Internet Usage and the Cognitive Function of Retirees

ABSTRACT: Cognitive decline amongst older people is associated with poor health and lower quality of life. Previous studies demonstrate that retirement is a particularly critical period for cognitive decline and highlight the importance of post-retirement behaviours. Using longitudinal data from the Survey of Health, Ageing and Retirement in Europe, this study examines the effect of information technology usage on cognitive function, focusing specifically on internet usage. To address the endogenous relationship between cognitive function and IT usage, we adopt an instrumental variable approach that exploits variation in pre-retirement computer exposure due to the uneven computerisation of occupations across countries during the 1980s and 90s. Our results suggest moderating effects of IT usage on the cognitive decline of retirees. These results are concentrated amongst people who worked in middle-skill occupations, occupations that have previously been shown to have experienced large-scale computerisation.

KEYWORDS: Cognitive function; internet; computers; retirees

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1. Introduction

Across developed economies, the share of older people in the population is increasing. A feature of this increase is that more people are living substantially beyond retirement age, even while these retirement ages have been rising. Previous research has highlighted that retirement from the workforce is a critical period for cognitive function (Rohwedder and Willis, 2010; Bonsang *et al.,* 2012; Mazzonna and Peracchi, 2012; Celidoni *et al.,* 2017; Atalay *et al*., 2019). It is also well-known that cognitive function declines with age, and that cognitive function predicts a range of key health outcomes amongst older people. Atalay et al (2019) further demonstrate how certain behaviours, particularly mental activities, can have a moderating effect on post-retirement cognitive decline. Related to this, other studies have suggested a role of various forms of information technology in promoting behaviours that are protective of cognitive function. In practice, however, little is known about the relationship between IT usage and cognitive function over larger populations, and the existing evidence cannot typically be interpreted causally. Our study returns to this issue and aims to provide estimates of the effect of IT usage on the cognitive function of older people. We do this using a large, multi-country, longitudinal dataset, and we adopt empirical strategies that aim to provide estimates that can be interpreted causally.

Why might IT usage affect the cognitive function of older people? A range of potential benefits from computer usage have been highlighted such as the facilitation of routine tasks, access to information, entertainment, social connection, and mental stimulation, all of which have the potential to improve quality of life (Czaja *et al*., 1993, 2001; Jones and Bayen 1998; McConatha *et al*., 1994). The potential for computers to affect cognitive function has motivated a series of small scale experimental studies, primarily in psychology, to assess the effect of computer and internet usage on various outcomes such as loneliness, depression, physical functioning, and general life satisfaction (White *et al*., 2002; Shapira *et al*., 2007; Slegers *et al*., 2008, 2009). In general, these studies did not find a relationship between measures of computer competency or usage, and well-being. However, these results are difficult to interpret and generalise because of the non-random computer usage of older people, a lack of pre-study controls for personal characteristics salient to cognitive function, and also because these studies often utilise convenience samples drawn from older people living in community dwellings or nursing homes.

A related body of literature uses larger cross-sectional datasets to examine conditional associations between computer usage and life outcomes of older people. This literature has found mixed results. For instance, Lelkes *et al., (*2012) examines the European Social Survey and reports a positive and statistically significant association between regular internet usage and life satisfaction after controlling for many personal characteristics. Similar associations have been found using U.S. datasets such as the Health and Retirement Study (HRS) and Midlife in the United States (MIDUS) (Tun and Lachman 2012; Heo *et al*., 2015). At the same time, Elliot *et al*., (2014) found no association between computer usage and mental health using the National Health and Aging Trends Study for the US.

That computer-based activities might influence many aspects of older people's cognitive function such as attention, memory, spatial abilities, and problem solving has been widely discussed (see Rogers *et al.,* 2005). But relatively few studies have focused explicitly on the effect of computer usage on the cognitive function of older people. Earlier studies showed a positive effect of computer-based interventions on cognitive function (McConatha *et al.,* 1994). However, Slegers *et al.,* (2009), again in a small-scale experimental setting, found no effect of a training program and subsequent computer usage on cognitive function. In contrast, evidence from larger samples suggest a positive association between computer usage and cognitive function across adulthood when conditioning on a range of controls for personal characteristics (Tun and Lachman 2012; Slegers *et al.,* 2012). Overall, although there is a widespread belief that computer usage improves older people's cognitive function, the current literature provides mixed evidence.

The critical challenge in identifying the effect of computer usage on cognitive function is the endogenous nature of computer usage. The incidence and frequency of computer usage among older people reflects a range of factors that, themselves, are likely to be related to cognitive function. In the absence of an empirical strategy to address this endogeneity, it is unwise to interpret statistical associations between computer usage and cognitive function causally. For instance, omitted or inaccurately measured factors such as wealth and income are likely to influence both cognitive function and computer usage.[1] Likewise, there is a clear potential for reverse causality between cognitive function and computer usage.[2] This makes it difficult, for example, to interpret cross-sectional associations between computer usage and cognitive function. At the same time, panel fixed effects approaches which difference out individual time invariant characteristics are problematic because the changes in computer usage these approaches rely upon may be subject to a range of time varying biases. For example, decline in cognitive function may reduce the utility and ability of using computers amongst retirees.

We estimate the effect of computer usage on the cognitive function of retirees using a sample drawn from a large longitudinal dataset, the Survey of Health, Ageing and Retirement in Europe (SHARE). Partly due to measurement issues in the data, we focus on a particular form of IT usage: internet usage. Insofar as, during the time period in question, internet usage and IT usage are tightly linked. We view our estimates as informative about the effect of IT usage more generally. We focus on a specific sample of those who have been retired since at least 2004, and examine their cognitive function in 2015. Our choice of sample has two advantages. First, it reduces the influence of interconnections between computer usage, retirement decisions, and cognitive function on our estimates (Friedberg 2003; Banks *et al.*, 2010; Bonsang *et al.,* 2012; Mazzonna and Peracchi 2012). Second, the retirees in our sample embarked on careers before the general introduction of workplace computers that occurred from the 1980s onwards, and retired before computers became ubiquitous in workplaces (nonetheless, in robustness checks that follow, we examine the potential role for non-random post-retirement re-entry

[1] A range of research in gerontology and psychology attempts to explain the determinants of computer usage among older people (e.g. Zheng *et al*., 2015; Silver 2014). Education, income, health, and prior computer experience are predictive of computer usage among older people. Similarly, a mixture of qualitative and quantitative studies about the attitudes and perceptions of computer and internet usage among older people suggests that barriers to usage include the cost of equipment, learning difficulties, sceptical attitudes towards computers, lack of social connections, and physical and cognitive problems (Gatto *et al.,*2008; Lee *et al.,*2011).

[2] Recently, Kamin and Lang (2020) use the same waves of SHARE as in this paper to examine the relationship between cognitive function and internet usage of individuals. They use a cross-lagged panel analysis, and demonstrate a reciprocal relationship between cognitive function and internet usage, albeit one that is substantially stronger in the direction of earlier internet usage to later cognitive function.

into the labour force to affect our estimates). The timing of the computerization of workplaces motivates our instrumental variable strategy, where we rely on differential rates of computerization across occupations and countries that occurred during these individuals' working lives but that are unlikely to have been a feature of their original occupational choice. We use this within-career cross-country cross-occupation variation in pre-retirement computer usage as a source of exogenous variation in the likelihood of post-retirement internet usage. Our main empirical models control for prior cognitive function such that the exclusion restriction to our instrumental variable strategy is that past computer exposure does not directly influence changes in cognitive function *conditional on past cognitive function*. In summary, we demonstrate a robust effect of post-retirement internet usage that suggests that IT usage has a protective effect on the cognitive function of retirees. These results are concentrated amongst people who worked in middle-skill occupations, occupations that have previously been shown to have experienced large-scale computerisation. Together, this evidence suggests marked roles for IT usage in retirement in reducing the rate of cognitive decline.

In the next section, Section 2, we describe our data. In Section 3, we discuss our model. In Section 4, we present our main results. In Section 5, we present our robustness checks. Finally, in Section 6, we summarize our findings.

2. Data

Our data are drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE), a large longitudinal pan-European study that collects information about health, employment history, and the socio-economic status of older people. People aged fifty and older were eligible to participate in SHARE, which started in 2004. In our main analysis, we restrict our sample to participants observed in the first (2004), fifth (2013), and sixth (2015) waves of SHARE because these waves contain all the information necessary for our analysis. For example, the first wave contains detailed information about the previous occupations of the participants. While in the fifth and sixth waves, participants were asked about internet usage, computer skills, and computer (or a tablet) usage at their current job or their final job before retirement.[3]

While SHARE is a panel/longitudinal dataset and contains multiple measures of cognitive function for each participant at different points of time, there are only two observations of post-retirement internet usage. Furthermore, as we later discuss in detail, there is little within-individual variation in internet usage over time, and a concern is that the variation that does exist may result from time varying factors that cannot be addressed by methods that seek to difference out time invariant factors.

Appendix Table A1 shows the construction of our final sample. To reduce concerns about the endogeneity of retirement with respect to cognitive function, we restrict our sample to retirees only. Specifically, we restrict our sample to those who retired before the first wave of SHARE in 2004 and who did not later re-join the workforce.[4] As our IV strategy relies on variation in the introduction of computers in workplaces, we restrict our sample to those who retired after 1980. Extending our sample before that period risks conflating the effects of computerization of workplaces with the effect of age or socioeconomic group (e.g. only those working in highly specialized jobs would have used computers before 1980). As a result of our restrictions, the age of the participants in 2013 (Wave 5 of SHARE) ranges between 59 and 85. However, more than 95% of the participants were older than 65 in 2013.

Additionally, we also exclude those who had never worked from our main sample because we are concerned about how selection into this group might be correlated with cognitive function in later life. Furthermore, it is unclear why our instrument should influence computer usage amongst this group. In the Appendix that follows, we replicate our main analysis when relaxing the above restrictions to the definition of the main sample (see Table A6). We find that the overall pattern of results are essentially

[3] Specifically, participants are asked "'During the past 7 days, have you used the internet, for emailing, searching for information, making purchases, or for any other purpose at least once?". The question about computer usage in the final job asks, "Did your last job before retiring require using a computer?" where a computer could be a PC or a tablet. This question is only asked if participants had retired.
[4] Just 129 of those who retired before 2004 reported that they were working in 2013. Including these people in the sample made no significant difference to either our OLS or IV results.

unchanged by variations in sample choice. Likewise, we also find that the overall pattern of results is qualitatively similar regardless of changing our definition of retirement (e.g. people might declare themselves to be retired, even though they sometimes do paid work). We also exclude the very small number of individuals, fewer than 20, who worked in the ICT industry or in ICT professions. Again, this exclusion does not materially change any of the estimates of interest.

