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 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 model for cognitive ability includes 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 non-linearity in the effect of working hours on cognitive functioning. For working hours up to around 25 hours a week, an increase in working hours has a positive impact on cognitive functioning. However, when working hours exceed 25 hours per week, an increase in working hours has a negative impact on cognition. These results suggest that people in old age could maintain their cognitive ability by working in a part-time job such as 20–30 working hours per week. Interestingly, there is no statistical difference in the effects of working hours on cognitive functioning between men and women.

Keywords: cognitive ability, endogeneity, retirement, working hours
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1. Introduction

Maintaining a sustainable social security system in the era of an ageing population is a key political challenge facing many governments. A delay in the retirement age is an obvious policy option to deal with some of the problems generated by an ageing population, and many countries have already increased their retirement ages by delaying the age for which people are eligible to start receiving 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 working provides (Potter et al., 2008; Small, 2002). The relationship between retirement and cognitive functioning has attracted much attention in recent years. The effects of work on cognitive functioning in later life are a contentious issue. Recent studies have not reached consensus on whether the so called ‘use it or lose it’ hypothesis is valid. After controlling for the endogeneity of retirement, Mazzonna and Peracchi (2012) and Rohwedder and Willis (2010) found that there was a significant and negative effect of retirement on cognitive skills, while Coe and Zamarro (2011) did not find such a causal effect. Bonsang et al. (2012) found that the effects of retirement on cognitive function appeared with a lag, and concluded that there were positive externalities of a delayed retirement for older individuals.

Although these previous studies provide important insights into the relationship retirement and cognitive functioning, these studies focus on the impact of retirement, but not on quality or quantity of work. 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 task can cause fatigue and stress which potentially damage cognitive functions. Thus, the degree of intellectual stimulation of work may depend on the required task and working hours, that is, the quality and the quantity of work. There are number of studies which examine the effects of the quality of work (job type and job task) on cognitive functioning (Kajitani et al., 2014; Schooler et al., 1999; Bosma et al., 2003; Potter et al., 2008; Finkel et al., 2009; Marquié et al., 2010; Van der Elst et al., 2012; Gow et al., 2014; Smart et al., 2014).

However, there seem to be extremely 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, Virtanen et al. (2009) do not compare the level of cognitive skills for workers with that of 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 required to examine the impact of working hours on cognitive functioning among middle-aged and older adults.

What are the channels in which labor hours affect cognitive functioning? One of the channels is stress (physical and/or psychological). Previous studies indicate the link between stress and cognitive functioning. Medical research suggests that stress affects cognitive function. 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 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. Cottini and Lucifora (2013) also find that long working hours increase stress. Thus, although engaging in work 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.

In this paper, we focus not on labor market participation (the extensive margin), but on working hours (the intensive margin). We examine the causal impact of working hours on cognitive functioning for middle-aged and older adults using a cross section sample from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. We deal with the potential endogeneity of decisions on working hours by using the instrumental variable estimation technique. One potential problem in using working hours as the variable of interest is that the working hours are left censored, that is, for individuals who are retired or unemployed, working hours are treated as zero. In order to take account of these zero values in the working hours, we apply a Tobit model when implementing instrumental variable approach.

Our empirical evidence shows that there is non-linearity in the effects of working hours on cognitive functioning. When working hours are less than around 25 hours a week, working hours have a positive impact on cognitive functioning. However, when working hours are more than 25 hours per week, working hours have negative impacts on cognition. These results suggest that peoples in old age could maintain their cognitive ability by working in a part-time job that requires them to work around 20–30 hours per week. In addition, 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 non-linearity in the effects of working hours on cognitive functioning, we consider the following model:

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

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 respondent's age, age squared, dummy variables which indicate his/her years of education, dummy variable which indicates the type of his/her qualification. We also include a dummy variable which takes 1 if the respondent has a spouse and 0 otherwise. This variable is included because communications and interactions with other family members may prevent decline in cognitive functioning. u_i is an error term, and the subscript i refer to the ith individual. The coefficients α_1 and α_2 capture the non-linear effect of the 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 $WH_i = \alpha_2/(2\alpha_1)$.

