sample is restricted to fully employed persons who work for pay, are not self-employed and who are aged 51-61 at baseline (N=25,308. The respondent's retirement status (0=working, 1=partially retired, 2=fully retired) is recorded in each subsequent wave, with person-wave observations dropped for respondents who have died prior to that wave. In all analyses, the sample person weight from the baseline is used to weight observations in all waves.

Descriptive statistics for the HRS cohort are presented in Table 1. To avoid dealing with selectivity issues in the panel, I only use the baseline values of variables that are observed only for people who are working. These include log earnings, occupational characteristics, and self-reported computer use. In addition, the baseline set of variables includes education, gender and marital status. Health and cognition variables are measured both at baseline and in panel. Health is coded on a five point scale from "excellent" = 1 to "poor" = 5 and cognition is coded on a 27-point scale which is described below following a more detailed discussion of occupational characteristics.

The HRS contains a complete occupational history of respondents from the time they enter the survey. In addition, HRS elicits the longest occupation the person engaged in prior to entry into the survey. The public use version of HRS reports 17 occupations formed by aggregating 3-digit detailed occupations that are available in the restricted version of the HRS. HRS contains self-reports about a large number of characteristics of the occupation including a question about whether the respondent's job involves the use of a computer "all or almost all the time, most of the time, some of the time, or not at all or almost not at all." Self-reported computer use was asked in 1992 and then in every wave from 2000 through 2010.

I have linked HRS occupations at both the aggregated and detailed levels to detailed descriptions of the abilities, activities and context characteristics of these occupations compiled by the O*NET project of the Bureau of Labor Statistics.[4] O*NET (the Occupational Information Network) was developed to replace the Dictionary of Occupational Titles (DOT) which had been the public standard description of occupations prior to 2000. The O*NET collects information on six domains in 949 occupational titles. Some of the domains are job oriented, and some are worker oriented. The domains are: worker requirements, worker characteristics, experience requirements, occupational requirements, occupational characteristics, and occupational specifics. The computer usage variable I use in this study is based on the "Interacting with computer" measure in the occupational requirements section. For each occupation, the O*NET provides information on the "importance" and "level" of required work activity. The coding of the this and other occupational characteristics follows Firpo et al. (2011) and assigns a Cobb-Douglas weight of two thirds to "importance" and one third to "level" to create a single measure of computer usage in occupations. This measure is then averaged for the somewhat less detailed

[4] I am grateful to Péter Hudomiet for providing me with occupational variables derived from the O*NET data that he has developed for his Ph.D. dissertation in the Department of Economics at the University of Michigan.

census occupation level. Finally, in order to collapse the information to our 3-digit occupations, a weighted average of the measure is taken, where the weights are the relative frequency of the occupations in the census within our more aggregated occupation categories. In addition, I use measure of occupational wages constructed by averaging the log wages of workers within each 3-digit occupation using CPS data.[5]

There is considerable agreement between the self-reported measure of occupation reported in the HRS and the degree of occupational computerization in O*NET—the correlation is about 0.6. Figure 1 displays the kernel densities of the O*NET measure for HRS workers who say that use computers "most or all of the time" on their job versus those who report using computers "sometimes or never." Among those who report intensive use of computers on their job, there is a concentration of the O*NET occupations in the most computer-intensive range (0.6-0,8) whereas, for those who report little computer use, the distribution is almost uniform over the entire range (0.1-0.9).

Following Crimmins et al. (2011), I measure cognition on a 27-point scale based on several cognitive tests that have been administered to self-respondents in the HRS who are 51 years old and older at each wave of the survey. The scale includes a 10-word immediate and delayed recall test (0 to 20 points) that measures episodic memory, a serial 7s test that measures working memory (0 to 5 points), and a backwards-counting test that measures mental processing

[5] It is important to note that the public use version of the HRS records 17 occupations while occupations coded at the 3-digit level are restricted data. In this paper, I have estimated models with occupational characteristics coded at both the 3-digit and aggregated levels in the public use data, but report only results using the 3-digit classification. To aid investigators contemplating applying for access to the restricted data, I comment briefly in a footnote later in the paper about the loss of precision and bias from using the public use measures. Estimates using restricted data in this paper were conducted in the HRS data enclave at the University of Michigan.

speed (0 to 2 points).[6] These tasks were derived from the Telephone Interview for Cognitive Status (Brandt et al., 1988), which has been validated for use as a screening instrument (Welsh et al., 1993; Plassman et al., 1994).

4. Econometric Framework

I use a simple ordered probit model to analyze the determinants of retirement for a subsample consisting of members of the original HRS cohort who were fully employed at the time they entered the survey in 1992 for all subsequent currently available survey waves from 1994 through 2010. The dependent variable is a trichotomous variable indicating whether the person reports him or herself to be working (=1), partially retired (=2) or fully retired(=3). Partial retirement and full retirement may be considered to be competing risks. While standard competing risk models assume that the competing outcomes are independent, conditional on covariates, this assumption obviously makes no sense in this case. Instead, the ordered probit model makes the polar opposite assumption that there is a one-dimensional random variable which triggers the passage from work to partial or full retirement, conditional on covariates, where the cut point for partial retirement is smaller than the cut point for full retirement. In all estimates of the model, repeated observations for an individual are treated as a cluster with standard errors estimated accordingly. Since individual transitions in retirement status are not modeled, the data may be regarded as a repeated cross-section. At any given age, the

