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Use it Too Much and Lose it? The Effect of Working Hours on Cognitive Ability

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【Abstract】
Using data from Wave 12 of the Household Income and Labour Dynamics in Australia (HILDA) Survey, we examine the causal impact of working hours on the cognitive ability of people living in Australia aged 40 years and older. Three measures of cognitive ability are employed: the Backward Digit Span; the Symbol Digits Modalities; and a 25-item version of the National Adult Reading Test. In order to capture the potential non-linear dependence of cognitive ability on working hours, the models for cognitive ability include working hours and its square. We deal with the potential endogeneity of the decision of how many hours to work by using the instrumental variable estimation technique. Our findings show that there is a non-linearity in the causal effect of working hours on cognitive functioning. For working hours up to around 22–26 hours a week for men and for 22–30 hours a week for women, an increase in working hours has a positive impact on cognitive functioning. However, when working hours exceed these hours per week, an increase in working hours has a negative impact on cognition. Working in excess of 44–52 hours for men and 44–60 hours for women leads to cognitive scores that are worse than a person does not work at all. Interestingly, there is no statistical difference in the causal effects of working hours on cognitive functioning between men and women.

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Use it Too Much and Lose it?

The Effect of Working Hours on Cognitive Ability*

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Declarations

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Abstract

Using data from Wave 12 of the Household Income and Labour Dynamics in Australia (HILDA) Survey, we examine the causal impact of working hours on the cognitive ability of people living in Australia aged 40 years and older. Three measures of cognitive ability are employed: the Backward Digit Span; the Symbol Digits Modalities; and a 25-item version of the National Adult Reading Test. In order to capture the potential non-linear dependence of cognitive ability on working hours, the models for cognitive ability include working hours and its square. We deal with the potential endogeneity of the decision of how many hours to work by using the instrumental variable estimation technique. Our findings show that there is a non-linearity in the causal effect of working hours on cognitive functioning. For working hours up to around 22–26 hours a week for men and for 22–30 hours a week for women, an increase in working hours has a positive impact on cognitive functioning. However, when working hours exceed these hours per week, an increase in working hours has a negative impact on cognition. Working in excess of 44–52 hours for men and 44–60 hours for women leads to cognitive scores that are worse than a person does not work at all. Interestingly, there is no statistical difference in the causal effects of working hours on cognitive functioning between men and women.

Keywords: cognitive ability, endogeneity, gender differences, retirement, working hours
JEL Classification Numbers: I10, J22, J26

Highlights

- A non-linear relationship between working hours and cognitive ability is observed.
- Cognitive ability peaks somewhere between 22–30 hours of work for both men and women.
- Working more than 44–60 hours can be worse than not working at all.
- Significant gender differences are not observed.

1. Introduction

Many countries have already increased their retirement ages by delaying the age at which people are eligible to start receiving government pension payments. This means that more people continue to work in the later stages of their life. Some claim that delaying the retirement age can potentially help reduce the deterioration of cognitive functioning because of the continued intellectual stimulation that work provides (Potter *et al.*, 2008; Small, 2002). The relationship between retirement and cognitive functioning has attracted much attention in recent years, but recent studies have not reached consensus on whether the so called 'use it or lose it' hypothesis is valid. The 'use it or lose it' hypothesis argues that not working (not using the brain) leads to a loss of cognitive functioning. After controlling for the endogeneity of retirement, Mazzonna and Peracchi (2012, 2017) and Rohwedder and Willis (2010) find that there was a significant and negative effect of retirement on cognitive skills, while Coe and Zamarro (2011) do not find such a causal effect. Bonsang *et al.* (2012) find that the effects of retirement on cognitive function appeared with a lag, and conclude that there were positive externalities of a delayed retirement for older individuals.

Although these previous studies provide important insights into the relationship between retirement and cognitive functioning, they do not examine the impact of the quality or quantity of work on cognitive functioning. Work can be a double-edged sword, in that it can stimulate brain activity, but at the same time, long working hours and certain types of tasks can cause fatigue and stress which potentially damage cognitive functions. Thus, the degree of intellectual stimulation of work may depend on the required tasks and working hours, that is, the quality and quantity of work. There are number of studies which examine the effects of the quality of work (job type and job tasks) on cognitive functioning (Schooler *et al.*, 1999; Bosma *et al.*, 2003; Potter *et al.*, 2008; Finkel *et al.*, 2009; Marquié *et al.*, 2010; Smart *et al.*, 2014; Kajitani *et al.*, 2016).

However, there seem to be very few studies discussing the impact of the quantity of work (working hours) on cognitive functioning. Working individuals with longer hours of work have more incentive to invest in cognitive repair activities in order to maintain their cognition while working longer. In contrast, longer hours of work *per se* could reduce their cognitive performance. Using the Whitehall II Study sample of British civil servants, Virtanen *et al.* (2009) examine the relationship between long working hours and cognitive skills in middle age. They find that vocabulary test scores which measure crystallized intelligence are relatively lower among workers with long working hours, and point out that long working hours may have a negative effect on cognition in middle age. However, their sample is limited to working civil servants. Moreover, Virtanen *et al.* (2009) do not compare the level of cognitive skills of workers and non-workers. Middle aged and elderly persons tend to retire or decrease their working hours by being employed as a non-regular worker, so it is important to examine the impact of working hours on cognitive functioning among middle-aged and older adults.

What are the channels through which labor hours might affect cognitive functioning? One of the channels is physical and/or psychological stress. Medical research suggests that stress affects cognitive functioning. McEwen and Sapolsky (1995) indicate that stress affects cognition rapidly via catecholamines, and more slowly via glucocorticoids. Martin *et al.* (2011) find that chronic stress has effects on cognition, and increases the vulnerability to mental illness. Proctor *et al.* (1996) indicate that long working hours have adverse effects on the mental health of workers in the automobile industry. In an analysis across 15 European countries, Cottini and Lucifora (2013) also find that long working hours increase stress. Thus, although engaging in work by stimulating the brain may help reduce the pace of cognitive impairment, such positive effects may be offset by the negative impacts caused by mental and physical stress associated with long labor hours. An alternative possibility is that as an individual's wage rate becomes higher, he/she has a stronger incentive to engage in activities that restore damage to his/her brain, and this incentive may be stronger as he/she works more hours.