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 (leisure is a normal good), the impact of wage rate 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.

The standard two stage least squares (2SLS) procedure is to find instruments which indicate the factors of labor demand or the factors which is related to their 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 (i.e. retirees report 0 working hours). Rather than directly using variables which correlate with labor hours, but do not correlate with cognitive functioning, we use these variables for creating the fitted values for *squared of working hours* and *working hours* as instruments. We consider the following model to explain the working hours: First, the following equation is estimated:

$$\begin{aligned} WH_i^* = {} & \gamma_1 Vacancy\ rate_i + \gamma_2 Inter\ regional_i + \gamma_3 Outer\ regional_i + \gamma_4 Remote_i \\ & + \gamma_5 Very\ remote_i + \gamma_6 Number\ of\ dependent\ children_i \\ & + \gamma_7 Parent\ is\ still\ alive_i + \gamma_8 Other\ public\ benefits_i \\ & + \gamma_9 Australian\ citizen_i + \gamma_{10} Work\ experience_i + \gamma_{11} Own\ house_i \\ & + X_i\delta + e_i \qquad (2), \end{aligned}$$

$$\begin{aligned} WH_i &= 0 && \text{if } WH_i^* \leq 0 \\ &= WH_i^* && \text{if } 0 < WH_i^*, \end{aligned}$$

where WH_i^* denotes an unobserved latent variable which is connected to the observed working hours WH_i. $Vacancy\ rate_i$ is the job vacancy over the number of employed persons in the state where individual *i* lives. $Inter\ regional_i$, $Outer\ regional_i$, $Remote_i$, and $Very\ remote_i$ are 0–1 dummy variables taking the value unity if the respondent lives in the relevant area, respectively. These variables are designed to capture factors related to labor demand. On the other hand, $Number\ of\ dependent\ children_i$ denotes the number of dependent children under the age of 24 years old in his/her household, $Parent\ alive_i$ indicates whether his/her father or mother still alive, and $Other\ public\ benefits_i$ indicates whether he/she receives public payment except the Age Pension. $Australian\ citizen_i$ indicates whether the respondent is an Australian citizen, $Work\ experience_i$ is the number of years of work experience the respondent has, and $Own\ house_i$ indicates whether the respondent owns his/her house., These variables are designed to capture the factors which impact on the labor supply of the respondent, but not on their cognitive functioning. X_i is the same vector of control variables as 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 the retiree or the unemployed, we observe his/her working hours per week as zero. Therefore, we estimate this model with left censoring using the Tobit technique. Since it is well known that the labor supply behavior of men and women are quite different, both equations (1) and (2) are estimated for men and women separately for men and women.

First, we estimate the parameters in equation (2) using a Tobit estimator to obtain estimates of the parameters of γ_k $(k = 1, \cdots, 11)$ and δ, $\widehat{\gamma_k}$ and $\hat{\delta}$, respectively. From equation (2), the conditional expectations of WH_i can be computed as

$$E(WH_i \,|Z_i) = \Phi\left(\frac{Z_i\varepsilon}{\sigma}\right) Z_i\varepsilon + \sigma\phi\left(\frac{Z_i\varepsilon}{\sigma}\right) \qquad (3).$$

Where Z_i is the vector of regressors in (2), ε is the vector of parameters in (2), $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution function, and $\phi(\cdot)$ is the probability distribution function (see Greene 2008, p. 871). With estimates of the parameters of equation (2), this conditional expectation can be estimated. After that, we use this estimate of the conditional expectation of WH_i : $\widehat{WH_i}$ and $\widehat{WH_i}^2$ 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 the "Household, Income and Labour Dynamics in Australia (HILDA) Survey." The HILDA Survey which is conducted by the Melbourne Institute of Applied Economics and Social Research is a broad social and economic longitudinal survey. Since 2001, the HILDA Survey has asked Australian respondents about their economic and subjective well-being, family structures and labor market dynamics. Household included in the survey were selected using a three-stage approach. 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 Wave 11. One aim of this replenishment was to provide better coverage of migrants for inclusion in the HILDA Survey.[2]