Our final sample consists of 2105 older people from across ten European countries: Austria; Belgium; Denmark; France; Germany; Italy; Israel; Spain; Sweden; and Switzerland. In later tables of results, we repeat the analysis that follows when excluding each country in turn and find that the overall pattern of results is not influenced by any particular country (see Table 8).

Throughout the analysis, our main outcome of interest is cognitive function measured at Wave 6 of SHARE in 2015. In SHARE, there are a range of measures of cognitive function relating to different aspects such as orientation, vocabulary, numeracy, verbal memory, etc. These are also asked in multiple waves. We focus on the word recall test in which older people are told a list of ten words and are then asked to recall the words immediately and then again after a delay of five minutes. While our main analysis focuses on the delayed word recall, in additional analyses, we also examined immediate word recall and alternative measures of cognitive function. From Table 1, we can see that the average number of words recalled was 3.38. This was a decrease from 2013, when the average number of words recalled was 3.48.

INSERT TABLE 1

The aim of our study is to examine whether computer usage among older people affects their cognitive function. In Table 1, we can see that 32% of older people reported using the internet during the past seven days. For these people, it is less likely that their internet usage is through using a smartphone or other mobile device. For instance, in 2012/2013 nearly 70% of older people in the UK reported using a desktop or laptop computer as their device to access internet (Matthews and Nazroo, 2015). From Table 1, we can also see that, on average, 30% of our sample used a computer in their final job before retirement. The relationship between pre-retirement computer usage and post-retirement internet usage forms the basis of our instrumental variable strategy that we discuss in the next section.

INSERT FIGURE 1

Figure 1 displays a range of patterns in both post-retirement internet usage and computer usage in the participant's final job before retirement. It shows that the proportion of internet users decreases with age and years since retirement. We can also see that the proportion of those who used a computer in their final job before retirement increases along the distribution of cognitive function, while decreasing with age and years in retirement. In relation to the income distribution, there is a "U"-shaped relationship between position in the distribution and internet usage. Usage is lowest among the second quartile. Furthermore, as can be seen in the Appendix, the frequency of internet usage in the ten European countries in our sample varies: no more than 12% report internet usage in Italy, but the figure is over 60% in Denmark.[5]

Table 1 also shows the descriptive statistics of the other covariates used throughout the analysis. In terms of life history, the average person in the sample was 75.3 years old in 2013; hence, they were born during the late-1930s. On average, they attended full-time education for 10.32 years. By Wave 5 of SHARE in 2013, they had been retired for an average of 15.79 years; hence, they had retired on average during the mid- to late-1990s. In terms of household characteristics, 67% of the sample were married or cohabiting, 20% were widows or widowers, and the remainder were single or divorced/separated. On average, there were 1.84 people in each household. 11% lived in a large city, 31% lived in rural areas, and the remainder lived in towns or suburbs. 76% owned their own home. The average annual income was €21,942 after adjusting for differences in prices between countries. Additionally, the descriptive statistics show generally poor health and variation in health behaviours among people in the sample. For example, average Body Mass Index was 26.92, and the average person visited their doctor 8.19 times in

[5] See Appendix Table A2 for more detail of cross-country differences in cognitive function. Later, in Table 8, we demonstrate that our results are not driven by the any particular country.

the previous year. 85% of the sample had at least one chronic disease. 11% were physically inactive; 11% had drank more than two glasses of wine or equivalent each day; and 45% were daily smokers at some point in their lives.

The final two columns of Table 1 show the difference in the means of these variables between those who use the internet versus those who do not. On average, internet users can recall 1.22 extra words on the recall test compared to non-internet users. However, internet users are also clearly different in other characteristics compared to non-users. They are more likely to be male, younger, better educated, and have been retired for a shorter period. Furthermore, internet users appear to be in better health, although they drink and smoke more. Most of these differences are statistically significant at standard levels. These differences motivate our multivariate analysis that aims to control for these observable differences. But these differences also suggest that unobservable factors influence internet usage; thus, the need for an empirical strategy to address this.

3. Methodology

For our initial estimates, we estimated the following value-added production function:

$$Y_{it} = \alpha_1 Y_{it-1} + \gamma Internet_{it-1} + \alpha_2 X_{it-1} + \varepsilon_{it} \quad (1)$$

In the fifth and sixth waves of SHARE, people were tested in immediate and delayed word recall, verbal fluency and numeracy. Hence Y_{it} is cognitive function measured at time *t* (at Wave 6 of SHARE in 2015) for individual *i*. Initially, we focus on the raw score and the standardized score of the delayed recall test.[6] In our main estimates, we adopt a specification where we include a lagged measure of cognitive function, Y_{it-1}, measured at Wave 5 of SHARE in 2013. A strength of this approach is to account for previous inputs, albeit imperfectly, by the inclusion of this lagged variable (see for instance, Todd and Wolpin 2003). A weakness is that it cannot account for individual heterogeneity in the *decline*

[6] As an alternative, we could estimate (1) using a log transformation of the dependent variable, but this transformation would result in the loss of 375 observations where individuals could not recall any words. In Appendix Table A5, we demonstrate that our results do not reflect the contribution of individuals with very low cognitive function.

in cognitive function that is fixed over time and which could be linked to internet usage. Andrabi et al. (2011) provide an instructive overview of value-added models and alternative models, albeit in the context of child development.

In additional estimates, we demonstrate that our main findings are robust to alternative functional forms with respect to past cognitive function. $Internet_{it-1}$ is a binary variable indicating whether an individual used the internet for e-mailing, searching for information, shopping, or for any other purpose at least once during the seven days before the survey took place. Thus γ is the main parameter of interest. X_{it-1} is a vector of individual level characteristics used to control for demographics, life history, health status, and household conditions. A full list of these controls is included as notes to the main tables of estimates (see, for instance, Table 2). The demographic and life history variables include gender, age, country of survey, years of education, and years since retirement. The measures of health status are Body Mass Index, the number of visits to a doctor per year, whether the participant has long-term chronic diseases, whether the participant drinks more than two glasses of wine or equivalent every day, and whether the participant ever smoked every day. The measures of household characteristics were marital status, household size, living in urban or rural areas, home ownership, and annual household income.[7] A concern with a number of these variables is that they themselves might be a function of internet access and/or prior cognitive function. In this way, they might constitute 'bad controls' (Angrist and Pischke, 2008). In our empirical analysis, we examine the robustness of our results to the inclusion of controls that could, conceivably, be outcomes themselves.

It is important to note that non-random variation in internet access and usage means that γ cannot be readily interpreted as a causal effect. Unobservable factors that influence internet usage are likely to also influence the rate of cognitive decline. Additionally, there might be feedback between cognitive function and internet usage. Those with lower levels of cognitive function might be less likely to use the

[7] In our main specification, the measure of income is a multi-stage imputed measure obtained by an aggregation at the household level of all individual income components. Additional information about the imputation procedure can be found in De Luca *et al.,(*2015).

internet. These problems motivate our use of an instrumental variable strategy. As a source of variation in post-retirement internet usage, we rely upon individuals' work history, motivated by the non-uniform computerization of occupations that occurred from the 1980s onwards, as documented in a large literature (see for instance, Autor *et al.*, 1998, 2003, 2015).[8] The intuition behind our strategy follows from two main observations. First, those in the SHARE sample began working during the 1950s and 1960s, long before the computerization of workplaces that occurred from the 1980s onwards. Hence, these people are likely to have made important career decisions before expectations of computerisation could reasonably have been formed.[9] Second, this computerisation, while not random, was unevenly spread across the distribution of jobs. Thus, we observe variation in work-life exposure to computers which is likely to affect post-retirement internet usage.

In practice, we observe computer usage in the participant's final job before retirement as measured by the following question: "Did your last job before retiring require using a computer?" A concern is that while differences in computer usage between occupations might be random with respect to individuals' original job choices, individual variation in actual computer usage within occupation might be non-random. For instance, people might be sorted into workplaces, or into specific tasks within workplaces, based on their computer aptitude, and this aptitude could be related to later cognitive function. To mitigate the effects of this type of sorting, we generate a variable, $Exposure,$ as the average computer usage in the participant's final occupation where the average values were generated from the SHARE data (excluding the i^{th} individual) and are specific to the country and year of retirement of the participant[10], to incorporate differential computerisation rates across Europe.[11]

[8] As noted by Bresnahan (1999), the diffusion of computer technology started to increase after the late 1950s. After which, personal computers (e.g. Apple II in 1977, IBM in 1981) emerged and spread.
[9] Also, it is unlikely that these older people, or most of them, would have trained in computing while in school or university.
[10] In our main specifications, we do this on the basis of banded years of retirement (numbers in each group in parentheses): 1980-1989 (130), 1990-1994 (474), 1995-1999 (699), and 2000-2004 (802).
[11] Ideally, we would utilize information from external sources rather than from within the SHARE data. Unfortunately, to our knowledge, no such data exist at a fine enough level of disaggregation. The only pan-European survey data with questions about IT usage we can identify is the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, but these data are incomplete for some countries and, crucially, only dates from the mid-2000s.

Our Instrumental Variable strategy is to estimate the following set of equations:

$$Y_{it} = \alpha_1 Y_{it-1} + \gamma Internet_{it-1} + \alpha_2 X_{it-1} + \varepsilon_{it} \quad \text{(2a)}$$

$$Internet_{it-1} = \beta_1 Y_{it-1} + \vartheta Exposure_i + \beta_2 X_{it-1} + \mu_{it} \quad \text{(2b)}$$

The most important feature of equations (2a) and (2b) is that, when combined with our control for prior cognitive function, our exclusion restriction is that pre-retirement computer usage does not directly influence the rate of post-retirement cognitive decline, holding cognitive function at time *t-1* constant. Controls for prior cognitive function along with controls for education mean that exposure should not be a function of, for instance, the skill level of the worker. Later, we demonstrate that our IV results are concentrated amongst workers in middle-skill occupations. This fits with the idea that it is these middle-skill workers who were most likely to have had shocks to computer usage during their working life. While later we provide further descriptive information showing the uneven spread of computerisation across industries and occupational groups, Figure A1 provides summary information on computerisation rates at time of retirement by country and occupation. This figure reveals two points. Our instrument will have little power for low skill occupations, and there is marked cross-country variation in occupational computerisation. The latter leads us to later provide estimates which seek to assess the robustness of our results to excluding particular countries (see Table 8).