We examine the causal impact of working hours on cognitive functioning for middle-aged and older adults living in Australia using a cross section sample from Wave 12 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. In contrast to the 'use it or lose it' hypothesis, we examine what we term the 'use it too much and lose it' hypothesis, namely, that in terms of cognitive ability working too much can be worse than not working at all. In examining this hypothesis, it is important to deal with the potential endogeneity of decisions on working hours by using an instrumental variable estimation technique. One potential problem in using working hours as the explanatory variable of interest is that the working hours are left censored, that is, for individuals who are retired or who are not in education, employment or training (NEET), working hours are treated as zero. In order to take account of these zero values in the reported working hours, we apply a Tobit model and then use the nonlinear fitted values from the Tobit model as the new instrument for working hours when the model for cognitive functioning is estimated by an instrumental variable estimator.

Our empirical evidence shows that there is non-linearity in the effects of working hours on cognitive functioning. More precisely, there is an inverted U-shaped relationship. When working hours are less than around 22 hours a week, working hours have a positive impact on cognitive functioning. However, when working hours are more than 26 hours per week for men and 30 hours per week for women, working hours have negative impacts on cognition. These results suggest that compared to not work at old people in old age could maintain or improve their cognitive ability by working in a part-time job that requires them to work around 22 hours per week.

We estimate our models on samples of males and females separately as Matud (2004) suggests that there are differences in the extent to which males and females suffer stress and cope with stress. Since stress is suggested in the medical literature as one of the reasons for labor hours affecting cognitive functioning, Matud's evidence suggests a possible difference in the connection between working hours and cognitive functioning for men and women. However, we find that there is no statistically significant gender difference in the effects of working hours on cognitive functioning.

The rest of this paper is organized as follows: Section 2 presents the empirical framework used in this paper. Section 3 describes the data, and Section 4 reports the results of estimation and discusses their implications. The last section concludes this paper.

2. Estimation model and identification strategy

Our identification strategy exploits the variation in working hours, while controlling for individual characteristics. In order to capture a possible non-linearity in the effects of working hours on cognitive functioning, we consider the following model[1]:

$$COG_i = \alpha_1 {WH_i}^2 + \alpha_2 WH_i + X_i\beta + u_i, \qquad (1)$$

where COG_i denotes a cognitive test score, ${WH_i}^2$ is the square of working hours, and WH_i is working hours. X_i denotes a vector of control variables which consists of a constant, the

[1] An alternative to the parametric model in equation (1) to account for the non-linear effect of working hours on cognitive functioning would be to estimate a semi-parametric or non-parametric model. However, such an approach makes it rather difficult to deal with the potential endogeneity between working hours and cognitive functions. Here, we put priority on dealing with the potential endogeneity of working hours.

respondent's age, age squared, dummy variables which indicate his/her years of education, dummy variables which indicate the type of his/her educational qualification, and his/her previous work experience. We also include a dummy variable which takes the value unity if the respondent has a spouse and zero otherwise. This variable is included because communications and interactions with other family members may prevent declines in cognitive functioning. Moreover, in order to control the effects of space between the day of interview and the previous weekend, we include dummy variables which indicate what day of the week the respondent was interviewed. To take account of regional variations, we also include four 0–1 regional dummies. The unknown parameters to be estimated are α_1, α_2 and β. u_i is an error term, and the subscript i refers to the ith individual. The coefficient α_1 captures the non-linear effect of working hours on cognitive functioning. Given the discussion in section 1 that some work is better than no work, and that too much work may be worse than some work, it is expected that $\alpha_1 < 0$ and $\alpha_2 > 0$. Holding everything else constant, it is easy to see that the cognitive test score is maximized when $WH_i = -\alpha_2/(2\alpha_1)$, and that for $WH_i = -\alpha_2/\alpha_1$ the cognitive test score is the same as it would be if individual i was not working.

The possibility of the endogeneity of the respondents' working hours in equation (1) is a major obstacle to estimating the *causal* impact of working hours on cognitive functioning. Individuals whose cognitive abilities are lower (or higher) may decide to leave the workforce earlier (or later). On the other hand, the reverse causality between cognitive skills and working hours can be more ambiguous. Previous studies observe that a high wage rate is associated with cognitive skills (for example, Wooden, 2013; Capatina, 2014). In a neoclassical model of consumer behavior where there is a trade-off between consumption and leisure, and leisure is a normal good, the impact of the wage rate (and thus cognitive skills) on working hours depends on whether the substitution effect dominates the income effect or vice versa. Individuals whose cognitive abilities are higher, who tend to earn a relatively higher wage, could decide to reduce their hours of work even further.

For equation (1), the standard two stage least squares (2SLS) procedure is to find variables which are correlated with an individual's labor supply, but unrelated to their cognitive skills. However, we have another issue in examining the effects of labor hours on cognitive functioning, that is, labor hours are censored (for example, retirees reporting zero working hours). Rather than directly using variables which correlate with hours worked, but do not correlate with cognitive functioning, we use these variables for creating the fitted values for *squared of working hours* and *working hours* that are then used as instruments. The following model is assumed to explain observed working hours:

$$WH_i^* = \gamma_1 Interview\ July\ or\ August_i + \gamma_2(Age_i - Eligibility\ Age_i)$$
$$+\gamma_3(Age_i - Eligibility\ Age_i)^2 + X_i\delta + e_i, \qquad (2)$$

$$\begin{aligned} WH_i &= 0 \quad \text{if} \quad WH_i^* \leq 0, \\ &= WH_i^* \quad \text{if} \quad 0 < WH_i^*, \end{aligned} \qquad (3)$$

where WH_i^* denotes an unobserved latent variable which is connected to the observed working hours WH_i through equation (3). $Interview\ July\ or\ August_i$ is a 0–1 dummy variable which takes the value one if the respondent is interviewed in July or August, and zero otherwise. This variable is intended to capture seasonal variation in labour supply which may be due to school holidays occurring in July. $Age_i - Eligibility\ Age_i$ is the difference between the respondent's age at the time of the survey, Age_i, and the age at which the respondent is eligible for a pension, $Eligibility\ Age_i$. In the existing literature, the age at which an individual is eligible for a pension is one of the standard instruments used to analyze the causal relationship between retirement and cognitive functioning (Bonsang *et al.* 2012, Coe and Zamarro 2011, Mazzonna and Peracchi 2012 & 2017, Rohwedder and Willis, 2010). Here, we use a measure of the respondent's 'distance' from their retirement. These instruments, $Interview\ July\ or\ August_i$, $Age_i - Eligibility\ Age_i$, and $(Age_i - Eligibility\ Age_i)^2$, are designed to capture the factors which impact on the labor supply of a respondent, but not on his/her cognitive abilities. X_i is exactly the same vector of control variables as is used in equation (1), and e_i is a disturbance which is assumed to be normally, independently and identically distributed with a zero mean and variance σ^2. For a retiree or an unemployed person, we observe his/her working hours per week as zero.