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

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

the HILDA Survey. Wave 12 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). These measures were selected survey by following the evaluation results of pilot test for the Wave 12 survey. We use BDS, SDM and MART25 scores as measures of the 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 single-digit numbers, the respondent is required to repeat those strings in reverse order. The longest sequence administered is eight digits. In the BDS test, questions are divided into eight 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 one 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 16 and the minimum possible score is zero. *BDSscore* denotes the respondent's score on the BDS test. 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.[3] *SDMscore* is the respondent's score of SDM and is defined as the number of items correctly matched within a 90 second time interval. NART25 is a reading test for providing a measure of mainly crystallized intelligence. In the NART25 test, the respondent is required to correctly read 50 irregularly spelled words which are listed roughly in order of difficulty. *MART25score* is his/her score of MART25 and is also defined as the number of words correctly pronounced.

Table I shows descriptive statistics on all the variables used in the analysis.[4] The sample is restricted to individuals who meet the following criterion: (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 an outlier; and (v) information on all the relevant variables is available. In our sample, the maximum values of *BDSscore, SDMscore, and MART25score are* 14, 104 and 24, respectively. *Working hours* is the respondent's usual hours of working per week. The mean values of *Working hours* for males and females are 26.92 and 16.60 respectively.

[Table I around here]

[3] Strauss et al. (2006) provides details of the SDM test.
[4] The definitions of all the variables are summarized in the Appendix Table I.

Table II describes the percentage of the respondents by the current employment status, gender and age group. 84.1% of males aged 40–54 work full-time (35 hours and over), 6.8% of them work part-time (34 hours and less) and 9.1% of them are not working. On the other hand, although 43.6% of males aged 55–69 still work full-time, 17.1% of them work part-time and 39.2% of them are not working. Moreover, 8.3 % of males aged 70 and over continue to work in some way. For females, 41.2% of those aged 40–54 and 21.6% of those aged 55–69 work full-time, respectively, and 39.3% of those aged 40–54 and 24.0% of those aged 55–69 work part-time, respectively.

[Table II around here]

Are these differences of working hours associated with cognitive ability? Figure 1 shows the distribution of the cognitive ability measures for males and females for three groups: respondents whose working hours are 35 hours per week or more; those whose working hours are greater than zero but 34 hours per week or less; and those who are not working. Panels A1 and B1 in Figure 1 show the BDS score distributions which are estimated by kernel density estimation for the three groups for males and males, respectively. The panels show that the BDS score distributions for those who are not working are located slightly to the left of the BDS score distributions for those who work full-time or part-time. Moreover, comparing the distributions of the SDM score among these three groups in Panels A2 and B2, the distributions for those who are not working are clearly located to the left of the SDM score distributions for those who work full-time or part-time. In Panels A3 and B3, the distributions of the NART25 scores for males and females who are not working are also located to the left of the other NART25 score distributions.

[Figure 1 around here]

A comparison of the distributions of cognitive ability between those who work full-time and those who work part-time suggests that there are some differences between them. Comparing the distributions of SDM score for males between full-time and part-time workers presented in Panel A2 indicates that the distribution for males who work part-time is located to the left of the distribution for males who work full-time. In contrast, the NART25 score distribution for males who work full-time is located to the left of the NART25 sore distributions for males who work part-time (in Panel A3). These differences indicate that each measure may capture different dimensions of cognitive ability. For females, the distribution of SDM score for full-time workers is slightly located to the right of the distribution of SDM score for part-time workers(in Panel B2), while there are not clear differences between full-time work and part-time work in both the distributions of BDS and the NART25 scores (Panels B1 and B3).

Thus, we can observe that there appears to be some differences in the locations of the distributions of cognitive ability among the three groups (full-time, part-time and not working). An important issue is whether these differences come from differences in working hours *per se*. In the next section, estimation results for the impact of working hours on the BDM, SDM and NART25 scores adjusted for the other covariates are presented, respectively.