[6] Scores from waves in 2006 and earlier include imputations for missing data (Fisher et al., 2009), while those from 2008 are raw scores and do not include imputations.

individual's retirement status is predicted by a set of baseline variables and another set of variables pertaining to conditions during the wave in which the individual is a given age.[7]

To illustrate the age patterns of work, partial retirement and full retirement, I first estimate an ordered probit of the probability of each state as function of age without any other covariates. As is well known from the enormous literature on retirement, the probability of retirement has a major spike at age 62—the minimum age to claim Social Security benefits—and a lesser spike at age 65 which I capture with two dummy variables, one indicating that the person is at least 62 and the other that he or she is at least 65. I also enter linear and quadratic terms in age. This functional form appears to do a good job in capturing a common age pattern of retirement status.[8]

Estimates of the model without other covariates are presented in the first column of Table 2 for the sample of members of the original HRS cohort who were working full time when they entered the survey in 1992. All four age variables are highly significant. The predicted probabilities of each state for ages from 51 through 80 are given by the three curves in Figure 2. The percentage working falls from 100 percent at age 51 to 65.3 percent at age 61, just prior to Social Security eligibility, drops sharply to 40.4 percent by age 63 and then continues to fall to 23.6 percent by age 66. At later ages there is a gradual decline in work, with 6.7 percent of surviving members of the original HRS cohort who have survived to age 80 year predicted to be still reporting themselves as working.

[7] Given the ordering the dependent variable, an independent variable that increases the probability that a person is retired and reduces the probability he or she is working will have a positive sign.

[8] A model with the two dummy variables and linear age fails the linktest that is implemented in Stata, but the model does not fail this test when age squared is added. According to the Stata manual, "Although linktest "is formally a test of the specification of the dependent variable, it is often interpreted as a test that, conditional on the specification, the independent variables are specified incorrectly." In addition, the coefficients of the four age variables remain almost perfectly constant as various sets of covariates are added.

The transition to full retirement often involves an ambiguous state that is self-reported as partial retirement. Partial retirement sometimes involves stopping work altogether with the idea of possibly resuming work later and sometimes involves shifting to part time work or self-employment. In Figure 1, one can see that the percentages of partially retired and fully retired are about equal prior to age 62, with the fraction shifting to fully retired increasing sharply at age 62. At later ages, the percentages of partially retired and working both decline slowly and are of about equal magnitude. By age 80, somewhat over 83.8 percent of the surviving members of the HRS cohort are predicted to be fully retired while 9.5 percent are partially retired and 6.7 percent are working.

5. Analysis of Work and Retirement

In the second through fifth columns of Table 2, I present multivariate estimates of the ordered probit model of retirement applied to members of the HRS entry cohort of 1992 who were employed full time at baseline. Table 2a presents the average marginal effect of each variable on the probability of being fully retired. This model uses data for waves from 1994 through 2010. In addition to the controls for age that were discussed in the preceding section, the model has controls for baseline age, marital status, health, gender, education and log earnings and two longitudinal covariates, self-reported health and cognition, which are measured in panel independently of the respondent's labor force status. Column 2 estimates a model without any occupational measures and the next three columns add occupational variables based on 3-digit occupations. Column 3 adds a measure of occupational computerization, column 4 instead adds the mean wage in the occupation and column 5 adds both occupational variables. Both of these variables are based on 3-digit occupations.

I first describe the results for column 2. Baseline age attempts to control for selectivity caused by the restriction of the sample to respondents who were fully employed at baseline. The negative coefficient of baseline age controls for the fact that, for example, a sample person who was 61 at baseline is more likely to be employed when observed in 1994 than is another sample person who was 51 at baseline when he is observed at age 61 in 2004. The other control variables have a more substantive interpretation. Marital status, gender and education are all insignificant, controlling for baseline log earnings and for baseline and panel measures of self-reported health and cognition. As expected, people in worse health have lower probability of working, especially as their health declines in panel, and correspondingly higher probabilities of retirement.[9] Baseline log earnings have a strong negative effect on work (or positive effect on retirement), suggesting that, other things equal, high earners may have saved enough to retire early.

The baseline cognitive score has a significant positive effect on working and, holding the baseline score constant, cognition at later ages has a marginally significant positive effect. This is consistent with the hypothesis that people with higher cognitive ability may be better able to maintain their skills as they age and, conversely, that cognitive decline is one factor that may push people into retirement. However, it should be stressed that we do not have direct evidence on investment to maintain skills, nor have we yet exploited information on the various aspects of self-reported work demands that are contained in the HRS. Moreover, there is considerable evidence in the economic literature suggesting that mathematical ability—both the fluid ability to think and reason in mathematical contexts and the crystallized mathematical knowledge obtained

[9] Recall that higher values of the self-reported health variable correspond to poorer health. Also, note that Bound, et al. (2011) show that self-reported health has a larger negative effect on labor supply than a more robust measure of health that they develop in the context of a computationally intensive structural model using HRS data on the 1992 cohort. Nonetheless, poor health in their model has a strong negative effect on labor supply.

through education and self-instruction—may be more important in economic behavior than the abilities measured by the 27-point scale.[10] With the introduction of the number series test into the HRS beginning in 2010, it will be possible to explore these issues in more depth in future research. It is notable that coefficients of the cognition measure in Table 2 do not change when measures of computerization or occupational wage are added.[11]