Table I summarizes the ages at which males and females are eligible for pensions at the time of Wave 12 of the HILDA survey. As can be seen from this Table, there is much more variation in the pension eligibility ages for women than there is for men. Table I also indicates the distribution of our sample across the ages for pension eligibility. Although the eligibility age for men born before or on 30 June, 1952 is 65, the proportion of our sample in this category is just 40.8%. In contrast, the proportion of men whose pension eligibility age is 67 is 46.2% of our sample.

[Table I around here]

Given the left censoring of working hours, we estimate equations (2) and (3) using a Tobit estimator to obtain estimates of γ_k $(k = 1, 2, 3)$ and δ, $\widehat{\gamma_k}$ and $\hat{\delta}$, respectively. From equations (2) and (3), and the assumptions about the distribution of e_i, the conditional expectation of WH_i can be computed as

$$E(WH_i \,|Z_i) = \Phi\left(\frac{Z_i\varepsilon}{\sigma}\right)Z_i\varepsilon + \sigma\phi\left(\frac{Z_i\varepsilon}{\sigma}\right), \tag{4}$$

where Z_i and ε are the vectors of regressors and parameters in equation (2), respectively, and $\Phi\,(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution and probability distribution functions of the standard normal distribution, respectively (see Greene 2008, p. 871). Given the estimates of the parameters of equation (2), the estimates of the conditional expectation in equation (4) are denoted by $\widehat{WH_i}$. Then, $\widehat{WH_i}$ and $\widehat{WH_i}^2$ are used as instruments for WH_i and $WH_i^{\,2}$, respectively, in equation (1) in a 2SLS procedure (see Wooldridge 2010, p. 268).

3. Data: Overview of the HILDA Survey

Our data are drawn from Wave 12 of the HILDA Survey which is conducted by the Melbourne Institute of Applied Economics and Social Research, and is a broad social and economic longitudinal survey. Since 2001 when Wave 1 was collected, the HILDA Survey has asked people living in Australia about their economic and subjective well-being, family structures, and labor market dynamics. Households included in this survey were selected using a three-stage approach.[2] First, a sample of 488 Census Collection Districts (CDs) were randomly selected from across Australia. Second, within each of these CDs, a sample of dwellings was selected based on expected response rates and occupancy rates. Finally, within each dwelling, up to three households were selected to be part of the sample. In addition, the sample was replenished in between July 2011 and mid-February 2012 in Wave 11.

Although most questions in the HILDA Survey are repeated every year, there are questions on several topics that are not repeated every year or are only asked once. Information on the respondent's cognitive ability has only been collected in Wave 12 of the HILDA Survey[3]. Wave 12 which was collected in between July 2012 and mid-February

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[2] Detailed information on the sample design of the HILDA Survey is available in Wooden *et al.* (2002) and Watson and Wooden (2013).

[3] Wooden (2013) discusses in detail the measurement of cognitive ability in Wave 12 of the HILDA Survey.

2013 contains three measures of cognitive ability: the Backward Digit Span (BDS); the Symbol Digits Modalities (SDM); and a 25-item version of the National Adult Reading Test (NART25). We use BDS, SDM, and NART25 scores as measures of a respondent's cognitive ability. BDS is a test of working memory span and is used in many traditional intelligence tests. After reading out longer strings of numbers, the respondent is required to repeat those strings in reverse order. The shortest and longest sequence administered are two and eight digits, respectively. In the BDS test, questions are divided into seven levels, and there are two trials at each level. When the respondent's response for the first trial for a given level is correct, he/she is allocated a score of two for that level, and then moves on to the next level. When his/her response on the first trial is incorrect, he/she moves on the second trial. If the respondent's answer on the second trial is correct, he/she is allocated a score of one for that level, and then moves onto the next level. If his/her answer on the second trial is also incorrect, he/she is allocated a score of zero for that level, and this test is discontinued; that is, he/she is allocated a score of zero for all the subsequent questions. Finally, the BDS score is the sum of the scores at each level, so the maximum possible score for the respondent is 14, and the minimum possible score is zero. *BDSscore* denotes the respondent's BDS test score. SDM is a general test for divided attention, visual scanning, and motor speed. The respondent is required to match symbols to numbers using a printed key.[4] *SDMscore* is the respondent's score on the SDM test, and is defined as the number of items correctly matched within a 90 second time interval. NART25 is a reading test, and provides a measure of mainly crystallized intelligence. In the NART25 test, the respondent is required to correctly read 25 irregularly spelled words which are listed roughly in order of difficulty. *NART25score* is his/her score on the NART25 test, and is also defined as the number of words correctly pronounced. Definitions of these variables and the other variables used in the analysis that follows are provided in Appendix I.

Table 1 in Melbourne Institute (2014, p. 9) provides details of the distribution of interviews across months of the year for Waves 1–12, and indicates that for the recurrent sample in Wave 12 interviews were conducted over the period July 2012 to February 2013 with the vast majority of interviews being conducted in either August 2012 (42.5%) or September (38.1%). Interviewers do not randomly choose an interview month for a respondent. The fieldwork for each wave is split into 3 periods - starting end of July–early October (Period 1), end October–early December (Period 2) and early January–early February (Period 3) and the interviewers are issued households to approach in each of these

[4] Strauss *et al.* (2006) provide details of the SDM test.

periods. If a respondent is too busy or away overseas, or temporarily incapable, the interviewer returned at a time that is more appropriate for the respondent. In the second and subsequent waves, although respondents were free to choose when they were interviewed however most respondents were interviewed within 1 month anniversary of their interview in the previous wave[5].

The sample used in this paper is restricted to individuals who meet all of the following five criterion for Wave 12 of the HILDA data set: (i) males and females aged 40 and over; (ii) all three scores relating to cognitive ability are available; (iii) English is their first language; (iv) their reported working hours are not deemed to be outliers, namely, those values that are not in the top 1 percentile[6]; and (v) information on all the relevant variables is available. For individuals meeting these five criterion, Table II shows descriptive statistics for all the variables used in the analysis. In our sample, the maximum values of *BDSscore, SDMscore, and NART25score* for males (females) are 14 (14), 95 (104) and 24 (24), respectively. *Working hours* is defined as being the respondent's usual or average hours of work per week, and it can be seen from Table II that the mean values of *Working hours* for males and females are 27.2 and 16.9 hours, respectively.