4. Estimation results

All regression results reported in this section are estimated using STATA version 13. Panel B in Table III presents estimates of the coefficients of the variables that are included in equation (2) but not equation (1), that is, the variables that are used to generate exclusion restrictions. The estimation results in Columns (1) and (2) in Panel B indicate that the exclusion restriction variables are jointly statistically significant in explaining working hours for males (F-statistics is 55.94) and females (F-statistic is 64.23). The rural area dummies (*Outer regional*, *Remote* and *Very remote*), *Number of dependent children* and *Work experience* have significantly positive impacts on the working hours of males. In contrast, males who receive public benefits excluding the Age Pension (*Other public benefits*) significantly reduce their working hours compared to males who do not receive these benefits. In Column (2) in Panel B, while the exclusion variables which indicate the factor of labor demand are statistically insignificant, *Number of dependent children* and *Other public benefits* are significantly negative impacts on hours of working for females. *Work experience* has a significantly positive impact on the working hours of females.

[Table III around here]

Panel A in Table III reports the results of estimating equation (1) taking account of the endogeneity of working hours. After controlling for the respondent's human capital and demographic variables, as shown in Columns (1)–(3), the coefficients of *Squared of working hours* are significantly negative and the coefficients of *Working* *hours* are also significantly positive for males. Moreover, for females, both the negative impacts of *Squared of working hours* and the positive impacts of *Working hours* reported in Columns (4)–(6) are statistically significant.

These results indicate that, for both males and females, the magnitude of the positive impact of working hours on their cognitive ability is decreasing until working hours reaches a threshold, and above that, 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. Crystallized intelligence tends to be maintained through occupational or cultural experiences. Assuming that hours of working are associated with degree of occupational experiences, working hours *per se* could be regarded as cognitive repair activities, while investments for repair activities may result in hours of working. Similarly, although fluid intelligence is subject to a decline as people get older, fluid intelligence could be also maintained by working in time closer to the threshold.

Then, where is the threshold? In other word, when does the impact of working hours on cognitive ability change from being positive to negative? In Figure 2, we calculate the magnitude of impacts of working hours on cognitive measures after controlling for other variables, using the estimated coefficients presented in Panel A of Table III. For men the peaks occur around 25 hours for BDS, 30 hours for SDM and 25 hours for NART25. For women the peaks occur a little earlier, around 22 hours for BDS, 27 hours for SDM and 24 hours for NART25. Moreover, Figure 2 also shows that the cognitive ability of those working extremely long hours can be lower than those who are not working. For example, the SDM score of those who are usually 60 hours per week is lower than the SDM score of those who are not working both for males and females (Panels A2). This suggests that longer working hours can lead to a deterioration of cognitive functioning. Figure 2 suggests that as working hours increase, females reach the peak earlier, and their cognitive test scores decline faster compared to male counter parts. We conducted tests if these visual differences are statistically significant. However, it is found that the coefficients of working hours and working hour squares are not statistically different from zero between two gender groups.

[Figure 2 around here]

The results presented in Table III and graphed in Figure 2 show that there is 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 for 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 middle age. Our results indicate that the part-time work is an effective way to maintain to cognitive functioning relative to retirement or unemployment.

5. Concluding remarks

We examined the causal impact of working hours on the cognitive ability of middle-aged and older aged males and females living in Australia using the Household Income and Labour Dynamics in Australia (HILDA) Survey dataset. The literature in this area is very limited. This study is unique in that we focused on extensive margin (labor participation) rather than intensive margin (working hours) and that we investigated the optimal working hours for 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 25-30 hours per week have a positive impact on cognition for males depending on the measure and up to 22 to 27 hours for females. After that, working hours have a negative impact on cognitive functioning. This indicates that the difference in working hours is an important factor for maintaining cognitive functioning in middle and older adults. In other words, in the middle and older age, working style as part-time work could be effective to maintain their cognitive ability. It is worth noting that our findings did not show any statistical gender difference in the effects of working hours on cognitive functioning. Previous studies on retirement and cognitive functioning indicate that increasing the qualifying age for pension can not only reduce the government social security expenditures but can potentially reduce the risk of cognitive deterioration. However, our study highlights that too much work can have adverse effects on cognitive functioning.