The degree of computerization in the baseline occupation is entered into the model in column 3 of Table 2. Consistent with our theoretical discussion of the challenges faced by older workers to maintain their skills in the face of rapidly changing technology, I find that computerization has a highly significant effect of increasing the probability of retirement and decreasing the probability of working. From Table 2a, we see that the average marginal effect of computerization on full retirement is 0.09. This implies that a one standard deviation in computerization (std. = 0.19) , is predicted to increase the probability of retirement by 1.7 percentage points. In column 4, I replace the computerization variable with the occupational wage to see if the effect occurs because computerized jobs are high wage jobs. This is definitely not the case since the occupational wage variable totally insignificant. However, when the computerization variable and occupational wage are entered together in column 5, the computerization variable becomes larger in magnitude and the occupational wage becomes significant and negative.

Focusing on the results in the final column of Table 2, it appears that the negative effect of computerization on work is partially offset by the positive effect of higher occupational wages. There is a strong positive correlation of 0.65 between the occupational wage and

[10] See McArdle and Willis (2012) for a brief discussion of literature on the importance of mathematical ability for economic success.

[11] In work not reported in this paper, I found no significant interaction effects of cognition and occupational computerization on work and retirement.

occupational computerization, indicating that occupations with high degrees of computerization command a substantial skill premium. However, the incentive for early retirement implied by the highly significant computerization variable is far too large to be offset by any plausible (e.g., two standard deviation) increases in the occupational wage or the respondent's baseline cognition.

As computerization spread, it had potentially very different effects for men and women. As discussed earlier, members of the HRS 1992 cohort had to learn about computers on the job and many women in this cohort did not begin sustained labor force attachment until after childbearing was completed and their children reached school age. The differences between male and female careers contribute to a high degree of occupational segregation by gender and an associated difference in the kinds of tasks performed by men and women.   This is illustrated in Table 3 which presents the proportion of females, degree of occupational computerization, and mean education and log wage of the baseline occupation for each of the 17 occupations in the public use version of the HRS. Women dominate clerical/administrative assistant jobs and health services while men dominate most of the blue collar jobs; there is an even gender mix in professional jobs (but less even at the 3-digit level); and about one-third of managers are women. Simple calculations show (a) that there is no significant difference is mean occupational computerization or mean occupational education by gender, but (b) that mean occupational wages are about 15 percent lower for females than for males, holding occupational computerization and education constant. By construction, the occupational variables do not vary by gender. Thus, the entire gender difference in mean occupational wages is due to the difference in the occupational distributions of men and women.

Table 4 presents the same ordered probit regressions from column (1) of Table 2 separately for males and females from the 1992 cohort. It is notable that the effects of being married at baseline are significant but have opposite signs for males and females, with marriage pushing women to retire and men to stay in the labor force. Most interesting, however, is that the coefficient of baseline occupational computerization on retirement is nearly twice as large for women than for men.

To investigate these gender differences further, I run the same regressions with detailed interactions between baseline computerization and dummy variables for single years of age from age 54 to 70. Table 5 presents coefficient estimates of this model for the total sample, for males and females separately and, in the final column, for differences in the coefficients between males and females. Table 5A presents the corresponding table of average partial effects. The age profiles of average marginal effects and error bars of the single-year age interaction effects with computerization are plotted separately for males and females in Figure 3.

There are striking gender differences in these profiles. The profile for females shows that computerization has a significant positive effect on the probability of retirement that is roughly constant in magnitude over the entire age range from 54 to 70. In contrast, the profile for males is about the same as for females from age 54 to 61, but then falls sharply to zero at age 62—the age of eligibility for Social Security claiming—and increases modestly (but not significantly different from zero) at later ages. While male-female differences are insignificant before age 62, they differ significantly from age 62 through 67.

An possible explanation for these strikingly different patterns may lie in differences in the costs and benefits that men and women face in dealing with potential erosion of the skills they require in order to perform the tasks needed for their jobs in the face of rapidly changing computer technology. Many of the women in the HRS cohort were in clerical and administrative occupations in which the scope of work was expanding beyond typing text, a task that their supervisors and other co-workers were increasingly doing for themselves, to management of computer based information relevant to their workplace, ranging from personnel matters, to purchasing , to financial records and so on. As the internet became more important and the technology of communication and presentation shifted from paper to electronics, still more computer skills were needed, encompassing the full range of Microsoft Office (Word, Excel, Powerpoint and other more specialized programs) and its competitors. The pecuniary benefits to older women from acquiring these skills was probably quite limited because of relatively rigid compensation programs within firms and because of competition from younger, more computer savvy workers entering these occupations.   Figure 3 suggests that that computerization created a substantial incentive for retirement for women at all ages from their mid-50s onward.

The story for some men seems to mimic the account that I just gave for women. These men are probably in a range of occupations in which, following Autor, et al. (2003), computers substitute for the human capital these men had built up during their careers. As computers became increasingly important, the value of their skills decreased; competition from younger computer savvy workers increased and Social Security eligibility came closer. These men decided not to invest heavily in maintaining their skills or in acquiring the skills need to switch occupations. Rather, they tended to exit the full time labor force at or before age 62. However, there appears to be a second set of men, perhaps mostly those in occupations for which computers complement their human capital—again following Autor, et al. (2003)—who remain working after age 62. This latter group of men may continue to invest keeping their computer and non-computer skills from eroding as they pursue longer careers.