An additional concern are differences in retirement age patterns across individuals. Our main strategy is to focus solely on those who retired before 2004 and did not return to work. Hence, our sample have all been retired for several years before our main period of analysis. Thus, we address the likely effects of endogenous retirement that has been a focus of recent literature (Banks *et al*., 2010; Mazzonna and Peracchi 2012). In further robustness checks (see Appendix Table A5), we examine alternative treatments of the timing of retirement, and years since retirement, and we find the same pattern of results.

We allow for within-group clustering when calculating standard errors. For Equation 1, which is estimated using OLS, the standard errors are clustered at the household level reflecting the household nature of the survey. For Equation 2a and Equation 2b, which are estimated using IV, the standard errors are clustered at country and ISCO level to account for the construction of the instrumental variable, pre-retirement computer exposure.

4. Initial Results

Table 2 provides initial estimates of (1) and provides the association between internet usage and the delayed recall test. In the first two columns, the sample includes both men and women. The estimates indicate that people who use the internet after they retired can recall 0.271 more words in the delayed Frecall test.[12] To aid interpretation of the magnitude of this relationship, the second column presents a corresponding estimate where the dependent variable is instead the standardized number of words. The results show that internet usage is associated with an increase of around 0.129 of a standard deviation in the delayed recall test.

INSERT TABLE 2

Table 2 also reports selected coefficients of other covariates. In general, the signs of the coefficients fit with expectations. Current cognitive function is strongly related to cognitive function two years previous. Cognitive function declines with age but is positively correlated with education and income. There are substantial gender differences in cognitive function with males having 0.134 (approx. 2/3 of a word) of a standard deviation reduction in cognitive function. This gender difference motivates us to estimate models separately for men and women. The middle and right panels of Table 2 display

[12] Appendix Table A3 shows that, without conditioning for other variables, internet usage is associated with a 0.582 standardized deviation increase in the delayed word recall test, approximately 1.23 more words recalled from a list of ten words. Controlling for education decreases the size of the coefficient. The inclusion of additional controls has little effect on estimates of our parameter of interest. In particular, health and household characteristics leave the main result essentially unaffected. This is worth noting as these variables might be viewed as bad controls. We highlight that, in practice, their inclusion does not change our main results. This remains true for all additional models. Finally, adding cognitive function tested two years prior decreases the coefficient considerably.

the estimated coefficients when we split the sample by gender. We can see in these panels that the size of the internet usage coefficient is larger and statistically significant only for women.

As discussed above, non-random patterns of home computer ownership and internet usage present a challenge to the interpretation of these estimates. We use computer usage in pre-retirement jobs as a source of exogenous variation in the likelihood of post-retirement internet usage. Figure 2 shows the variation at occupation-level in average computer usage in the participants' final jobs before retirement. Computer usage was widespread across a range of professional, technical, and managerial jobs. Beyond these jobs, there is lot of variation in pre-retirement exposure by occupation. This fits with a view of occupational spread of computerisation that was not simply a function of worker skill level. It is this variation in computerisation that provides us with variation conditional on prior cognitive function and education level.

Figure 3 provides similar information focusing on industries rather than occupations.[13] Industries which experienced a high exposure to computers were financial services and research and development.[14] Most manufacturing jobs are near the middle range of our ranking of computer usage. On the other hand, computers were rarely used in industries such as recycling and agriculture. Figure 2 and Figure 3 also show that pre-retirement computer usage in work is highly correlated with post-retirement internet usage. In general, people who rarely used a computer in their final job have lower rates of post-retirement internet usage.

INSERT FIGURE 2

INSERT FIGURE 3

[13] Country specific versions of Figures 2 and 3 are reported as Figures A1 and A2 in the Appendix.
[14] Unsurprisingly, the computer and related services industry ranks the highest in average pre-retirement computer usage in the workplace with over 80% of those workers having used a computer at work before retiring, a percentage far higher than the overall average of 26%. We exclude this group from our main analysis, but when we re-estimated our main OLS and IV estimates including those working in the computer industry, our results were largely unaffected.

As discussed earlier, rather than utilising individual pre-retirement computer usage, we rely upon country-occupation-year of retirement variation in pre-retirement computer usage (in last job) as a source of exogenous variation in post-retirement internet usage. Table 3 presents the resultant estimates from using this an instrument for current internet usage and correspond to equations (2a) and (2b). The bottom panel reports the first stage coefficient of country-occupation-year specific average pre-retirement computer usage on current post-retirement internet usage. This coefficient is of a large magnitude: those who retire from a specific occupation in specific country and year are 23.2 percentage points more likely to use the internet after they retire if their workplace was completely computerised relative to those who came from a workplace that was completely non-computerised. The effect of average computer usage in pre-retirement work increases the likelihood of using the internet by between 21.6 and 23.9 percentage points depending on whether we split the sample by gender. This coefficient is statistically significant at the 1% level, even conditional on a variety of individual characteristics relating to prior cognitive function, income, education, health, and the household, and passes standard thresholds for weak instruments.[15]

INSERT TABLE 3

The top panel of Table 3 reports the IV estimates of the effect of internet usage on word recall, where again we report these estimates for the entire sample and for separate samples of men and women only. These estimates reveal positive effects that are larger than the OLS estimates. These are large effects, and we discuss this in more detail later. For instance, the pooled estimates suggest that internet usage increases word recall by over one and a half words. These estimates also reveal gender differences. Women who use the internet can recall 2.370 more words than similar women; whereas men who use

[15] A fuller set of first stage coefficients is shown in Appendix Table A4. Because the endogenous variable is binary, we also display the marginal effects from a logistic regression. As one can see, the average marginal effect of our instrumental variable from the logistic regression is a little smaller than coefficient in the linear probability models, but is nonetheless around the same magnitude as the LPM coefficients. The average marginal effects of the other variables in the logistic regression are more or less the same as the LPM coefficients.

the internet can recall about 0.938 more words than similar men. Notably, the IV estimates for men are not statistically significant.

We sought to further examine the potential for consequent selection on unobservables remaining in our IV strategy using the test set out by Oster (2019).[16] These tests reveal that the degree of selection on unobservables required for our IV estimates to be zero are in the order of 1.127 times as large as the degree of selection on observables.

5. Robustness

5.1 Alternative Outcomes, Specifications, and Covariates

We have shown that internet usage amongst retirees increases cognitive function, focusing on delayed word recall. In this section, we explore a range of further estimates to assess the robustness of these findings across alternative outcomes and empirical specifications.

First, while we have focused on delayed word recall, alternative measures of cognitive function are available in SHARE. For example, immediate word recall is also available. This measure of cognitive function is similar to delayed word recall with the obvious difference that participants say the words they remember immediately after the list is read out. Estimates of the effect of internet usage on immediate word recall, estimated by OLS and IV, are reported in Panel A of Table 4. For women, these results have a similar pattern to those in previous tables. For men, the OLS estimate of the effect of internet usage on immediate recall is statistically significant whereas it did not have a significant effect on delayed recall. In relation to the IV estimates for men, the estimated effect of internet usage on immediate recall are larger than the OLS estimates but were not statistically different from zero. In Panel B of Table 4, we show the effect of internet usage on the sum of immediate and delayed recall. This sum is often used as a measure of memory in the literature (e.g. Banks and Mazzonna, 2012). From the OLS

[16] Built on Altonji et al., (2008), Oster derived a general estimator under proportional selection (where selection on unobservables is proportional to the degree of selection on observables) with a coefficient of proportionality δ. Under the assumption that the unobservable and the observables are equally related to the treatment variable, the bias-adjusted estimate is approximately given by: $\beta *= \hat{\beta} - (\beta' - \hat{\beta})(R_{max} - \hat{R})/(\hat{R} - R')$ where $\widehat{\beta}$ and $\hat{R}$ are the coefficient estimate and R square from the controlled regression, and $\beta'$and R' are from the uncontrolled regression.

and IV estimates, we see that internet usage increases the sum of immediate and delayed recall by 0.151 and 0.729 of a standard deviation.

Next, in Panel C, we show estimates of the effect of internet usage on verbal fluency as measured by the animal naming test. In the animal naming test, participants must name as many animals as they can within one minute. Successful performance on this test requires word knowledge, self-initiated activity, organisation, and abstraction (e.g. categorising animals into groups such as domestic, wild, birds, dogs, etc.), and mental flexibility (e.g. moving to a new category when no more animals come to mind from a previous category). We can see from Panel C that internet usage has a positive effect on verbal fluency as measured by the standardized score in the animal test. Compared to using OLS, the effect is larger, but less precisely estimated using IV.

INSERT TABLE 4

Next, we examine the robustness of our results to a variety of alternative model specifications and control variables. In the upper panel of Table 5, we report estimates of two models that make different assumptions to the baseline value-added model. Alternative Model A simply removes the control for prior cognitive function. In comparison with our baseline value-added model, under Alternative Model A, the effect of internet usage is more than twice as large for the OLS estimate and one and a half times larger for the IV estimate. This result suggests that the lagged dependent variable in the baseline model captures unobserved characteristics which affect both internet usage and cognitive scores.

In Alternative Model B, we regress cognitive function in 2015 (Wave 5 of SHARE) on post-retirement internet usage in 2015. That is, we no longer control for lagged post-retirement internet usage as we do in the other models, instead we control for contemporaneous internet usage. Here, in Alternative Model B, we see that the OLS estimate is bigger but the IV estimate is smaller than the corresponding estimates in the baseline model. However, in both cases the estimates of Alternative Model B are of a similar magnitude to when we include lagged post-retirement internet usage. This similarity suggests that reverse causality from cognitive function to internet usage might not be a substantial source of bias.

While our estimates in the top panel Table 5 show that our results are robust to different models, one might question whether first difference or fixed effects models could be used to elucidate the relationship between cognitive function and internet usage. While we have two waves of post retirement internet usage data, in practice there is little variation in individual responses across this two year period. 92% of participants did not change their internet usage from Wave 5 to Wave 6. Of the 8% who did change internet usage, about two thirds started using and about one third stopped using the internet. This lack of change in internet usage motivates our use of a lagged model rather than a first difference model. Moreover, for those who do change, a concern is that this change may reflect time-varying shocks, for instance reverse causality from cognitive decline or a more general decline in health. While our instrument, pre-retirement computer exposure, is relevant for post-retirement internet usage more generally, our instrument does not explain time-varying unobservables that determine changes in internet usage during retirement.