[Table II around here]

Table III provides information on the current employment status of respondents by gender and age group. For all age groups, a higher percentage of males are working full-time than females, and for both males and females as age rises the proportion of full-time workers falls.

[Table III around here]

4. Estimation results

All regression results reported in this section are estimated using STATA version 14 (StataCorp 2015). Table IV presents estimates of the coefficients of the three variables that are included in equation (2) but not equation (1), that is, the variables that are used to

[5] Summerfield *et al.* (2016) contains further information on the HILDA's data collection process.

[6] We have investigated the robustness of our results by dropping observations where the reported working hours are in the top 5% percentile, and found that are results are largely unchanged.

generate exclusion restrictions. The results in Table IV indicate that the three instruments are all individually statistically significant, and that the null hypothesis that the exclusion restriction variables are jointly irrelevant in explaining working hours is rejected for both males (F-statistics is 14.95) and females (F-statistic is 7.28). The value of the Cragg-Donald (1993) Wald F-statistic for males (16.5) and females (13.8) which are shown in Table V, suggest that there is not a problem of "weak" instruments.

[Table IV around here]

Table V reports the results of estimating equation (1) taking account of the endogeneity of working hours. As shown in columns (1A)–(1C), after controlling for the respondent's human capital and demographic variables, the estimated coefficients of *Working hours-squared* are significantly negative, and the estimated coefficients of *Working hours* are also significantly positive for males. As can be seen from the results in columns (2A)–(2C), the same is true for females except for the SDM score.

[Table V around here]

These results indicate that, for both males and females, there is an inverse U relationship between cognitive ability and working hours. As the number of working hours increases from zero, the magnitude of the positive impact of working hours on their cognitive ability is decreasing until working hours reaches a threshold. Above that threshold, further increases in working hours have a negative impact on their cognitive functioning. As Wooden *et al.* (2012) point out, BDM and SDM are measures of fluid intelligence, while NART25 is a measure of crystallized intelligence. It has been argued that crystallized intelligence tends to be maintained through occupational or cultural experiences, so that assuming hours of work are associated with the degree of occupational experiences, working hours *per se* could potentially be regarded as cognitive repair activities Similarly, although fluid intelligence is subject to a decline as people get older, fluid intelligence could be also maintained by working hours closer to the threshold.

If we compare the estimated coefficients for men and women associated with working hours and the square of working hours reported in Table V, there is no statistical difference between these coefficients for any of the cognitive scores. The t-values for these tests are -0.15 and 0.00 for BDS, 1.35 and -1.28 for SDM, -0.48 and 0.55 for NART25, respectively.

The lack of a gender difference is perhaps surprising since women tend to engage in more work in the household that may matter here.

Where does the threshold occur? In other words, when does the impact of working hours on cognitive ability change from being positive to negative? Using the coefficient estimates reported in Table V for men, the peaks occur at 23 hours for BDS, 26 hours for SDM, and 22 hours for NART25. For women, the peaks also occur at 22 hours for BDS, 29 hours for SDM[7], and 22 hours for NART25.

In Figure 1, using the estimated coefficients presented in Table V, we plot the estimated relationship between working hours and cognitive ability for the three test scores the evaluating other control variables at their sample means. The inverted U shape relationship between cognitive ability and working hours is clear from this Figure. Figure 1 also suggests that the cognitive ability of those working extremely long hours can be lower than those who are not working at all. For example, the BDS score of those who usually work 60 hours per week is lower than the BDS score of those who are not working both for males and females (Panel A). This suggests that longer working hours can lead to a deterioration of cognitive functioning.

There is a possibility that the functional relationship between cognitive scores and working hours could be more complicated than the quadratic form assumed in equation (1). In order to examine this possibility, we added the cube of *Working hours* to equation (1) and tested its significance. The estimated coefficients associated with the *Working hours-cubic* and their standard errors are reported at the bottom of Table V. None of these coefficients are statistically significant. These results support our use of a quadratic functional form.

[Figure 1 around here]

The results presented in Table V and graphed in Figure 1 indicate that there is a non-linearity in the effects of working hours on cognitive functioning for middle aged and older males and females living in Australia. Even after including retirees and taking account of the endogeneity and censoring of working hours, our findings are consistent with Virtanen *et al.*'s (2009) findings, that is, long working hours have a negative effect on cognition in

[7] The reader should keep in mind that for women the working hours and its square are not statistically significant for SDM.

middle age. Our results indicate that part-time work is an effective way to maintain cognitive functioning relative to retirement or unemployment.

Using the estimated working hours where the cognitive scores are maximized and where cognitive scores are the same as when working hours are zero, Table VI indicates for each cognitive score the proportion of the sample working more than the threshold and working so much (for ease of exposition referred at as "working too much") that their cognitive scores are worse than people not working at all. Depending on the score, 11% to 28% of men are "working too much", whereas only 2% to 8% of women "work too much".

[Table VI around here].

5. **Concluding remarks**

We examine the causal impact of working hours on the cognitive ability of middle-aged and older aged males and females living in Australia using Wave 12 of the HILDA Survey dataset. This study is unique in that it focuses on not only the extensive margin (labor force participation) but also the intensive margin (working hours) and investigates the optimal level of working hours for the cognitive levels of middle aged and older workers. Using the test scores of memory span and cerebral dysfunction for the respondents, it is found that working hours up to 22–26 hours per week have a positive impact on cognition for males depending on the measure and up to 22–30 hours for females. After that, working hours have a negative impact on cognitive functioning. This indicates that the differences in working hours is an important factor explaining differences in the level of cognitive functioning for middle and older adults. In other words, in middle age and old age, working part-time could effective in maintaining cognitive ability compared to not working at all. It is worth noting that our findings did not show any statistically significant gender differences in the effects of working hours on cognitive functioning.

Our study also highlights that too much work can have adverse effects on cognitive functioning to the extent that for cognitive function scores working too much can be worse than not working at all. We find support for the 'Use it too much and lose it hypothesis'.