6. Conclusion

This paper explores the implications for the length of working life of older workers of the cognitive demands posed by computerization.   I focus on the work and retirement experience of members of the original cohort in the Health and Retirement Study, born in 1931-41, from the time they entered survey in 1992 at age 51-61 through 2010 when they were 69-79 years of age. I use extremely rich and, as yet, largely untapped data on cognition and detailed occupations in the HRS linked to a detailed characterization of the intensity of computer use in these occupations by O*NET (formerly Dictionary of Occupational Titles) project of the Bureau of Labor Statistics.

The development of computers and the ubiquitous spread of computerization throughout the economy largely occurred after members of the 1992 cohort had completed their formal education and, in many cases, after they had chosen an occupation during their early labor market careers. Economic theory implies that rapid technological change will lead to obsolescence of a worker's skills unless the worker (and the employer) makes investments in human capital to keep up with and adapt to the new technology.   In addition, recent literature suggests that advances in computer technology substitute for the tasks performed by many mid-skilled workers while complementing the skills of many workers in high skilled jobs. Thus, theory predicts that workers in computer-intensive occupations will tend to retire earlier than workers in other occupations unless they possess high levels of skill than are complemented by advancing technology. Such workers may be induced to work longer in order to capture the gains from their higher productivity.

A major empirical finding of the paper is that computerization does, on average, have a significant effect in inducing earlier retirement. However, this effect differs dramatically across genders. For women, computerization has a strong negative effect on work that is basically invariant with age from the mid-50s onward. For men before age 62, computerization provides an even stronger work disincentive. But after age 62, the disincentive effect falls to zero and remains at a low insignificant level at older ages. A possible explanation for this pattern is there are two distinct groups of men. In one group, computers substitute for the tasks they used to do or younger computer savvy workers can master new technologies more easily. To these workers, the returns on investments in learning new skills or in keeping up with new technologies appear to be low and they opt for early retirement. In the other group, new computer technologies are complementary to their skills and, with heightened productivity, the choose make investments to keep up with technology and choose to work longer to capture the return from these investments.

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Table 1. Descriptive Statistics of Analytic Variables (Weighted)

Variable	Mean	Std.
Works	0.41	0.49
Partly retired	0.15	0.35
Fully retired	0.45	0.50
Computerized occupation at baseline, detailed occupations (O*NET)	0.53	0.19
Computerized occupation at baseline, publicly available occupations (O*NET)	0.53	0.16
Used computers at work at baseline (Self Report)	0.36	0.48
Occupational wage at baseline (CPS)	6.55	0.34
Cognition in 1992	0.12	0.95
Cognition	-0.07	0.99
Health excellent at baseline	0.30	0.46
Health very good at baseline	0.35	0.48
Health good at baseline	0.26	0.44
Health fair at baseline	0.07	0.26
Health poor at baseline	0.02	0.12
Health excellent	0.15	0.36
Health very good	0.35	0.48
Health good	0.32	0.47
Health fair	0.14	0.35
Health poor	0.04	0.18
Married at baseline	0.73	0.45
Age at baseline	55.25	3.05
Age	64.68	6.00
Female	0.46	0.50
High school degree	0.35	0.48
Some college	0.21	0.40
College degree	0.11	0.31
Post graduate	0.15	0.36
Log Earnings at baseline	10.17	0.74
Obs	25308.00	

Sample: HRS Cohort, Age 51-61 in 1992, Fully Employed at Baseline

Table 2: Ordered probit estimates of working (=0), partial retirement (=1) and full retirement (=2) in the 1992 cohort

	[1]	[2]	[3]	[4]	[5]
Computerized occupation at baseline			0.315***		0.438***
			[0.104]		[0.118]
Occupational wage at baseline				-0.038	-0.159**
				[0.064]	[0.072]
Age in years	0.449***	0.450***	0.452***	0.450***	0.453***
	[0.047]	[0.047]	[0.048]	[0.047]	[0.048]
Age squared	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age at least 62	0.389***	0.399***	0.399***	0.400***	0.400***
	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]
Age at least 65	0.145***	0.123***	0.122***	0.123***	0.123***
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Age at baseline		-0.018***	-0.018***	-0.018***	-0.018***
		[0.006]	[0.006]	[0.006]	[0.006]
Married at baseline		0.06	0.054	0.061	0.056
		[0.042]	[0.042]	[0.042]	[0.042]
Health at baseline		0.037*	0.038*	0.037*	0.036*
		[0.020]	[0.020]	[0.020]	[0.020]
Health		0.113***	0.115***	0.113***	0.116***
		[0.015]	[0.016]	[0.015]	[0.016]
Female		0.049	0.024	0.044	-0.005
		[0.038]	[0.039]	[0.038]	[0.041]
High school dropout			reference category		
High school degree		0.039	0.005	0.042	0.005
		[0.049]	[0.050]	[0.049]	[0.049]
Some college		0.004	-0.044	0.01	-0.036
		[0.057]	[0.059]	[0.058]	[0.059]
College degree		-0.087	-0.152**	-0.076	-0.132*
		[0.073]	[0.075]	[0.075]	[0.076]
Post-graduate		-0.01	-0.072	0.001	-0.048
		[0.072]	[0.074]	[0.075]	[0.075]
Log earnings at baseline		0.119***	0.105***	0.124***	0.122***
		[0.028]	[0.028]	[0.029]	[0.029]
Cognition at baseline		-0.042**	-0.048**	-0.041*	-0.047**
		[0.021]	[0.021]	[0.021]	[0.021]
Cognition		-0.026*	-0.030*	-0.025	-0.029*
		[0.016]	[0.016]	[0.016]	[0.016]
First cut point	18.098***	18.875***	18.926***	18.683***	18.136***
	[1.564]	[1.598]	[1.600]	[1.624]	[1.632]
Second cut point	18.610***	19.395***	19.447***	19.203***	18.657***
	[1.565]	[1.599]	[1.601]	[1.625]	[1.633]
Pseudo R2	0.211	0.22	0.221	0.22	0.221
N	25237	25237	25237	25237	25237