Additionally, we used the approach set out in Conley et al. (2012) to assess the sensitivity of our main IV estimates to violations of the exclusion restriction. The critical threshold for our results to hold at a 95% level is a direct effect of plus or minus 0.08.

The lower panel of Table 5 demonstrates the robustness of our main estimates to a range of alternative controls, such as household assets, years since reaching national statutory retirement age, measures of depression, and partner's age and education. All of these controls are potential confounding factors, although one must be careful when interpreting the resultant estimates because, again, these control variables themselves could be influenced by cognitive function and hence could be considered 'bad controls'. With this said, the estimates of interest are largely unaffected by the inclusion of these alternative controls. The only exception are models where we include both measures of depression and partner's education and age. In those models, while OLS estimates are unchanged, the IV estimates are smaller and are not statistically significant even at the 10% level.

INSERT TABLE 5

In Table 6, we further investigate the role of different skilled jobs in post-retirement internet usage. Notably, the growth in workplace computerisation was concentrated in high skill occupations, but also in medium skill occupations where jobs consisted disproportionately of tasks that were routine in nature and hence more readily replicated by algorithm (Autor et al. 2003). We sorted occupations into four skill-level groups according to ISCO (International Labour Organisation, 1990) classification: elementary; medium-level; technicians and associate professionals; and professionals. Table 6 reports OLS and IV estimates for these four occupational groups. Splitting the sample into smaller groups raises the problem of small sample sizes. For example, for the elementary group, the OLS estimate is large and negative, but the IV estimate is large and positive. Both estimates are very imprecise. Across the other groups, OLS estimates reveal a positive relationship between internet usage and cognitive function, a relationship largest amongst middle skill workers. However, the IV effects are precisely estimated only amongst medium skill workers where the instrument is a strong predictor of internet usage for this group only. These results fit with the interpretation of the local average treatment effect estimated by our IV strategy described earlier. People who otherwise might not have been exposed to computers are those who benefit from internet usage. Higher skilled workers are more likely computer adopters even in the absence of workplace exposure. In this sense, they could be viewed as always-takers who do not contribute to the identification of the IV estimates. While low skill workers were, in general, not exposed to computers through work during their career and do not contribute to these estimates. While we argue this makes sense, it also raises caveats regarding our results. Naturally, we cannot say anything causal about these always-takers, nor can we say anything about those not exposed to the instrument. At the same time, one other aspect of the process of computerisation of routine jobs is the reduction of employment in medium skill jobs and movement into lower skill jobs, although the extent of this varies by country (Goos et al., 2008).

INSERT TABLE 6

5.2 Heterogeneity

Another related issue is that our estimates might be disproportionately generated by people from socio-economically advantaged backgrounds. For example, people with more schooling or greater ability are more likely to select skilled occupations that involve more computer usage, and their health outcomes, including cognitive function, are likely to be better irrespective of computer usage. To investigate this issue, we estimated our models separately across education qualifications using three combined categories of the International Standard Classification of Education (ISCED). These estimates are presented in Table 7. When we stratify by education, for the sake of precision, we estimate models pooled across genders. OLS estimates in Table 7 suggest that internet usage increases cognitive function across all three educational categories. There is some indication that these effects, while present, are smaller for people with tertiary education as their highest qualification. On the other hand, the IV estimates suggest that internet usage affects those with secondary education, but the effect is not statistically significant for the least and most educated group. Some caution must be taken as these estimates, particularly the IV estimates, are quite imprecise and the confidence intervals overlap for the primary and secondary educational categories.

INSERT TABLE 7

A second concern is the potential for age to affect attitudes towards technology and to affect cognitive function. Younger cohorts might have more positive attitudes towards new technology, and they were more exposed to technological change in the workplace after the 1980s. This is confirmed in our data in which we observe that 44% of people younger than 70 in 2013 reported using the internet; whereas, only 27% of people older than 75 reported using the internet. In unreported estimates, we find very little variation in either OLS or IV estimates when we omit certain groups, for instance younger individuals (59-70) or older individuals (80+).[17] Likewise, we examined robustness to excluding those more recently retired (<10 years) or those who had been retired for a long time (20+ years). Again, there was little indication of variation by years since retirement. These results for age and retirement are

[17] Estimates available from the authors.

additionally helpful in so for as our results were largely unchanged in younger (< 70) and shorter retirement period (< 15 years) groups where attrition due to death and incapacity will be less of a problem.[18]

Another concern relates to country variation. For example, in Appendix Table A2, one can see that Spain and Italy's average cognitive function scores are below average and the proportion of people using computers in these countries is much lower than in other countries. Although our main empirical models include country fixed effects, one might be concerned that the main estimates disproportionately reflect the effect of particular countries. In Table 8, we estimate our main models, by OLS and IV, omitting each country one-by-one. Table 8 demonstrates that our results do not appear to reflect the role of specific countries.

Lastly, we carried out a number of robustness checks related to the definition of the sample under analysis. These checks are summarised in Appendix Table A5. In our main models, we excluded specific groups who either might have substantially different patterns of computer usage and cognitive function and/or for whom our instrumental variable strategy is less likely to be applicable. However, in Appendix Table A5, we display results where we include those specific groups in our analysis. We can see that the estimated effect of post-retirement internet usage on cognitive function is largely stable regardless of the sample restrictions that we make. First, in column 1, we re-estimated our models including people who never worked. Clearly, these people cannot have been directly affected by computerisation patterns in the workforce, so they do not contribute to identifying the IV estimates. Second, in column 2, we included people who claimed to have retired before SHARE began, but who still reported that they had done some paid work around the time of the SHARE survey. These people might be quite different from the rest of the sample. For example, they might have retired early for some reason and/or have returned

[18] To address concerns about attrition, we generated our own weights using the inverse probability of individuals being observed in the later waves conditional on initially (in Wave 1) being in our working sample. We report weighted OLS results as column 10 of Appendix Table A3 and find that the weighted estimate is similar to the unweighted estimate. Furthermore, the unreported IV estimate of the effect of computer usage on the standardized value of delayed recall is 0.825 with a standard error of 0.293 – a result very close to the unweighted IV result of 0.759.

to work because their health was much better than expected at their age. In column 3, we included people younger than 59 or older than 85 in 2013 regardless of timing of retirement. On the one hand, we are concerned about younger people because they might have retired early due to negative health shocks which, in turn, might affect their post-retirement cognitive function and internet usage. On the other hand, we are concerned about much older people in our sample because of the potential relationship between cognitive function and longevity at older ages.

In column 4, we include people who have been retired for more than thirty years, even though these people likely retired before the introduction of computers into workplaces. Additionally, in column 5, we restrict our sample to those who retired between 1980 and 1999. Specifically, we restrict the sample to those who retired before the millennium because of concerns that, by then, computers were ubiquitous. However, on close inspection, among the 802 people who retired between 2000 and 2004 (when SHARE began), 43.1% used a computer in their final job. So computers were not quite yet ubiquitous between 2000 and 2004. Finally, in column 6 of Appendix Table A5, we show our estimates when restricting the sample to over 65s only. On the one hand, restricting the sample to over 65s might address concerns about the endogeneity of early retirement relative to cognitive function. On the other hand, these data are drawn from throughout Europe, so there might be considerable variation in mandatory retirement ages by gender, cohort, country, sector, and occupation. Overall, one can see from the first six columns of Appendix Table A5 that the OLS and IV estimates of the effect of post retirement internet usage on cognition is similar regardless of the sample that we use.

Finally, those with particularly low cognitive function might both perform poorly on cognitive tests but also provide unreliable answers about internet usage and other survey questions. We re-estimated our main models excluding individuals who were in the bottom 20% of the cognitive function distribution (in terms of word recall) in 2013. Omitting this group (see column 7 of Table A5) does not markedly change our results.

6. Conclusion

Cognitive decline amongst older people is a leading indicator of a range of negative outcomes. This study examined the role of information technology, specifically internet usage, in influencing the cognitive function of people after retirement. In a large-scale multi-country setting, we estimate a value added model which demonstrates a positive association between internet usage and cognitive function. Furthermore, we adopt an instrumental variable strategy based on pre-retirement workplace exposure to computers to provide estimates of the effect of post-retirement IT usage on cognitive function. In this way, we go beyond existing correlational studies regarding how technology affects the well-being of older people.

We demonstrate that internet usage has substantial effects on the cognitive function of older people. Our IV estimates suggest that internet usage increases word recall by approximately 0.759 of a standard deviation. These results are larger for women, and are robust to a range of alternative measures of cognitive function, sample selection, functional form, and potential violations of our exclusion restriction. These results are concentrated amongst people who worked in middle-skill occupations, occupations that have previously been shown to have experienced large-scale computerisation. In practice, these effects could be generated by a range of mechanisms and future research should focus on identifying the specific mechanisms through which IT usage influences the cognitive function of retirees.

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Table 1: Summary statistics

	Mean	Std. dev.	Min.	Max.	Average difference between internet users and mean of non-users	p-value of difference by internet usage
Cognitive function:						
Delayed word recall (2015)	3.38	2.10	0	10	1.22	0.000***
Delayed word recall	3.48	2.06	0	10	1.33	0.000***
Computer usage:						
Uses internet (post-retirement)	0.32	0.47	0	1		
Used computer in final job (pre-retirement)	0.30	0.46	0	1	0.43	0.000***
Demographics and life history:						
Male	0.51	0.50	0	1	0.10	0.000***
Age	75.3	5.12	59	85	-1.82	0.000***
Years of education	10.32	4.42	0	25	3.58	0.000***
Years retired	15.79	4.76	9	30	-2.00	0.000***
Household characteristics:						
Married or living with partner	0.67	0.47	0	1	0.02	0.000***
Widow(er)	0.20	0.40	0	1	-0.05	0.007***
Household size	1.84	0.70	1	7	-0.03	0.320
Resides in large city	0.11	0.32	0	1	0.05	0.002***
Resides in rural area	0.31	0.46	0	1	-0.12	0.000***
Home owner	0.76	0.43	0	1	0.03	0.179
Total annual household income in euro	21942	31225	0	895719.1	4055.3	0.003***
Health:						
Body mass index	26.92	4.46	16.0	54.3	-0.79	0.000***
Number of visits to doctor	8.19	9.63	0	96	-1.17	0.006***
Has long-term chronic disease	0.85	0.35	0	1	-0.05	0.002***
Physically inactive	0.11	0.32	0	1	-0.06	0.000***
Ever drank more than two glasses of wine daily	0.11	0.32	0	1	0.03	0.062*
Ever smoked every day	0.45	0.50	0	1	0.07	0.003***