[Appendix Table I around here]

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Table I: Descriptive Statistics

	Male (obs.=2,965)				Female (obs.=3,502)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
BDSscore	7.21	2.60	0	14	7.23	2.53	2	14
SDMscore	43.83	12.07	0	95	46.41	12.74	2	104
MART25score	14.56	5.23	0	24	14.70	4.82	0	24
Working hours-squared/100	12.35	12.55	0	64	6.21	8.79	0	64
Working hours	26.92	22.60	0	80	16.60	18.59	0	80
Vacancy rate	1.45	0.36	0.9	2.45	1.43	0.35	0.9	2.45
Inner regional	0.27	0.44	0	1	0.28	0.45	0	1
Outer regional	0.13	0.34	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
Number of dependent children	0.59	1.02	0	7	0.52	0.94	0	7
Parent is still alive	0.51	0.50	0	1	0.50	0.50	0	1
Other public benefits	0.13	0.34	0	1	0.18	0.38	0	1
Australian citizen	0.94	0.23	0	1	0.95	0.21	0	1
Work experience	35.42	10.41	0	69.56	26.10	11.80	0	68
Ownhouse	0.82	0.39	0	1	0.81	0.39	0	1
Age-squared/100	35.16	15.08	16	88.36	35.85	15.70	16	100
Age	58.01	12.27	40	94	58.52	12.64	40	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	0.31	0	1	0.16	0.37	0	1
Non-indigenous origin	0.99	0.11	0	1	0.98	0.13	0	1
Married	0.67	0.47	0	1	0.58	0.49	0	1

Source: Authors' calculations using the HILDA Survey dataset.

Table II: 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
Male				
Aged 40–54	84.1%	6.8%	9.1%	1,345
Aged 55–69	43.6%	17.1%	39.2%	1,038
Aged 70 and over	2.6%	5.7%	91.8%	582
Total	53.9%	10.2%	35.9%	2,965
Female				
Aged 40–54	41.2%	39.3%	19.5%	1,535
Aged 55–69	21.6%	24.0%	54.4%	1,233
Aged 70 and over	0.7%	3.5%	95.8%	734
Total	25.8%	26.4%	47.8%	3,502

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

Table III: Estimated Results: The Impacts of Working hours on Cognitive skills

Panel A

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
	BDSscore	SDMscore	MART25score	BDSscore	SDMscore	MART25score
Working hours-squared/100	-0.206 **	-0.946 ***	-0.270 *	-0.369 ***	-1.323 **	-0.551 **
	[0.090]	[0.334]	[0.158]	[0.142]	[0.534]	[0.243]
Working hours	0.103 **	0.576 ***	0.135 *	0.163 ***	0.704 ***	0.269 ***
	[0.044]	[0.163]	[0.077]	[0.058]	[0.219]	[0.099]
Age-squared/100	-0.011	-0.322 ***	-0.054	-0.112 ***	-0.748 ***	-0.209 ***
	[0.028]	[0.122]	[0.056]	[0.025]	[0.100]	[0.045]
Age	-0.004	0.041	0.145 **	0.140 ***	0.522 ***	0.372 ***
	[0.036]	[0.147]	[0.068]	[0.033]	[0.128]	[0.056]
School years 7-10	0.638 **	5.921 ***	3.426 ***	0.757 **	5.305 ***	4.501 ***
	[0.262]	[1.292]	[0.625]	[0.302]	[1.308]	[0.572]
School years 11 and over	1.315 ***	10.055 ***	6.864 ***	1.288 ***	7.925 ***	6.925 ***
	[0.274]	[1.321]	[0.636]	[0.314]	[1.347]	[0.588]
University	0.924 ***	3.413 ***	3.532 ***	0.833 ***	1.533 ***	3.689 ***
	[0.140]	[0.493]	[0.225]	[0.144]	[0.540]	[0.224]
Technical college	-0.095	0.040	0.243	-0.149	0.376	0.593 **
	[0.123]	[0.478]	[0.229]	[0.145]	[0.548]	[0.255]
Other school	0.286 *	1.670 **	0.866 ***	-0.050	-0.140	0.877 ***
	[0.168]	[0.655]	[0.317]	[0.137]	[0.510]	[0.235]
Non-indigenous origin	0.781 **	2.262	1.464 **	0.346	2.505 *	1.660 ***
	[0.392]	[1.421]	[0.679]	[0.322]	[1.385]	[0.608]
Married	0.155	1.655 ***	0.137	-0.053	0.811 *	-0.036
	[0.110]	[0.422]	[0.201]	[0.107]	[0.414]	[0.181]
Constant	5.451 ***	36.383 ***	-0.186	1.102	29.245 ***	-9.130 ***
	[1.194]	[4.717]	[2.173]	[1.120]	[4.308]	[1.866]
Cragg-Donald Wald F statistic for weak instruments	25.22	25.22	25.22	20.31	20.31	20.31
Sample size	2,965	2,965	2,965	3,502	3,502	3,502
F-test H_0: all the coef. except the constant are jointly zero	-7023	-10897	-8610	-8395	-13063	-10121
Log likelihood	30.26 ***	187.2 ***	132.5 ***	23.83 ***	223.2 ***	121.0 ***