Table 2A: Average partial effects of being fully retired, based on the ordered probit estimates in Table 2

	[1]	[2]	[3]	[4]	[5]
Computerized occupation at baseline			0.090***		0.125***
			[0.030]		[0.034]
Occupational wage at baseline				-0.011	-0.045**
				[0.018]	[0.021]
Age in years	0.130***	0.128***	0.129***	0.128***	0.129***
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age at least 62	0.113***	0.114***	0.114***	0.114***	0.114***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Age at least 65	0.042***	0.035***	0.035***	0.035***	0.035***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Age at baseline		-0.005***	-0.005***	-0.005***	-0.005***
		[0.002]	[0.002]	[0.002]	[0.002]
Married at baseline		0.017	0.015	0.017	0.016
		[0.012]	[0.012]	[0.012]	[0.012]
Health at baseline		0.011*	0.011*	0.011*	0.010*
		[0.006]	[0.006]	[0.006]	[0.006]
Health		0.032***	0.033***	0.032***	0.033***
		[0.004]	[0.004]	[0.004]	[0.004]
Female		0.014	0.007	0.013	-0.002
		[0.011]	[0.011]	[0.011]	[0.012]
High school dropout			reference category		
High school degree		0.011	0.002	0.012	0.001
		[0.014]	[0.014]	[0.014]	[0.014]
Some college		0.001	-0.012	0.003	-0.01
		[0.016]	[0.017]	[0.017]	[0.017]
College degree		-0.025	-0.043**	-0.022	-0.038*
		[0.021]	[0.022]	[0.021]	[0.022]
Post-graduate		-0.003	-0.02	0	-0.014
		[0.021]	[0.021]	[0.021]	[0.021]
Log earnings at baseline		0.034***	0.030***	0.035***	0.035***
		[0.008]	[0.008]	[0.008]	[0.008]
Cognition at baseline		-0.012**	-0.014**	-0.012*	-0.014**
		[0.006]	[0.006]	[0.006]	[0.006]
Cognition		-0.007*	-0.009*	-0.007	-0.008*
		[0.004]	[0.004]	[0.004]	[0.004]
N	25237	25237	25237	25237	25237

Table 3. Selected Characteristics of Occupations

	% Female	O*NET Computerization	Occupational Wage
01.managerial	0.33	0.66	6.95
02.professional	0.51	0.65	6.79
03.sales	0.46	0.53	6.45
04.clerical/admin support	0.82	0.65	6.29
05.service, clearning	0.98	0.14	6.04
06.service:protection	0.15	0.49	6.55
07.service: food prep	0.85	0.33	5.89
08.health services	0.95	0.30	6.06
09.personal services	0.66	0.24	6.05
10.farming/forestry/fishing	0.14	0.32	6.17
11.mechanics/repair	0.03	0.47	6.54
12.constr trade/extractors	0.02	0.21	6.50
13.precision production	0.20	0.41	6.51
14.operators: machine	0.45	0.37	6.28
15.operators: transport, etc	0.10	0.28	6.45
16.operators: handlers, etc	0.23	0.32	6.26
17.member of armed forces	NA	NA	NA
Total	0.459	0.507	6.497

Table 4: Ordered probit estimates of working (=0), partial retirement (=1) and full retirement (=2) in the 1992 cohort, by gender

	Males	Females
Computerized occupation at baseline	0.374**	0.704***
	[0.162]	[0.181]
Occupational wage at baseline	-0.205*	-0.118
	[0.105]	[0.101]
Age in years	0.527***	0.359***
	[0.061]	[0.074]
Age squared	-0.003***	-0.002***
	[0.000]	[0.001]
Age at least 62	0.402***	0.406***
	[0.046]	[0.052]
Age at least 65	0.087**	0.159***
	[0.039]	[0.043]
Age at baseline	-0.019**	-0.012
	[0.008]	[0.009]
Married at baseline	-0.158**	0.221***
	[0.071]	[0.050]
Health at baseline	0.031	0.047
	[0.027]	[0.029]
Health	0.104***	0.136***
	[0.021]	[0.022]
High school dropout	refrence category	
High school degree	0.055	-0.113
	[0.066]	[0.077]
Some college	0.081	-0.227**
	[0.078]	[0.092]
College degree	-0.144	-0.148
	[0.105]	[0.113]
Post-graduate	-0.118	0.014
	[0.102]	[0.111]
Log earnings at baseline	0.117***	0.126***
	[0.039]	[0.043]
Cognition at baseline	-0.048	-0.043
	[0.029]	[0.031]
Cognition	-0.021	-0.039*
	[0.022]	[0.022]
First cut point	19.839***	16.118***
	[2.107]	[2.562]
Second cut point	20.424***	16.570***
	[2.107]	[2.563]
Pseudo R2	0.215	0.238
N	13278	11959