Although our study deals with Australian data, there is good reason to believe that a similar relationship between cognitive functioning and working hours will be found in other countries. The exact number of working hours at which cognitive functioning peaks may differ across countries due to institutional, cultural and other differences. Our study has focused on the impact of working hours, but what a person does in their non-working time, for example, housework and sleep, may also have an important impact on cognitive functioning. These issues are left for future research.

[Appendix I around here]

References

Atalay K, Barrett GF. 2015. The impact of age pension eligibility age on retirement and program dependence: Evidence from an Australian experiment. *Review of Economics and Statistics* 97(1): 71–87. DOI:10.1162/REST_a_00443

Bonsang E, Adam S, Perelman S. 2012. Does retirement affect cognitive functioning? *Journal of Health Economics* **31** (3): 490–501.

DOI: 10.1016/j.jhealeco.2012.03.005

Bosma H, van Boxtel MP, Ponds RW, Houx PJ, Burdorf A, Jolles J. 2003. Mental work demands protect against cognitive impairment: MAAS prospective cohort study. *Experimental Aging Research* **29**(1): 33–45. DOI: 10.1080/03610730303710

Capatina E. 2014. Skills and the evolution of wage inequality. *Labour Economics* **28**: 41–57. DOI: 10.1016/j.labeco.2014.03.003

Coe NB, Zamarro G. 2011. Retirement effects on health in Europe. *Journal of Health Economics* **30**(1): 77–86. DOI: 10.1016/j.jhealeco.2010.11.002

Commonwealth of Australia 2009. *Securable and Sustainable Pensions*. Accessed 4 December 2016. Available at URL:

http://www.budget.gov.au/2009-10/content/glossy/pension/download/pensions_overview.pdf#search='Securable+and+sustainable+pensions'

Cottini E, Lucifora C. 2013. Mental health and working conditions in European countries. *Industrial & Labor Relations Review* **66**(4): 958–987.

DOI: 10.1177/001979391306600409

Cragg JG, Donald SG. 1993. Testing identifiability and specification in instrumental variable models. *Econometric Theory* **9**(2): 222–240.

Finkel D, Andel R, Gatz M, Pedersen NL. 2009. The role of occupational complexity in trajectories of cognitive aging before and after retirement. *Psychology and Aging* **24**(3): 563–573. DOI: 10.1037/a0015511

Greene WH. 2008. *Econometric Analysis*, 6th edition. Pearson: New Jersey.

Kajitani S, Sakata K, McKenzie C. 2016. Occupation, retirement and cognitive functioning. Accepted for publication in *Ageing & Society*. DOI: 10.1017/S0144686X16000465

Marin MF, Lord C, Andrews J, Juster RP, Sindi S, Arsenault-Lapierre G, Fiocco AJ, Lupien SJ. 2011. Chronic stress, cognitive functioning and mental health. *Neurobiology of Learning and Memory* **96**(4): 583–595. DOI: 10.1016/j.nlm.2011.02.016

Marquié JC, Duarte LR, Bessières P, Dalm C, Gentil C, Ruidavets JB. 2010. Higher mental stimulation at work is associated with improved cognitive functioning in both young and older workers. *Ergonomics* **53**(11): 1287–1301.

DOI: 10.1080/00140139.2010.519125

Matud MP. 2004. Gender differences in stress and coping styles. *Personality and Individual Differences* **37**(7): 1401–1415. DOI: 10.1016/j.paid.2004.01.010

Mazzonna F, Peracchi F. 2012. Ageing, cognitive abilities and retirement. *European Economic Review* **56**(4): 691–710. DOI: 10.1016/j.euroecorev.2012.03 .004

Mazzonna F, Peracchi F. 2017. Unhealthy retirement? *Journal of Human Resources*, 52(1): 128–151. DOI:10.3368/jhr.52.1.0914-6627R1

McEwen BS, Sapolsky RM. 1995. Stress and cognitive function. *Current Opinion in Neurobiology* **5**(2): 205–216. DOI: 10.1016/0959-4388(95)80028-X

Melbourne Institute 2014. *Household, Income and Labour Dynamics in Australia (HILDA) Survey Annual Report 2013*. Accessed 4 December 2016. Available from URL: https://www.melbourneinstitute.com/hilda/reports/annual_report.html

Potter GG, Helms MJ, Plassman BL. 2008. Association of job demands and intelligence with cognitive functioning measures among men in late life. *Neurology* **70**(19, part2): 1803–1808. DOI: 10.1212/01.wnl.0000295506.58497.7e

Proctor SP, White RF, Robins TG, Echeverria D, Rocskay AZ. 1996. Effect of overtime work on cognitive function in automotive workers. *Scandinavian Journal of Work, Environment & Health* **22**(2): 124–132.

Rohwedder S, Willis RJ. 2010. Mental retirement. *Journal of Economic Perspectives* **24**(1): 119–138. DOI: 10.1257/089533010797456247

Schooler C, Mulatu MS, Oates G. 1999. The continuing effects of substantively complex work on the intellectual functioning of older workers. *Psychology and Aging* **14**(3): 483–506. DOI: 10.1037/0882-7974.14.3.483

Small GW. 2002. What we need to know about age related memory loss. *British Medical Journal* **324**(7352): 1502–1505.

Smart EL, Gow AJ, Deary IJ. 2014. Occupational complexity and lifetime cognitive abilities. *Neurology* **83**(24): 2285–2291. DOI: 10.1212/WNL.0000000000001075

StataCorp. (2015). *Stata Glossary and Index: Release 14*. College Station, TX: StataCorp LP.

Strauss E, Sherman EMS, Spreen O. 2006. *A Compendium of Neuropsychological Tests: Administration, Norms, and Commentary*, 3rd edition. Oxford University Press: Oxford.

Summerfield M, Freidin S, Hahn M, Li N, Macalalad N, Mundy L, Watson N, Wilkins R, Wooden M. 2016. *HILDA USER Manual - Release 14*. Faculty of Business and Crommerce, The University of Melbourne. Accessed 4 December 2016. Available from URL: http://www.melbourneinstitute.com/hilda/doc/doc_hildamanual.html

Virtanen M, Singh-Manoux A, Ferrie JE, Gimeno D, Marmot MG, Elovainio M, Jokela M, Vahtera J, Kivimäki M. 2009. Long working hours and cognitive function: The Whitehall II study. *American Journal of Epidemiology* **169**(5): 596–605.