Panel B

	(1)	(2)
	Working hours	Working hours
Vacancy rate	1.038	0.552
	[1.125]	[1.322]
Inner regional	-0.431	-1.916 **
	[0.928]	[0.974]
Outer regional	2.391 *	1.553
	[1.347]	[1.369]
Remote	9.285 **	10.450
	[4.267]	[7.191]
Very remote	14.901 **	-7.754
	[6.933]	[9.368]
Number of dependent children	0.851 **	-1.292 ***
	[0.396]	[0.461]
Parent is still alive	2.747 ***	-0.158
	[1.045]	[1.109]
Other public benefits	-24.660 ***	-19.415 ***
	[2.100]	[1.465]
Australian citizen	0.170	0.867
	[1.600]	[2.077]
Work experience	2.037 ***	1.092 ***
	[0.139]	[0.065]
Ownhouse	0.257	-0.479
	[1.124]	[1.210]
F-test H_0: the coef. on these variables are jointly zero	55.94 ***	64.23 ***

Notes:

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

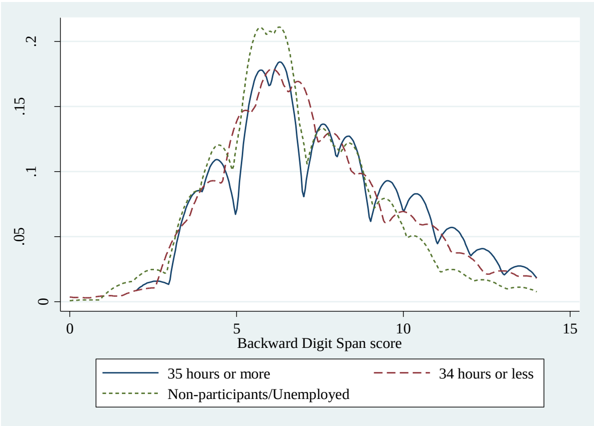
2) The models in Panel A are estimated by instrumental variable estimation, and the models in Panel B are estimated by the Tobit method. Figures reported in square brackets are standard errors adjusted for heterogeneity.

3) The Cragg-Donald Wald F statistic reported in Panel A is computed using the "ivreg2" command in STATA 13.

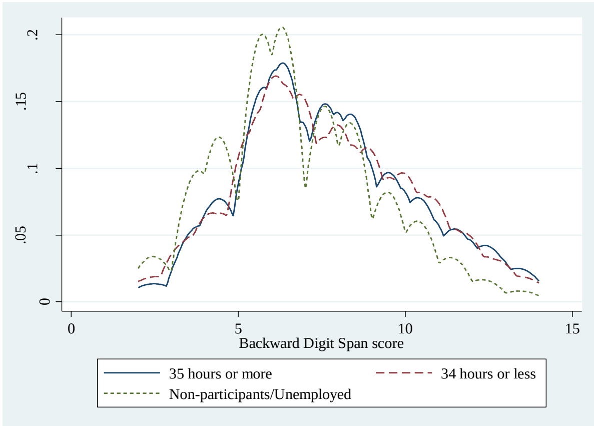
4) The first step models reported in Panel B also include the same variables in Panel A. Estimates associated with these variables are not reported.