Table 4A: Average partial effects of being fully retired, based on the ordered probit estimates in Table 4

	Males	Females	Difference
Computerized occupation at baseline	0.107**	0.196***	0.088
	[0.046]	[0.050]	[0.068]
Occupational wage at baseline	-0.059*	-0.033	0.026
	[0.030]	[0.028]	[0.042]
Age in years	0.151***	0.099***	-0.052*
	[0.018]	[0.021]	[0.027]
Age squared	-0.001***	-0.001***	0.000**
	[0.000]	[0.000]	[0.000]
Age at least 62	0.115***	0.113***	-0.002
	[0.013]	[0.014]	[0.019]
Age at least 65	0.024**	0.045***	0.02
	[0.011]	[0.012]	[0.016]
Age at baseline	-0.005**	-0.003	0.002
	[0.002]	[0.002]	[0.003]
Married at baseline	-0.045**	0.062***	0.107***
	[0.020]	[0.014]	[0.024]
Health at baseline	0.009	0.013	0.004
	[0.008]	[0.008]	[0.011]
Health	0.030***	0.038***	0.008
	[0.006]	[0.006]	[0.009]
High school dropout		reference category	
High school degree	0.016	-0.031	-0.047
	[0.019]	[0.022]	[0.029]
Some college	0.023	-0.063**	-0.086**
	[0.022]	[0.026]	[0.034]
College degree	-0.041	-0.041	0
	[0.030]	[0.031]	[0.043]
Post-graduate	-0.034	0.004	0.038
	[0.029]	[0.031]	[0.042]
Log earnings at baseline	0.034***	0.035***	0.002
	[0.011]	[0.012]	[0.016]
Cognition at baseline	-0.014	-0.012	0.002
	[0.008]	[0.009]	[0.012]
Cognition	-0.006	-0.011*	-0.005
	[0.006]	[0.006]	[0.009]
N	25237		

Table 5: Ordered probit estimates of working (=0), partial retirement (=1) and full retirement (=2) in the 1992 cohort, detailed interactions with age

	[1]		[2]	
	Total sample	Males	Females	Difference
Computerized occupation at baseline				
X Age below 55	0.448*	0.670**	0.441	-0.229
	[0.264]	[0.334]	[0.449]	[0.558]
X Age 55	0.691***	0.806***	0.787**	-0.02
	[0.226]	[0.296]	[0.359]	[0.464]
X Age 56	0.753***	0.959***	0.713**	-0.246
	[0.204]	[0.262]	[0.340]	[0.430]
X Age 57	0.652***	0.898***	0.590**	-0.308
	[0.175]	[0.233]	[0.281]	[0.366]
X Age 58	0.632***	0.749***	0.708***	-0.041
	[0.173]	[0.230]	[0.267]	[0.350]
X Age 59	0.690***	0.959***	0.634**	-0.325
	[0.162]	[0.217]	[0.249]	[0.328]
X Age 60	0.699***	0.897***	0.689***	-0.208
	[0.167]	[0.227]	[0.254]	[0.339]
X Age 61	0.870***	1.009***	0.937***	-0.072
	[0.169]	[0.228]	[0.258]	[0.342]
X Age 62	0.08	-0.184	0.677***	0.862***
	[0.151]	[0.200]	[0.236]	[0.309]
X Age 63	0.225	-0.047	0.858***	0.904***
	[0.150]	[0.200]	[0.233]	[0.306]
X Age 64	0.263*	0.084	0.765***	0.681**
	[0.154]	[0.205]	[0.239]	[0.315]
X Age 65	0.421***	0.202	0.847***	0.645**
	[0.146]	[0.199]	[0.225]	[0.302]
X Age 66	0.472***	0.341*	0.780***	0.439
	[0.143]	[0.195]	[0.219]	[0.296]
X Age 67	0.406***	0.177	0.851***	0.674**
	[0.145]	[0.197]	[0.221]	[0.297]
X Age 68	0.437***	0.333*	0.718***	0.385
	[0.145]	[0.199]	[0.223]	[0.302]
X Age 69	0.406***	0.215	0.751***	0.536*
	[0.148]	[0.200]	[0.226]	[0.303]
X Age above 69	0.355**	0.252	0.581**	0.328
	[0.148]	[0.198]	[0.231]	[0.305]
Occupational wage at baseline	-0.158**	-0.198*	-0.125	0.073
	[0.072]	[0.104]	[0.103]	[0.148]
Age in years	0.340***	0.434***	0.204	-0.23
	[0.103]	[0.127]	[0.178]	[0.218]
Age squared	-0.002**	-0.003***	-0.001	0.002
	[0.001]	[0.001]	[0.001]	[0.002]
Age at least 62	0.736***	0.935***	0.432***	-0.503**
	[0.100]	[0.125]	[0.168]	[0.209]
Age at least 65	0.025	-0.031	0.16	0.191
	[0.080]	[0.102]	[0.136]	[0.170]

(Table 5, continued)