DOI: 10.1093/aje/kwn382

Watson N, Wooden M. 2013. Adding a top-up sample to the Household, Income and Labour Dynamics in Australia Survey. *Australian Economic Review* **46**(4): 489–498. DOI: 10.1111/1467-8462.12027

Wooden M, Freidin S, Watson N. 2002. The Household, Income and Labour Dynamics in Australia (HILDA) Survey: Wave 1. *Australian Economic Review* **35**(3): 339–348. DOI: 10.1111/1467-8462.00252

Wooden M. 2013. The measurement of cognitive ability in wave 12 of the HILDA Survey. HILDA Project Discussion Paper no. 1/13, Melbourne Institute of Applied Economic and Social Research, The University of Melbourne. Accessed 7 December 2016. Available at the following URL:

https://www.melbourneinstitute.com/downloads/hilda/Bibliography/Hilda_Discussion_Papers/hdps113.pdf

Wooden M, Mackinnon A, Rodgers B, Windsor T. 2012. The development of cognitive ability measures in the HILDA Survey. HILDA Project Discussion Paper no. 1/12, Melbourne Institute of Applied Economic and Social Research, The University of Melbourne. Accessed 7 December 2016. Available at the following URL:

https://www.melbourneinstitute.com/downloads/hilda/Bibliography/HILDA_Technical_Papers/htec112.pdf

Wooldridge J. 2010. *Econometric Analysis of Cross Section and Panel Data*, 2nd edition, MIT Press: Cambridge.

Table I: Australian Age Pension Eligibility Age and the Sample Distribution

Birth Cohort	Males		Females	
	Pension eligibility age	Sample	Pension eligibility age	Sample
Before 1 July, 1935	65	9.3%	60	10.5%
1 July, 1935 to December 31, 1936	65	2.7%	60.5	2.4%
1 January, 1937 to 30 June, 1938	65	1.2%	61	1.6%
1 July, 1938 to December 31, 1939	65	2.9%	61.5	2.9%
1 January, 1940 to 30 June, 1941	65	1.5%	62	1.9%
1 July, 1941 to December 31, 1942	65	3.6%	62.5	3.2%
1 January, 1943 to 30 June, 1944	65	1.7%	63	2.1%
1 July, 1944 to December 31, 1945	65	4.1%	63.5	3.7%
1 January, 1946 to 30 June, 1947	65	2.7%	64	2.7%
1 July, 1947 to December 31, 1948	65	4.4%	64.5	4.5%
1 January, 1949 to 30 June, 1952	65	6.8%	65	6.7%
1 July 1952 to 31 December 1953	65.5	5.6%	65.5	5.0%
1 January 1954 to 30 June 1955	66	1.9%	66	2.7%
1 July 1955 to 31 December 1956	66.5	5.5%	66.5	5.8%
From 1 January 1957	67	46.2%	67	44.5%
Total		100.0%		100.0%
Total sample size		3174		3698

Source: For pension eligibility ages: see Atalay and Barrett (2015), p. 73, Table 1, and Commonwealth of Australia (2009), p. 9. Sample proportions in each group are computed by the author using data from Wave 12 of the HILDA Survey.

Table II: Descriptive Statistics

	Males (obs.=3174)				Females (obs.=3698)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
BDSscore	7.19	2.60	0	14	7.22	2.54	2	14
SDMscore	43.66	12.26	0	95	46.39	12.82	2	104
NART25score	14.46	5.30	0	24	14.67	4.83	0	24
Working hours	27.21	22.61	0	80	16.86	18.64	0	70
Working hours-squared	1251.31	1258.44	0	6400	631.59	873.10	0	4900
Age	57.88	12.35	40	94	58.36	12.72	40	100
Age-squared/100	35.02	15.19	16	88.36	35.68	15.83	16	100
School years 7–10	0.45	0.50	0	1	0.48	0.50	0	1
School years 11 and over	0.53	0.50	0	1	0.50	0.50	0	1
University	0.30	0.46	0	1	0.28	0.45	0	1
Technical college	0.27	0.44	0	1	0.17	0.37	0	1
Other school	0.10	0.30	0	1	0.16	0.37	0	1
Non-indigenous origin	0.99	0.12	0	1	0.98	0.13	0	1
Married	0.67	0.47	0	1	0.57	0.49	0	1
Interview Sunday	0.09	0.28	0	1	0.07	0.26	0	1
Interview Saturday	0.13	0.34	0	1	0.12	0.33	0	1
Number of dependent children	0.59	1.02	0	7	0.52	0.94	0	7
Parent is still alive	0.52	0.50	0	1	0.51	0.50	0	1
Ownhouse	0.81	0.39	0	1	0.81	0.40	0	1
Work experience	35.26	10.51	0	72	26.01	11.86	0	72
Inner regional	0.27	0.44	0	1	0.28	0.45	0	1
Outer regional	0.13	0.33	0	1	0.11	0.32	0	1
Remote	0.01	0.10	0	1	0.01	0.10	0	1
Very remote	0.00	0.04	0	1	0.00	0.04	0	1
Age *minus* Aged pension eligibility age	-8.18	13.18	-27	29	-6.59	15.12	-27	40
Squared of (Age *minus* Aged pension eligibility age)	240.60	220.43	0	841	271.93	238.57	0.25	1600
Interview July or August	0.45	0.50	0	1	0.46	0.50	0	1

Source: Authors' calculations using data from Wave 12 of the HILDA Survey.

Table III: Current Employment Status by Age and Gender

	Full-time 35 hours and more	Part-time 34 hours and less	Non participants/ Unemployed	Total Sample Size
Males				
Aged 40–54	83.6%	7.0%	9.4%	1467
Aged 55–69	44.4%	17.1%	38.6%	1089
Aged 70 and over	2.9%	5.5%	91.6%	618
Total	54.4%	10.1%	35.4%	3174
Females				
Aged 40–54	41.5%	38.9%	19.6%	1647
Aged 55–69	22.2%	24.1%	53.7%	1284
Aged 70 and over	0.7%	3.5%	95.8%	767
Total	26.3%	26.4%	47.2%	3698

Source: Authors' calculations using data from Wave 12 of the HILDA Survey.