Notes:
N=2105
* significant at 10% level; ** significant at 5% level; ***significant at 1% level.
All values are for 2013 unless otherwise indicated

Table 2: OLS estimates of the effect of internet usage on cognitive test score

Y_t: Delayed recall test score (2015)	***All observations***		***Men only***		***Women only***	
	$\boldsymbol{Y_t}$	$\boldsymbol{Standardized\ Y_t}$	$\boldsymbol{Y_t}$	$\boldsymbol{Standardized\ Y_t}$	$\boldsymbol{Y_t}$	$\boldsymbol{Standardized\ Y_t}$
Uses internet (d=1)	**0.271*** **	**0.129*** **	**0.105**	**0.050**	**0.503*** **	**0.239** **
	(0.095)	**(0.038)**	**(0.131)**	**(0.062)**	**(0.138)**	**(0.076)**
Y_{t-1} (2013)	0.477***	0.467***	0.492***	0.482***	0.458***	0.449***
	(0.022)	(0.039)	(0.031)	(0.059)	(0.030)	(0.037)
Age	0.106	0.050	-0.088	-0.042	0.307	0.145
	(0.176)	(0.077)	(0.240)	(0.106)	(0.247)	(0.110)
$Age^2/100$	-0.104	-0.050	0.029	0.014	-0.246	-0.117
	(0.118)	(0.052)	(0.161)	(0.075)	(0.167)	(0.074)
Men	-0.283***	-0.134**				
	(0.086)	(0.048)				
Years of education	0.037***	0.017**	0.039***	0.018***	0.037**	0.017
	(0.011)	(0.006)	(0.014)	(0.006)	(0.016)	(0.010)
Income (25%-50%)	-0.300*	-0.143*	-0.180	-0.086	-0.324	-0.154**
	(0.167)	(0.064)	(0.234)	(0.113)	(0.220)	(0.053)
Income (top 25%)	0.037	0.017	0.221	0.105	-0.062	-0.030
	(0.194)	(0.070)	(0.274)	(0.115)	(0.263)	(0.076)
R-squared	0.380		0.362		0.411	
N	2105		1071		1034	

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at household level (n=1881) in parentheses. 1071 clusters for men and 1033 for women. Regressions also control for years retired, health status, household characteristics, country fixed effects and retirement year fixed effects. Health status comprised standardized body mass index, standardized number of doctor visits, whether has long-term chronic disease, whether physically inactive, whether drinks (more than two glasses) every day, and whether smokes every day. Household characteristics comprised marital status, household size, living in city, town or countryside, home ownership, and quartiles of total household income (transformed using PPP index).

Table 3: IV estimates of the effect of internet usage on cognitive test score

Y_t: Delayed recall test score (2015)	**All**	**Men**	**Women**
Uses internet (d=1)	**1.598*** **	**0.938**	**2.370*** **
	[0.759]	[0.446]	[1.126]
	(0.534)	(0.937)	(0.755)
Y_{t-1} (2013)	0.423***	0.457***	0.383***
	(0.037)	(0.074)	(0.036)
Age	0.173	-0.003	0.288
	(0.163)	(0.264)	(0.199)
$Age^2/100$	-0.139	-0.020	-0.224*
	(0.108)	(0.181)	(0.134)
Men	-0.488***		
	(0.126)		
Years of education	0.007	0.017	0.001
	(0.013)	(0.023)	(0.016)
Income (25%-50%)	-0.306***	-0.175	-0.337**
	(0.107)	(0.222)	(0.147)
Income (top 25%)	0.413***	0.142	-0.297
	(0.158)	(0.297)	(0.247)
IV first-stage coefficient			
ISCO-country-year computer usage	0.232***	0.216***	0.239***
mean in final job before retirement	(0.039)	(0.049)	(0.038)
Reduced-form coefficient			
ISCO-country-year computer usage	0.370***	0.202	0.566***
mean in final job before retirement	(0.139)	(0.223)	(0.203)
Kleibergen-Paap F statistic	35.83	19.46	38.68
R-squared	0.317	0.335	0.301
N	2105	1071	1034
N (country clusters)	10	10	10
N (ISCO clusters)	362	284	221

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
ISCO-country-year computer usage mean is the average proportion who used a computer in their final job before retirement by 33 two-digit ISCO codes, ten countries and four retirement periods (1980-1989, 1990-1994, 1995-1999, 2000-2004).
Estimates where outcome is standardized measure of cognition are shown in square brackets.
Robust standard errors clustered at country and occupational level (ISCO code) are in parentheses.
Coefficients of selected controls variables are shown, but the estimated models included the same control variables as per Table 2.

Table 4: Effect of internet usage on other measures of cognitive function

Panel A	***Immediate word recall (2015)***					
	All observations		***Men only***		***Women only***	
	OLS	***IV***	***OLS***	***IV***	***OLS***	***IV***
Uses internet (d=1)	**0.211*****	**0.715*****	**0.168*****	**0.446**	**0.263*****	**1.170*****
	(0.044)	**(0.207)**	**(0.059)**	**(0.316)**	**(0.070)**	**(0.440)**
N	2105		1071		1034	
Kleibergen-Paap F statistic		36.78		21.50		36.42

Panel B	***Sum of immediate and delayed recall (2015)***					
	All observations		***Men only***		***Women only***	
	OLS	***IV***	***OLS***	***IV***	***OLS***	***IV***
Uses internet (d=1)	**0.151*****	**0.729*****	**0.083**	**0.414**	**0.242*****	**1.167*****
	(0.042)	**(0.230)**	**(0.057)**	**(0.392)**	**(0.065)**	**(0.348)**
N	2105		1071		1034	
Kleibergen-Paap F statistic		37.72		21.43		37.78

Panel C	***Verbal fluency (2015)***					
	All observations		***Men only***		***Women only***	
	OLS	***IV***	***OLS***	***IV***	***OLS***	***IV***
Uses internet (d=1)	**0.152*****	**0.429***	**0.215*****	**0.460**	**0.081**	**0.477***
	(0.041)	**(0.249)**	**(0.061)**	**(0.336)**	**(0.057)**	**(0.267)**
N	2105		1071		1034	
Kleibergen-Paap F statistic		40.89		24.38		42.01

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at household level are in parentheses in OLS estimation.
Robust standard errors clustered at country and occupational level are in parentheses in IV estimation.
All controls are as per Table 2.
Scores were standardized.

Table 5: Alternative specifications and alternative control variables

Upper panel: Alternative specifications	**Baseline Model Y_t**		**Baseline Model Standardized Y_t**		**Alternative Model A Standardized Y_t**		**Alternative Model B Standardized Y_t**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**
Uses internet (d=1)	**0.271*****	**1.598*****	**0.129*****	**0.759*****	**0.314*****	**1.164*****	**0.191*****	**0.717*****
	(0.095)	**(0.759)**	**(0.038)**	**(0.254)**	**(0.049)**	**(0.240)**	**(0.044)**	**(0.235)**
Prior cognitive score	✓	✓	✓	✓			✓	✓
R-squared	0.380	0.317	0.380	0.317	0.212	0.064	0.383	0.338
N	2105		2105		2105		2105	
Kleibergen-Paap F statistic		35.83		30.74		30.74		32.36
Lower panel: Alternative controls	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**
Uses internet (d=1)	**0.136*****	**0.878*****	**0.113*****	**0.709*****	**0.127*****	**0.746*****	**0.125****	**0.578**
	(0.045)	**(0.273)**	**(0.046)**	**(0.264)**	**(0.045)**	**(0.251)**	**(0.056)**	**(0.378)**
Alternative controls								
Household asset	✓	✓						
Years since statutory retirement age			✓	✓				
Depression score					✓	✓	✓	✓
Partner's age and education							✓	✓
R-squared	0.377	0.289	0.381	0.325	0.381	0.316	0.373	0.331
N	2088		2014		2105		1405	
Kleibergen-Paap F statistic		38.06		29.86		35.41		43.46

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at household level are in parentheses in OLS estimation.
Robust standard errors clustered at country and occupational level are in parentheses in IV estimation.
The upper panel shows alternative specifications. In Alternative Model A, we do not control for prior cognitive function. In Alternative Model B, we control for Wave 6 internet usage rather than lagged (Wave 5) internet usage.
In the lower panel, the outcome variable is standardized score of the delayed word recall test in 2015. The lower panel shows alternative controls such as retirement year, household net worth, depression scores (EURO-D) in the year 2004, and partner's information

Table 6: OLS and IV estimates by occupation

Outcome: standardized delayed word recall (2015)								
	Elementary		***Medium***		***Technicians & associate profs***		***Professionals***	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**
Uses internet (d=1)	**-0.174**	**2.243**	**0.121***	**0.653****	**0.071**	**0.512**	**0.075**	**-0.927**
	(0.189)	**(3.424)**	**(0.070)**	**(0.309)**	**(0.106)**	**(2.872)**	**(0.092)**	**(1.966)**
Mean: delayed word recall	2.49		3.10		4.00		4.35	
Mean: uses internet	0.10		0.22		0.49		0.56	
Mean: used computer in final job	0.04		0.22		0.50		0.46	
N	235		1016		317		486	
Kleibergen-Paap F statistic		0.52		134.94		0.49		1.10

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at household level are shown in parentheses in OLS estimation.
Robust standard errors clustered at country and ISCO level are shown in parentheses in IV estimation.
All controls are as per Table 2.
Occupation skills level is defined by the International Labour Organization (ILO). “elementary” group covers occupations whose main tasks is selling goods in the street, door keeping, cleaning, or labouring in agriculture, fishing, mining, construction and manufacturing. “technician and associate professionals” group includes occupations whose main tasks require technical knowledge and experience in one or more fields of physical and life sciences, or social sciences. “medium” group includes clerks, service workers, shop sales assistants, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators and assemblers. “professionals” group includes occupations whose main task require a high level of professional knowledge and experience such as professionals, legislators, senior officers and managers. More details are in Table A6.

Table 7: OLS and IV estimates by education

Outcome: standardized delayed word recall(2015)						
	ISCED categories					
	Pre-primary & primary		**Secondary**		**Bachelor & above**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Uses internet (d=1)	**0.147**	**0.511**	**0.136****	**0.585****	**0.031**	**11.52**
	(0.091)	**(0.404)**	**(0.066)**	**(0.289)**	**(0.098)**	**(41.12)**
Mean: delayed word recall	2.56		3.63		4.32	
Mean: uses internet	0.13		0.37		0.64	
Mean: used computer in final job	0.10		0.37		0.53	
N	762		921		422	
Kleibergen-Paap F statistic		20.10		33.79		0.06

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at household level are shown in parentheses in OLS estimation.
Robust standard errors clustered at country and occupational level are shown in parentheses in IV estimation.
All controls are as per Table 2.