Age at baseline	-0.018***	-0.019**	-0.014	0.005
	[0.006]	[0.007]	[0.009]	[0.011]
Married at baseline	0.055	-0.160**	0.225***	0.384***
	[0.042]	[0.070]	[0.051]	[0.086]
Health at baseline	0.037*	0.031	0.049	0.018
	[0.020]	[0.027]	[0.030]	[0.040]
Health	0.116***	0.102***	0.139***	0.037
	[0.016]	[0.021]	[0.023]	[0.031]
High school dropout		reference category		
High school degree	0.006	0.055	-0.111	-0.166
	[0.050]	[0.066]	[0.078]	[0.103]
Some college	-0.035	0.081	-0.228**	-0.309**
	[0.059]	[0.077]	[0.094]	[0.122]
College degree	-0.132*	-0.14	-0.148	-0.008
	[0.076]	[0.103]	[0.115]	[0.154]
Post-graduate	-0.047	-0.113	0.019	0.133
	[0.075]	[0.101]	[0.113]	[0.151]
Log earnings at baseline	0.122***	0.118***	0.128***	0.01
	[0.029]	[0.038]	[0.044]	[0.057]
Cognition at baseline	-0.047**	-0.046	-0.044	0.002
	[0.021]	[0.029]	[0.032]	[0.043]
Cognition	-0.029*	-0.024	-0.039*	-0.015
	[0.016]	[0.022]	[0.022]	[0.031]
Common parameters				
Female	-0.004	5.827		
	[0.041]	[7.608]		
First cut point	14.520***	16.982***		
	[3.581]	[4.366]		
Second cut point	15.043***	17.509***		
	[3.581]	[4.366]		
Pseudo R2	0.222	0.227		
N	25237	25237		

Table 5A: Average partial effects of being fully retired, based on the ordered probit estimates in Table 5

	[1]		[2]	
	Total sample	Males	Females	Difference
Computerized occupation at baseline				
X Age below 55	0.128*	0.194**	0.121	-0.074
	[0.075]	[0.097]	[0.123]	[0.156]
X Age 55	0.197***	0.233***	0.216**	-0.02
	[0.065]	[0.086]	[0.099]	[0.130]
X Age 56	0.214***	0.277***	0.196**	-0.084
	[0.058]	[0.076]	[0.093]	[0.120]
X Age 57	0.186***	0.260***	0.162**	-0.1
	[0.050]	[0.067]	[0.077]	[0.103]
X Age 58	0.180***	0.217***	0.194***	-0.024
	[0.049]	[0.067]	[0.073]	[0.098]
X Age 59	0.196***	0.277***	0.174**	-0.106
	[0.046]	[0.063]	[0.068]	[0.092]
X Age 60	0.199***	0.259***	0.189***	-0.073
	[0.047]	[0.066]	[0.069]	[0.095]
X Age 61	0.248***	0.292***	0.257***	-0.037
	[0.048]	[0.066]	[0.070]	[0.096]
X Age 62	0.023	-0.053	0.186***	0.238***
	[0.043]	[0.058]	[0.065]	[0.086]
X Age 63	0.064	-0.014	0.235***	0.247***
	[0.043]	[0.058]	[0.064]	[0.086]
X Age 64	0.075*	0.024	0.210***	0.184**
	[0.044]	[0.059]	[0.065]	[0.088]
X Age 65	0.120***	0.059	0.232***	0.172**
	[0.042]	[0.057]	[0.061]	[0.084]
X Age 66	0.135***	0.099*	0.214***	0.114
	[0.041]	[0.056]	[0.060]	[0.083]
X Age 67	0.116***	0.051	0.233***	0.181**
	[0.041]	[0.057]	[0.060]	[0.083]
X Age 68	0.124***	0.096*	0.197***	0.099
	[0.041]	[0.057]	[0.061]	[0.084]
X Age 69	0.116***	0.062	0.206***	0.142*
	[0.042]	[0.058]	[0.061]	[0.085]
X Age above 69	0.101**	0.073	0.159**	0.085
	[0.042]	[0.057]	[0.063]	[0.085]
Occupational wage at baseline	-0.045**	-0.057*	-0.034	0.024
	[0.020]	[0.030]	[0.028]	[0.042]
Age in years	0.097***	0.126***	0.056	-0.07
	[0.029]	[0.037]	[0.049]	[0.061]
Age squared	-0.001**	-0.001***	0	0.001
	[0.000]	[0.000]	[0.000]	[0.000]
Age at least 62	0.210***	0.270***	0.119***	-0.154***
	[0.029]	[0.036]	[0.046]	[0.058]
Age at least 65	0.007	-0.009	0.044	0.053
	[0.023]	[0.030]	[0.037]	[0.048]

(Table 5A, continued)

Age at baseline	-0.005***	-0.005**	-0.004	0.002
	[0.002]	[0.002]	[0.002]	[0.003]
Married at baseline	0.016	-0.046**	0.062***	0.108***
	[0.012]	[0.020]	[0.014]	[0.024]
Health at baseline	0.010*	0.009	0.013	0.004
	[0.006]	[0.008]	[0.008]	[0.011]
Health	0.033***	0.030***	0.038***	0.008
	[0.004]	[0.006]	[0.006]	[0.009]
High school dropout		reference category		
High school degree	0.002	0.016	-0.03	-0.046
	[0.014]	[0.019]	[0.022]	[0.029]
Some college	-0.01	0.024	-0.062**	-0.086**
	[0.017]	[0.022]	[0.026]	[0.034]
College degree	-0.038*	-0.041	-0.041	0
	[0.022]	[0.030]	[0.031]	[0.043]
Post-graduate	-0.013	-0.033	0.005	0.038
	[0.021]	[0.029]	[0.031]	[0.042]
Log earnings at baseline	0.035***	0.034***	0.035***	0.001
	[0.008]	[0.011]	[0.012]	[0.016]
Cognition at baseline	-0.013**	-0.013	-0.012	0.001
	[0.006]	[0.008]	[0.009]	[0.012]
Cognition	-0.008*	-0.007	-0.011*	-0.004
	[0.004]	[0.006]	[0.006]	[0.009]
N	25237	25237		