Table IV: Check of the exclusion restriction variables

Dependent variable	Working hours	
	Males	Females
	(1)	(2)
Age *minus* Aged pension eligibility age	-16.963 ***	-4.393 **
	[2.740]	[2.151]
Squared of (Age *minus* Aged pension eligibility age)	-0.801 ***	0.079 **
	[0.137]	[0.036]
Interview July or August	-1.604 **	-1.767 **
	[0.797]	[0.832]
Sample size	3174	3698
F-test H_0: the coef. on the exclusion restriction variables are jointly zero	14.95 ***	7.28 ***

Notes:

1) *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

2) The models are estimated using a Tobit estimator. Figures reported in square brackets are robust standard errors adjusted for heterogeneity.

3) The first step models reported also include the explanatory variables (excluding the variables related to working hours) that are reported in Table V. Coefficient estimates associated with these control variables are not reported.

Table V: Impacts of Working hours on Cognitive Skills Estimated Using an IV Estimator

Variables	Males			Females		
	(1A)	(1B)	(1C)	(2A)	(2B)	(2C)
	BDSscore	SDMscore	NART25score	BDSscore	SDMscore	NART25score
Working hours-squared	-0.003 ***	-0.015 ***	-0.004 **	-0.003 *	-0.005	-0.006 **
	[0.001]	[0.005]	[0.002]	[0.002]	[0.006]	[0.003]
Working hours	0.147 **	0.779 ***	0.182 *	0.133 **	0.314	0.255 **
	[0.061]	[0.227]	[0.099]	[0.067]	[0.258]	[0.115]
Age-squared/100	-0.027	-0.265 *	-0.104 *	-0.110 ***	-0.675 ***	-0.188 ***
	[0.032]	[0.138]	[0.060]	[0.029]	[0.114]	[0.051]
Age	0.012	-0.146	0.192 **	0.141 ***	0.384 **	0.331 ***
	[0.049]	[0.197]	[0.083]	[0.041]	[0.154]	[0.069]
School years 7–10	0.663 **	5.219 ***	2.663 ***	0.775 ***	4.918 ***	4.326 ***
	[0.266]	[1.259]	[0.644]	[0.293]	[1.334]	[0.565]
School years 11 and over	1.378 ***	9.424 ***	6.076 ***	1.288 ***	7.473 ***	6.707 ***
	[0.277]	[1.291]	[0.655]	[0.303]	[1.366]	[0.580]
University	0.928 ***	3.425 ***	3.460 ***	0.771 ***	1.128 **	3.561 ***
	[0.150]	[0.539]	[0.231]	[0.152]	[0.558]	[0.244]
Technical college	-0.035	0.390	0.315	-0.159	0.292	0.509 **
	[0.130]	[0.514]	[0.232]	[0.142]	[0.532]	[0.252]
Other school	0.296 *	1.772 ***	0.906 ***	-0.024	-0.113	0.783 ***
	[0.174]	[0.685]	[0.314]	[0.128]	[0.470]	[0.224]
Non-indigenous origin	0.930 **	2.358	1.392 **	0.397	1.656	1.388 **
	[0.409]	[1.517]	[0.648]	[0.301]	[1.193]	[0.566]
Married	0.183	1.641 ***	0.160	-0.031	0.474	-0.195
	[0.120]	[0.478]	[0.215]	[0.097]	[0.371]	[0.167]
Interview Sunday	-0.075	0.918	0.712 **	0.067	0.137	0.566 *
	[0.192]	[0.751]	[0.316]	[0.210]	[0.770]	[0.329]
Interview Saturday	0.033	0.320	0.545 **	0.133	-0.237	0.450 **
	[0.160]	[0.583]	[0.254]	[0.134]	[0.515]	[0.223]
Number of dependent children	0.137 *	0.610 **	0.228 *	0.061	0.495	0.045
	[0.078]	[0.287]	[0.128]	[0.091]	[0.344]	[0.148]
Parent is still alive	0.292 **	0.863	0.368	0.075	0.961 **	0.044
	[0.147]	[0.542]	[0.230]	[0.121]	[0.430]	[0.202]
Ownhouse	0.124	0.959 *	0.557 **	0.030	2.000 ***	0.657 ***
	[0.142]	[0.555]	[0.250]	[0.138]	[0.512]	[0.240]
Work experience	0.005	0.115 **	0.005	0.000	0.071 ***	0.014
	[0.011]	[0.048]	[0.021]	[0.005]	[0.020]	[0.009]
Inner regional	0.144	-0.790	-0.667 ***	-0.082	-0.178	-0.319 *
	[0.133]	[0.510]	[0.220]	[0.104]	[0.401]	[0.174]
Outer regional	0.258	-1.234	-1.003 ***	-0.156	-0.577	-1.296 ***
	[0.198]	[0.776]	[0.326]	[0.138]	[0.486]	[0.233]
Remote	0.510	-0.322	-1.628 *	-0.105	-2.651	-0.912
	[0.490]	[1.879]	[0.853]	[0.444]	[1.684]	[0.852]
Very remote	0.118	12.187 ***	1.416	-0.215	0.084	1.285 *
	[1.207]	[4.671]	[2.839]	[0.849]	[4.348]	[0.768]
Constant	4.549 ***	41.679 ***	-0.593	0.949	33.741 ***	-7.400 ***
	[1.701]	[6.576]	[2.718]	[1.414]	[5.318]	[2.360]
Sample size		3174			3698	
Log likelihood	-7765	-11992	-9366	-8765	-13616	-10676
F-test H_0: all the coefficients except the constant are jointly zero	16.20 ***	99.38 ***	72.33 ***	13.48 ***	133.8 ***	72.48 ***
Working hours-cubic	-0.036	-0.075	-0.053	-0.051	-0.036	0.021
	[0.026]	[0.078]	[0.038]	[0.163]	[0.338]	[0.137]
Cragg-Donald Wald F statistic for weak instruments		16.45			13.77	

Notes:

1) *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

2) These models are estimated by instrumental variable estimation. Figures reported in square brackets are robust standard errors adjusted for heterogeneity.

3) The Cragg-Donald Wald F statistic is computed using the "ivreg2" command in STATA 14.