Table 8: OLS and IV estimates when excluding each country

Outcome: standardized delayed recall test score (2015)										
Excluded country:	Austria	Germany	Belgium	France	Switzerland	Spain	Italy	Denmark	Sweden	Israel
OLS estimate	0.148***	0.123***	0.141***	0.119**	0.147***	0.118***	0.126***	0.130***	0.116**	0.112**
	(0.047)	(0.047)	(0.052)	(0.049)	(0.046)	(0.046)	(0.047)	(0.047)	(0.049)	(0.046)
IV estimate	0.741**	0.914***	0.708**	0.920***	0.724***	0.819***	0.772***	0.661**	0.633**	0.701***
	(0.290)	(0.207)	(0.279)	(0.296)	(0.242)	(0.255)	(0.275)	(0.258)	(0.292)	(0.268)
First-stage coefficient	0.227***	0.247***	0.237***	0.204***	0.250***	0.224***	0.241***	0.239***	0.217***	0.226***
	(0.044)	(0.037)	(0.045)	(0.038)	(0.035)	(0.040)	(0.039)	(0.044)	(0.041)	(0.042)
Kleibergen-Paap F statistic	26.64	44.45	27.27	28.07	50.61	31.71	38.73	29.95	27.57	28.74
Mean: delayed word recall	3.33	3.36	3.35	3.38	3.38	3.48	3.47	3.34	3.34	3.37
Mean: uses internet	0.339	0.331	0.315	0.323	0.334	0.354	0.389	0.317	0.318	0.328
Mean: used computer in final job	0.303	0.300	0.301	0.295	0.301	0.323	0.353	0.298	0.271	0.299
N	1927	1947	1682	1813	2047	1954	1735	1984	1842	2014

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Robust standard errors clustered at country and occupational level are shown in parentheses in IV estimation.
Robust standard errors clustered at household level are shown in parentheses in OLS estimation.
All controls are as per Table 2.

Figures

Figure 1: ICT usage in subgroups

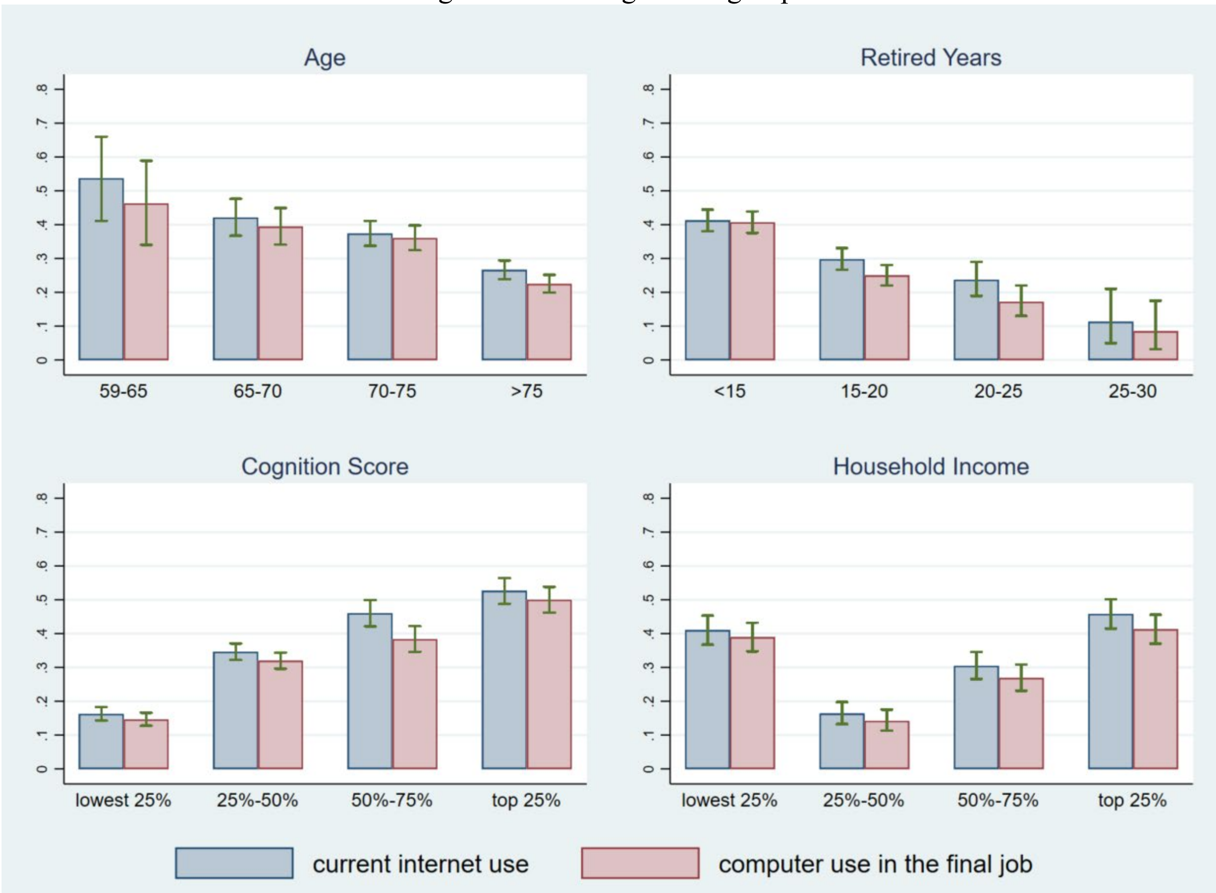
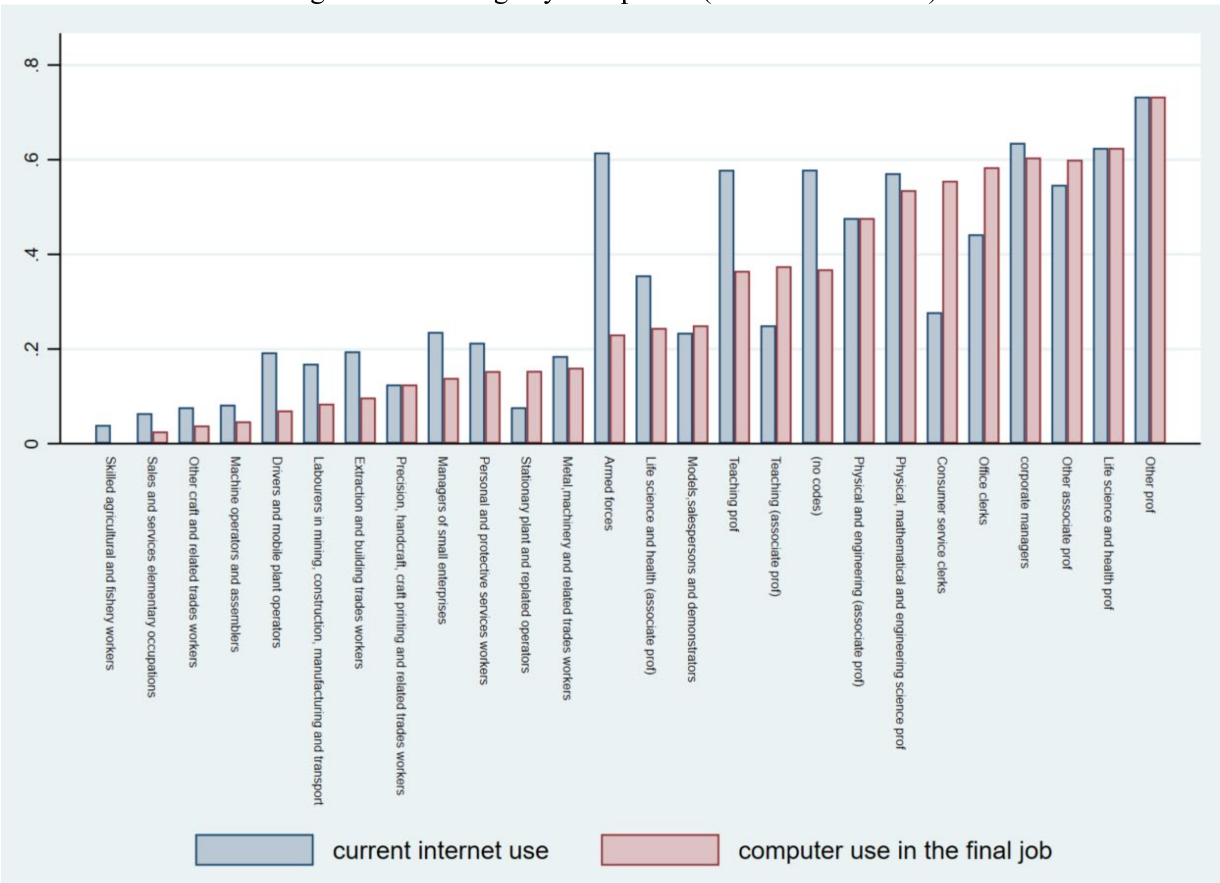
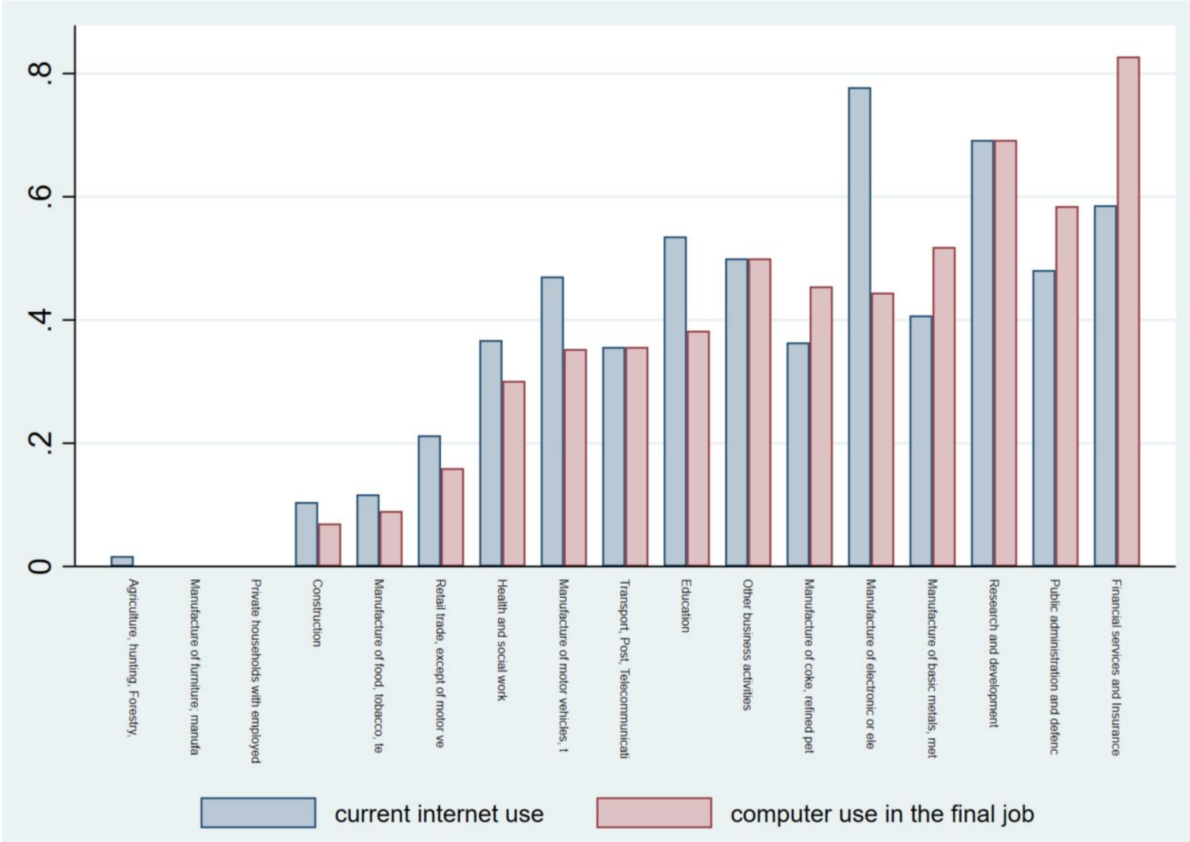