Figure 1 : Kernel estimates of the the disribution of cognitive skills by working hours

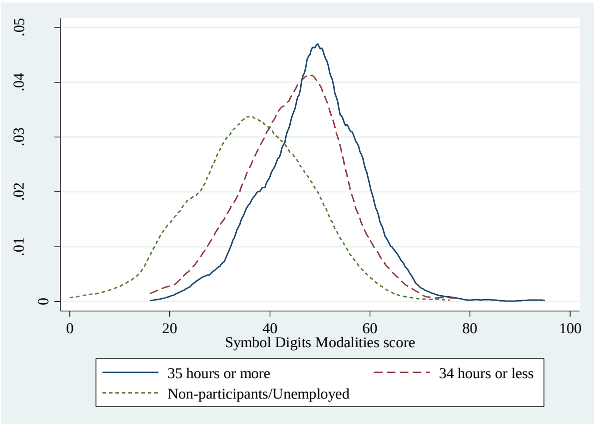
Panel A1: Backward Digit Span (male)



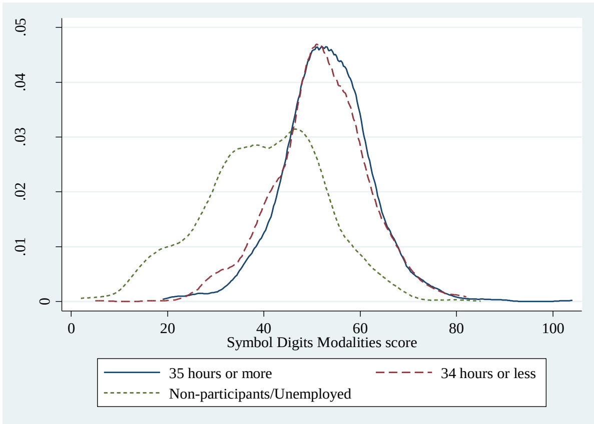
Panel B1: Backward Digit Span (female)



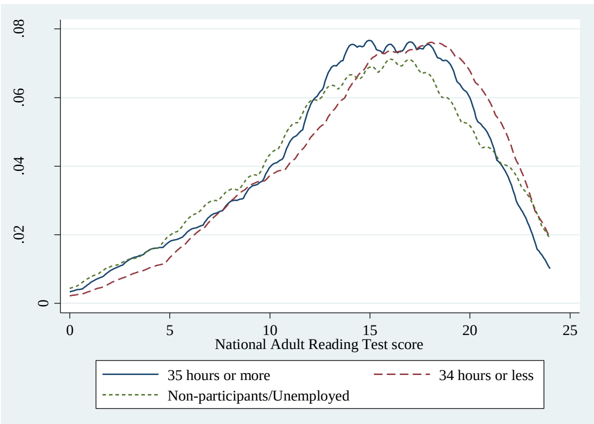
Panel A2: Symbol Digits Modalities (male)



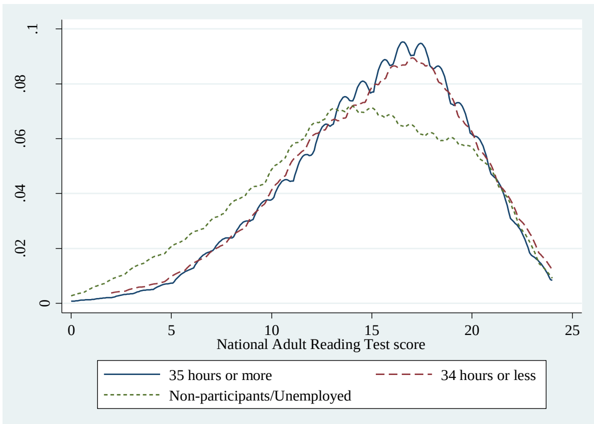
Panel B2: Symbol Digits Modalities (female)



Panel A3: National Adult Reading Test (male)