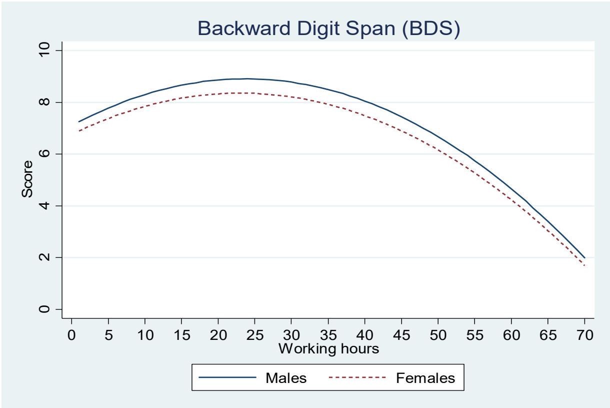
Table VI: Proportion of the Sample Above the Threshold and Working "Too Much"

	Males		Females	
	Proportion of the Sample Working More than the Threshold	Proportion of the Sample Working "Too Much"	Proportion of the Sample Working More than the Threshold	Proportion of the Sample Working "Too Much"
BDSscore	59.0%	21.0%	40.0%	7.9%
SDMscore	57.7%	11.1%	33.2%	1.6%
NART25score	59.1%	28.1%	40.0%	5.8%

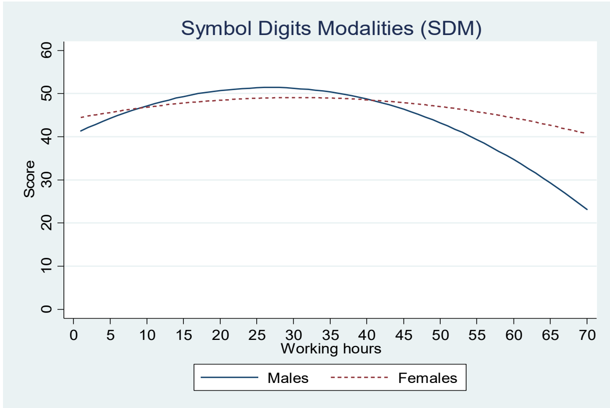
Source: Authors' computations based on the estimated results in Table V and data from Wave 12 of the HILDA survey.

Figure 1 : Estimated impacts of working hours on cognitive skills

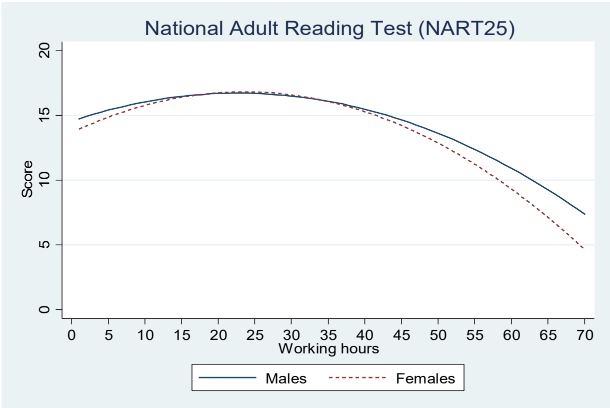
Panel A



Panel B



Panel C



Note: The fitted values of these scores are computed using the estimated coefficients reported in Columns (1A)–(2C) in Table V where all variables except *Working hours-squared* and *Working hours* are evaluated at their sample mean values.

Appendix I: Definitions of Variables

Name	Definition
BDSscore	The question consists of seven levels. At each level the respondent has a maximum of two trials. When the respondent gets the answer correct on the first trial he/she is awarded a score of two, and moves on to the next level. When the respondent's answer on the first trial is incorrect, he/she moves onto the second trial. If his/her response on the second trial is correct, he/she is awarded a score of one and moves on to the next level. When both his/her responses at the same level are incorrect, he/she is awarded a score of zero and this test is finished at that point. The sum of the scores at each level is the BDS score
SDMscore	The number of items correctly matched within a 90 second time interval.
NART25score	The number of words the respondent correctly pronounces.
Working hours	The number of usual or average working hours per week the respondent works.
Working hours-squared	=(Working hours)^2
Age	Respondent's age in years at the time of the survey
Age-squared/100	=(The squared of Age)/100
School years 7–10 (benchmark: the respondent's highest years of school completed are under 7)	0–1 dummy variable taking the value unity if the respondent's highest years of school completed are between 7 and 10, and 0 otherwise.
School years 11 and over (benchmark: the respondent's highest years of school completed are under 7)	0–1 dummy variable taking the value unity if the respondent's highest years of school completed are 11 and over, and 0 otherwise.
University (benchmark: the respondent did not obtain post-school qualification)	0–1 dummy variable taking the value unity if an educational institution where the respondent obtained his/her highest post-school qualification is a University, Teachers' college/College of Advanced Education, Institute of Technology, and 0 otherwise.
Technical college (benchmark: the respondent did not obtain post-school qualification)	0–1 dummy variable taking the value unity if an educational institution where the respondent obtained highest post-school qualification is Technical college/TAFE/College of Technical and Further Education , and 0 otherwise.
Other school (benchmark: the respondent did not obtain post-school qualification)	0–1 dummy variable taking the value unity if an educational institution where the respondent obtained highest post-school qualification is other organizations, and 0 otherwise.
Non-indigenous origin	0–1 dummy variable taking the value unity if the respondent is *not of* Aboriginal or Torres Strait Islander origin, and 0 otherwise.
Married	0–1 dummy variable taking the value unity if the respondent is currently married, and 0 otherwise.
Interview Sunday	0–1 dummy variable taking the value unity if interview date is Sunday, and zero otherwise.
Interview Saturday	0–1 dummy variable taking the value unity if interview date is Saturday, and zero otherwise.
Number of dependent children	The number of children who reside with the parent or guardian and who are aged 0 to 24.
Parent is still alive	0–1 dummy variable taking the value unity if the respondent's parent is still alive, and zero otherwise.
Ownhouse	0–1 dummy variable taking the value unity if the respondent owns his/her own house or is currently paying off a mortgage, and zero otherwise.
Work experience	=Total years the respondent is(was) in paid work
Inner regional	0–1 dummy variable taking the value unity if the respondent lives in inner regional Australia, and 0 otherwise.
Outer regional	0–1 dummy variable taking the value unity if the respondent lives in outer regional Australia, and 0 otherwise.
Remote	0–1 dummy variable taking the value unity if the respondent lives in remote Australia, and 0 otherwise.
Very remote	0–1 dummy variable taking the value unity if the respondent lives in very remote Australia, and 0 otherwise.
Age *minus* Aged pension eligibility age	=(Respondent's age in years at the time of the survey)-(Aged pension eligibility age)
Squared of (Age *minus* Aged pension eligibility age)	=(Age minus Aged pension eligibility age)^2
Interview July or August	0–1 dummy variable taking the value unity if the respendent is interviewed in July or August, and zero otherwise.