Figure 2: ICT usage by occupation (based on ISCO-88)



Note: sorted by computer usage in the final job before retirement by country and retirement period.

Figure 3: ICT usage by industry



Note: sorted by computer usage in the final job before retirement by country and retirement period.

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Appendix

Table A1: Sample selection and descriptive statistics

Wave participation	***Interviewed***	***Age (59-85)*** (in 2013)	***Retired***	***Never worked***	***Retirement year*** (1980-2004)
Wave 1 (2004)	30434	28029	12577	2287	10653
Waves 1 & 5 (to 2013)	12812	11449	7291	751	4438
Waves 1, 5 & 6 (to 2015)	9250	8406	5785	582	3298

Note: the final sample of 2105 is derived after deleting observations with missing values for variables used in the analysis

Table A2: Summary statistics by country

Country	*N*	*Delayed word Recall*	*Uses internet (mean)*	*Used computer in final job (mean)*
Austria	178	3.93	0.28	0.3
Belgium	423	3.5	0.41	0.31
Denmark	121	4.05	0.62	0.39
France	292	3.41	0.4	0.35
Germany	158	3.73	0.37	0.34
Israel	91	3.59	0.46	0.4
Italy	370	2.8	0.12	0.13
Spain	151	2.11	0.07	0.05
Sweden	263	3.76	0.44	0.52
Switzerland	58	3.4	0.34	0.38

Table A3: OLS estimate of the effect of internet usage on cognitive function

Outcome: standardized delayed recall test score (2015)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Uses internet	0.582***	0.423***	0.424***	0.329***	0.311***	0.304***	0.309***	0.314***	0.129***	0.119*	0.050	0.239**
(d=1)	(0.044)	(0.047)	(0.047)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.045)	(0.069)	(0.062)	(0.066)
Male		-0.225***	-0.224***	-0.216***	-0.226***	-0.216***	-0.258***	-0.262***	-0.134**	-0.033		
		(0.041)	(0.041)	(0.040)	(0.040)	(0.042)	(0.045)	(0.046)	(0.041)	(0.055)		
Age		-0.044***	0.100	0.103*	0.111*	0.106	0.102	0.102	0.050	0.002	-0.042	0.146
		(0.004)	(0.089)	(0.088)	(0.088)	(0.088)	(0.088)	(0.094)	(0.083)	(0.082)	(0.114)	(0.118)
Age2/100			-0.096	-0.097*	-0.102*	-0.099*	-0.094	-0.096	-0.050	-0.025	0.014	-0.117
			(0.060)	(0.059)	(0.059)	(0.059)	(0.059)	(0.063)	(0.056)	(0.056)	(0.077)	(0.079)
Years of education				0.040***	0.038***	0.037***	0.036***	0.036***	0.018***	0.017***	0.018***	0.018**
				(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.008)
Household income (25%-50%)					-0.154*	-0.151*	-0.155*	-0.150*	-0.143*	0.031	-0.086	-0.154
					(0.084)	(0.085)	(0.085)	(0.087)	(0.079)	(0.094)	(0.111)	(0.105)
Household income (50%-75%)					-0.009	0.007	0.001	-0.001	-0.059	0.132	0.017	-0.112
					(0.092)	(0.094)	(0.094)	(0.096)	(0.088)	(0.109)	(0.124)	(0.117)
Household income (top 25%)					0.064	0.080	0.070	0.069	0.017	0.072	0.105	-0.030
					(0.096)	(0.100)	(0.100)	(0.102)	(0.092)	(0.113)	(0.130)	(0.125)
Married and living with spouse						0.019	0.026	0.033	0.019	0.005	-0.012	0.033
						(0.063)	(0.063)	(0.063)	(0.056)	(0.070)	(0.087)	(0.074)
Lives in big city						0.072	0.096	0.087	-0.008	-0.100	-0.073	0.035
						(0.079)	(0.079)	(0.080)	(0.071)	(0.092)	(0.096)	(0.103)
Physical inactive							-0.272***	-0.274***	-0.139**	-0.363***	-0.122	-0.131
							(0.066)	(0.067)	(0.060)	(0.076)	(0.086)	(0.084)
Drinking							0.079	0.082	0.043	-0.015	-0.038	0.251**
							(0.065)	(0.065)	(0.058)	(0.078)	(0.066)	(0.113)
Delayed recall score (2013)									0.467***	0.466***	0.482***	0.449***
									(0.021)	(0.028)	(0.031)	(0.030)
Country fixed effects		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household characteristics						✓	✓	✓	✓	✓	✓	✓
Health controls							✓	✓	✓	✓	✓	✓
Retirement controls								✓	✓	✓	✓	✓
Adjusted r-squared	0.075	0.161	0.161	0.182	0.186	0.184	0.192	0.191	0.363	0.464	0.328	0.378

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
N=2105 for specifications (1) to (10); n=1071 in male sample (11); n=1034 in female sample (12). Robust standard errors clustered at household level are in parentheses. Specification (10) presents weighted estimates using a self-derived inverse probability of remaining in our working sample. The probability is estimated based on Wave 1 variables (income, education, health, demographic and household characteristics).

Health controls are physical inactivity, standardized body mass index, standardized number of doctor visits, whether has long-term chronic disease, whether drank (more than two glasses) every day, whether smoke every day. Retirement controls include years retired and the retirement year. Household characteristics were controls for marital status, household size, living area (urban, rural, or town), home ownership, and four quantiles of total household income (transformed using PPP index).

Table A4: First stage results of instrumental variable estimation

First-stage coefficients	*Whether uses internet (2013)*			
	All observations	**Men only**	**Women only**	**Alternative specification**
	OLS	**OLS**	**OLS**	**Logit**
ISCO-country-year computer usage mean	**0.232*** **	**0.216*** **	**0.238*** **	**0.180*** **
	(0.039)	**(0.049)**	**(0.038)**	**(0.031)**
Cognitive function (2013)	0.075***	0.080***	0.075***	0.074***
	(0.012)	(0.019)	(0.020)	(0.010)
Age	-0.051	-0.098	0.010	-0.045
	(0.056)	(0.082)	(0.059)	(0.049)
Men	0.150***			0.153***
	(0.031)			(0.033)
Years of education	0.020***	0.023***	0.016***	0.019***
	(0.003)	(0.004)	(0.003)	(0.003)
Household income (top 25%)	0.112**	0.077	0.121**	0.170***
	(0.052)	(0.075)	(0.060)	(0.065)
BMI (standardized)	-0.024**	-0.034***	-0.018	-0.025**
	(0.010)	(0.011)	(0.012)	(0.012)
Doctor visits (standardized)	-0.008	-0.025***	0.010	-0.005
	(0.006)	(0.008)	(0.007)	(0.009)
Physical inactive	0.001	-0.017	-0.041	-0.009
	(0.024)	(0.039)	(0.042)	(0.031)
Household size	-0.028**	-0.028*	-0.048*	-0.045*
	(0.018)	(0.031)	(0.029)	(0.024)
Never married	-0.112***	-0.068	-0.166*	- 0.146*
	(0.039)	(0.061)	(0.088)	(0.063)
Lives in big city	0.055***	0.092**	0.037	0.077***
	(0.021)	(0.040)	(0.024)	(0.022)
Lives in suburbs	0.075***	0.117***	0.031	0.081***
	(0.024)	(0.033)	(0.020)	(0.025)
N	2105	1071	1034	2087

Notes: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
Cluster robust standard errors are in parentheses.
Regressions also include all other controls used in our main specification, but this table only presents a few selected controls of interest.
The column of estimated logit model reports average marginal effect.

Table A5: Estimation in alternative samples. Outcome is standardized score on delayed recall test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OLS estimate	0.130***	0.141***	0.139***	0.129***	0.099*	0.137***	0.128**
	(0.042)	(0.043)	(0.042)	(0.045)	(0.059)	(0.045)	(0.058)
IV estimate	0.644***	0.777***	0.765***	0.747***	0.946*	0.688***	1.329***
	(0.159)	(0.257)	(0.297)	(0.251)	(0.552)	(0.256)	(0.504)
Reduced form estimate	0.210***	0.187***	0.180**	0.173***	0.166*	0.171**	0.237***
	(0.081)	(0.068)	(0.083)	(0.066)	(0.091)	(0.069)	(0.082)
First-stage coefficient	0.326***	0.241***	0.235***	0.231***	0.176***	0.248***	0.178***
	(0.062)	(0.042)	(0.042)	(0.037)	(0.045)	(0.041)	(0.046)
Kleibergen-Paap F statistic	27.50	32.42	31.16	38.15	14.89	37.23	15.18
Mean delayed recall	3.41	3.43	3.30	3.37	3.15	3.36	4.09
Mean of internet use	0.333	0.355	0.321	0.332	0.272	0.331	0.421
Mean pc use in last job	0.294	0.315	0.288	0.302	0.224	0.300	0.392
N	2332	2310	2308	2126	1303	2060	1345

Note: * significant at 10% level; ** significant at 5% level; ***significant at 1% level.
In addition to our general sample restriction, alternative samples defined above:
(1) including people who never worked. Computer usage in final job is coded zero for those who never worked.
(2) includes people who claimed retirement before 2004 but did some paid work recently.
(3) includes people older than 85 or younger than 59 in 2013.
(4) includes people retired more than 30 years.
(5) only includes people retired between 1980 and 1999.
(6) only includes people aged over 65 in 2013.
(7) excludes people within the lowest 20% of delayed recall score in 2013.