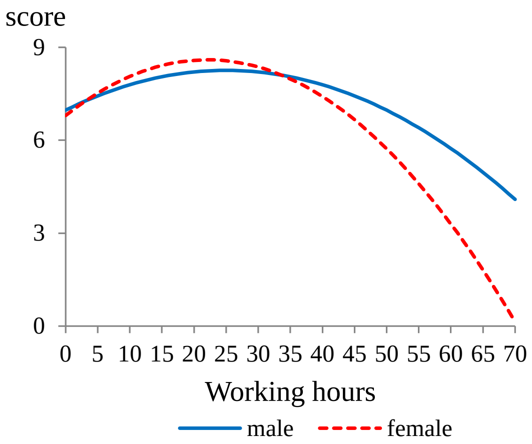
Panel B3: National Adult Reading Test (female)



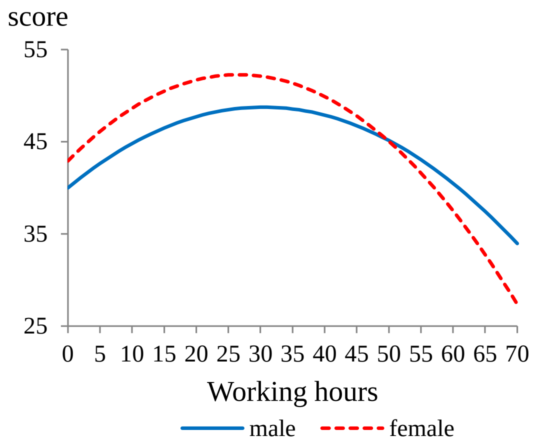
Source: Authors' calculations using the HILDA Survey wave 12.

Figure 2 : Estimated impacts of working hours on cognitive skills

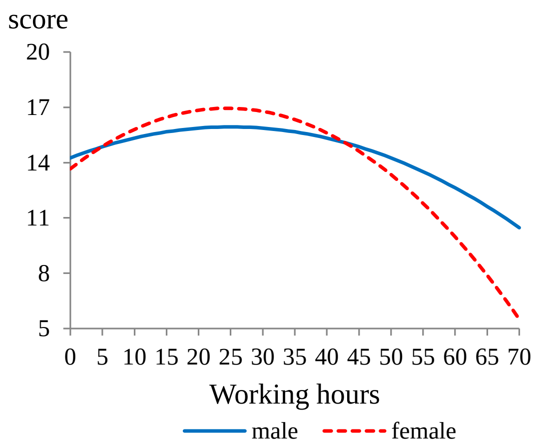
Panel A1: Backward Digit Span



Panel A2: Symbol Digits Modalities



Panel A3: National Adult Reading Test



Note: The fitted values of these scores are computed using the estimated coefficients reported in Panel A of Table III where all variables except *Working hours-squared/100* and *Working hours* are evaluated at their sample mean values.

Appendix I: Definitions of Variables

Name	Definition
BDSscore	The question consists of eight 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 award 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.
MART25score	The number of words the respondent correctly pronounces.
Working hours-squared/100	$(\text{Working hours})^2/100$
Working hours	The number of usual or average working hours per week the respondent works.
Vacancy rate	(Job vacancy/Employed)*100, where Job vacancy denotes the number of job vacancies in state where the respondent lives on November 2012 which are reported by the Australian Bureau of Statistics (ABS), and Employed denotes the number of total employed persons in the relevant state on November 2012 which are reported by the ABS.
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.
Number of dependent children	The number of the respondents' children who reside with the parent or guardian and who are aged under 15 years or aged 16–24 years and enrolled in full-time education.
Parent is still alive	0-1 dummy variable taking the value unity if either the respondent's father or his/her mother still alive, and 0 otherwise.
Other public benefits	0-1 dummy variable taking the value unity if the respondent receives any income from the government in the form of benefit, pension or allowance *except the age pension* , and 0 otherwise.
Australian citizen	0-1 dummy variable taking the value unity if the respondent is an Australian citizen, and 0 otherwise.
Work experience	Total years the respondent is(was) in paid work
Ownhouse	0-1 dummy variable taking the value unity if the respondent owns his/her own house or currently paid off mortgage, and 0 otherwise.
Age-squared/100	(The squared of Age)/100
Age	Squared of Respondent's age in years at the time of the survey
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 highest post-school qualification is 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* 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.