Figure 1. Degree Occupation is Computerized by Self-Report of Computer Use on Job

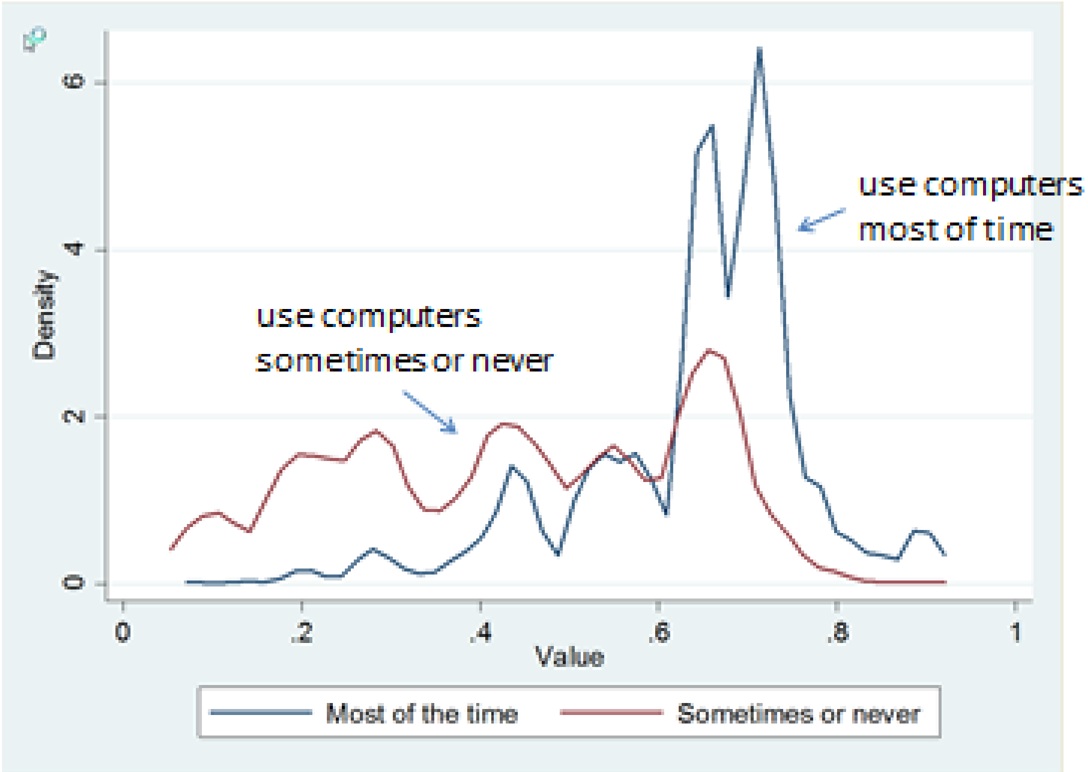

Figure 2. Predicted Age Patterns of Work and Retirement from Ordered Probit Without Covariates

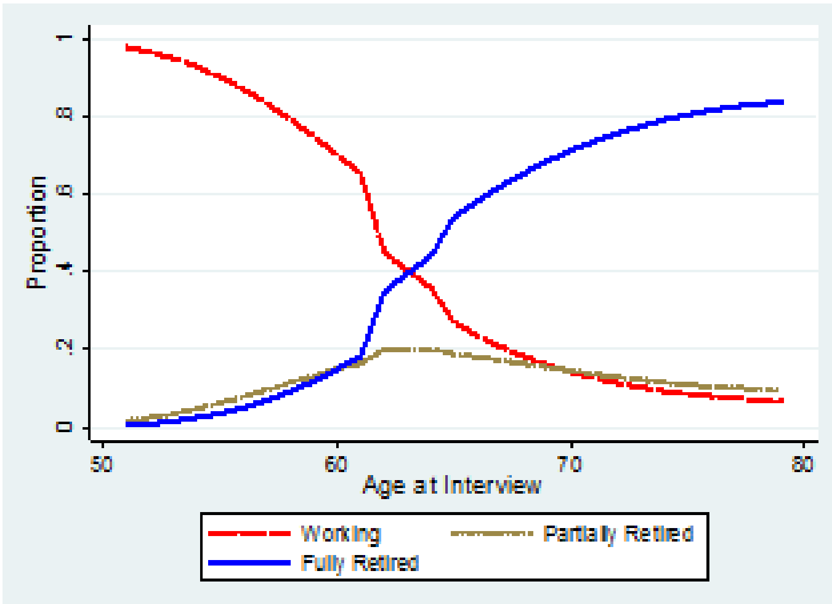

Figure 3. Average Partial Effects of Computerization by Age for Males and Females