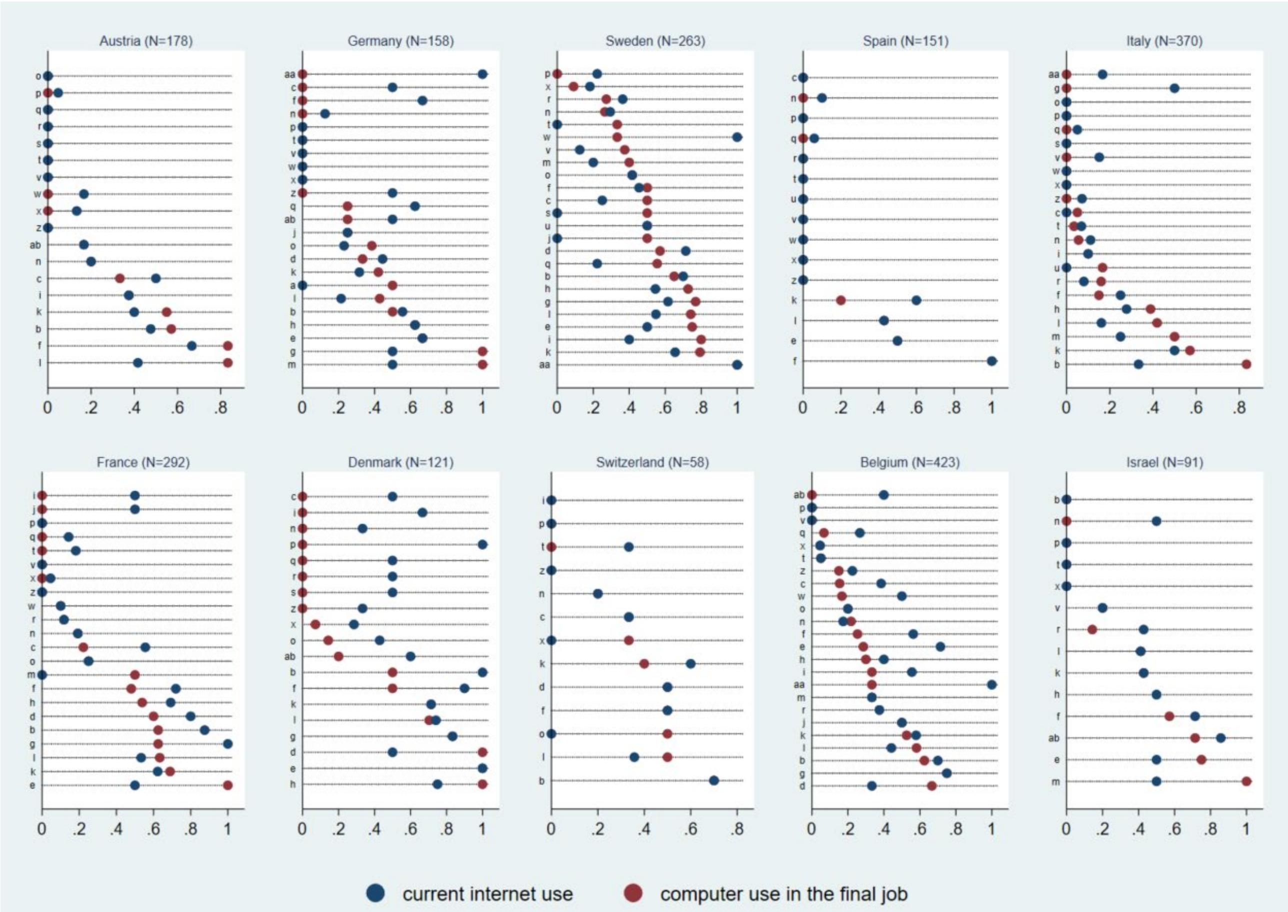
Table A6: Occupation labels

Label	Two-digit ISCO	Skill level	Context
A	11		Legislation and senior officials
B	12		Corporate managers
C	13		Managers of small enterprises
D	21	High	Physical, mathematical and engineering science professionals
E	22	(level 4)	Life science and health professionals
F	23		Teaching professionals
G	24		Other professionals
H	31		Physical and engineering (associate professionals)
I	32	High	Life science and health (associate professionals)
J	33	(level 3)	Teaching (associate professionals)
K	34		Other associate professionals
L	41		Office clerks
M	42		Consumer service clerks
N	51		Personal and protective services workers
O	52		Models, salespersons and demonstrators
P	61		Skilled agricultural and fishery workers
Q	71	Medium	Extraction and building trades workers
R	72	(level 2)	Metal, machinery and related trades workers
S	73		Precision, handcraft, craft printing and related trades workers
T	74		Other craft and related trades workers
U	81		Stationary plant and related operators
V	82		Machine operators and assemblers
W	83		Drivers and mobile plant operators
X	91	Low	Sales and services elementary occupations
Y	92	(level 1)	Agricultural, fishery and related labourers
Z	93		Labourers in mining, construction, manufacturing and transport
Aa	01	Not applicable	Armed forces
Ab	00		No codes

Table A7: Industry label

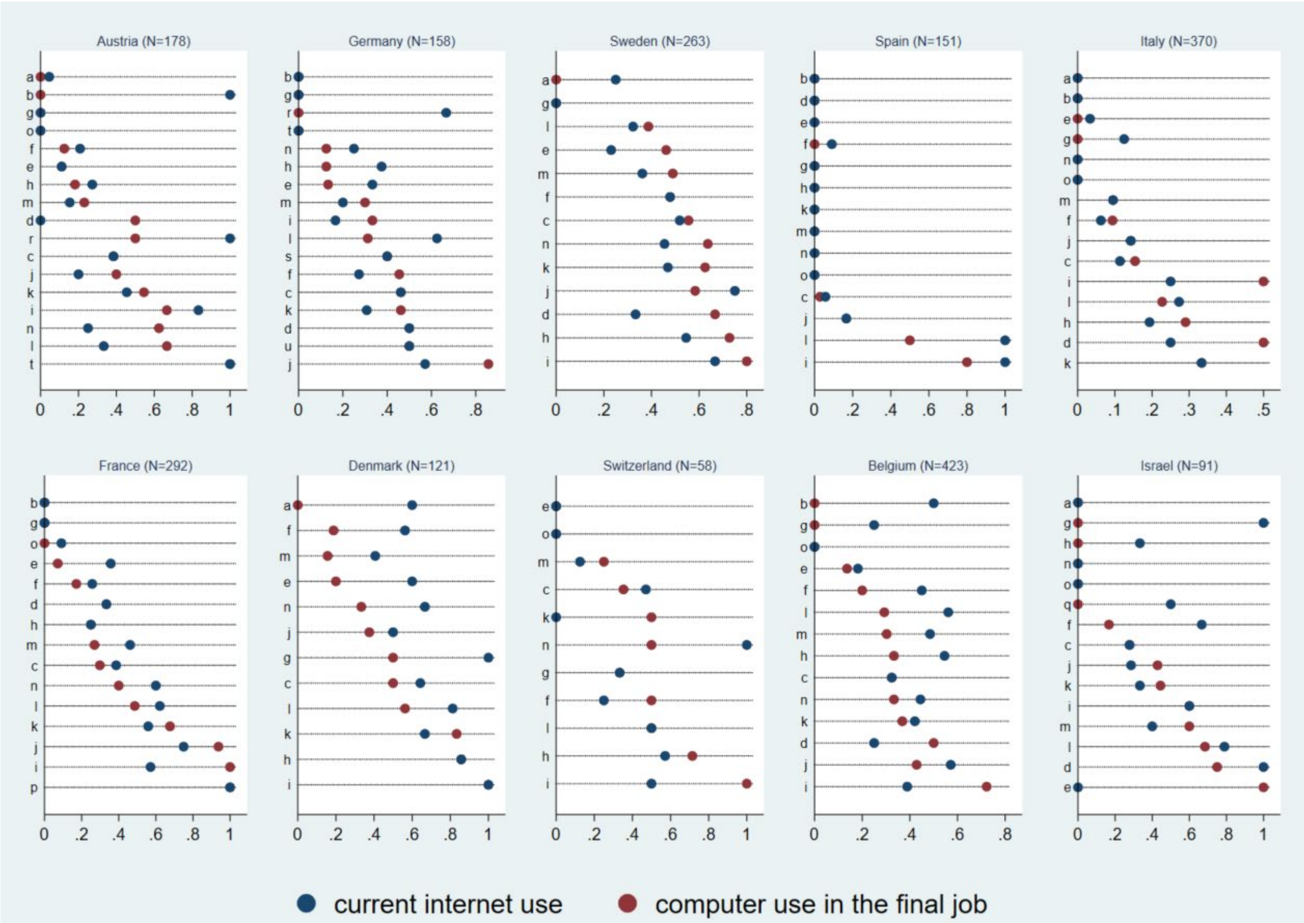
Label	Context
A	Agriculture, hunting and forestry, fishing
B	Mining
C	Manufacturing
D	Electricity, gas and water supply
E	Construction
F	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household good
G	Hotels and restaurants
H	Transport, storage and communication
I	Financial intermediation
J	Real estate, renting and business activities
K	Public administration and defence; compulsory social security
L	Education
M	Health and social work
N	Other community, social and personal service activities
O	Activities of households
P	Extra-territorial organizations and bodies
Q	NA/no code
R	Soldiers, military
S	Services (no further specification)
T	Production, industry
U	Illegible
V	DK/REF
W	Engineering(no specification)

Figure A1: ICT usage by occupations in country



Note: sorted by the computer usage in the final job before retirement by retirement period. Occupation categories are illustrated in Table A6.

Figure A2 ICT use by NACE Industry in Country



Note: Sorted by computer usage in the final job before retirement by retirement period. Industry categories are illustrated in Table A7.